# INFORMATION TECHNOLOGY IN AGRICULTURE: THE VALUE OF IMPLEMENTING A WHOLE-CHAIN TRACEABILITY SYSTEM TO TRANSFER INFORMATION IN BEEF INDUSTRY AND USING EYE-TRACKING TECHNOLOGY TO IMPROVE CONJOINT ANALYSIS

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Abstract:
Information technology has been widely used in agricultural industries. This dissertation evaluates the benefits of two newly-developed information technologies, whole-chain traceability in the beef industry and eye tracking in the turfgrass industry.

Implementing a whole-chain traceability system (WCTS) in the beef industry may bring many benefits. Chapters II and III focus on the topic of estimating the value of information in a fragmented beef supply chain. The difficulty of transferring information in a fragmented supply chain as in the U.S. beef industry is that animals move through several stages of production and ownership, a price incentive for a specific attribute at the consumer level can be greatly diluted or even nonexistent at the producer level. The value of transferring valuable information, tenderness genetics and injection site information, in this research, and the optimal allocation of compensation to each supply chain participant that provides additional value, are estimated in Chapters II and III. Results indicate that implementing a whole-chain traceability system to transfer tenderness genetics and injection information brings extra profits to supply chain participants. But the value of benefit depends on the actual characteristics of operation actions.

Conjoint analysis is widely used in marketing and consumer research, as it indicates consumers' preferences on products/service. However, the conjoint analysis does not provide much information about the decision-making process. Eye-tracking technology, when combined with conjoint analysis, record consumers' eye movements. Eye movements are good behavioral indicators of visual attention and information acquisition. In Chapter IV, the impacts of including eye fixation data on estimated willingness-to-pay and scale of the variance in the conjoint analysis were studied. When including eye fixation in the logit models, the estimated willingness-to-pay for turfgrass attributes change, but in an uncertain direction. Including eye fixation data also influences the scale parameter. The longer attention received by one choice task, the smaller scale parameter is. Thus, longer fixation on one choice task indicates a more uncertain choice.

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# CHAPTER I

## INFORMATION TECHNOLOGY IN AGRICULTURE

Information technology has helped immensely in understanding the physical world and in exploiting that understanding to increase human welfare. Cox (2002, p.94) notes that some of the application of information technology to agriculture "can be grouped under the general heading of Precision Agriculture (or Precision Farming), which include applications to livestock production as well as the spatially-variable field operations made possible by the satellite Global Positioning System (GPS)." The concept of precision agriculture rose to prominence about three decades ago. A traditional view of precision agriculture is that it uses newly available technologies to improve application of fertilizers by varying rates and blends as needed within fields (Robert 2002). As Cox (2002) notes, though, the development of new technologies, has expanded the concept of precision agriculture to application to a variety of practices. Precision agriculture includes applying the information gathered to decision-making in agricultural production, as well as extending ability to control operation automatically (Cox 2002), and can be understood as a concept to reduce decision uncertainty (Schellberg et al. 2008). Use of precision agriculture thus increases the number of (correct) decisions per unit resource per unit time with associated net benefits (McBratney et al. 2005). With precision agriculture, the quantity and/or quality of products can be increased using the same or fewer inputs (McBratney et al. 2005; Schellberg et al. 2008).

Realization of precision agriculture needs the development of information technology. McBratney et al. (2005) suggest that the development of proper decision-support systems for implementing precision decisions remains a major stumbling block to adoption. With current information technology, new vistas have been opened for supporting agricultural crop and livestock management (Schellberg et al. 2008).

This work is composed of three studies that evaluate newly-developed information technologies applied to the beef and turfgrass industries:

1) Measure the value of transferring genetic information about beef tenderness through a multistage whole-chain traceability system from cow/calf producers to beef processors;
2) Measure the value of transferring information about multiple attributes – beef tenderness genetics and injection sites – through a multistage whole-chain traceability system from cow/calf producers to feedlots and beef processors;
3) Determine the improvement that can be obtained from using eye-tracking technology to interpret a conjoint analysis conducted for the turfgrass industry.

*An Overview of Each Study*

In Chapter II, the benefits and costs of implementing a whole-chain traceability system in recording and passing information about genetics that influence beef tenderness along a beef supply chain are estimated. Although beef consumers value beef tenderness and are willing to pay premiums for it, this market signal is not transmitted in the form of money incentives to those who can increase beef tenderness, the cow-calf producers. Even though cow-calf producers can select preferred genetics by using artificial insemination (AI) or natural breeding services (NBS) with carefully-selected breeding animals, they are not motivated to do that if they do not receive sufficient incentives. With a whole-chain traceability system, meat packers can use genetic information about the cattle slaughtered to reward individual cow-calf producers who provide more valuable genetics. In addition, implementing a whole-chain traceability system may save meat packers the expense of physical tests for meat tenderness.

In Chapter III, the study in Chapter II is extended from one product attribute in a two-stage supply chain to two attributes in a three-stage supply chain. The model developed expands models developed in the literature and provides a more realistic evaluation of value-added opportunities in a segmented supply chain, common in the beef industry. This chapter highlights a specific advantage of implementing a proprietary whole-chain traceability system, in which each participant can choose what information to share, and who to share it with. For example, if one can assume that beef tenderness is only influenced by genetics, cow-calf producers only need to share genetic information with meat processors, skipping over all intermediate stages. Similarly, meat packers need only reward cow-calf producers, skipping intermediate stages such as feedlots. Thus, the money incentives provided by meat packers are exactly the money incentives received by cow-calf producers, with feedlots receiving no incentives. In contrast, injection-site lesions may be caused by both cow-calf producers and feedlots. In this case, information about injection sites is relevant to more than two stages, so that information must be provided to each affected stage, and money incentives allocated across each stage.

The data used in these two traceability studies are from secondary, publicly available sources. For the first study, consumers' willingness-to-pay for tenderness, cattle carcass attributes, genetic frequencies, Warner-Bratzler shear force values, and costs of implementing a whole-chain traceability system are the data used, along with data on other costs. For the second study, results from the first study, injection-site lesion frequencies and costs, cattle carcass attributes, and separate traceability costs for each stage are the data used.

In Chapter IV, the effect of combining eye-tracking technology in conjoint analysis when studying consumers' buying decisions in purchasing turfgrass is measured. Conjoint analysis is a widely-using tool in exploring consumers' decision-making process on various products. But participants in conjoint analysis do not equally evaluate every piece of information given in one choice set, so the estimated attribute preference and willingness-to-pay may be biased. Eye-tracking technology can identify and record the eye movements for predefined area of interests when participants are analyzing conjoint tasks, thus allowing the investigator to measure attention given to each piece of information. The data used in this study is from an on-site survey with 32 respondents. Available fixation data include time to first fixation, total fixation duration, fixation counts, and total visit durations. Turfgrass attributes include "winter kill reduction", "shade tolerance", "drought tolerance", "saline tolerance", and "10% maintenance reduction".

# CHAPTER II

# MEASURING THE VALUE OF TRANSMITTING INFORMATION THROUGH A WHOLE-CHAIN TRACEABILITY SYSTEM: THE CASE OF GENETIC INFORMATION ABOUT BEEF TENDERNESS

## Introduction

Beef is one of the main meat sources for U.S. consumers. In 2015, total beef consumption in the U.S. was 24.8 billion pounds, with a retail equivalent value of $105 billion (USDA-ERS). Per capita consumption of beef in 2016 in the U.S. was 56.5 pounds (USDA 2016). Tenderness is an important attribute of beef, and consumers are willing to pay premiums for tender steaks ranging from $0.42/lb. to $7.35/lb. (Feuz et al. 2004; Gao, Schroeder, and Yu 2010; Loureiro and Umberger 2004; Lusk et al. 2001; Miller et al. 2001; Schroeder, Riley, and Fraisier 2008). Thus, there is potential for meat packers to increase profits by providing more tender meat cuts. While some beef supply chains are vertically integrated, allowing information about consumer demands to be specifically communicated, most beef production in the U.S. is marketed through segmented supply chains, in which ownership of animals is transferred at each stage of the production process. In such supply chains, market prices do not fully convey consumer preferences to producers. While the commonly used grid pricing system includes market-determined signals about general measures of quality, these are only partially correlated with the specific attribute of tenderness (Riley et al. 2009).

Information asymmetry between buyers and sellers in food supply chains can sometimes be overcome by vertical integration (Hennessy (1996). According to Ward (1997), though, the beef industry has a low degree of vertical integration and many barriers to overcome to develop vertically integrated systems. A possible way to reduce asymmetry and transfer desired information along beef supply chains is to implement a whole-chain traceability system (WCTS).

Many countries have introduced food traceability systems in an attempt to provide relevant information about the food process (Choe et al. 2009). A WCTS in the beef industry could potentially facilitate pricing for individual attributes such as tenderness since a WCTS could allow a segmented supply chain to transmit information as if the supply chain were vertically integrated (Bosona and Gebresenbet 2013; Crandall et al. 2013; Hobbs 2004). Here, we estimate the profitability of using a WCTS in a 3-stage supply chain to provide animals with more tender meat, determining whether the added value to producers justifies the cost of producing animals with more tender meat and participating in a WCTS.

**Background and Literature**

In the U.S. beef industry, grid pricing systems are commonly used. Grid pricing systems use market-determined base prices for average carcasses. For carcasses with qualities above or below the base, there are specified premiums and discounts (Schroeder, Riley, and Fraisier 2008). Even though grid pricing sends clearer market signals from the wholesale level to fed cattle level (Ward, Feuz, and Schroeder 1999), it does not fully consider consumer-valued attributes, such as tenderness (Riley et al. 2009). Riley et al. (2009) found that a tenderness-augmented price grid would increase fed cattle value by almost $5.00/cwt on average, relative to grid-pricing systems.

According to Schroeder, Riley, and Fraisier (2008) and Ward, Feuz, and Schroeder (1999), the beef industry is interested in moving toward a value-based marketing or pricing system, which should improve pricing efficiency. Value-based marketing and pricing mean that price and meat attributes are linked more accurately, which better communicates consumer demands to producers. However, value-based marketing and pricing are hard to achieve (Schroeder, Riley, and Fraisier 2008). Since the number of traded cattle to feedlots and meat packers is large, it could be very costly for them to differentiate cattle with specific attributes. A WCTS can make such differentiation more feasible, since attribute-related information can be transferred along the supply chain electronically at relatively low cost.

Quantifying the relationship between consumers' willingness-to-pay for tender beef and objective measures of tenderness, Schroeder, Riley, and Fraisier (2008) developed an equation of tenderness premium/discount as a function of Warner-Bratzler Shear Force (WBSF) measures. The estimated coefficient of WBSF was -46.1077, indicating that a 1-kg decrease in the WBSF is associated with an increase in tenderness premium of $46.1077/cwt.

Tenderness of beef cuts can be improved by selecting preferred genetics. Casas et al. (2006), Schenkel et al. (2006), and Van Eenennaam et al. (2007) found that cattle carrying specific genotypes produced more tender beef cuts than cattle carrying other genotypes, although there is some disagreement about which genotypes lead to more tender beef. Van Eenennaam et al. (2007) showed that specific genotype pairs are related to lower WBSF values of beef cuts, separate from feeding regimens and other factors. Thus, cow-calf producers may be able to increase the supply of cattle that would be more likely to produce more tender meat by selecting favorable genetics. Although feeding regimens may influence beef tenderness as well. According to Andersen et al. (2005), a decreasing rate of protein degradation leads to increased muscle growth and decreased meat tenderness. However, this article focuses on the impact of genetics on beef tenderness.

Even though consumers are willing to pay for more tender beef cuts, tenderness premiums are not transferred easily to up-stream supply chain participants such as cow-calf producers and cattle feeders. As a result, upstream participants have little incentive to improve beef tenderness. Instead, their incentive is to reduce costs rather than to increase value to processors.

Thus, although cow-calf producers can potentially select particular genotypes so that tenderness of beef cuts could be improved, their incentive to do so is muted by limited information flow through the segmented supply chain. Moreover, producers at other stages in the supply chain may prefer animals with other traits. For example, cattle feeders may prefer genetics that favor traits such as feed efficiency rather than tenderness.

Directing meaningful incentives to beef suppliers of desired traits is difficult in a segmented supply chain. If consumers are willing to pay a premium for tender beef products, such a premium would go to retailers, and then presumably to meat processors.[1] However, the cost of selecting genetics to produce more tender meat occurs mostly at the cow-calf producer level. Since cow-calf producers bear extra costs for selecting preferred genetics, if they are not compensated enough to cover costs, they may not be willing to do so. Correspondingly, although producers may know the genetic traits of the calves they produce, which could affect processors' profits, they have little ability to share this potentially valuable information with meat processors at any reasonable cost.

A WCTS could overcome this information asymmetry problem, and permit genetic information to be passed along the supply chain at low cost. An electronic-based traceability system involves two kinds of costs: initial investment costs and ongoing costs (Blasi et al. 2009;

[1] A way to translate consumer willingness to pay for tender meat into premiums to processors, such as branding "tender beef," would also be needed. This article does not address that aspect of the problem.

Chryssochoidis et al. 2009). According to Blasi et al. (2009) and Seyoum (2013), cow-calf producers would bear a proportionally higher cost per animal of implementing a WCTS than supply chain participants further downstream.

Traceability is an extended concept of animal identification, which was mainly used for animal ownership identification, or animal disease control; it is the ability to trace the history and activities of what is under consideration. Thakur and Hurburgh (2009) distinguish between tracing (backward), identifying the origin of the products used in a particular trade unit, and tracking (forward), following the downstream path of a particular trade unit in the supply chain. With a WCTS, meat packers can reward or penalize cow-calf producer for providing cattle with more or less tender meat cuts.

The objective of this article is to determine the extent to which a WCTS can increase profitability in a livestock supply chain by facilitating economic incentives for producers to take actions to improve tenderness of meat produced. The stylized beef supply chain modeled here is simpler than most segmented beef supply chains, but the analysis generates valuable insights.

**Conceptual Model**

We measure the profitability to beef producers at three stages of the beef supply chain – cow-calf producers, cattle feeders, and packers/processors – from fully using a WCTS system to improve beef tenderness. It is assumed that cattle move through normal market channels whether or not information is passed through a WCTS. In order to focus on the value of information flow, abstracting from the complications that could arise from imperfect price transmission across stages in the supply chain, we assume that price transmission across stages is perfect. It is assumed that each stage of the supply chain makes choices that maximize profit for the entire supply chain, in essence making choices as a vertically-integrated firm would. These simplifying assumptions imply that the results here are upper bound estimates of the value of information transmitted through a WCTS. Although many kinds of value-added information could be transferred across stages through a WCTS, here we estimate the increased profitability from beef production enterprises transferring information specifically about genetics related to beef tenderness.

This three-stage chain has several choices about information transfer in a WCTS. The cow-calf producer stage can choose the proportion $\lambda$ ($0 \leq \lambda \leq 1$) of cows that are artificially inseminated (AI) to enhance tenderness genetics (increasing the percentage of calves with preferred tenderness genotypes), and the WCTS permits it to record and transmit the genetic information through the chain. At one end of this choice set, the chain can choose to not employ AI ($\lambda = 0$), and to not implement a WCTS, a baseline case. At the other end, the chain can choose to employ AI on all cows ($\lambda =1$), so that all calves are produced from AI and information about all calves is passed through the WCTS. We also estimate the costs and benefits of conducting WBSF tenderness tests to provide additional verification of beef tenderness. In other words, the processing stage has the option to conduct WBSF tenderness tests when processing meat, providing the opportunity to receive potentially higher premiums for meat cuts that are verified tender.

Employing AI only on those cows that are genetically more likely to give birth to calves that produce tender meat would save some AI costs, but would incur costs of testing DNA of each cow. Accordingly, the chain maximizes profit by selecting the proportion of the cow herd to be bred employing AI ($0 < \lambda \leq 1$), and implementing a WCTS if $\lambda > 0$. Possible values of $\lambda$ are determined by the frequencies of genetics in a representative cow herd. The difference between premiums received for tender meat cuts and the total cost of testing DNA, employing AI, implementing a WCTS, and running WBSF tests, is the extra earning/loss for this supply chain.

When $\lambda$ is 1, AI is employed on the entire cow herd. An initial estimate of the value of employing AI on all cows in a representative herd to improve tenderness genetics is obtained by predicting the average gain in the proportion of tenderness times an estimated premium that could be obtained for increased average meat tenderness.

A more interesting question, though, is whether a WCTS can be used to more precisely identify animals with more tender meat. This may provide more incentive for cow/calf producers to produce animals with genetics favorable to tender meat, since the WCTS would permit processors to identify and compensate the producers of those animals.

The supply chain could pursue one of several alternative strategies using a WCTS.

1. use genetic information about the parents of each animal to predict meat tenderness, recognizing that the prediction has some randomness so that animals with genetics for tenderness may not always yield tender meat.
2. conduct WBSF tests on animals genetically predicted to produce tender meat to verify that meat is actually tender
3. conduct WBSF tests on all animals, to identify tender meat regardless of whether it was genetically predicted or not.

The analysis will compare the profitability of these strategies to determine the extent to which a WCTS can increase value added in a beef supply chain

The chain's profit maximization problem is a discrete choice problem:

(1) $$\max_{\{\lambda,\varphi\}} \Delta\Pi_i = TR_i(\lambda,\varphi) - TC_i(\lambda,\varphi)$$

$$= \left(\sum_{j=1}^{9} \Delta P_j(\lambda,\varphi) * TP_j(\lambda,\varphi)\right) * w * \rho - TC_i(\lambda,\varphi), i = 1,2,3,4$$

where $\lambda$ is the proportion of animals bred specifically for tenderness, either with AI or NBS, $\varphi$ indicates the method by which tenderness is verified ($\varphi = 1$ if tenderness is tested using WBSF on all carcasses, $\varphi = 0$ if tenderness genotypes are verified using a WCTS, and $\varphi = \lambda$ if WBSF is used to test tenderness on only the proportion $\lambda$ of carcasses that are specifically bred for tenderness), $TR_i(\lambda, \varphi)$ is the total tenderness premiums received by the supply chain while raising breed $i$, and $TC_i(\lambda, \varphi)$ is the total costs of improving tenderness for breed $i$, $\Delta P_j(\lambda, \varphi)$ is the change in proportion of tender meat for genotype pair $j$, $TP_j(\lambda, \varphi)$ is the unit tenderness premium for genotype pair $j$, $w$ is the average dressed weight, and $\rho$ is the proportion of meat cuts for which consumers are willing to pay tenderness premiums.

**Empirical Procedure**

Revenues are calculated as the product of tenderness proportions, carcass weight, and tenderness premiums. Costs are the sum of selective breeding (AI or NBS), DNA test, WBSF tests, and traceability costs. The value of $\lambda$ influences tenderness proportions, cost of selective breeding, and traceability costs. Tenderness premiums received may also be influenced by whether or not a WCTS is in use to identify and market meat tenderness. When cow/calf producers apply AI on part or all of the cows, and a WCTS is used to identify cattle carrying favored genotype pairs (without using a WBSF test), genetics of cattle born from selective breeding are identified and receive tenderness premiums based on cows' genetics. For example, if a cow carries genotype pair CC.CC, it gives birth to calves carrying genotype pairs CC.CC only. Thus, cattle born from cows carrying genotype pair CC.CC produce the most tender meat. But cows carrying genotype pair CC.CG may give birth to calves carrying genotype pairs CC.CC or CC.CG. Unless DNA tests are conducted on the calves born, the cow/calf producers are not able to distinguish between calves carrying the two above genotype-pairs. Even though carrying genotype pair CC.CC decreases WBSF value by 0.27 kg, because of the uncertainty, the tenderness premium that could be received would be lower than the highest possible premium.

Three genotype pairs (CC.CC, CG.CC, and CC.CG) produce meat cuts with WBSF lower than 4.6 kg (break point for tenderness). Genotype pair CC.CC produces meat cuts with the lowest WBSF values (a reduction of 0.2653 kg from the 4.6kg threshold), while genotype pairs CG.CC and CC.CG reduce WBSF values by 0.1692 kg and 0.1582 kg, respectively.

When selective breeding is employed on cows with genotype pairs CC.CC, CG.CC, CC.CG, CC.GG, and GG.CC, only calves with favored genotype pairs are produced:

1) CC.CC produces calves with genotype pair CC.CC,
2) CG.CC produces calves with genotype pairs CC.CC and CG.CC,
3) CC.CG produces calves with genotype pairs CC.CC and CC.CG,
4) CC.GG and GG.CC produces calves with genotype pairs CC.CG and CG.CC.

Calves produced by selective breeding from cows carrying genotype pair CC.CG may carry genotype pairs CC.CC or CC.CG. Only one of these five genotype pairs (CC.CC) produces tender meat with 100% certainty. For calves born from cows carrying the other four genotype pairs, tenderness premium received is reduced as only the low premiums can be guaranteed.

**Identification of Parameters**

*Carcass Traits*

We refer to Cornell[2] (2012), Nold (2013) and Raines (undated) for the dressing percentage of beef cattle. Cornell (2012) stated that the dressing percentage is between the ranges of 58% to 62%. Raines (undated) claimed the dressing percentage to vary between 60% to 62%; and Nold

[2] Cornell University, 2012

(2013) claimed that it varies from 62% to 64%. For the default analysis, we set cattle ending weight at 1,300 lb., with dressing percentage equaling 60% as the base line.

*Genotypes and WBSF*

Van Eenennaam et al. (2007) studied the associations between commercial genetic marker panels and beef quality traits. In order to focus on the correlation of genetics and beef tenderness, we use their results from the Igenity *Tender*GENE marker panel. This panel analyzes μ-calpain single-nucleotide polymorphisms (SNP) and calpastatin SNP (Van Eenennaam et al. 2007).

According to Destefanis et al. (2008), beef tenderness can be identified by the value of WBSF test – lower values are associated with greater tenderness. Since C alleles are correlated with increased tenderness (smaller WBSF value), for both calpastatin ($U_0$G-CAST1) and μ-calpain (CAPN1 316), they are favorable for tenderness. Table II-1 shows the frequencies of calpastatin and μ-calpain haplotypes C and G, for four cattle breeds: Charolais × Angus, Brangus, Red Angus, and Brahman.

For the Charolais × Angus cross, frequencies of alleles C and G are 79% and 21%, respectively, for calpastatin ($U_0$G-CAST1). We assume that these are the probabilities of passing allele C for calpastatin in Charolais × Angus cross, since Table II-1 shows that the calculated frequencies of calpastatin and μ-calpain haplotypes for each breed are very similar to the real frequencies of calpastatin and μ-calpain. Calculation of frequencies of calpastatin haplotype CC is done by multiplying probability of C by probability of C (for example, for Charolais × Angus cross, 0.79 x 0.79 = 0.62).

Cattle carrying haplotype CC pass down allele C at all times (100%), while cattle carrying haplotype GG pass allele C at no time (0%). The probability of individual cattle with calpastatin haplotype CG in breed $i$ ($i$ = 1, 2, 3, 4) passing allele C is calculated as

$$\left(\frac{\text{probability}^{i}_{\text{allele C}} - \text{probability}^{i}_{\text{haplotype CC}} * 100\% - \text{probability}^{i}_{\text{haplotype GG}} * 0\%}{\text{probability}^{i}_{\text{haplotype CG}}}\right).$$

For example, the probability of cattle with calpastatin haplotype CG passing allele C in Charolais × Angus crossbreed equals $\frac{0.79-0.62*1-0.05*0}{0.33}$, which is 51.52%. The probability of individual cattle with haplotype CG in this breed passing allele G is calculated as (1-51.52%), which is 48.48%. Similarly, probabilities of individual cattle passing calpastatin haplotype allele C and G in the Brangus, Red Angus, and Brahman breeds are calculated to be 50.00%, 50.00%, and 48.94%, respectively. Similar calculations are done for μ-calpain (CAPN1 316). Probabilities of individual cattle with μ-calpain haplotype CG passing allele C in the Charolais × Angus cross, Brangus, Red Angus, and Brahman breeds are calculated to be 51.35%, 51.61%, 50.00%, and 50.00% respectively.

For both SNPs, the haplotype CC results in lower WBSF, indicating higher tenderness. Since genotype pair CC.CC decreases WBSF values the most, it is assumed that producers select it as the one used for AI. The frequencies of genotype pairs combining calpastatin and μ-calpain for each breed are calculated as shown in Table II-2, assuming that the probabilities of calpastatin ($U_0$G-CAST1) and μ-calpain (CAPN1 316) are independent. For breeding with natural service, it is assumed that probabilities of tenderness alleles in the bulls follow the same frequencies as those of the representative herd.

Calculated frequencies are displayed in the left part of Table II-1, under the row of "Regular Frequencies", which are assumed to be frequencies of genotypes with natural service (NS). The probabilities of each genotype pair resulting from employing AI are presented in the right part of Table II-2, under the row headed "Modified Frequencies." For example, by employing AI on the entire herd (assuming AI success rate is 70%), the percentage of the most favored genotype pair CC.CC increases nine percentage points for Charolais × Angus cross, from 3.30% (NS) to 13.71% (AI). Genotype pairs CC.CG and CG.CC are also preferred, as cattle carrying these genotypes have decreased WBSF values of 0.67 kg and 0.66 kg, respectively. The overall percentage of these two genotypes increases from 23.87% to 53.13% for Charolais × Angus cross. Meanwhile, employing AI on the entire cow herd also decreases the percentages of cattle producing meat cuts with high WBSF values, such as genotype pair GG.GG. In the Charolais × Angus cross, for example, the probability of genotype pair GG.GG decreases from 2.61% to 0.78%. Even if the success rate of artificial insemination is only 60%, the percentages of favored genotype pairs are much higher than employing NS (see Appendix Table II-A1). Thus, employing AI on the entire herd increases the proportion of favored genotype pairs among the calves born.

*Determination of λ*

The cow/calf producer can use either NBS from bulls with specific genetics, or AI to increase the proportion of tenderness-improving genetics. In another word, throughout this article, NBS could be used instead of AI to achieve selective breeding in favor of more tender meat. Even with NBS, selective breeding generates higher costs to cow-calf producers, as bulls with specific genetics may be much more expensive. In order to simplify the explanations, AI is used throughout the analysis as the primary tool for selective breeding, and differences in costs between AI and NBS are noted in the conclusions. Employing AI on cows may cost more than using NBS, depending on the success rate. Since employing AI on cows with genotype pair GG.GG will not produce calves carrying any of the favored genotype pairs, there is no benefit from employing AI on them. However, employing AI on cows carrying favored genotype pairs increases the proportion of calves carrying favored genotype pairs. By choosing the proportion ($\lambda$) of the cowherd on which AI will be employed, producers can select only those cows carrying specific genotype pairs, giving a higher probability of producing calves with favorable genotype pairs, such as CC.CC, CC.CG, and CG.CC. Unlike the situation in which the chain uses AI on the whole herd, cow-calf producers conduct DNA tests on cows in the herd to determine which cows have genotype pairs that, when combined with AI, will produce calves with more tender meat.

According to the genotype pairs and decreased WBSF values shown in Table II-3, the proportion of cows bred using AI, $\lambda_i$, is set to take one of the following five values: $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$. $\lambda_1$ is set to be 0%, meaning that the cow-calf producer decides not to employ AI on any cows, nor does it use the traceability system. The value of $\lambda_5$ is 100%, meaning that the cow/calf producer employs AI on the entire cowherd.

The values of $\lambda_2, \lambda_3$ and $\lambda_4$ vary across different breeds, depending on the proportion of cows carrying genotype pairs that produce tender meat. As shown in Table II-3, a total of nine genotype pairs exist: CC.CC, CG.CC, CC.CG, CC.GG, CG.CG, GG.CC, CG.GG, GG.CG, and GG.GG. Genotype pairs CC.CC, CG.CC, and CC.CG produce tender meat cuts, and are the three favored genotype pairs. Cattle carrying genotype pair CC.CC produce the most tender meat cuts (highest decrease in WBSF value). For $\lambda_2$, the cow-calf producer only employs AI on cows carrying genotype pair CC.CC, thus producing calves with genotype pair CC.CC. For Charolais × Angus cross, Brangus, Red Angus, and Brahman breeds, $\lambda_2$ takes the value of 3.30%, 2.02%, 2.90%, and 0.01%, respectively.

For $\lambda_3$, AI is employed on cows carrying genotype pairs CC.CC, CG.CC, CC.CG, CC.GG, and GG.CC so that $\lambda_3$ is set to equal the summation of frequencies of the five genotype pairs mentioned above – 75.92%, 73.28%, 70.43%, and 20.43%, respectively, for Charolais × Angus cross, Brangus, Red Angus, and Brahman breeds.

If AI is employed on cows carrying an expanded range of genotype pairs – CC.CC, CG.CC, CC.GG, CC.GG, GG.CC, CG.CG, CG.GG, and GG.CG – there is a reduced, though still positive, probability, that calves will be produced with one or more of the three favored genotype pair(s) (CC.CC, CG.CC, and CC.CG). Since GG.GG is the only genotype pair that does not produce calves with any of the favored genotype pairs, to avoid including cows carrying the GG.GG genotype, $\lambda_4$is set to equal one minus the probability of GG.GG, which gives 93.79%, 97.03%, 95.99%, and 68.80%, respectively for the four breeds.

*AI and Breeding Costs*

As stated previously, in order to improve the percentage of calves carrying preferred genetics that improve tenderness, the cow/calf producer uses AI to improve the proportion of preferred genetics. AI success rate refers to the percentage of cows receiving AI getting pregnant. According to Johnston (2012) and Perry (2012), AI success rate varies between 60% and 70%. Jacobsen (2010) also stated that the success rate of AI may vary from 60% to 80%. In the default analysis, we take the value of 70% as the AI success rate. For the cost differences between AI and NS, we refer to the breeding cost worksheet from Wilson, Stockton, and Berger (2015). Based on the worksheet, we calculated the cost differences. Under standard assumptions (for NS, one bull is appropriate for 30 cows, and AI success rate is 70%), Wilson, Stockton, and Berger (2015) shows that AI costs $14.65 more per calf weaned.

*Cost of Implementing a WCTS*

Costs of whole-chain traceability systems are obtained from Resende-Filho and Buhr (2008) and Seyoum (2013). Seyoum (2013), summarizing and synthesizing work by Blasi et al. (2009) and Butler et al. (2010), estimated the costs of participating in a whole-chain traceability system for cow-calf producers and feedlots at $5.44/calf and $0.84/head, respectively. A large proportion of the traceability system cost would be incurred primarily in the cow-calf stage (as the cost of tagging is approximately $2/head) (Blasi et al. 2009; Seyoum 2013). In contrast, the costs that meat processors would incur in participating in a whole-chain traceability system are $0.73/animal, assuming a 100% success rate in recording and transferring information (Resende-

Filho and Buhr (2008). Adjusted to 2017 dollars, the total cost of implementing a whole-chain traceability system from cow-calf producer to slaughter and packing plant is estimated to be $6.83/head.

*Cost of DNA and tenderness testing*

The cost of conducting a DNA test on a cow is a one-time cost applying to the whole productive life of the cow. We refer to UCD (UC Davis Veterinary Medicine) on the cost of "Parentage/Genetic Marker Report" as $30 per head. Cows' productive lives are assumed to be ten years. Assuming one calf born per year, the DNA test cost is $3/calf. Adjusted to 2017 dollars, the cost of a DNA test is $3.31/calf. The cost of conducting a WBSF test is set to be $20.30/head,[3,4] including the amortized cost of a Warner Bratzler shear force device, cost of labor, cost of discarding a valuable meat cut, and the cost of slowing down the meat processing time.

*Tenderness Premiums*

Tenderness premiums are based on willingness-to-pay measures summarized by Schroeder, Riley, and Fraisier (2008), who estimated that every 1-kg decrease in WBSF brings $46.1077/cwt extra profit. However, according to Schroeder, Riley, and Fraisier (2008), retail-level tenderness premiums between tender and tough steaks vary from $0.42/lb. to $7.35/lb. from multiple studies. Considering only results of the non-hypothetical studies, tenderness premiums range from

[3]The cost of a Warner-Bratzler machine is obtained from www.tallgrassproducts.com, which is $3,850 (accessed at Sep 21, 2017). Cost of labor is estimated by Lanz (2016) at approximately $5.00/test.

[4] O'Quinn (2016) suggests that the Warner-Bratzler shear force test is not commonly used in industry as it takes a long time and wastes a valuable cut of meat, and that the slice shear force test may be a more industry-appropriate test to evaluate. However, cost data and tenderness data are not available for the slice shear force measure, so cost of a WBSF is used here to provide a baseline. To the extent WBSF costs may be higher than what processors would actually pay; these results are biased against tenderness testing.

$0.59/lb. to $6.90/lb. Taking the highest tenderness premium, the retail-level tenderness premium is assumed to be at $6.90/lb., which is adjusted to the wholesale level using a five-year-average wholesale to retail price ratio. The WBSF difference between tender steaks and tough steaks is 2kg (Schroeder, Riley, and Fraisier 2008). For every 1-kg decrease in WBSF value, the tenderness premium is $345.00/cwt. Following Schroeder, Riley, and Fraisier (2008), the tenderness premium is applied to 20% of the carcass weight.

Changes of WBSF values from different genotype pairs are taken from the calculations in Van Eenennaam et al. (2007). The mean WBSF value in their sample was 4.6kg. The calculated WBSF values for different genotype pairs are shown in Table II-3. According to Schroeder, Riley, and Fraisier (2008), a WBSF value of 4.6 kg is a reasonable threshold for moving from tender to tough steaks. With this threshold, meat cuts with a WBSF value less than 4.6 would receive a premium for improved tenderness. According to Table II-3, only three genotype pairs lead to meat cuts with WBSF less than 4.6: CC.CC, CG.CC, and CC.CG.

*Tenderness Proportion*

Tenderness proportion refers to the percentage of primal or sub-primal meet cuts that go the retail market. As indicated by Schroeder, Riley, and Fraisier (2008), the tenderness proportion varies from 17% to 22%, where 20% is an approximate middle point. However, Schroeder, Riley, and Fraisier (2008) also stated that other meat cuts, such as roast, may receive tenderness premium as well. Thus, we widen the range of tenderness proportion from 15% to 25%.

Table II-4 summarizes the parameters used in the model, and the range of values that previous studies have suggested that might be appropriate for those parameters. The 3rd column of this table indicates the parameter values selected as baseline values.

## Scenarios and Results

The benefits from implementing a whole-chain traceability system to market beef tenderness exceed the costs for some breeds considered, but not all. Moreover, the profitability depends on breed, actual tenderness premiums received, and the cost of doing WBSF tests.

### ***$\lambda$ = 0: AI is not employed***

When $\lambda$ equals 0, AI is not employed to improve the proportion of favorable genotype pairs. The baseline is when processors do not test tenderness, and additional profits are zero. However, if processors test tenderness of meat cuts using WBSF, they would receive premiums for meat cuts that meet the tenderness threshold. Changes in profit for each breed when processors test meat tenderness are shown in Table II-5. For example, for Charolais × Angus crossbreed, the revenue obtained from identifying meat tenderness is \$13.99/head, while the extra cost (cost of WBSF) is \$20.30/head, resulting in a loss to the supply chain of \$6.30/head from testing meat tenderness. With the Brangus and Red Angus breeds, the chain obtains smaller revenues of \$10.88/head and \$12.54/head, respectively. After deducting the cost of WBSF, the chain loses \$9.42/head and \$7.76/head, respectively, for these breeds. The Brahman breed has the lowest profit; testing tenderness only brings \$0.36/head revenue, so that the chain loses \$19.94/head. Results when $\lambda$ = 0 indicate that it is not profitable to market meat tenderness even for the most profitable breed, Charolais × Angus. In results indicate that without improving the proportion of preferred genetics, marketing for tenderness generates losses instead of profits. This may explain why in the current marketing system, beef products marketed as "guaranteed tender" are rarely seen. Under the existing genetic distributions, beef producers do not benefit from marketing improved tenderness.

***$\lambda$ > 0: AI is employed***

As stated previously, the proportion of preferred genetics can be improved from selective breeding, either with NBS or AI. Normally, using AI for breeding purpose causes more than using NS. However, for genetics-selection purpose, the genotype of bulls is restricted to genotype pair CC.CC. Purchasing bulls with the specific genetics may generate higher cost than bulls with normal genotypes. Thus, in this article, we use AI as the default tool to select and improve genetics. When $\lambda$ is greater than 0, a WCTS is implemented and AI is employed to improve the proportion of favorable genotype pairs. In order to precisely identify carcasses with tender meat, and receive potentially higher premiums, processors can use WBSF tests either on all animals or only on cattle born from AI.

*$\lambda = \lambda_{2i}$ (3.30%; 2.02%; 2.90%; 0.01%)*

In this case, cow/calf producers employ AI on cows with genotype CC.CC only. The parameter $\lambda_2$ takes values of 3.30%, 2.02%, 2.90%, and 0.01%, respectively, for Charolais × Angus cross, Brangus, Red Angus, and Brahman breeds. The supply chain can apply one of the three strategies – 1) use WBSF test on all carcasses; 2) use WBSF on only carcasses from animals produced using AI, and 3) use WCTS to track genetic information without using WBSF – to maximize profit.

Table II-5 shows changes in profit for the four breeds selected. For Charolais × Angus cross, if WBSF tests are conducted on all carcasses, there is a loss of $9.38/head. If WBSF tests are used only for AI-produced carcasses, there is a loss of $2.56/head. If no WBSF test is used to identify tenderness, but a WCTS is used instead, the chain receives the same average revenue as if a WBSF test is used only for AI cattle. But the cost of using a WCTS to identify tenderness is higher than the revenue, resulting in a net loss of $2.16/head.

For Brangus and Red Angus animals, the results are similar with the Charolais × Angus animals. No extra profits are gained from identifying tender meat cuts. When using WBSF tests to test tenderness on all carcasses, the supply chain loses most money. And the lowest losses occur when a WCTS is implemented to identify meat tenderness

Situation with the Brahman breed is slightly different. Using WBSF tests on all carcasses generates much higher loss than the other two options. The possible reason for this is that proportion of cows carrying tenderness genes is so small in the Brahman breed. Thus, testing tenderness for the Brahman breed does not generate much revenue, but incurs high costs.

Since no positive profits are obtained when employing AI on cows with the genotype pair CC.CC, the supply chain should not market meat tenderness with implementing AI only on cows carrying genotype pair CC.CC. The lowest loss occurs when a WCTS is in use to identify and market meat tenderness for all four breeds.

*$\lambda = \lambda_{3i}$ (75.92; 73.28; 70.43%; 20.43%)*

In this case, AI is employed on cows with genotype pairs CC.CC, CG.CC, CC.CG, CC.GG, and GG.CC. Employing AI on these five genotype pairs produces calves with favored genotype pairs only.

For the Charolais × Angus crossbreed, when processors test tenderness of all animals with a WBSF test, they receive full tenderness premiums for all tender meat cuts. For Charolais × Angus crossbreed, the net premiums for tenderness. However, cost is greater than the revenue, resulting in a loss of $3.81/head. If processors conduct WBSF tests only on animals originating from AI, the loss is $3.25head. When a WCTS is used to verify tenderness genetics, a net profit of $4.70/head is achieved. The revenue from implementing a WCTS is the lowest among the three strategies, as it does not identify the precise genotypes of some animals, and thus does not permit receiving the best possible tenderness premiums. However, even though revenue is reduced, the cost is reduced even more, because cost of conducting WBSF tests is eliminated.

Profit changes in the Brangus and Red Angus breeds have the same rankings as indicated in the Charolais × Angus crossbreed, with the highest profits achieved when using the WCTS to market beef tenderness, which are $4.91/head, and $4.05 /head, respectively. The alternative of running WBSF tests on all carcasses generates losses of $5.64/head for Brangus and $5.60/head for Red Angus, while running WBSF tests on only carcasses originating from AI generates losses of $3.22/head for Brangus and $3.56/head for Red Angus.

However, Brahman animals do not generate extra profit in this case. All three strategies generate negative profits, -$19.80/head, -$ 3.09/head, and -$0.07/head, with implementing a WCTS as the least negative.

Overall, a higher profit is earned when employing AI on cows carrying any of the five genotype pairs – CC.CC, CC.CG, CG.CC, CC.GG, and GG.CC – than when employing AI only on cows carrying genotype pair CC.CC. The supply chain could earn extra profits of $4.70/head, $4.91/head, and $4.05/head from employing AI on Charolais ×Angus cross, Brangus, Red Angus breeds, respectively. But the Brahman breed is not good for marketing tenderness –no matter which strategy the chain chooses, the Brahman breed does not generate positive profit.

*$\lambda = \lambda_{4i}$ (97.39%; 97.03%; 95.99%; 68.80%)*

At this level of $\lambda$, the chain applies AI on all beef cows except cows carrying genotype pair GG.GG, since employing AI on cows carrying genotype pair GG.GG does not produce calves carrying favored genotype pairs.

According to Table II-5, no breeds give positive profits in this case. For all four breeds, the lowest losses – $0.18/head, $0.31/head, and $1.44/head, for Charolais × Angus cross, Brangus, and Red Angus breeds, respectively –when using a WCTS to identify and market meat tenderness. Brahman animals do not generate positive profits; instead, they generate a loss of at least \$8.78/head. Using WBSF tests on all carcasses generates the second lowest losses for Charolais × Angus cross, Brangus, and Red Angus breeds, which are \$1.45/head, \$3.59/head, and \$3.14/head. The highest losses for Charolais × Angus cross, Brangus, and Red Angus breeds are \$3.64/head, \$4.75/head, and \$4.48/head. For Brahman breed, the second lowest loss, \$10.26/head, occurs when WBSF tests are run on carcasses originated from AI. The highest loss, \$18.52/head, occurs when WBSF tests are run on all carcasses.

In this case, no breed generates positive profits from marketing meat tenderness. The supply chain does not earn any extra profits from identifying and marketing tenderness when applying AI on all cows except the ones with genotype pair GG.GG.

*λ = 100%*

When *λ* equals 100%, the chain uses AI to breed all cows. If beef processors decided to test meat tenderness using WBSF test, there would be no need to test DNA of all beef cows. If processors, however, decided to identify meat tenderness using the WCTS, DNA tests would be still required for all cows.

For Charolais × Angus crossbreed, employing artificial insemination on the entire cow herd increases the probability of calves carrying one of the three favored genotype pairs, CC.CC, CC.CG, and CG.CC, to %. Compared with the corresponding probability of using natural service, which is %, this is almost % increase. When the supply chain tests tenderness using WBSF test, the profit gain is \$1.43/head. When the chain tests WBSF values on those carcasses originating from AI, it receives a loss of \$4.77/head. When a WCTS is implemented to record parental genetic information and identify meat tenderness, there is a \$0.89/head extra loss.

For Brangus and Red Angus breeds, there are no positive profits from improving tenderness proportion and using WBSF tests to market for beef tenderness, when applying AI to the entire cow herds. The lowest losses -- $0.77/head and $0.52/head -- occur when WBSF tests are run on all carcasses, respectively. The highest losses -- $6.02/head and $6.27/head – occur when WBSF tests are run on partial carcasses. Implementing a WCTS to identify and marketing tenderness generates extra losses of $1.10/head for Brangus breed and $2.56/head for Red Angus breed.

For Brahman breed, no positive profits are obtained with any of the three strategies as well. Further, the losses -- $19.79/head, $21.89/head, and $15.90/head – are much higher than those of the other three breeds.

When AI is applied to entire cow herds, Charolais × Angus crossbreed generates positive profits of $1.43/head. For the other three breeds, though, improving tenderness by applying AI on entire cow herds does not generate positive profits at all. For Brangus and Red Angus breeds, the lowest losses occur when WBSF tests are run on all carcasses. But for Brahman breed, the lowest loss occurs when a WCTS is implemented to identify and market meat tenderness.

Overall, with 70% AI success rate, 20% tenderness proportion, $345.00/cwt/kg retail-level tenderness premium, and 60% dressing percentage, the highest profit change is $4.70/head. Among the four breeds picked, Brangus generates the highest profit, while Charolais × Angus crossbreed and Red Angus breeds generate the second and third highest profit changes. Improving meat tenderness for Brahman breed does not make any profit. Instead, there is at least $0.07/head loss. In order to obtain the highest profit for each breed, the best strategy is to apply AI on the top five genotype pairs and implement a WCTS to identify and market beef tenderness. Positive profits indicate that the supply chain would be better off from improving meat tenderness. Brahman breed should not be chosen, as no positive profits are generated. For the other three breeds, the beef supply chain can benefit from applying AI on cows carrying the top five genotype pairs.

## Discussion

### *Varying One Factor*

Tables II-6, II-7, and II-8 show results under alternative AI success rates, tenderness proportions, and tenderness premiums. We select Charolais × Angus crossbreed to illustrate these results.

#### *AI Success Rate*

The AI success rate influences two variables in the models: breeding cost per calf, and calves' genotypic frequencies. A pregnancy rate of 60% to 70% is a good for AI (Perry, 2012). In this paper, we extend the range of AI success rate to 80%, in order to discuss the potential impact of higher AI success rate on the profits gained As AI success rate increases, the difference between AI and NBS breeding costs per calf decreases, as shown in Appendix Table II-2. Also, as AI success rate increases, the proportion of favored genotype pairs gets higher. Appendix Table II-1 shows the frequencies of each genotype pair with alternative AI success rates for Charolais × Angus crossbreed. Table II-6 is a summary of profits when AI success rate changes, with tenderness premium applying to 20% of carcass weight, \$345.00/cwt/kg retail-level tenderness premium (per kg deduction of WBSF), and 60% dressing percentage. As AI success rate increases, profit increases, given the level of $\lambda$. The highest profit change, \$12.31/head, is observed when AI success rate is 80%, with $\lambda$ equal 75.53%.

When AI success rate equals 60%, the supply chain bears losses from improving meat tenderness using AI. When AI success rate increases to 65%, the supply chain earns positive profit. By applying artificial insemination to cows carrying the top five genotype-pairs, the profit change is \$0.90/head. When AI success rate is 70%, the supply chain earns extra profits from employing artificial insemination on cows carrying the top five genotype-pairs. When AI success rate is 75% and 80%, the supply chain receives positive profit in all levels of λ except for when λ is in its first non-zero level. The highest profit, $12.31/head, occurs when artificial insemination is applied on cows carrying the top five genotype pairs, and a WCTS is used to identify meat tenderness.

Results in Table II-6 indicate that as AI success rate increases, profit increases. Although the highest positive profit occurs when using the WCTS to identify tenderness, as the AI success rate increases, profit of running WBSF on all carcasses gets closer to profit of implementing a WCTS. As AI success rate increases, more calves with favored genotype pairs are produced. The fact that more cattle carry favored genotype pairs means more cattle produce tender meat. Thus, it is less likely that running WBSF test on a carcass wastes the cost. Since implementing a WCTS to identify and market tenderness is not precise, which wastes part of the tenderness premiums, a WCTS is less preferred when the proportion of tenderness-improved meat gets larger. But when AI success rate is not as high, a WCTS is preferred to WBSF tests in identifying cattle carrying favored genotype pairs.

*Tenderness Proportion*

Information on tenderness-related characteristics and premiums are taken from Schroeder, Riley, and Fraisier (2008). Those authors assume 20% of carcass weight as the tenderness proportion, which is the amount of meat cuts for which consumers are willing to pay premiums. However, they note that this assumption is debatable as tenderness of other beef cuts might matter to consumers as well (Schroeder, Riley, and Fraisier 2008). Thus, several tenderness levels are selected as shown in Table II-7, to evaluate the impact of tenderness proportions on profit change. When tenderness proportion is 15%, the supply chain bears losses from improving tenderness, no matter which method is selected to identify meat tenderness. The lowest level of loss with 15%

tenderness proportion occurs when the chain applies AI on cows carrying the top five genotype-pairs and uses the WCTS to identify tenderness. When tenderness proportion is 17%, the extra gain is no higher than $1.45/head, which occurs when applying artificial insemination on top five genotype-pairs and uses a WCTS to identify meat tenderness. When the tenderness proportion is 20%, using a WCTS and WBSF tests both generate positive profit, which are $4.70/head and $1.43/head, respectively. When tenderness proportion is 22%, using the WCTS to identify tenderness generates the highest profits, $6.87/head, while running WBSF test on all carcasses generates the second highest profits, $5.04/head. When tenderness proportion increases to 25%, the highest profit, $10.47/head, occurs when using WBSF tests to identify tenderness, while the second highest profit, $10.11/head, occurs when using a WCTS to identify tenderness.

When the tenderness proportion is low, the chain benefits more from implementing a WCTS to identify tenderness. But as the tenderness proportion is high enough, 25% in this study, the supply chain benefits more from running WBSF tests on all carcasses. The higher the tenderness proportion, the higher profit the supply chain receives from marketing meat tenderness. When tenderness proportion is not high enough, costs exceed revenue when running WBSF on all carcasses, thus using the WCTS is a better choice. However, since using the WCTS does not let the chain obtain all possible tenderness premiums, when tenderness proportion is high enough, the chain does better by running WBSF test on all carcasses in order to obtain every possible premium for tenderness.

*Tenderness Premium*

Tenderness premiums are taken from Schroeder, Riley, and Fraisier (2008). Even though Schroeder, Riley, and Fraisier (2008) stated that a 1-kg decrease in WBSF values brings a tenderness premium of $46.1077/cwt, this value is relatively low among the published range of tenderness premiums. Here, we select $345.00/cwt as a baseline retail-level tenderness premium for every 1-kg decrease in WBSF values. In order to find out how tenderness premium changes impact the profits earned, results for four alternative levels of tenderness premiums are presented in Table II-8, assuming 70% AI success rate, 20% tenderness proportion, and 60% dressing percentage.

The results indicate that when the tenderness premium is lower than or equal to $256.00/cwt, the supply chain does not earn any profits from improving tenderness. As expected, as tenderness premium increases, profit increases as well. When the tenderness premium is as high as $345.00/cwt, the chain earns at most $4.70/head from improving tenderness and using the WCTS to identify tenderness.

*Cost of WBSF Test*

Little information can be obtained about the cost of a WBSF test. In this article, we set the cost of WBSF test to be $20.30/head, with $5.30/head as the cost of machine and labor, and $15.00/head the estimated cost of discarding a valuable piece of meat cut and slowing down processing time. Because the support for this estimate is weak, though, we estimate the break-even WBSF costs – the maximum that the chain can afford to pay for the test to make the maximized profit from implementing a WCTS equal the maximized profit of doing WBSF test for all four breeds, as shown in Table II-9. If the actual cost of using WBSF test is higher than the calculated break-even costs, as listed in Table II-9, the supply chain profits more from implementing a WCTS. Otherwise, the chain would profit more from using WBSF tests to market beef tenderness.

***Varying Two Factors Simultaneously***

Tables II-10 to II-16 summarize the results from varying two factors simultaneously, including AI success rate, tenderness proportion, tenderness premiums, and dressing percentage. As in the analyses above, the Charolais × Angus crossbreed is selected as representative.

*AI Success Rate & Tenderness Proportion*

Table II-10 summarizes the profit changes under alternative AI success rates and tenderness proportions, while holding other factors fixed. When tenderness proportion is at the lowest level, 15%, the chain can earn extra profit from implementing a WCTS when AI success rate is higher than or equal to 75%. Or, the chain earns extra profit from using WBSF tests, when AI success rate is 80%. When tenderness proportion is 17%, the chain earns extra profit with one level lower AI success rate. In other words, implementing a WCTS generates extra gain to the chain at 70% success level of AI, while WBSF tests generates extra profit at 75% success level of AI. Similarly, for tenderness proportions of 20% and 22%, the chain starts to earn extra profit from implementing a WCTS at 65% success level of AI; for WBSF tests, the success level of AI is 70% and 75% for 20% and 22% tenderness proportion, respectively. If tenderness proportion is 25%, either implementing a WCTS or using WBSF tests generates positive profits to the chain, with any AI success rate.

Under the same level of AI success rate, profits increase as tenderness proportion increases. But the preferred tool to identify tenderness switches from WCTS to WBSF tests, along with the increase of tenderness proportion. For tenderness proportions under 22%, the highest profit occurs when using a WCTS to identify meat tenderness. But for higher tenderness proportions, the highest profit occurs when using WBSF tests to identify meat tenderness.

*AI Success Rate & Tenderness Premiums*

Table II-11 summarizes the profit changes under alternative AI success rates and tenderness premiums, while holding other factors are fixed. As with the earlier analysis from Table II-10, when AI success rate is under 65%, the supply chain bears losses. Also, when tenderness premium is under $107.00/cwt/kg, there is no incentive for the chain to increase the proportion of cattle with more tender genetics. The lowest positive profit, $0.90/head, is obtained when AI success rate reaches 65%, and tenderness premium is $345.00/cwt/kg, with a WCTS implemented.

Along with the increase of AI success rate and tenderness premium, the supply chain gains higher profits from improved meat tenderness. Implementing a WCTS generates higher profits compared to using WBSF tests. But as AI success rate and tenderness premium both increase, the profit difference between using WBSF tests and a WCTS decreases.

*AI Success Rate & Dressing Percentage*

Table II-12 shows results when AI success rate and dressing percentage are varied simultaneously. No positive profits result until AI success rate reaches at least 65%. Beginning this point, implementing a WCTS generates positive profits. Using WBSF tests generates positive profits when AI success rate is no lower than 70%, for all dressing percentages considered.

When AI success rate is 65%, 70%, 75%, and 80%, a WCTS is more profitable for the supply chain. Even though the profits generated from using WBSF tests do not exceed the profits generated from implementing a WCTS, the differences get smaller as the levels of AI success rate and dressing percentage increase.

*Tenderness Premiums & Tenderness Proportion*

Table II-13 summarizes the results under alternative tenderness premiums and tenderness proportions. The supply chain does not experience positive profits unless tenderness premium is $256/cwt/kg or greater. For tenderness proportion at 15%, the chain does not earn positive profits for all levels of tenderness premiums. Similar to previous results, the preferred tool changes from a WCTS to WBSF tests as tenderness premiums and proportions get higher.

### *Dressing Percentage & Tenderness Proportion*

Table II-14 summarizes results under alternative dressing percentage and tenderness proportions. Tenderness proportion must reach at least 17% for the chain to experience positive profits. For tenderness proportion at 17%, the chain can only earn profits from implementing a WCTS for 60% and 62% dressing percentages. For tenderness proportion higher than 17%, the chain can receive extra profit from either implementing a WCTS, or using WBSF tests. Increases in both tenderness proportion and dressing percentage are associated with increasing profits for the chain. When the tenderness proportion is 20%, and dressing percentage is 62%, the profit of using WBSF tests is higher than that of implementing a WCTS. But in other cases, implementing a WCTS is more preferred than running WBSF tests.

### *Dressing Percentage & Tenderness Premiums*

Table II-15 summarizes results under alternative dressing percentages and tenderness premiums. No positive profits are identified with tenderness premiums less than $256.00/cwt/kg. For tenderness premium of $256.00/cwt/kg or more, implementing a WCTS generates positive profits for all levels of dressing percentages. With a tenderness premium of $345.00/cwt/kg, implementing a WCTS and using WBSF tests both generate positive profits for all levels of dressing percentages. Similarly, the chain's preference switches from implementing a WCTS to using WBSF tests, as dressing percentage and tenderness premium both increase.

### *Breeding Costs & AI Success Rate*

Cost differences between AI and NS not only depend on the success rate of AI, but also the number of cows one bull covers in NS. The more cows one bull can cover, the lower cost NS has. Since the success rate of AI is around 80% at most, cover-up bulls are needed for the cows not pregnant from AI. Table II-16 shows the results of changing AI success rate and number of cows covered by one bull. When the costs of NS is low (one bull covers more cows) but the cost of AI is high (low success rate), the supply chain bears losses for both WBSF tests and WCTS. When the cost of NS is high (one bull covers less cows) but the cost of AI is low (with higher success rate), the supply chain gains positive profits from improving and marketing for tenderness, using both WBSF tests and WCTS. When the cost of NS is the highest level and AI success rate is no lower than 70%, the supply chain prefers using WBSF tests to identify meat tenderness. When the cost of NS is lower than or equal to the second level (one bull covers 30 cows) and AI success rate is higher than 60%, a WCTS brings extra gains to the chain and is preferred compared to WBSF tests. When the cost of NS is at the third level (one bull covers 25 cows), the chain prefers a WCTS when AI success rate is lower than 80%. Otherwise, WBSF tests are preferred.

**Conclusion**

We find that implementing a WCTS and AI can bring extra profit to the supply chain. In order to receive premiums for improved tenderness, the supply chain could either run WBSF tests, or use a WCTS to verify tenderness or tenderness genetics. If the AI success rate, tenderness proportion, and tenderness premium are high enough, the chain will earn extra profits, using either WCTS or WBSF tests to identify tenderness. If AI success rate, tenderness proportion, or tenderness premiums are relatively low, the chain benefits more from using the WCTS to identify tenderness. If AI success rate, tenderness proportion, and tenderness premiums are high enough, the chain earns higher profit from running WBSF test on carcasses. When profits are positive, the highest profit of implementing a WCTS always occur when the chain uses AI on cows carrying any of the top five genotype pairs. The highest positive profit of using WBSF tests always occur when the chain uses AI on the entire cow herd.

This analysis represents an attempt to provide an initial estimate of the value of a WCTS in a beef supply chain for one attribute, beef tenderness. The assumption used here that firms act to optimize profits for the entire supply chain may over-estimate gains from using a WCTS since the analysis ignores inefficiencies in price transmission. On the other hand, the analysis may under-estimate gains from using a WCTS since tenderness is only one of the many possible value-added attributes and other potential benefits of using a WCTS.

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**Table II-1. Allelic Frequencies for SNPs - $U_0$G-CAST1 and CAPN1 316**

| **U0G-CAST** | | | | | | | **Probability of offspring inheriting allele** | |
|---|---|---|---|---|---|---|---|---|
| | **Sample Size**[a] | **C**[a] | **G**[a] | **CC%**[a] | **CG%**[a] | **GG%**[a] | **C** | **G** |
| **Charolais × Angus** | 412 | 79.00% | 21.00% | 62.00% | 33.00% | 5.00% | 51.52% | 48.48% |
| **Brangus** | 203 | 79.00% | 21.00% | 63.00% | 32.00% | 5.00% | 50.00% | 50.00% |
| **Red Angus** | 305 | 74.00% | 26.00% | 56.00% | 36.00% | 8.00% | 50.00% | 50.00% |
| **Brahman** | 344 | 43.00% | 57.00% | 20.00% | 47.00% | 33.00% | 48.94% | 51.06% |
| **Total** | 1,264 | **Averaged probability of offspring inheriting alleles:** | | | | | 50.20% | 49.80% |
| **CAPN1 316** | | | | | | | | |
| | **Sample Size**[a] | **C**[a] | **G**[a] | **CC%**[a] | **CG%**[a] | **GG%**[a] | **C** | **G** |
| **Charolais × Angus** | 435 | 23.00% | 77.00% | 4.00% | 37.00% | 58.00% | 51.35% | 48.65% |
| **Brangus** | 217 | 18.00% | 82.00% | 2.00% | 31.00% | 67.00% | 51.61% | 48.39% |
| **Red Angus** | 307 | 23.00% | 77.00% | 5.00% | 36.00% | 59.00% | 50.00% | 50.00% |
| **Brahman** | 674 | 2.00% | 98.00% | 0.00% | 4.00% | 96.00% | 50.00% | 50.00% |
| **Total** | 1,633 | **Averaged probability of offspring inheriting alleles:** | | | | | 50.57% | 49.43% |

[a]: Table 2 (p. 895-896)& table 7 (p.898) in Van Eenennaam et al. 2007

**Table II-2. Frequencies of Genotypes-Original and 100% Artificial Inseminated (AI success Rate = 70%)**

| Breed | Genotype Pairs | Regular Frequencies [a] | AI-Modified Frequencies |
|---|---|---|---|
| | CC.CC | 3.30% | 13.71% |
| | CG.CC | 22.11% | 49.21% |
| | CC.CG | 1.76% | 3.92% |
| | CC.GG | 37.00% | 11.10% |
| **Charolais × Angus** | GG.CC | 11.75% | 14.84% |
| | GG.CG | 0.23% | 0.09% |
| | CG.GG | 19.67% | 5.90% |
| | GG.CG | 1.56% | 0.44% |
| | GG.GG | 2.61% | 0.78% |
| | CC.CC | 2.02% | 10.56% |
| | CG.CC | 18.42% | 50.87% |
| | CC.CG | 1.08% | 2.97% |
| | CG.CG | 41.96% | 12.59% |
| **Brangus** | CC.GG | 9.79% | 14.99% |
| | GG.CC | 0.14% | 0.06% |
| | GG.CG | 22.31% | 6.69% |
| | CG.GG | 1.30% | 0.37% |
| | GG.GG | 2.97% | 0.89% |
| | CC.CC | 2.90% | 12.78% |
| | CG.CC | 19.40% | 45.70% |
| | CC.CG | 2.04% | 4.81% |
| | CG.CG | 32.47% | 9.74% |
| **Red Angus** | CC.GG | 13.63% | 18.10% |
| | GG.CC | 0.36% | 0.15% |
| | GG.CG | 22.81% | 6.84% |
| | CG.GG | 2.39% | 0.66% |
| | GG.GG | 4.01% | 1.20% |
| | CC.CC | 0.01% | 0.60% |
| | CG.CC | 0.72% | 29.72% |
| | CC.CG | 0.02% | 0.80% |
| | CG.CG | 17.76% | 5.33% |
| **Brahman** | CC.GG | 1.92% | 39.68% |
| | GG.CC | 0.01% | 0.00% |
| | GG.CG | 47.08% | 14.12% |
| | CG.GG | 1.27% | 0.38% |
| | GG.GG | 31.20% | 9.36% |

[a] Calculated from Table 7 (p.898) in Van Eenennaam et at. 2007

**Table II-3. Frequencies of Genotypes and Calculated WBSF Values**

| Genotypes | ΔWBSF[a] (*kg*) | WBSF (*kg*)[b] |
|---|---|---|
| **CC.CC** | -0.76 | 4.3447 |
| **CG.CC** | -0.67 | 4.4518 |
| **CC.CG** | -0.66 | 4.4408 |
| **CG.CG** | -0.47 | 4.6826 |
| **CC.GG** | -0.43 | 4.6375 |
| **GG.CC** | -0.42 | 4.6908 |
| **GG.CG** | -0.31 | 4.9047 |
| **CG.GG** | -0.20 | 4.8033 |
| **GG.GG** | 0.00 | 5.1092 |

[a] Calculated from Table 7 (p.898) in Van Eenennaam et al. 2007; [b] Calculated from Tables 1 (p.892) and 7 (p.898) in Van Eenennaam et al. (2007)

**Table II-4. Summary of Variable Parameters**

| Parameters | Range | Base Point | Reference |
|---|---|---|---|
| Dressing Percentage | 58%-62% | | Cornell (2012) |
| | 60%-62% | 60% | Raines (undated) |
| | 62%-64% | | Nold (2013) |
| AI Success Rate | 60%-80% | | Jacobsen (2010) |
| | 60%-70% | 70% | Johnston ( 2012) |
| | 60%-70% | | Perry (2012) |
| Tenderness Premium | $29.5-345/cwt/kg | $345/cwt/kg | Schroeder, Riley, and Fraisier (2008) |
| Tenderness Proportion | 17%-22% | 20% | Schroeder, Riley, and Fraisier (2008) |

**Table II-5. Profits ($/head) from using tenderness testing (WBSF) and whole-chain traceability system (WCTS) to increase tenderness**

| **Breed** | **Tenderness Identification Options** | **$\lambda = 0$ no AI** | | | **$\lambda_2$ AI only CC.CC** | | | **$\lambda_3$ AI top 5 genotype pairs** | | | **$\lambda_4$ AI all except GG.GG** | | | **$\lambda_5$ AI all animals** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost |
| Charolais × Angus | WBSF all | -6.30 | 13.99 | 20.30 | -9.38 | 14.58 | 23.96 | -3.81 | 30.70 | 34.52 | -1.45 | 36.18 | 37.63 | 1.43 | 36.18 | 34.75 |
| | WBSF AI | | -- | | -2.64 | 1.38 | 4.02 | -3.25 | 24.43 | 27.66 | -3.64 | 31.98 | 35.62 | -4.77 | 31.98 | 36.74 |
| | WCTS | | -- | | -2.29 | 1.38 | 3.67 | 4.70 | 21.65 | 16.95 | -0.18 | 21.65 | 21.83 | -0.89 | 21.65 | 22.53 |
| Brangus | WBSF all | -9.42 | 10.88 | 20.30 | -12.59 | 11.19 | 23.79 | -5.64 | 28.59 | 34.23 | -3.59 | 33.98 | 37.57 | -0.77 | 33.98 | 34.75 |
| | WBSF AI | | -- | | -2.97 | 0.70 | 3.67 | -3.22 | 23.76 | 26.97 | -4.75 | 30.72 | 35.47 | -6.02 | 30.72 | 36.74 |
| | WCTS | | -- | | -2.79 | 0.70 | 3.49 | 4.91 | 21.43 | 16.52 | -0.31 | 21.43 | 21.74 | -1.10 | 21.43 | 22.53 |
| Red Angus | WBSF all | -7.76 | 12.54 | 20.30 | -10.76 | 13.25 | 24.01 | -5.60 | 28.23 | 33.83 | -3.14 | 34.23 | 37.37 | -0.52 | 34.23 | 34.75 |
| | WBSF AI | | -- | | -2.56 | 1.56 | 4.11 | -3.56 | 22.41 | 25.98 | -4.48 | 30.47 | 34.95 | -6.27 | 30.47 | 36.74 |
| | WCTS | | -- | | -2.16 | 1.56 | 3.71 | 4.05 | 19.97 | 15.92 | -1.44 | 19.97 | 21.41 | -2.56 | 19.97 | 22.53 |
| Brahman | WBSF all | -19.94 | 0.36 | 20.30 | -23.25 | 0.36 | 23.61 | -19.80 | 6.96 | 26.77 | -18.52 | 14.96 | 33.48 | -19.79 | 14.96 | 34.75 |
| | WBSF AI | | -- | | -3.31 | 0.00 | 3.31 | -3.09 | 6.72 | 9.81 | -10.26 | 14.85 | 25.12 | -21.89 | 14.85 | 36.74 |
| | WCTS | | -- | | -3.31 | 0.00 | 3.31 | -0.07 | 6.63 | 6.70 | -8.78 | 6.63 | 15.41 | -15.90 | 6.63 | 22.53 |

Tenderness Proportion = 20%; Tenderness Premium = $345.00/cwt/1kg; Dressing Percentage = 60%

**Table II-6. Profits ($/head) under Alternative AI Success Rates**

| AI Success Rate | Tenderness Identification Options | $\lambda = 0$ no AI | | | $\lambda_2$ AI only CC.CC | | | $\lambda_3$ AI top 5 genotype pairs | | | $\lambda_4$ AI all except GG.GG | | | $\lambda_5$ AI all animals | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost |
| 60% | WBSF all | -6.30 | 13.99 | 20.30 | -9.63 | 14.50 | 24.12 | -11.10 | 28.32 | 39.41 | -10.91 | 33.01 | 43.92 | -8.22 | 33.01 | 41.23 |
| | WBSF AI | | -- | | -2.95 | 1.18 | 4.13 | -9.71 | 20.94 | 30.65 | -11.89 | 27.41 | 39.30 | -13.10 | 27.41 | 40.51 |
| | WCTS | | -- | | -2.65 | 1.18 | 3.83 | -2.90 | 18.56 | 21.45 | -8.92 | 18.56 | 27.48 | -9.78 | 18.56 | 28.33 |
| 65% | WBSF all | -6.30 | 13.99 | 20.30 | -9.51 | 14.54 | 24.04 | -7.46 | 29.51 | 36.97 | -6.18 | 34.59 | 40.77 | -3.40 | 34.59 | 37.99 |
| | WBSF AI | | -- | | -2.79 | 1.28 | 4.07 | -6.48 | 22.68 | 29.16 | -7.77 | 29.69 | 37.46 | -8.93 | 29.69 | 38.63 |
| | WCTS | | -- | | -2.47 | 1.28 | 3.75 | 0.90 | 20.10 | 19.20 | -4.55 | 20.10 | 24.65 | -5.33 | 20.10 | 25.43 |
| 70% | WBSF all | -6.30 | 13.99 | 20.30 | -9.38 | 14.58 | 23.96 | -3.81 | 30.70 | 34.52 | -1.45 | 36.18 | 37.63 | 1.43 | 36.18 | 34.75 |
| | WBSF AI | | -- | | -2.64 | 1.38 | 4.02 | -3.25 | 24.43 | 27.66 | -3.64 | 31.98 | 35.62 | -4.77 | 31.98 | 36.74 |
| | WCTS | | -- | | -2.29 | 1.38 | 3.67 | 4.70 | 21.65 | 16.95 | -0.18 | 21.65 | 21.83 | -0.89 | 21.65 | 22.53 |
| 75% | WBSF all | -6.30 | 13.99 | 20.30 | -9.26 | 14.62 | 23.88 | -0.17 | 31.90 | 32.07 | 3.27 | 37.76 | 34.48 | 6.25 | 37.76 | 31.51 |
| | WBSF AI | | -- | | -2.49 | 1.48 | 3.97 | -0.02 | 26.17 | 26.19 | 0.48 | 34.26 | 33.78 | -0.60 | 34.26 | 34.86 |
| | WCTS | | -- | | -2.11 | 1.48 | 3.59 | 8.50 | 23.19 | 14.69 | 4.19 | 23.19 | 19.01 | 3.56 | 23.19 | 19.64 |
| 80% | WBSF all | -6.30 | 13.99 | 20.30 | -9.14 | 14.66 | 23.80 | 3.47 | 33.09 | 29.62 | 8.01 | 39.34 | 31.33 | 11.08 | 39.34 | 28.26 |
| | WBSF AI | | -- | | -2.33 | 1.58 | 3.91 | 3.22 | 27.92 | 24.70 | 4.61 | 36.55 | 31.93 | 3.58 | 36.55 | 32.97 |
| | WCTS | | -- | | -1.93 | 1.58 | 3.51 | 12.31 | 24.74 | 12.43 | 8.57 | 24.74 | 16.17 | 8.01 | 24.74 | 16.73 |

Tenderness Proportion = 20%; Tenderness Premium = $345.00/cwt/1kg; Dressing Percentage = 60%; Charolais x Angus crossbreed

**Table II-7. Tenderness Profits ($/head) under Alternative Tenderness Proportions**

| Tenderness Proportion | Tenderness Identification Options | $\lambda = 0$ no AI | | | $\lambda_2$ AI only CC.CC | | | $\lambda_3$ AI top 5 genotype pairs | | | $\lambda_4$ AI all except GG.GG | | | $\lambda_5$ AI all animals | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost |
| | WBSF all | -9.80 | 10.50 | 20.30 | -13.03 | 10.94 | 23.96 | -11.49 | 23.03 | 34.52 | -10.50 | 27.13 | 37.63 | -7.62 | 27.13 | 34.75 |
| 15% | WBSF AI | | -- | | -2.99 | 1.03 | 4.02 | -9.36 | 18.32 | 27.68 | -11.64 | 23.98 | 35.62 | -12.76 | 23.98 | 36.74 |
| | WCTS | | -- | | -2.63 | 1.03 | 3.67 | -0.71 | 16.24 | 16.95 | -5.59 | 16.24 | 21.83 | -6.30 | 16.24 | 22.53 |
| | WBSF all | -8.40 | 11.90 | 20.30 | -11.57 | 12.39 | 23.96 | -8.42 | 26.10 | 34.52 | -6.88 | 30.75 | 37.63 | -4.00 | 30.75 | 34.75 |
| 17% | WBSF AI | | -- | | -2.85 | 1.17 | 4.02 | -6.91 | 20.76 | 27.68 | -8.44 | 27.18 | 35.62 | -9.56 | 27.18 | 36.74 |
| | WCTS | | -- | | -2.50 | 1.17 | 3.67 | 1.45 | 18.40 | 16.95 | -3.43 | 18.40 | 21.83 | -4.13 | 18.40 | 22.53 |
| | WBSF all | -6.30 | 13.99 | | -9.38 | 14.58 | 23.96 | -3.81 | 30.70 | 34.52 | -1.45 | 36.18 | 37.63 | 1.43 | 36.18 | 34.75 |
| 20% | WBSF AI | | -- | | -2.64 | 1.38 | 4.02 | -3.25 | 24.43 | 27.66 | -3.64 | 31.98 | 35.62 | -4.77 | 31.98 | 36.74 |
| | WCTS | | -- | | -2.29 | 1.38 | 3.67 | 4.70 | 21.65 | 16.95 | -0.18 | 21.65 | 21.83 | -0.89 | 21.65 | 22.53 |
| | WBSF all | -4.91 | 15.39 | 20.30 | -7.93 | 16.04 | 23.96 | -0.74 | 33.78 | 34.52 | 2.16 | 39.79 | 37.63 | 5.04 | 39.79 | 34.75 |
| 22% | WBSF AI | | -- | | -2.50 | 1.52 | 4.02 | -0.81 | 26.87 | 27.68 | -0.45 | 35.17 | 35.62 | -1.57 | 35.17 | 36.74 |
| | WCTS | | -- | | -2.15 | 1.52 | 3.67 | 6.87 | 23.81 | 16.95 | 1.98 | 23.81 | 21.83 | 1.28 | 23.81 | 22.53 |
| | WBSF all | -2.81 | 17.49 | 20.30 | -5.74 | 18.23 | 23.96 | 3.86 | 38.38 | 34.52 | 7.59 | 45.22 | 37.63 | 10.47 | 45.22 | 34.75 |
| 25% | WBSF AI | | -- | | -2.30 | 1.72 | 4.02 | 2.86 | 30.54 | 27.68 | 4.35 | 39.97 | 35.62 | 3.23 | 39.97 | 36.74 |
| | WCTS | | -- | | -1.94 | 1.72 | 3.67 | 10.11 | 27.06 | 16.95 | 5.23 | 27.06 | 21.83 | 4.53 | 27.06 | 22.53 |

Tenderness Proportion = 20%; Tenderness Premium = $345.00/cwt/1kg；Dressing Percentage = 60%; Charolais x Angus crossbreed

**Table II-8. Profits ($/head) under Alternative Tenderness Premiums**

| **Tenderness Premiums** | **Tenderness Identification Options** | **$\lambda = 0$ no AI** | | | **$\lambda_2$ AI only CC.CC** | | | **$\lambda_3$ AI top 5 genotype pairs** | | | **$\lambda_4$ AI all except GG.GG** | | | **$\lambda_5$ AI all animals** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost | Profit | Revenue | Cost |
| | WBSF all | -18.43 | 1.87 | 20.30 | -22.02 | 1.95 | 23.96 | -30.42 | 4.10 | 34.52 | -32.79 | 4.83 | 37.63 | -29.91 | 4.83 | 34.75 |
| 46.11 | WBSF AI | | -- | | -3.84 | 0.18 | 4.02 | -24.41 | 3.26 | 27.68 | -31.35 | 4.27 | 35.62 | -32.47 | 4.27 | 36.74 |
| | WCTS | | -- | | -3.48 | 0.18 | 3.67 | -14.05 | 2.89 | 16.95 | -18.94 | 2.89 | 21.83 | -19.64 | 2.89 | 22.53 |
| | WBSF all | -15.96 | 4.34 | 20.30 | -19.44 | 4.52 | 23.96 | -25.00 | 9.52 | 34.52 | -26.41 | 11.22 | 37.63 | -23.53 | 11.22 | 34.75 |
| 107.00 | WBSF AI | | -- | | -3.59 | 0.43 | 4.02 | -20.10 | 7.58 | 27.68 | -25.70 | 9.92 | 35.62 | -26.83 | 9.92 | 36.74 |
| | WCTS | | -- | | -3.24 | 0.43 | 3.67 | -10.23 | 6.71 | 16.95 | -15.12 | 6.71 | 21.83 | -15.82 | 6.71 | 22.53 |
| | WBSF all | -9.91 | 10.38 | 20.30 | -13.14 | 10.82 | 23.96 | -11.74 | 22.78 | 34.52 | -10.79 | 26.84 | 37.63 | -7.91 | 26.84 | 34.75 |
| 256.00 | WBSF AI | | -- | | -3.00 | 1.02 | 4.02 | -9.55 | 18.13 | 27.68 | -11.89 | 23.73 | 35.62 | -13.02 | 23.73 | 36.74 |
| | WCTS | | -- | | -2.64 | 1.02 | 3.67 | -0.88 | 16.06 | 16.95 | -5.77 | 16.06 | 21.83 | -6.47 | 16.06 | 22.53 |
| | WBSF all | -6.30 | 13.99 | | -9.38 | 14.58 | 23.96 | -3.81 | 30.70 | 34.52 | -1.45 | 36.18 | 37.63 | 1.43 | 36.18 | 34.75 |
| 345.00 | WBSF AI | | -- | | -2.64 | 1.38 | 4.02 | -3.25 | 24.43 | 27.66 | -3.64 | 31.98 | 35.62 | -4.77 | 31.98 | 36.74 |
| | WCTS | | -- | | -2.29 | 1.38 | 3.67 | 4.70 | 21.65 | 16.95 | -0.18 | 21.65 | 21.83 | -0.89 | 21.65 | 22.53 |

Tenderness Proportion = 20%; AI Success Rate=70%; Dressing Percentage = 60%; Charolais x Angus crossbreed

**Table II-9. Break-Even Costs of WBSF ($/head)**

| Breed | Maximized Profit ($/head) | Break-Even WBSF Costs ($/head) | Highest Profit with WCTS | Highest Profit with WBSF |
|---|---|---|---|---|
| Charolais × Angus | 4.70 | 17.03 | $\lambda = \lambda_{3i}$ | $\lambda = 100\%$ |
| Brangus | 4.91 | 14.62 | | |
| Red Angus | 4.05 | 15.73 | | |
| Brahman | -0.07 | 1.85 | | $\lambda = \lambda_{4i}$ |

AI Success Rate = 70%; Tenderness Proportion = 20%; Tenderness Premium = $345.00/cwt/kg; Dressing Percentage = 60%

**Table II-10. Profits ($/head) under Alternative AI Success Rates & Tenderness Proportions**

| AI Success Rate / Tenderness Proportion | 60% | | 65% | | 70% | | 75% | | 80% | |
|---|---|---|---|---|---|---|---|---|---|---|
| | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS |
| 15% | -3.24[2] | -2.94[2] | -3.11[2] | -2.79[2] | -2.99[2] | -0.71[3] | -2.86[2] | 2.70[3] | 1.25[5] | 6.12[3] |
| 17% | -3.13[2] | -2.82[2] | -2.99[2] | -2.11[3] | -2.85[2] | 1.45[3] | 0.59[5] | 5.02[3] | 5.18[5] | 8.60[3] |
| 20% | -2.95[2] | -2.65[2] | -2.79[2] | 0.90[3] | 1.43[5] | 4.70[3] | 6.25[5] | 8.50[3] | 11.08[5] | 12.30[3] |
| 22% | -2.83[2] | -1.04[3] | 0.06[5] | 2.91[3] | 5.04[5] | 6.87[3] | 10.03[5] | 10.82[3] | 15.02[5] | 14.78[3] |
| 25% | 0.03[5] | 1.74[3] | 5.25[5] | 5.93[3] | 10.47[5] | 10.11[3] | 15.69[5] | 14.30[3] | 20.92[5] | 18.49[3] |

Tenderness Premium = $345.00/cwt/kg; Dressing Percentage = 60%;

[1, 2, 3, 4, 5] indicates the level of $\lambda$, which is the proportion of cows receiving AI.

**Table II-11. Profits ($/head) under Alternative AI Success Rate & Tenderness Premiums**

| AI Success Rate / Tenderness Premiums | 60% | | 65% | | 70% | | 75% | | 80% | |
|---|---|---|---|---|---|---|---|---|---|---|
| | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS |
| 46.11 | -3.97[2] | -3.67[2] | -3.90[2] | -3.58[2] | -3.84[2] | -3.48[2] | -3.77[2] | -3.39[2] | -3.70[2] | -3.30[2] |
| 107.00 | -3.76[2] | -3.46[2] | -3.68[2] | -3.35[2] | -3.59[2] | -3.24[2] | -3.51[2] | -3.13[2] | -3.42[2] | -3.02[2] |
| 256.00 | -3.25[2] | -2.95[2] | -3.13[2] | -2.80[2] | -3.00[2] | -0.88[3] | -2.87[2] | 2.52[3] | 0.94[5] | 5.92[3] |
| 345.00 | -2.95[2] | -2.65[2] | -2.79[2] | 0.90[3] | 1.43[5] | 4.70[3] | 6.25[5] | 8.50[3] | 11.08[5] | 12.31[3] |

Tenderness Proportion = 20%; Dressing Percentage = 60%;

[1, 2, 3, 4, 5] indicates the level of $\lambda$, which is the proportion of cows receiving AI.

**Table II-12. Profits ($/head) under Alternative AI Success Rate & Dressing Percentage**

| AI Success Rate | 60% | | 65% | | 70% | | 75% | | 80% | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dressing Percentage | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS |
| 58% | -2.99[2] | -2.69[2] | -2.84[2] | 0.23[3] | 0.22[5] | 3.98[3] | 4.99[5] | 7.73[3] | 9.77[5] | 11.48[3] |
| 60% | -2.95[2] | -2.65[2] | -2.79[2] | 0.90[3] | 1.43[5] | 4.70[3] | 6.25[5] | 8.50[3] | 11.08[5] | 12.31[3] |
| 62% | -2.91[2] | -2.28[3] | -2.25[5] | 1.57[3] | 2.63[5] | 5.42[3] | 7.51[5] | 9.27[3] | 12.40[5] | 13.13[3] |

Tenderness Proportion = 20%; Tenderness Premium = $345.00/cwt/kg;

[1, 2, 3, 4, 5] indicates the level of $\lambda$, which is the proportion of cows receiving AI

**Table II-13. Profits ($/head) under Alternative Tenderness Premiums & Tenderness Proportion**

| Tenderness Premiums | 46.11 | | 107.00 | | 256.00 | | 345.00 | |
|---|---|---|---|---|---|---|---|---|
| Tenderness Proportion | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS |
| 15% | -3.88[2] | -3.53[2] | -3.70[2] | -3.35[2] | -3.25[2] | -2.90[2] | -2.99[2] | -0.71[3] |
| 17% | -3.86[2] | -3.51[2] | -3.66[2] | -3.30[2] | -3.15[2] | -2.80[2] | -2.85[2] | 1.45[3] |
| 20% | -3.84[2] | -3.48[2] | -3.59[2] | -3.24[2] | -3.00[2] | -0.88[3] | 1.43[5] | 4.70[3] |
| 22% | -3.82[2] | -3.46[2] | -3.55[2] | -3.20[2] | -2.89[2] | 0.72[3] | 5.04[5] | 6.87[3] |
| 25% | -3.79[2] | -3.44[2] | -3.49[2] | -3.13[2] | -1.20[5] | 3.13[3] | 10.47[5] | 10.11[3] |

AI Success Rate = 70%; Dressing Percentage = 60%;

[1, 2, 3, 4, 5] indicates the level of $\lambda$, which is the proportion of cows receiving AI.

**Table II-14. Profits ($/head) under Alternative Dressing Percentage & Tenderness Proportion**

| Retail Yield Percentage / Tenderness Proportion | 58% | | 60% | | 62% | |
|---|---|---|---|---|---|---|
| | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS |
| 15% | -3.02[2] | -1.25[3] | -2.99[2] | -0.71[3] | -2.95[2] | -0.17[3] |
| 17% | -2.89[2] | 0.84[3] | -2.85[2] | 1.45[3] | -2.81[2] | 2.07[3] |
| 20% | 0.22[5] | 3.98[3] | 1.43[5] | 4.70[3] | 2.63[5] | 5.42[3] |
| 22% | 3.72[5] | 6.07[3] | 5.04[5] | 6.87[3] | 6.37[5] | 7.66[3] |
| 25% | 8.96[5] | 9.21[3] | 10.47[5] | 10.11[3] | 11.98[5] | 11.02[3] |

AI Success Rate = 70%; Tenderness Premium = $345.00/cwt/kg;
[1, 2, 3, 4, 5] indicates the level of $\lambda$, which is the proportion of cows receiving AI.

**Table II-15. Profits ($/head) under Alternative Dressing Percentage & Tenderness Premiums**

| Dressing Percentage | 58% | | 60% | | 62% | |
|---|---|---|---|---|---|---|
| Tenderness Premiums | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS |
| 46.11 | -3.80[2] | -3.44[2] | -3.79[2] | -3.44[2] | -3.78[2] | -3.43[2] |
| 107.00 | -3.50[2] | -3.15[2] | -3.49[2] | -3.13[2] | -3.47[2] | -3.12[2] |
| 256.00 | -2.78[2] | 2.46[3] | -1.20[5] | 3.13[3] | -0.08[5] | 3.80[3] |
| 345.00 | 8.96[5] | 9.21[3] | 10.47[5] | 10.11[3] | 11.98[5] | 11.02[3] |

AI Success Rate = 70%; Tenderness Proportion = 20%;

[1, 2, 3, 4, 5] indicates the level of $\lambda$, which is the proportion of cows receiving AI.

**Table II-16. Profits ($/head) under Alternative AI Success Rate & Differences between Breeding # of Cows Covered by One Bull**

| AI Success Rate / # of Cows Covered by One Bull | 60% | | 65% | | 70% | | 75% | | 80% | |
|---|---|---|---|---|---|---|---|---|---|---|
| | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS | WBSF | WCTS |
| 35 | -3.02[2] | -2.72[2] | -2.81[2] | 0.29[3] | -1.33[5] | 2.62[3] | 0.25[5] | 3.97[3] | 5.11[5] | 7.80[3] |
| 30 | -2.95[2] | -2.65[2] | -2.79[2] | 0.90[3] | 1.43[5] | 4.70[3] | 6.25[5] | 8.50[3] | 11.08[5] | 12.31[3] |
| 25 | -2.32[5] | 1.56[3] | 2.45[5] | 5.32[3] | 7.23[5] | 9.08[3] | 12.01[5] | 12.85[3] | 16.78[5] | 16.61[3] |
| 20 | 6.42[5] | 8.16[3] | 11.13[5] | 11.88[3] | 15.86[5] | 15.60[3] | 23.72[5] | 21.70[3] | 28.43[5] | 25.41[3] |

AI Success Rate = 70%; Tenderness Proportion = 20%; Tenderness Premium = 345/cwt/kg;

[1, 2, 3, 4, 5] indicates the level of $\lambda$, which is the proportion of cows receiving AI.

**Appendix Table II-A1. AI Success Rate and Genotype Frequencies (Charolais × Angus Cross)**

| Genotype Pairs | Original Frequencies | Frequencies under Different AI Success Rate 60% | 65% | 70% | 75% | 80% |
|---|---|---|---|---|---|---|
| CC.CC | 3.30% | 12.22% | 12.97% | 13.71% | 14.45% | 15.20% |
| CG.CC | 1.76% | 3.61% | 3.76% | 3.92% | 4.07% | 4.22% |
| CC.CG | 22.11% | 45.34% | 47.28% | 49.21% | 51.15% | 53.09% |
| CC.GG | 37.00% | 14.80% | 12.95% | 11.10% | 9.25% | 7.40% |
| CG.CG | 11.75% | 14.40% | 14.62% | 14.84% | 15.07% | 15.29% |
| GG.CC | 0.23% | 0.12% | 0.11% | 0.09% | 0.08% | 0.06% |
| CG.GG | 19.67% | 7.87% | 6.89% | 5.90% | 4.92% | 3.93% |
| GG.CG | 1.56% | 0.58% | 0.51% | 0.44% | 0.36% | 0.29% |
| GG.GG | 2.61% | 1.05% | 0.92% | 0.78% | 0.65% | 0.52% |

**Appendix Table II-A2. Costs of Natural Breeding vs. Costs of Artificial Insemination ($/calf weaned)**

| Natural Breeding | | Artificial Insemination (Cost Differences) | | |
|---|---|---|---|---|
| | | 80% Success rate | $67.25 | ($14.25) |
| | | 75% Success rate | $70.75 | ($17.75) |
| Bull covers 30 cows | $53.00 | 70% Success rate | $70.75 | ($17.75) |
| | | 65% Success rate | $74.24 | ($21.24) |
| | | 60% Success rate | $77.74 | ($24.74) |
| | | | | |
| | | 80% Success rate | $67.11 | ($7.84) |
| | | 75% Success rate | $70.56 | ($11.29) |
| Bull covers 30 cows | $59.27 | 70% Success rate | $74.01 | ($14.74) |
| | | 65% Success rate | $77.46 | ($18.18) |
| | | 60% Success rate | $80.91 | ($21.64) |
| | | | | |
| | | 80% Success rate | $70.35 | ($1.68) |
| | | 75% Success rate | $73.75 | ($5.08) |
| Bull covers 25 cows | $68.67 | 70% Success rate | $77.15 | ($8.48) |
| | | 65% Success rate | $80.54 | ($11.87) |
| | | 60% Success rate | $83.94 | ($15.27) |
| | | | | |
| | | 80% Success rate | $73.45 | (-$10.90) |
| | | 75% Success rate | $80.13 | (-$4.22) |
| Bull covers 20 cows | $84 .35 | 70% Success rate | $84.37 | ($0.02) |
| | | 65% Success rate | $86.80 | ($2.45) |
| | | 60% Success rate | $90.14 | ($5.79) |

[*] number in the parentheses are difference in costs between NS and AI

# CHAPTER III

# VALUE-ADDED TRACEABILITY: USING A WHOLE-CHAIN TRACEABILITY SYSTEM TO TRANSFER INFORMATION ABOUT MULTIPLE ATTRIBUTES ALONG A MULTI-STAGE SUPPLY CHAIN

## Introduction

As cattle/beef products are transferred along the supply chain, the existence of information asymmetry causes market inefficiency and economic loss to the U.S. beef industry. For example, as Resende-Filho and Buhr (2008) – hereafter RFB – show, when cow-calf producers or cattle feeders vaccinate their animals, injection-site lesions may result. The existence of injection-site lesions causes meat packers to trim the lesion locations, or degrade the quality of the meat, causing large economic losses (Roeber et al. 2001).

The probability of lesions could be reduced by injecting in the animal's neck area or using a needle-free injection method (Resende-Filho and Buhr 2008). Since cow-calf producers and cattle feeders do not bear losses caused by injection-site lesions directly, they have no incentive to change from a higher-cost injection site to a lower-cost injection site. Meat packers are only able to verify the existence of injection-site lesions at the time of meat processing, after transactions have been made. Thus, costs of trimming meat with blemishes or degrading of meat cuts are bore entirely by meat processors.

In the U.S. beef industry, when beef cattle transactions occur, grid pricing systems are commonly used. Average carcasses receive base prices, while premiums and discounts are specified for carcasses with qualities above or below the base. However, grid pricing systems are unable to fully value all consumer-valued attributes, such as beef tenderness. Improving tenderness in beef may increase fed cattle value by almost $5/cwt (Riley et al. 2009). There is potential for U.S. beef producers to gain extra profit by improving tenderness of beef cuts.

According to Van Eenennaam et al. (2007), cattle carrying specific genotypes produce more tender meat. Thus, meat tenderness could be improved by appropriate selection of cattle genetics. Genetic selection would be done at the cow-calf producer stage, choosing better sire genetics using artificial insemination (AI).[5] But since cow-calf producers are not compensated for the value of improved meat tenderness, they have no incentive to pay the extra costs for using artificial insemination. On the other hand, even though meat processors may be willing to compensate producers for animals with preferred genetics, they likely cannot identify the source of those animals after moving through several stages of the supply chain.

According to Schroeder et al. (1998), the beef industry is interested in moving toward a value-based marketing/pricing system, which should improve pricing efficiency. With value-based marketing/pricing, meat price and meat quality attributes are linked more accurately, thus better communicates consumers demands to producers (Schroeder et al. 1998). Meat processors that can more efficiently identify beef quality may be able to build their own brand and gain

[5] Better sire genetics could also be achieved by choosing a bull with the appropriate genetics and using natural breeding services (NBS), but to simplify the discussion we initially assume that AI is used, and later on compare the results with those using NBS.

brand premiums (Schroeder et al. 1998). Beef traceability could be a feasible tool to achieve this goal.

Implementing a whole-chain traceability system (WCTS) can help solve the problems mentioned above. Moreover, traceability could reduce supply chain anonymity and information asymmetry (RFB). Reducing information asymmetry could facilitate allocating profits and costs more equitably in the beef supply chain, enhancing preferred behaviors that increase quality and reducing unwelcome operations that harm quality.

Implementing a WCTS in the beef industry could potentially provide other benefits also, such as improving food safety, enhancing disease prevention and mitigation, managing the supply chain more sufficiently, and providing value-added products to consumers (Golan et al. 2004). In order for a sufficiently large number of producers in a fragmented supply chain to voluntarily adopt whole-chain traceability, though, participants must believe that individual benefits exceed costs.

Traceability is the ability to trace the activities of commodities/products under consideration. According to Thakur and Hurburgh (2009), traceability includes tracking (forward) and tracing (backward). Tracking forward is the ability to follow the product from one stage to the next, while tracing backward is the ability to identify the origin of products through several stages (Thakur and Hurburgh 2009). A whole-chain traceability system traces and tracks the product through all stages along the supply chain. But true whole-chain traceability systems have not been implemented on a large scale in the U.S. in fragmented supply chains, partly because of cost, but also because participants would be forced to reveal proprietary information to every other participant in the supply chain. USDA's attempts to implement a National Animal Identification System faced much resistance from producers due to cost, lack of confidentiality, and lack of accuracy of the system. The resulting low participation led to abandonment of these attempts in 2010 (Schroeder and Tonsor, 2012).

Recent innovations in traceability technology offer the potential for WCTS systems that permit producers to provide the relevant information to those who are willing to pay for it, without giving up confidentiality of their information to other supply chain participants. The technology permits those who put information into the system to choose which participants in the supply chain have access to the information, and which pieces of the information they can access. This would reduce one of the disincentives producers face – lack of information confidentiality – when choosing whether to participate in a WCTS. Thus, value-added information can be transferred along the supply chain and traced back to a specific participant, which means that the producers who provide products with preferred attributes can be compensated by downstream participants who value the information.

Two valuable attributes in the beef industry are focused by this research: injection site and tenderness genetics. This research simulates a WCTS used along three stages of the beef supply chain: cow-calf producer, cattle feeder, and meat processor. Meat processors benefit from the information and improved attributes (injection site and tenderness genetics). They must choose how much of the added profitability to return to upstream participants (cow-calf producers and cattle feeders) in order to provide sufficient incentive for them to provide the information and the attributes, while maintaining or enhancing profitability.

The objective of this research is to determine the benefits relative to costs for an individual to participant in a WCTS in a fragmented beef supply chain. The specific objectives are:

1. Determine the benefits to a meat processor of implementing a WCTS for injection-site and tenderness genetics problem simultaneously;

2. Determine the optimized income transfers from meat processor to cattle feeder and cow-calf producer.

**Background and Literature**

Various grid pricing systems exist, which may differ in the carcass traits they seek to reward or penalize (Feuz et al. 2004). With grid pricing, beef cattle providers receive a price for each individual animal based on its actual carcass traits. Numerous specific attributes, though, such as injection sites and tenderness genetics, are not explicitly considered in grid pricing..

Vaccinating beef cattle prevents or reduces the occurrence of disease. But an injection can cause a lesion when given in the muscle. Lesions caused by injections remain concealed within the muscles and fat, so that damage is observable only during portioning of primal cuts (Roeber et al. 2001). Injection-site lesions caused great economic losses to the U.S. beef industry (RFB). According to Roeber et al. (2001), some producers have changed injection practices, so that the incidence of injection-site lesion in top sirloin butts decreased from 11.4% in November 1995 to 2.1% in July 2000 (Roeber et al. 2001).[6] However, the mean weight per injection-site lesion increased from 192.5 g to 249.8 g (Roeber et al. 2001), so injection-site lesions remain one of the quality challenges facing the U.S. beef industry. Roeber et al. (2001) also suggested that the majority of lesions happen at early stages, such as the cow-calf producer stage. Since meat processors do not directly interface with cow-calf producers, it is difficult for meat processors to control the occurrence of the injection-site lesions.

[6] It is assumed that the rates of injection-site lesions have not changed much compared with those reported by Roeber et al. (2001). It is unknown whether producers have continued to reduce incidence of lesions, but even if they have, the analysis is still helpful in illustrating the potential of a whole-chain traceability system for encouraging value-added practices. Analyzing lesions also helps to highlight the extensions of the work by Resende-Filho and Buhr.

Similarly, improving beef tenderness has great potential to increase revenues and improve value to consumers. According to Lusk et al. (2001), Feuz et al. (2004), and Schroeder et al. (2008), consumers are willing to pay a price premium for a tender steak. The range of consumers' willingness-to-pay in these studies varied from $0.42/lb. to $5.57/lb. Producers can improve tenderness by selecting specific genes as they breed cattle. Schenkel et al. (2006) concluded that calpastatin (CAST) single nucleotide polymorphism (SNP) was associated with shear force. Van Eenennaam et al. (2007) tested the associations among commercial DNA tests and beef quality traits. Combined effects of two SNPs were verified: CAST and μ-calpain (CANP). The results showed that the genotype CC for both SNPs were favorable for tenderness, with cattle carrying CC.CC producing the most tender meat compared to other genetics.

Thus, cow-calf producers could use artificial insemination (AI) technology to select favorable genetics and avoid unfavorable genetics. However, using AI increases costs to cow-calf producers. Without a direct connection between processors and cow-calf producers, tenderness premiums cannot be passed from meat processors to cow-calf producers (Riley et al. 2009), and without sufficient incentives, cow-calf producers would not be willing to incur the extra costs of providing animals with genetics that favor increased tenderness.

RFB estimated the value of a traceability system in controlling injection-site lesions. A two-stage production system including meat processor and cattle feeder implementing a beef traceability system was simulated. They concluded that even with a traceability success rate as low as 38.9%, cattle feeders would have sufficient incentive to give injections to cattle using a needle-free method. By implementing a traceability system, approximately $12.8 million savings could be generated for the beef industry per year (Resende-Filho and Buhr 2008).

This paper simultaneously considers both beef injection-site lesion control and improvement of beef tenderness. There are several contributions of this research. First, this research estimates benefits of implementing a WCTS in a multiple-stage beef supply chain. Second, this research estimates the benefits of improving more than one attribute simultaneously. Third, this research considers costs of implementing a WCTS at all stages, rather than at just the meat processor stage. Together, these will provide more realistic estimates of the benefits to individual beef producers from participating in a WCTS.

By quantifying benefits to individual producers from participating in a WCTS, this research will provide guidance to firms, the beef industry, and government agencies on the most promising incentives as well as remaining obstacles to implementing a voluntary whole chain traceability system. It will also provide a framework for evaluating other value-added opportunities, and will provide guidance for firms to use in allocating value-added benefits among supply chain participants.

## Model

The model extends the two-stage principal-agent model by RFB to three stages: meat processor (principal), cattle feeder (agent), and cow-calf producer (agent); and it considers two attributes simultaneously – meat tenderness and injection site.

### *Injection Site*

In RFB's principal-agent model, a meat processor (principal) purchases live animals from cattle feeders (agents). Prior to the transaction, cow-calf producers, cattle feeders, or both give injections to the cattle, which affects the frequencies and types of injection-site lesions in beef retail cuts. Three injection methods $a_i$ ($i$ = 1, 2, 3) are: give injections in the rear leg ($a_1$), give injections in the neck area ($a_2$), and give injections with a needle-free method ($a_3$). Giving injections in the rear leg is least preferred by the meat processor, as it can result in lesions in high-valued meat cuts. Giving injections in the neck area can result in lesions in lower-valued meat cuts. The needle-free injection method is the most costly, but is assumed to produce no lesions (RFB).

According to RFB and Roeber et al. (2001), a majority of injection-site lesions happen at the cow-calf and stocker stages, or very early in the finishing stages. Without a WCTS, meat processors do not typically connect with cow-calf producers directly, so they have little effect on the incidence of injection-site lesions at cow-calf producer stage. But with a WCTS, the meat processor could trace the origin, ownership, and location of each animal at each point in the production process, and can thus reward/penalize the cow-calf producer or feedlot for using injection methods preferred/not preferred by the meat packer.

Following RFB, there are eight possible events of injection-site lesions: “0” (no lesion detected), “c” (lesions in chuck area only), “r” (lesions in round area only), “s” (lesions in sirloin area only), “(c, r)” (lesions in chuck and round areas), “(c, s)” (lesions in chuck and sirloin areas), “(r, s)” (lesions in round and sirloin areas), “(c, r, s)” (lesions in chuck, round, and sirloin areas).

Also following RFB, the model includes two parts: the principal’s cost minimization, and agents’ utility maximization. In the model, a meat processor (principal) purchases live animals from cattle feeders (agent). Prior to the transaction, the cow-calf producer and/or cattle feeder give injections to the cattle, which affects the frequencies and types of injection-site lesions in beef retail cuts.

*Meat Tenderness*

In the tenderness problem, only the cow-calf producer and meat processor stages are considered. (Although feeding regimens by cattle feeders may also influence beef tenderness, this paper focuses specifically on the impact of genetics on beef tenderness.[7]) With a WCTS as described by Adam et al. (2016), participants can choose what information to share and with whom to share the information. With the WCTS, the meat processor can identify the origins of cattle purchased and then reward cow-calf producers directly according to the genetic information shared. Cow-calf producers have two choices, $b_k$, in this problem: $b_0$ for breeding calves using natural service (NS), and $b_1$ for breeding calves using AI.

*Part I. Principal's Cost Minimization*

Since this paper considers injection-site lesion and tenderness simultaneously, every event and its probability of occurrence must be identified. Variable $p_{(l)}$ represents the probability of one of the eight possible lesion events ($l$ = 0, c, r, s, (c,r),(c,s),(r,s),(c,r,s)). Subscript $l$ identifies the type of lesion or combination of lesions found in each carcass side. $p_{(l)}^{com}$ is the combined probability of $p_{(l)}^{1}$ and $p_{(l)}^{2}$, where $p_{(l)}^{n}$ is probability of lesion event $l$ in stage $n$ (cow-calf producer stage, $n$ = 1; cattle feeder stage, $n$ = 2). It is assumed that when cow-calf producers and cattle feeders give injections to cattle, they do not know injection actions at the other stage; their decisions are independent. The probabilities of each lesion event in each stage depend on the method of injection $a_i^n$ at each stage.

If cow-calf producers use AI, taking action $b_1$, to select genetics preferred by the meat processor, they receive rewards from meat processor accordingly. If cow-calf producers do not select genetics preferred by meat processor, taking action $b_0$, they do not receive rewards. It is assumed that tenderness does not influence the probabilities of injection-site lesions. However, if lesions are detected in valuable meat cuts when processing, the value of tenderness premium may be affected. When the proportion of tender meat cuts is improved, $k$ = 1; otherwise, $k$ = 0.

[7] The association of tenderness and genetics used here was obtained from Van Eenennaam (2007). In their paper, feeding regimens are not considered.

The traceability system has a success rate of $t$. When $t = 0$, the traceability system fails to work all the time. When $t = 1$, the traceability systems succeeds all the time. The principal (meat processor) makes income transfers $I^1_{m,(l),k}$ to cow-calf producers, and $I^2_{m,(l)}$ to cattle feeders, where $m$ is the indicator of traceability success ($m = 1$ when traceability succeeds; 0 otherwise).

The meat processor's objective is to minimize the expected costs of cattle including the incidence of lesions and existence of tenderness. Equation (1) is the meat processor's cost function, including the amount of income transfers the principal makes to agents, the cost of using a WCTS to meat processors, the cost of trimming/degrading beef cuts with lesions, and the premiums for improved tenderness.

$$(1) \qquad E_c\left(I^1_{0*}, I^1_{1,(0),0}, \dots, I^1_{1,(c,r,s),1}, I^2_{0*}, I^2_{1,(0),0}, I^2_{1,(c,r,s)}\right)$$

$$= 2\left[p_{0*}I^1_{0*} + \sum_{k=0}^{1}\sum_{l=(0)}^{(c,r,s)} p^{com}_{1,(l),k} I^1_{1,(l),k} + \sum_{m=0}^{1}\sum_{k=0}^{1} p^{com}_{m,(c),k} P_{(c),k} + \sum_{m=0}^{1}\sum_{k=0}^{1} p^{com}_{m,(r),k} P_{(r),k}\right.$$

$$+ \sum_{m=0}^{1}\sum_{k=0}^{1} p^{com}_{m,(s),k} P_{(s),k} + \sum_{m=0}^{1}\sum_{k=0}^{1} p^{com}_{m,(c,r),k}\left(P_{(c),k} + P_{(r),k}\right)$$

$$+ \sum_{m=0}^{1}\sum_{k=0}^{1} p^{com}_{m,(c,s),k}\left(P_{(c),k} + P_{(s),k}\right) + \sum_{m=0}^{1}\sum_{k=0}^{1} p^{com}_{m,(r,s),k}\left(P_{(r),k} + P_{(s),k}\right)$$

$$\left. + \sum_{m=0}^{1}\sum_{k=0}^{1} p^{com}_{m,(c,r,s),k}\left(P_{(c),k} + P_{(r),k} + P_{(s),k}\right) + p_{0*}I^2_{0*} + \sum_{k=0}^{1}\sum_{l=(0)}^{(c,r,s)} p^2_{1,(l),k} I^2_{1,(l),k}\right]$$

$$+ g(t) - r.$$

where $p_{0*}$ is the probability that traceability system fails to work, $I^1_{0*}$ and $I^2_{0*}$ are the income transfers from the principal to agents when the traceability system fails to work, $p^{com}_{1,(l),k}$ is the combined probability of a lesion occurring in ($l$) and tenderness level $k$, when the traceability system succeeds, $P_{(r),k}$ is the cost (\$/carcass side) to the meat processor to discard beef cuts at tenderness level *k* with lesions, *g(t)* is the cost ($/head) of a WCTS for the meat processor as a function of success rate *t*, and *r* is the tenderness premium ($/head) received by meat processor.

Generally, the net cost to the meat processor (principal) is the summation of income transfers to cattle feeders (agent) and cow-calf producers (agent), the cost of discarding meat cuts with injection-site lesions, and the cost of implementing a WCTS, minus the extra gain from improving meat tenderness.

*Part II. Agents' Utility Maximization*

Following RFB, constant relative risk aversion coefficients for cow-calf producer and feedlot are both set at 0.75, and Equation (2) is the agents' utility function.

$$(2)\qquad U^n\left(a_{i,j}^n \middle| I_{0*}^n, I_{1,(0),0}^n, \ldots, I_{1,(c,r,s),1}^n\right) = \gamma(a_i^n)\left[p_{0*}^n u(I_{0*}^n) + \sum_{l=0}^{(c,r,s)} p_{1,(l),k}^n u(I_{1,(l),k}^n)\right] - d(a_{i,j}^n)$$

where $U(.)$ is a von Neumann-Morgenstern utility function and $u(.)$ is a Bernoulli utility function. According to RFB, $\gamma(a_i^n)$ is set equal to $e^{\gamma^n(C_{a^n}+tr^n+br^n)}$, $u(I_{1,(l),k}^n) = -e^{-\gamma^n I_{m,(l),k}^n}$, and $d(a_i^n) = 0$. The von Neumann-Morgenstern utility function is represented as

$$(3)\qquad U\left(I_{m,(l),k}^n, a_{i,j}^n\right) = -e^{-\gamma^n(I_{m,(l),k}^n - C_{a^n} - tr^n - br^n)}$$

where $\gamma^n$ is the constant absolute risk aversion coefficient for agent *n*, $C_{a^n}$is the injection cost for agent *n* ($/head), $tr^n$ is the cost of participating in a WCTS for agent *n* ($/head), $br^n$is the breeding cost for agent *n* ($/calf).

Following RFB, the principal-agent problem with a WCTS is solved as a two-step numerical optimization. The first step is to solve the cost minimization problem for each combination of injection methods of cow-calf producer and cattle feeder, when *k* = 0 and *k* = 1.

Then the lowest expected cost per head is selected from among the calculated values in step one. The principal's cost minimization problem is:

(4)

$$\min_{I^1_{0*},I^1_{1,(0),0},\dots,I^1_{1,(c,r,s),1},I^2_{0*},I^2_{1,(0),0},I^2_{1,(c,r,s)}} E_c(I^1_{0*}, I^1_{1,(0),0}, \dots, I^1_{1,(c,r,s),1}, I^2_{0*}, I^2_{1,(0),0}, I^2_{1,(c,r,s)} | a^1_{i,j}, a^2_{i,j})$$

**Subject to:**

$$\text{(a) } U^n(a^n_{i,j} | I^n_{0*}, I^n_{1,(0),0}, \dots, I^n_{1,(c,r,s),1}) \geq \overline{U^n}$$

$$\text{(b) } U^n(a^n_{i,j} | I^n_{0*}, I^n_{1,(0),0}, \dots, I^n_{1,(c,r,s),1}) \geq U^n(a^n_j | I^n_{0*}, I^n_{1,(0),0}, \dots, I^n_{1,(c,r,s),1}) \ \forall a^n_{i,j} \neq a^n_{-i,-j}$$

where $\overline{U^n}$ is the opportunity utility for agent *n* calculated as trading with a meat processor that does not implement traceability and pays market price. Equation (4a) gives the participation constraint, that participating in the WCTS should generate agents' utilities no lower than their opportunity utilities. Equation (4b) gives the two incentive compatibility constraints, that agents receive the highest utility from choosing injection method *i* instead of injection method *j*. All constraints must be satisfied to obtain the optimal solution of the program.

**Identification of Parameters**

Parameters needed to solve the numerical problem include: costs of injections, frequencies of lesions using different injection methods, the original income transfers from the principal to agents, costs to meat processor of trimming/degrading beef cuts with lesion,extra costs of discarding beef cuts with lesions if tenderness is improved, costs of a WCTS to meat processor, cattle feeder, and cow-calf producer, cost of using AI.

Values for injection costs and lesion frequencies are those used by RFB. Costs of gving injections in the rear leg, in the neck, and needle-free are \$0 (base cost), \$0.17, and 0.204, respectively (RFB). According to RFB, 43% of lesions occur at the feedlot, and 57% originate at an earlier stage of production. The stocker stage is not considered here, so it is assumed that 57% of lesions originate at the cow-calf stage. Probabilities of lesions occuring in each meat cut are taken from RFB frequencies at the feedlot stage. These probabilities are adjusted for lesions occuring at the cow-calf stage by multiplying the RFB probabilities at the feedlot stage by 0.57/0.43, or $p^1_{(l)}$ $*0.57/0.43$.

As in Chapter II, the ending weight of cattle is set at 1,300 lbs., while the dressing percentage is 62%. The average carcass weight of 806 lbs is assumed to be sold for $480/carcass side ($1.22/lb.) The opportunity costs of a lesion occuring in a chuck steak ($P_c$), a bottom-round, and a top sirloin butt ($P_s$) are $2.50, $9.91, and $11.02, respectively.

If cattle are carrying preferred genes for tenderness, tenderness of beef cuts is improved, so opportunity costs of a lesion increase. According to Holland et al. (2010), the primal cuts of round and loin contain valuable sub-primal cuts, such as top round and sirloin. As top round and sirloin are the parts where a premium is offered for improved tenderness, lesions occurring in round or sirloin may cause extra losses to the meat processor. Beef cuts with lesions lose any potential tenderness premium.[8] According to Van Donkersgoed et al. (1999), injection-site lesions in a round and a top sirloin butt affect the value of 3.71 and 2 steaks, respectively. Average weight of a steak is 0.67 kg (Van Donkersgoed et al. 1999), or 1.474 lb. Warner-Bratzler shear force (WBSF) is the average measure of force needed to shear a core of steaks.The default tenderness premium we use for a 1-kg decrease in WBSF is set to be $345.00/cwt, at retail level. Chapter II calculates the decreased amount of WBSF from favorable genetics from Van Eenennaam (2007). The tenderness premium losses from lesions in a round and a top sirloin butt are $1.30 and $0.70, respectively.

[8] It is assumed that a beef cut with a lesion will be trimmed or graded lower. If the beef cut is trimmed, the meat processor loses all value of it, including any tenderness premium. If the beef cut is regraded and made into ground beef, the meat processor loses the difference in value, including any tenderness premium (Van Donkersgoed et al. 1999).

Traceability costs in cow-calf producer stage and cattle feeder stage are as used in Chapter II. Participating in a WCTS costs cow-calf producers and cattle feeders \$4.84/head, and \$0.75/head, respectively. Cow-calf producers pay a higher cost because of the cost of tagging the animals. According to RFB, cost of implementing a traceability system at the meat processor stage is a function of traceability success rate.

$$(4) \qquad g(t) = \eta t^2/2$$

where $\eta = 1.4539$ (RFB). Results are calculated for several potential values for the traceability success rate: 0 (no traceability), 0.389 (traceability succeeds 38.9% of time), 0.95 (traceability succeeds 95% of time. It is assumed that the WCTS only fails when there are breakdowns of devices or software. RFB chose 0.95 as the highest probability of a traceability system success, and 1 (traceability succeeds 100% of time), with costs of \$0.66/head, and \$0.73/head at meat processor stage, respectively.

Cost of cattle artificial insemination is as in Chapter II. Assuming the AI success rate of 70%, AI costs \$ 14.74/calf weaned more than using NS (one bull covers 30 cows). If the AI success rate increases to 80%, cost difference between AI and NS decreases to \$7.84/calf weaned.

In this chaper, we refer to the results in Chapter II and calculate the extra gain from verifying and marketing improved tenderness using a WCTS assuming a 70% AI success rate, \$345.00/cwt/kg tenderness premium, and a tenderness proportion of 20% (the proportion of meat for which consumers are willing to pay tenderness premiums, and a tenderness premium of \$21.65/head. This tendernss premium is obtained from identifying cattle's genetics, instead of using WBSF.[9]

[9] The U.S. beef industry does not implement WBSF test because of multiple limitations, including the value of meat damaged in the test and time needed to conduct the test (O'Quinn

### Scenarios and Results

Depending on the traceability success rate *t*, this paper has three scenarios. As a baseline case, $t = 0$ represents a situation in which no traceability system exists, and meat processors do not observe actions taken by cow-calf producers or cattle feeders at the time transactions occur. When $t = 1$, meat processors can observe the relevant actions cow-calf producers and cattle feeders take with no extra cost; thus information asymmetry is eliminated. When $t = 0.95$ (or any number between 1 and 0), meat processors observe actions taken by cow-calf producers and cattle feeders only when the WCTS works.

*t = 0 (without a WCTS)*

With no WCTS, meat processors (principal) do not observe actions by cow-calf producers and cattle feeders (agents), and do not pay incentives for no lesions or extra tenderness. The equlibrium for this scenario is for meat processors to pay the market price, $960/head, to cattle feeders, and nothing to cow-calf producers. Since cow-calf producers choose the lowest-cost method, they receive no incentives and do not select genetics. Processors pay $960/head to cattle feeders, and nothing to cow-calf producers. Since no incentives are received, cow-calf producers and cattle feeders would choose the most cost-saving method (inject in rear leg) to give injections. Similarly, cow-calf producers would not select genetics using AI. The expected cost in this scenario should equal the highest cost in information symmetric scenario, which is $967.23/head, including $7.23 from loss of lesion-damaged cuts.

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2016). A WCTS, as stated in Chapter II, could be used as another tool of indicating the tenderness of meat from identifying the genotypes of cattle *t = 1 (Symmetric Information)*

Under this information-symmetric scenario, any action taken by an agent is observable to the principal. Then, the principal chooses the lowest expected cost and contracts with agents to take actions consistent with that. When AI is not used to improve the proportion of more tender meat cuts, the meat processor bears the lowest costs when cow-calf producers and cattle feeders both use a needle-free injection method. According to Table III-2, When both agents take the middle action (injection in neck area), the cow-calf producer receives $0.10/carcass side, while the cattle feeder receives $480.09/carcass side as income transfer. When the cow-calf producer takes the least-preferred action (injection in rear leg), and the cattle feeder takes the most-preferred action (needle-free method), they receive an income transfer of $0.00/carcass side and $480.10/carcass side, respectively.

When the cow-calf producer takes the most-preferred action and the cattle feeder takes the least-preferred action, the income transfers to agents are $0.15/carcass side and $480.00/carcass side, respectively. When both agents take the most-preferred action, they receive income transfers of $0.15/carcass side and $480.13/carcass side, respectively. So if both agents take the least-preferred actions, they do not receive any reward from the principal. When both agents take the most-preferred action, they both receive the highest level of income transfer from the principal.

The meat processor can also contract with the cow-calf producer to use AI to increase the probabilities of favorable genetics that improve meat tenderness. In this case, the lowest cost to the meat processor is $948.18 per head, including $4.78/head and $480.13/carcass side income transfer to cow-calf producer and cattle feeder. The lowest cost in this case occurs when both agents use the most-preferred injection methods. The meat processor compensates the cattle feeder $0.13/carcass side to cover the extra costs of needle-free injection. The cow-calf producer receives a price premium of \$4.78/head to cover the cost of needle-free injection and artificial insemination. The income transfers to agents are lower than the extra costs they paid.The agents' risk aversion may be a reason for the willingness of agents to take lower income transfers and still take the preferred actions by the principal. As in the previous analysis, when both agents take the least-preferred action, they both receive the lowest level of income transfer. When both agents take the most-preferred action, they both receive the highest level of income transfer.

*t = 0.95*

When a WCTS is implemented yet some information asymmetry exists, the numerical problem is solved with two steps. Following RFB, additional constraints (5) are imposed to ensure a higher income transfer for more favorable actions taken. For example, if there is no lesion detected, the income transfers should be highest. If there are lesions found in chuck steaks, the income transfers should be higher than if lesions are found in sirloin steaks, as the losses from discarding sirloin steaks are higher than those of discarding chuck steaks.

(5)

$$I_{1,(0)}^{n} \geq I_{0*}^{n}; I_{0*}^{n} \geq I_{1,(c)}^{n}; I_{1,(c)}^{n} \geq I_{1,(r)}^{n}; I_{1,(r)}^{n} \geq I_{1,(s)}^{n}; I_{1,(s)}^{n} \geq I_{1,(c,r)}^{n}; I_{1,(c,r)}^{n} \geq I_{1,(c,s)}^{n}; I_{1,(c,s)}^{n} \geq I_{1,(r,s)}^{n}; I_{1,(r,s)}^{n} \geq I_{1,(c,r,s)}^{n}.$$

Results are shown in Tables III-3 and III-4. According to Table III-3, when cow-calf producers do not improve meat tenderness, the meat processor's lowest cost, \$965.19/head, occurswhen cow-calf producers and cattle feeders both choose a needle-free method. In this case, cow-calf producers and cattle feeders receive the highest income transfer -- \$2.84/carcass side and \$480.80/carcass side, respectively – when the traceability system works successfully and no lesions are detected. When both agents use a needle-free injection method, no injection-site lesion is generated. Thus, the values of estimated income transfer to agents when lesions are detected do not have a meaning, as the probability of lesions occurring is zero. Thus, we elimate these values in Table III-3. Compared to the results under symmetric information, the meat processor's loss due to asymmetric information is $4.49/head.

Table III-4 summarizes the results of optimizing injection-site lesion and improved tenderness characteristics simultaneously. When cow-calf producers select genetics to improve beef tenderness, the meat processor's lowest cost is $954.72/head. When cow-calf producers use AI to select genetics, and both agents vaccinate with a needle-free method, the meat processor's cost is the lowest. For each agent, switching from a less-preferred injection method to a more preferred injection method, for example, from injecting in rear leg to the neck area, would lead to a decrease in the principal's expected cost, as well as an increase in the income transfer to each agent. However, the highest level of income transfer to each single agent occurs when the agents takes the middle action (injecting in neck area), when fixing the action taken by the other agent. Assuming that only one agent can choose injection method, the highest level of income transfer always occurs when the agent gives injection to cattle in the neck area. This conclusion is different from that when information is symmetric. With symmetric information, the highest income transfer for both agents occurs when they take the most-preferred action.

Compared to results in Table III-3, when considering the benefit of improving the proportion of tenderness genetics using a WCTS, rather than considering only the injection-site lesion problem, the principal, the meat processor, gains an extra $10.47/head. However, when compared to the perfect information case, the meat processor still loses $6.54/head, because of asymmetric information. Although the loss due to asymmetric information was $4.49/head when considering only the injection-site lesion problem, the loss due to asymmetric information is $1.05/head more. The higher the value of attributes, the higher losses are generated due to information asymmetry.

Under circumstances when the WCTS fails (5% of the transactions), the meat processor transfers \$7.14/head to cow-calf producers, and \$480.71/head to cattle feeders. Those income transfers are to compensate the cow-calf producers' and cattle feeders' cost of participating in a WCTS, cow-calf producers using AI, and both cow-calf producers and cattle feeders vaccinating using a needle-free method. Since the WCTS fails to work during those transactions, the meat processor bears any potential losses from injection-site lesions and losing tenderness premiums. When the WCTS works, the meat processor transfers \$7.14/head to cow-calf producers, and \$480.72/head to cattle feeders, if genetic information is identified and no lesions are found. Since the probabilities of lesions detected are zero, the principal does not need to adjust the income transfer to the agents when they both use a needle-free method. The higher the loss caused by lesions, the lower is the income transfer.

Tables III-3 and III-4 show that as agents (cow-calf producer and cattle feeder) switch from injecting in the rear leg to the neck area, the principal (meat processor) offers higher income transfers when traceability fails and lesions are found in the chuck area. If one agent switches from a less-preferred injection method to a more-preferred injection method, while the other agent does not switch, the former would get higher income transfers when traceability fails to work and lesions are detected in the chuck area only, or when no lesions are detected when traceability works.

However, the principal (meat processor) decreases the income transfers when lesions are detected in other areas or a combination of areas. The reason for this may be that when agents (cow-calf producer and cattle feeder) switch from less-preferred to more-preferred injection methods, the probabilities of favorable occasions (no lesions, or lesions in chuck area only) increase, while the probabilities of unfavorable occasions (lesions in round, sirloin, or combinations) decrease. Thus, the principal (meat procesor) may reward agents more on the favorable occasions and decrease income transfer on unfavorable occasions.

*Comparisons of Scenarios*

With symmetric information ($t = 1$), the principal (meat processor) pays a minimum cost of $960.50/head when considering only the injection-site lesion problem, and $948.18/head when considering the tenderness improvement and injection-site lesion problems simultaneously. Thus, with symmetric information, considering tenderness improvement in a WCTS with injection-site lesion problem reduces the principal's cost by $12.32/head.

With t < 1 (second-best scenarios), when only considering injection-site lesion problem, the meat processor reduces the loss from $967.23/head, when both agents give injection in rear leg, to $ 965.19/head, when both agents use needle-free injection method, for a reduction of $2.04/head. When AI is used to improve tenderness proportion, loss is further reduced by $12.51/head. Whether traceability works or not, the principal (meat processor) pays a minimum cost of $954.72/head. Thus, information asymmetry costs the principal $6.54/head ($954.72 minus $948.18).

**Discussion**

*Under Alternative Risk Aversion Coefficient*

The constant absolute risk aversion coefficient used in the previous analyses is 0.75. In this section, we vary the risk aversion coefficient in order to assess the impact of changes in the risk aversion coefficient on the principal's expected costs and agents' actions. Table III-5 summarizes the results of using a coefficient of 0.38, halfway between 0.75 and 0, risk neutrality. As indicated in Table III-5, implementing a WCTS reduces the principal's expected cost to $954.72/head, which is the same as results using 0.75 as the risk aversion coefficient.

We also analyze the effect of changing the risk aversion coefficient on the income transfer from the principal to the agents. Table III-5 indicates the average income transfers to each agent with different combinations of actions taken, under risk aversion coefficients of 0.38 . When only the injection-site lesion problem is considered, the average income transfers are the same for different risk aversion coefficients.

But when both injection-site lesion and tenderness improvement are considered, average income transfers vary with risk aversion coefficients. For example, as tenderness is improved, when both agents give injection in rear leg, income transfers under the orginal risk aversion coefficient, 0.75, are $6.44/carcass side and $480.47/carcass side to cow-calf producer and cattle feeder, respectively. However, with a coefficient of 0.38, the income transfers are $7.03/carcass side and $480.62/carcass side to cow-calf producer and cattle feeder, respectively. For lower levels of risk aversion, agents require more of the income transfer to cover the costs they pay.

However, when considering tenderness improvement, and both agents take the most-preferred action for injection site, the income transfers to agents and expected costs of the principal are the same regardless of risk aversion coefficient. This may be because when both agents take the most-preferred action simultaneously, this is the best scenario, and income transfers cannot rise any higher.

**Summary and Conclusion**

Implementing a WCTS in the U.S beef supply chain may bring many benefits, such as improved food safety, improved supply chain management, and value-added opportunities. This analysis has shown that in a three-stage beef supply chain with two value-added attributes, injection site and tenderness genetics, implementing a WCTS reduces the expected net cost of the principal by as much as $12.51/head.

In a WCTS in which participants can choose what information to share in the system and with whom to share it with, incentives for providing value-added attributes, even those which are not easily identified at intermediate stages of the supply chain, can be more easily facilitated.

Even though this analysis considers only two attributes, a cost reduction, or profit improvement, of as much as $12.51/head can be realized. Implementing a WCTS in the beef industry can also reduce the loss due to asymmetric information. With no traceability system, the loss due to asymmetric information is $19.05/head, when considering both injection-site lesion and improved tenderness. However, when a WCTS is used, assuming a 95% success rate, the loss due to asymmetric information is reduced to $6.54/head. The higher the value of the information transferred in a WCTS, the greater the loss reduction achieved by reducing information asymmetry.

These results suggest that a WCTS could promote value-based pricing without forgoing the efficiencies of the current commodity-based system. The results with two sets of value-added information – injection site and tenderness genetics – indicate that the WCTS increases value to both the principal and agents, reducing information asymmetry. Including more attributes and more stages in the analysis could increase even further the potential benefit of implementing a WCTS.

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**Table III-1. Frequencies of Injection-Site Lesions**

| *Cow-Calf Producer* | Probabilities of Lesions in | *Cattle Feeder* Injection in Rear Leg | Injection in the Neck Area | Injection with Needle-Free Method |
|---|---|---|---|---|
| Injection in Rear Leg | Pc | 15.99% | 21.95% | 11.44% |
| | Pr | 18.55% | 14.39% | 13.15% |
| | Ps | 3.52% | 2.82% | 2.65% |
| | P(c,r) | 4.74% | 5.22% | 1.46% |
| | P(c,s) | 0.90% | 1.03% | 0.29% |
| | P(r,s) | 1.05% | 0.63% | 0.34% |
| | P(c,r,s) | 0.26% | 0.22% | 0.04% |
| | P0 | 54.99% | 53.75% | 70.64% |
| Injection in the Neck Area | Pc | 24.40% | 30.75% | 21.39% |
| | Pr | 12.87% | 9.22% | 6.94% |
| | Ps | 2.53% | 1.88% | 1.46% |
| | P(c,r) | 5.22% | 4.77% | 1.47% |
| | P(c,s) | 1.03% | 0.98% | 0.31% |
| | P(r,s) | 0.57% | 0.29% | 0.10% |
| | P(c,r,s) | 0.27% | 0.14% | 0.02% |
| | P0 | 53.1698% | 51.9621% | 68.30% |
| Injection with Needle-Free Method | Pc | 8.63% | 16.14% | 0.00% |
| | Pr | 9.92% | 5.24% | 0.00% |
| | Ps | 2.00% | 1.10% | 0.00% |
| | P(c,r) | 1.10% | 1.11% | 0.00% |
| | P(c,s) | 0.22% | 0.23% | 0.00% |
| | P(r,s) | 0.25% | 0.08% | 0.00% |
| | P(c,r,s) | 0.03% | 0.02% | 0.00% |
| | P0 | 77.85% | 76.08% | 100.00% |

**Table III-2. Expected Costs to the Principal and Income Transfers to Agents Under Symmetric Information**

| Cow-Calf Producer Selecting Genetics | Cow-Calf Producer's Injection | Cattle Feeder's Injection | Meat Processor's Expected Cost | Average Income Transfer to Cow-Calf Producer | Average Income Transfer to Cattle Feeder |
|---|---|---|---|---|---|
| | | Rear Leg | 967.23 | 0.00 | 480.00 |
| No | Rear Leg | Neck Area | 966.69 | 0.00 | 480.09 |
| | | Needle-Free | 964.56 | 0.00 | 480.10 |
| | | Rear Leg | 967.36 | 0.10 | 480.00 |
| No | Neck Area | Neck Area | 966.66 | 0.10 | 480.09 |
| | | Needle-Free | 966.64 | 0.08 | 480.10 |
| | | Rear Leg | 963.59 | 0.15 | 480.00 |
| No | Needle-Free | Neck Area | 962.95 | 0.15 | 480.09 |
| | | Needle-Free | 960.50 | 0.15 | 480.13 |
| | | Rear Leg | 955.53 | 4.61 | 480.00 |
| Yes | Rear Leg | Neck Area | 954.86 | 4.61 | 480.09 |
| | | Needle-Free | 952.58 | 4.61 | 480.10 |
| | | Rear Leg | 954.55 | 4.70 | 480.00 |
| Yes | Neck Area | Neck Area | 953.77 | 4.70 | 480.09 |
| | | Needle-Free | 951.47 | 4.70 | 480.10 |
| | | Rear Leg | 951.40 | 4.72 | 480.00 |
| Yes | Needle-Free | Neck Area | 950.61 | 4.72 | 480.09 |
| | | Needle-Free | 948.18 | 4.78 | 480.13 |

**Table III-3. Minimized Cost of the Principal and Income Transfers to Agents with Injection-Site Only with a P-WCTS (95% success rate)**

| Cow-Calf Producer's Injection | | Cattle Feeder's Injection | | |
|---|---|---|---|---|
| | | *Rear Leg* | *Neck Area* | *Needle-Free* |
| | *Minimized costs* | 967.23 | 966.91 | 966.94 |
| | Ia,0,* | 0.00 | 2.42 | 2.42 |
| | Ia,1,(c) | 0.00 | 2.42 | 2.42 |
| | Ia,1,(r) | 0.00 | 2.42 | 2.42 |
| | Ia,1,(s) | 0.00 | 2.42 | 2.42 |
| | Ia,1,(c,r) | 0.00 | 2.42 | 2.42 |
| | Ia,1,(c,s) | 0.00 | 2.42 | 2.42 |
| | Ia,1,(r,s) | 0.00 | 2.42 | 2.42 |
| | Ia,1,(c,r,s) | 0.00 | 2.42 | 2.42 |
| Rear Leg | Ia,1,(0) | 0.00 | 2.42 | 2.42 |
| | Ib,0,* | 480.00 | 480.86 | 480.91 |
| | Ib,1,(c) | 480.00 | 480.86 | 480.23 |
| | Ib,1,(r) | 480.00 | 480.86 | 480.23 |
| | Ib,1,(s) | 480.00 | 480.86 | 480.23 |
| | Ib,1,(c,r) | 480.00 | 480.86 | 480.23 |
| | Ib,1,(c,s) | 480.00 | 480.86 | 480.23 |
| | Ib,1,(r,s) | 480.00 | 461.49 | 480.23 |
| | Ib,1,(c,r,s) | 480.00 | 461.49 | 480.23 |
| | Ib,1,(0) | 480.00 | 480.86 | 480.91 |
| | *Minimized costs* | 966.90 | 966.58 | 966.11 |
| | Ia,0,* | 2.78 | 2.80 | 2.58 |
| | Ia,1,(c) | 2.78 | 2.80 | 2.58 |
| | Ia,1,(r) | 1.53 | 1.03 | 1.97 |
| | Ia,1,(s) | 1.53 | 1.03 | 1.97 |
| | Ia,1,(c,r) | 1.53 | 1.03 | 0.94 |
| | Ia,1,(c,s) | 1.53 | 1.03 | 0.94 |
| | Ia,1,(r,s) | 0.21 | 1.03 | 0.94 |
| | Ia,1,(c,r,s) | 0.21 | 1.03 | 0.98 |
| Neck Area | Ia,1,(0) | 2.78 | 2.80 | 2.58 |
| | Ib,0,* | 480.62 | 480.99 | 480.67 |
| | Ib,1,(c) | 480.62 | 480.99 | 480.67 |
| | Ib,1,(r) | 480.62 | 479.25 | 480.35 |
| | Ib,1,(s) | 480.62 | 479.25 | 480.35 |
| | Ib,1,(c,r) | 480.62 | 479.25 | 479.62 |
| | Ib,1,(c,s) | 480.62 | 479.25 | 479.62 |
| | Ib,1,(r,s) | 480.62 | 479.25 | 478.32 |
| | Ib,1,(c,r,s) | 480.62 | 479.25 | 478.32 |
| | Ib,1,(0) | 480.62 | 480.99 | 480.82 |

**Table III-3. (continued) Minimized Cost of the Principal and Income Transfers to Agents with Injection-Site Only with a P-WCTS (95% success rate)**

| Cow-Calf Producer's Injection | Cattle Feeder's Injection | | | |
|---|---|---|---|---|
| | | *Rear Leg* | *Neck Area* | *Needle-Free* |
| | *Minimized costs* | 966.94 | 965.51 | 965.19 |
| | Ia,0,* | 2.64 | 1.61 | 1.61 |
| | Ia,1,(c) | 2.64 | 1.61 | -- |
| | Ia,1,(r) | 1.79 | 0.30 | -- |
| | Ia,1,(s) | 1.79 | 0.30 | -- |
| | Ia,1,(c,r) | 1.79 | 0.22 | -- |
| | Ia,1,(c,s) | 1.22 | 0.22 | -- |
| | Ia,1,(r,s) | 0.53 | 0.00 | -- |
| | Ia,1,(c,r,s) | 0.53 | 0.00 | -- |
| *Needle-Free* | Ia,1,(0) | 2.64 | 1.85 | 1.84 |
| | Ib,0,* | 480.62 | 480.68 | 480.57 |
| | Ib,1,(c) | 480.62 | 480.68 | -- |
| | Ib,1,(r) | 480.62 | 479.10 | -- |
| | Ib,1,(s) | 480.62 | 479.10 | -- |
| | Ib,1,(c,r) | 480.62 | 479.10 | -- |
| | Ib,1,(c,s) | 480.62 | 479.10 | -- |
| | Ib,1,(r,s) | 480.62 | 476.77 | -- |
| | Ib,1,(c,r,s) | 480.62 | 476.77 | -- |
| | Ib,1,(0) | 480.62 | 480.68 | 480.81 |

**Table III-4. Minimized Costs of the Principal and Income Transfers to the Agents with Injection-Site and Tenderness Improvement**

| *Cow-Calf Producer's Injection* | | *Cattle Feeder's Injection* | | |
|---|---|---|---|---|
| | | *Rear Leg* | *Neck Area* | *Needle-Free* |
| | *Minimized costs* | 962.62 | 961.68 | 959.32 |
| | Ia,0,* | 7.03 | 7.03 | 6.88 |
| | Ia,1,(c) | 5.43 | 7.03 | 6.88 |
| | Ia,1,(r) | 5.43 | 7.03 | 6.88 |
| | Ia,1,(s) | 5.43 | 7.03 | 6.88 |
| | Ia,1,(c,r) | 5.43 | 7.03 | 6.88 |
| | Ia,1,(c,s) | 5.43 | 7.03 | 6.88 |
| | Ia,1,(r,s) | 5.43 | 7.03 | 6.88 |
| | Ia,1,(c,r,s) | 5.43 | 7.03 | 6.88 |
| *Rear Leg* | Ia,1,(0) | 7.37 | 7.03 | 7.11 |
| | Ib,0,* | 480.47 | 481.46 | 480.83 |
| | Ib,1,(c) | 480.47 | 481.46 | 480.83 |
| | Ib,1,(r) | 480.47 | 481.46 | 480.33 |
| | Ib,1,(s) | 480.47 | 481.46 | 480.33 |
| | Ib,1,(c,r) | 480.47 | 481.46 | 479.25 |
| | Ib,1,(c,s) | 480.47 | 474.53 | 479.25 |
| | Ib,1,(r,s) | 480.47 | 401.28 | 479.25 |
| | Ib,1,(c,r,s) | 480.47 | 401.28 | 479.25 |
| | Ib,1,(0) | 480.47 | 481.46 | 480.83 |
| | *Minimized costs* | 961.29 | 960.52 | 958.21 |
| | Ia,0,* | 7.84 | 7.91 | 7.10 |
| | Ia,1,(c) | 7.84 | 7.91 | 7.10 |
| | Ia,1,(r) | 4.52 | 3.09 | 6.33 |
| | Ia,1,(s) | 4.52 | 3.09 | 6.33 |
| | Ia,1,(c,r) | 4.52 | 3.09 | 6.33 |
| | Ia,1,(c,s) | 4.52 | 3.09 | 6.33 |
| | Ia,1,(r,s) | 4.52 | 3.09 | 6.33 |
| | Ia,1,(c,r,s) | 0.63 | 3.09 | 6.33 |
| *Neck Area* | Ia,1,(0) | 7.87 | 7.91 | 7.25 |
| | Ib,0,* | 481.16 | 480.86 | 480.78 |
| | Ib,1,(c) | 480.76 | 480.86 | 480.78 |
| | Ib,1,(r) | 480.76 | 480.86 | 480.78 |
| | Ib,1,(s) | 476.79 | 480.86 | 479.05 |
| | Ib,1,(c,r) | 476.79 | 480.86 | 479.05 |
| | Ib,1,(c,s) | 476.79 | 480.86 | 479.05 |
| | Ib,1,(r,s) | 476.79 | 466.50 | 479.05 |
| | Ib,1,(c,r,s) | 476.79 | 404.27 | 479.05 |
| | Ib,1,(0) | 481.16 | 480.86 | 480.78 |

**Table III-4. (continued) Minimized Costs of the Principal and Income Transfers to the Agents with Injection-Site and Tenderness Improvement**

| *Cow-Calf Producer's Injection* | | *Cattle Feeder's Injection* | | |
|---|---|---|---|---|
| | | *Rear Leg* | *Neck Area* | *Needle-Free* |
| | *Minimized costs* | 958.14 | 957.34 | 954.72 |
| | Ia,0,* | 6.79 | 7.18 | 7.14 |
| | Ia,1,(c) | 6.79 | 7.18 | -- |
| | Ia,1,(r) | 6.79 | 6.53 | -- |
| | Ia,1,(s) | 6.79 | 6.53 | -- |
| | Ia,1,(c,r) | 6.79 | 6.53 | -- |
| | Ia,1,(c,s) | 6.79 | 6.53 | -- |
| | Ia,1,(r,s) | 6.79 | 6.53 | -- |
| | Ia,1,(c,r,s) | 6.79 | 6.53 | -- |
| *Needle-Free* | Ia,1,(0) | 7.26 | 7.18 | 7.14 |
| | Ib,0,* | 480.62 | 480.75 | 480.71 |
| | Ib,1,(c) | 480.62 | 480.75 | -- |
| | Ib,1,(r) | 480.62 | 480.14 | -- |
| | Ib,1,(s) | 480.62 | 480.14 | -- |
| | Ib,1,(c,r) | 480.62 | 480.14 | -- |
| | Ib,1,(c,s) | 480.62 | 480.14 | -- |
| | Ib,1,(r,s) | 480.62 | 480.14 | -- |
| | Ib,1,(c,r,s) | 480.62 | 480.14 | -- |
| | Ib,1,(0) | 480.62 | 480.75 | 480.72 |

**Table III-5. Expected Costs to the Principal and Income Transfers to Agents Under Alternative Relative Risk Aversion Coefficient**

| Cow-Calf Producer Selecting Genetics | Cow-Calf Producer's Injection | Cattle Feeder's Injection | Meat Processor's Expected Cost | Average Income Transfer to Cow-Calf Producer | Average Income Transfer to Cattle Feeder |
|---|---|---|---|---|---|
| | | Rear Leg | 967.23 | 0.00 | 480.00 |
| No | Rear Leg | Neck Area | 966.91 | 2.42 | 480.71 |
| | | Needle-Free | 966.94 | 2.42 | 480.72 |
| | | Rear Leg | 966.91 | 2.51 | 480.62 |
| No | Neck Area | Neck Area | 967.08 | 2.51 | 480.71 |
| | | Needle-Free | 967.11 | 2.51 | 480.72 |
| | | Rear Leg | 966.94 | 2.52 | 480.62 |
| No | Needle-Free | Neck Area | 967.11 | 2.52 | 480.71 |
| | | Needle-Free | 967.14 | 2.52 | 480.72 |
| | | Rear Leg | 960.62 | 6.44 | 480.47 |
| Yes | Rear Leg | Neck Area | 961.60 | 7.03 | 480.71 |
| | | Needle-Free | 959.32 | 7.03 | 480.72 |
| | | Rear Leg | 955.53 | 4.61 | 480.00 |
| Yes | Neck Area | Neck Area | 953.76 | 4.70 | 480.09 |
| | | Needle-Free | 958.21 | 7.12 | 480.72 |
| | | Rear Leg | 958.14 | 7.14 | 480.62 |
| Yes | Needle-Free | Neck Area | 957.34 | 7.14 | 480.71 |
| | | Needle-Free | 954.72 | 7.14 | 480.72 |

# CHAPTER IV

# WHAT DO SOD PRODUCERS VALUE IN IMPROVED CULTIVARS? USING CONJOINT CHOICE AND EYE-TRACKING TECHNOLOGY TO IDENTIFY PREFERENCES

## Introduction

Conjoint analyses have been widely used in marketing and consumer research, in order to determine consumers' preferences when making purchasing decisions. Even though highlighting information in consumers' decisions, conjoint analyses provide limited information in how respondents' process information (Meißner & Decker, 2010; Reisen, Hoffrage, & Mast, 2008). Process tracing data describes the decision-making process, thus would benefit decision-making research. According to Reisen et al. (2008), process tracing supports to understand consumers' decision-making process by monitoring information acquisition and search. As attention plays an active role in constructing decisions (Orquin & Loose, 2013), eye movements are great tools of process tracing. Recording and analyzing respondents' eye movements when they take the survey may help better understand participants' decision-making process. According to Vidal et al.(2013) and Behe et al. (2014), eye movements indicate visual attention and information acquisition behaviors, thus may be good indicators of information searching process. Eye tracking records which information elements are fixated and how long the fixation lasts (Johnson & Orme, 1996) and provides an insight into how respondents process the given information. An advantage of eye tracking is that eye movements are not entirely under cognitive control, so it is difficult for respondents to control their eye movements (Reisen et al., 2008). Eye-tracking technology improves the interpretation of results from the conjoint analysis, as it indicates the attention all variables get when visually processed by respondents (Vidal et al., 2013). Our first objective is to identify whether including eye fixation data in the conjoint analysis changes respondents' willingness-to-pay (WTP) for attributes. Since the distributions of WTPs are unknown, we apply the complete computational approach from Poe, Giraud, and Loomis (Poe, Giraud, & Loomis) to make comparisons between two sets of WTPs.

When dealing with conjoint analysis, participants usually face multiple choice-tasks. Within each choice task, they are asked to evaluate a set of alternatives with different product/service attributes and choose the most-preferred alternative. In order to observe a large set of data, survey designers often prefer a large number of repeated choice tasks, which may increase sampling efficiency (Campbell, Boeri, Doherty, & Hutchinson, 2015). However, this is based on an assumption that respondents understand their preferences and behave fully rationally with stable and consistent preferences (Brouwer, Dekker, Rolfe, & Windle, 2010; Meißner & Decker, 2010). According to Campbell et al. (2015) and Hess, Hensher, and Daly (2012), as repeated choice experiment offers each respondent multiple choice sets in a sequence, respondents' choice pattern may vary across choice tasks, thus may need special attention. Day et al. (2012) stated that there are possible trade-offs between the large number of choice sets included to recover information from survey participants and the usefulness of additional information to inform participants' preferences. Evidence of ordering effects, for instance, challenges the degree of useful additional information obtained from repeat-response formats (Day et al., 2012). According to Day et al. (2012), there are six categories of ordering effects, including preference learning, institutional learning, fatigue, starting point effect, strategic behaviors effect, and reference price behavior effect (Carlsson, Mørkbak, & Olsen, 2012). In this paper, we focus on analyzing the impact of learning effect and fatigue effect. Learning occurs because of the repeating nature of the conjoint analysis along with choice tasks, respondents may gradually reduce uncertainty, discover exact preferences, obtain useful information more efficiently and make choices with fewer mistakes along choice tasks (Brouwer et al., 2010). With the existence of learning effect, responses are more accurate and the error variance of the utility function is decreased (Czajkowski, Giergiczny, & Greene, 2014; Day et al., 2012). On the other hand, when dealing with multiple repetitions of choice alternatives, respondents to choice experiment may also get fatigue or bored (Hess et al., 2012). In contrary to learning effect, with the existence of fatigue effect, respondents get tired with too many choice tasks and do not observe sufficient useful information, thus have larger variability when making choices. According to Campbell et al. (2015), addressing learning/fatigue effect influences the model fit and willingness-to-pay estimates. Learning/fatigue effect may also cause respondents' preference to vary across choice tasks (Campbell et al., 2015; Carlsson et al., 2012; Czajkowski et al., 2014; Savage & Waldman, 2008). Our second objective is to identify whether there are preference changes along the sequence of choice tasks, when not addressing learning/fatigue effect. We divide the entire data into early, middle, and late stages, obtain the respective preferences/WTPs and make respective comparisons.

Besides possible preference change, learning/fatigue effect may also affect the variances along the sequence of choice tasks. When learning effect is present, respondents discover their exact preferences and thus become more precise in making choices. With fatigue effect, respondents make more mistakes when making choices, thus error variance increases. Our third objective is to check whether variances are stable along the sequence of three stages. Scale heteroscedastic multinomial models are run in order to identify scale changes.

In the following content, we show how considering eye fixation affects WTP-estimates, as well as the analysis of learning and/or fatigue effect. Previous literature analyzed how eye fixations on attributes influence WTPs and choice, but not fixation on alternative as a whole. This study evaluates the effect of including alternative-based fixation to preference/WTP estimates and scales. The study describes in this paper also contributes to the ordering effects literature by analyzing the influence of including eye fixation variable when investigating in the issue of ordering effects in choice experiments, learning effect and fatigue effect, in particular. To the best of our knowledge, not much literature considers eye fixation information when analyzing learning or fatigue effect.

We also make a contribution to data grouping when analyzing learning effect and fatigue effect. Several previous literature analyzed learning effect and/or fatigue effect based on choice-task specific models (Czajkowski et al., 2014; Hess et al., 2012). Running choice-task specific models makes the pattern of learning effect and/or fatigue effect more clearly. But the small sample size may limit the reliability of estimation for some models (Hess et al., 2012). Other literature analyzed learning effect and/or fatigue effect based on group data. But there are no standard data-grouping criteria. Savage and Waldman (2008) and Day et al. (2012) split the entire dataset into two or three groups evenly, with an equal number of choice questions in each group. Campbell et al. (2015) ran a series of models with different number of choice tasks in three phases and selected the set with the most significant gains in model fit, which was stated to gave an insight into the pattern of learning effect and/or fatigue effect(Campbell et al., 2015)(Campbell et al., 2015)(Campbell et al., 2015)(Campbell et al., 2015). But if the number of choice task is large, this method might be time-consuming, with many possible combinations. In this study, we apply two grouping methods. The first method is to analyze the trend of fixations along with choice tasks. This gives a preliminary grouping suggestion. Then we refer to Muggeo (2003) to run segmented regression model to find the unknown break-points among choice tasks. Running segmented regression model saves the time and effort in running models.

This paper uses a case study on consumers' preference for turfgrass products. This case study was selected due to rapidly expanding turfgrass industry in the United States. The total value of sod turfgrass in the U.S. nation-wide summed to approximately $1.14 billion in sales in 2014 (USDA-NASS, 2015). Turfgrass can not only provides a pleasant surface for outdoor activities, but also stabilize soil, conserve water, and filter air and water (Ghimire, Boyer, Chung, & Moss, 2016). Determining consumers' preferences for turfgrass characteristics is necessary to developing and releasing a consumer desired turfgrass product. This study allows us to signal the preferences of warm-season variety producers for future varieties. As this group is small and can be hard to reach, having information on what varieties they would like to produce is significant.

## Literature Review

### *Conjoint Analysis & Eye Tracking Technology*

Conjoint analyses provide insights on consumers' preferences, but not information on consumers' decision-making process. Eye tracking technology, as an improvement technique, could be combined with conjoint analysis to provide some details on how consumers process information on products' attributes. Eye movements reflect the process of screening and evaluation of choice alternatives (Glaholt & Reingold, 2011). According to Behe et al. (2014) and Vidal et al. (2013), eye movements are good behavioral indicators of how consumers search for and process information. There are two elements of eye movements: fixations and saccades (Balcombe, Fraser, & McSorley, 2015). Fixations refer to the movements when the eye is "relatively still", while saccades refer to very rapid movements when shifting gaze to the area of interest (Balcombe et al., 2015). Glaholt and Reingold (2011) mentioned that when respondents view a display freely, they may process information outside of their gaze. However, since fixation and attention are tightly coupled during natural viewing (Balcombe et al., 2015; Glaholt & Reingold, 2011), this should not be taken as one limitation of eye tracking.

Meißner and Decker (2010) indicated that the fixations received by attributes were positively correlated with its importance. Behe et al. (2014), Rihn and Yue (2016), and Van Loo et al. (2015) had similar conclusion that consumers were more likely to fixate on attributes that were more important or valuable. However, Balcombe et al. (2015) and Vidal et al. (2013), had an opposite conclusion, reporting that there was no relationship between the value of attributes and the amount of attention received. Meanwhile, it influences the likelihood of the product being chosen. Behe, Bae, Huddleston, and Sage

(2015), Bialkova et al. (2014) and van der Laan, Hooge, De Ridder, Viergever, and Smeets (2015) concluded that the probability of a product being chosen increased with more fixations. Krajbich, Armel, and Rangel (2010) had a similar conclusion, given the value differences of products are controlled. Including attention in conjoint analysis increases the explanatory power of regression model (Bialkova et al., 2014). There are limited researches in studying the impact of fixation data on attributes' WTPs. Rihn and Yue (2016) estimated how fixation data affected the WTPs. They considered the fixation on each attribute and concluded that the inclusion of fixation changed the WTPs in some cases, but the direction was uncertain. Instead of considering fixations on the single attribute in the model, we included fixations on each alternative, which is the summation of fixations on each attribute in one alternative. Including the alternative-based fixation data in the regression gives us a better understanding of how the integrated fixation affect consumers WTPs for attributes.

*Learning & Fatigue*

Day et al. (2012) categorized ordering effects into preference learning, institutional learning, fatigue, starting point effect, and strategically behave effect. The latter two effects can be minimized by using a counterbalanced design, so each respondent faces with a different order of choice tasks (Czajkowski et al., 2014). But the presence of learning and/or fatigue effects can hardly be controlled by survey designer. Thus, a number of studies have been done on the analysis of learning and/or fatigue effects. The existence of learning/fatigue effect can be identified from parameter inconsistency and scale inconsistency. Change in parameters indicates consumers' preferences on products are inconsistent, while the change in scales indicates that consumers choice are inconsistent along with choice tasks. Carlsson et al. (2012), Czajkowski et al. (2014), Hess et al. (2012), and Savage and Waldman (2008) have explored the issue of preference consistency in discrete choice experiments. Czajkowski et al. (2014) took testing preference consistency as the first step of analysis and concluded that individual respondent's taste was consistent throughout the choice experiment, as there were no systematic changes in preferences associated with attributes. Hess et al. (2012) concluded of significant heterogeneity across choice tasks in attribute level, which was a sign of preference inconsistency. Campbell et al. (2015) reported that approximately two-thirds of the respondents showed stable preference, but the rest showed preference learning in the early phase and fatigue in the late phase. They also concluded that recognizing inconsistent preferences is more important than recognizing inconsistent error variance when studying learning and/or fatigue effect. Carlsson et al. (2012) conducted within sample tests, with the second half of choice sets exactly replicate the first half of choice sets. They concluded no change in consumers' preference on product attributes. However, they confirmed that consumers were less price-sensitive in the last sequence compared to the first sequence. Even though consumers' preferences stayed the same, with changing price sensitivity, the WTPs changes along the sequences. Campbell et al. (2015) had a similar conclusion on WTP estimates. They concluded that with different treatments of learning and/or fatigue effect, the derived WTPs were affected and indicated that it is important to assess the impact of inconsistent preferences have on the estimates of WTP estimates.

As stated previously, learning and/or fatigue effects can also be identified by scale change along the sequences. According to Czajkowski et al. (2014) and Hess et al. (2012), failing to account for scale change through a choice experiment lead to biased estimates, thus unreliable model results. Allowing for scale differences substantially improves model fit (Czajkowski et al., 2014). Campbell et al. (2015), Carlsson et al. (2012), Czajkowski et al. (2014), Hess et al. (2012), Meißner and Decker (2010), and Savage and Waldman (2008) analyzed the impact of scale change in discrete experiment. However, the conclusions were contradictory. Savage and Waldman (2008) concluded that variance increased significantly along choice tasks, which indicate a fatigue effect. Campbell et al. (2015) and Meißner and Decker (2010) both confirmed fatigue effect. But Campbell et al. (2015) concluded that most of the respondents had a consistent scale, while the rest had increased variance in the final sequence of tasks. Savage and Waldman (2008) conducted web-based and mail-in surveys, each with eight questions. They confirmed the appearance of increased variance until the eighth choice task for web-based respondents. For mail respondents, no learning and/or fatigue effects were identified. Carlsson et al. (2012), Hess et al.

(2012), and Kingsley and Brown (2010) confirmed the existence of learning effect. Carlsson et al. (2012) reported that the error variance in the second half was lower than that in the first half, which indicated learning effect. Czajkowski et al. (2014) confirmed the existence of learning effect, which stabled after the eighth to the twelfth choice task, but not fatigue effect. Holmes and Boyle (2005) and Kingsley and Brown (2010) found that the lowest error variance associated with the last choice tasks, indicating learning effects.

It is also mentioned that the first one of two choice tasks has more inconsistency compared to the rest of choice tasks (Campbell et al., 2015; Carlsson et al., 2012; Hess et al., 2012; Kingsley & Brown, 2010). Carlsson et al. (2012) concluded that respondents faced the most variability in the first choice task. Even for the first two choice sets, the error variance is very high. Kingsley and Brown (2010) reported that nearly 14% of respondents' first choices were inconsistent. Of the 20$^{th}$ choice, the proportion dropped to around 5% to 6%. Campbell et al. (2015) had a similar conclusion, that the first choice in the panel produced different scale parameter to subsequent choices. Carlsson et al. (2012) argued that the higher variance in the first choice task may indicate institutional uncertainty. Hess et al. (2012) explained one possible reason as respondents simplifying the first task by choosing the first alternative.

Our paper contributes to the learning and/or fatigue literature by including fixation when analyzing learning and/or fatigue effect. According to Orquin and Loose (2013), the drivers of eye movements in decision-making change dynamically within tasks. In another word, the amount of fixation received may have an impact on estimated WTPs, as well as on scales. Van Loo et al. (2015) reported that every one unit increase in fixation count and/or fixation duration for the price would decrease the WTP. In order to verify the relationship between fixation and scale, we referred to Balcombe et al. (2015) and included fixation variable in the scale function. This tells us whether fixation has an impact on variance.

## Econometric Models

*Conditional Logit Model*

The discrete choice experiment includes 12 choice tasks, which are divided into early, middle, and late stages. The order of choice tasks was randomly assigned to different respondents. Since the demographic characteristics of our sample vary slightly, we focus on estimating choice as a function of product attributes in the analysis, rather than individual characteristics. Thus, we apply the conditional logit models[10] as the first step. An individual's utility from any alternative is consists of a deterministic component, $\boldsymbol{X}'_{ijk}\boldsymbol{\beta}$, and a stochastic component, $\varepsilon_{ijk}$.

$$U_{ij} = \boldsymbol{X}'_{\boldsymbol{ijk}}\boldsymbol{\beta} + \varepsilon_{ijk} \tag{1}$$

where $\boldsymbol{X}_{ij}$ is a vector of choice-specific variables that relates to individual *i* and alternative *j,* of the *k*th choice task, $\boldsymbol{\beta}$ is a vector of parameters, and $\varepsilon_{ij}$ is an error component which has an *iid* Gumbel distribution. In the conditional logit models, all individuals are assumed to have homogeneous taste and scale.

To fulfill the first two objectives, we run conditional logit models with corresponding variables. The first step is to run conditional logit models on data excluding and including eye fixation variable, thus contrast the estimated WTPs between the two models. For the second objective, we run conditional logit models on data in early, middle, and late stages, respectively. After obtaining parameter estimates for all three stages, we calculate WTPs and make pairwise comparisons on preferences and WTPs.

[10] We also tried random parameter logit models. However, due to the restriction of sample size, we were unable to get the model converged.

*Scale Heterogeneity Model*

In the conditional logit model, the scale parameter is constantly set to one of the sequential choice tasks. In order to obtain the trend of scale change, the *iid* assumption for the random term needs to be relaxed. Relaxing the *iid* assumption allows the respondents' scale parameter to vary following a particular distribution (Czajkowski et al., 2014). The utility function of a scale heterogeneity model is (Fiebig, Keane, Louviere, & Wasi, 2010)

$$U_{ijk} = (\boldsymbol{\beta}\sigma_i)\boldsymbol{X_{ijk}} + \mu_{ijk} \tag{10}$$

Where the scale parameter, $\sigma_i$, is defined as an exponential function, $\sigma_i = \exp(\bar{\sigma} + \tau\mu_{0i})$, with $\tau$ as the indicator of individual scale heterogeneity in the sample, and $\mu_{0i} \sim N(0,1)$. Normalizing the scale coefficient to 1, $\bar{\sigma}$ equals $-\tau^2/2$. Thus, the scale is assumed to follow a log-normal distribution, $\sigma_i \sim LN(1, \tau)$, which makes the scale coefficient respondent specific.

In order to use the scale heterogeneity model to identify scale changes between stages, according to Czajkowski et al. (2014), we add stage-specific variables into the equation of scale parameter, that $\sigma_{it} = \exp(\bar{\sigma} + \tau\mu_{0i} + \boldsymbol{\varphi}'\boldsymbol{s}_{it})$, where $\boldsymbol{s}_{it}$ is a set of the scale-related variable based on stages *t*, and $\boldsymbol{\theta\varphi}'$ is a set of respective parameters. In this study, we refer to Balcombe et al. (2015), and specify the functional form of the scale parameter as:

$$\sigma_{it} = \exp\big(\varphi_1(\psi_t - \overline{\psi_t}) + \varphi_2\big(\sin(\psi_t\pi) - \overline{\sin(\psi_t\pi)}\big) + \varphi_3 v_{it}\big)$$

where $\psi_t = (\frac{t-1}{T-1})$, $v_{it}$ is the log of total visit duration by the *i*th individual in the *t*th stage (normalized so the mean equals zero), and the parameters to be estimated are $\varphi_1$, $\varphi_2$, $\varphi_3$. Subtracting the means in the first two components and normalizing the fixation are to make sure that the average variance over *t* is approximately one. Thus the heteroscedastic models are comparable with non-heteroscedastic in scales (Balcombe et al., 2015). If there is a change in scales along stages, the estimated parameter, $\varphi_1$, should be a non-zero value. The second sinusoidal function increases from the early stage to the middle stage, then decreases from the middle stage to the late stage. Since it peaks in the middle stage, the positive value of $\varphi_2$ indicates a "learning-then-fatigue" pattern (Balcombe et al., 2015). If the parameter for the last term is positive, the respondents who pay a longer visit to one specific stage of choice tasks have lower variance; thus, have more certainty on their choices. According to Balcombe et al. (2015) and Holmes and Boyle (2005), the scale parameter and preference parameters are in multiplicative form, so it is very difficult to distinguish between these two. In order to identify the scale change, we have to verify that the parameter estimates stay consistent along the stages.

**Choice Experiments**

To illustrate the proposed methods, we use data collected from an on-site questionnaire, which aims to study how consumers value different attributes in turf grass industry. For experimental design, we had 48 choice sets, which were divided into 4 blocks. A fractional factorial design consisting of 12 choice tasks with a 96.4% D-efficiency was used. In each choice task, there were two product alternatives, as well as a status quo. The first two alternatives (Option A and Option B) each described a turf grass product with or without valued attributes ("winter kill reduction", "shade tolerance", "drought tolerance", "salinity tolerance", and "10% maintenance reduction") and a respective price. Attributes and respective levels are as shown in Table IV-1. The turfgrass products in the first two alternatives carried at least one of the five valued attributes.The last alternative, as the status quo, was an opt-out no purchase option. Figure V-1 presents a sample choice task as seen by the respondents.

The respondents of experiments were recruited from participants of the Turfgrass Producers International Conference in San Diego, California, in 2015. We asked the recruited respondents to take the choice experiments with eye-tracking devices installed. Two working stations, Tobii TX 300 devices, were set up. Participants were first sit comfortably and aligned with the monitor of the eye tracker. Then a nine-point calibration was conducted to ensure proper eye tracking metrics. Participants then responded to the choice tasks and filled a follow up demographic survey. At the end of the experiment, each participant received a compensation fee of $30. Due to the long hours for each experiment, we have a relatively small sample size[11]. In total, 32 subjects participated in the survey. Four out of the 32 subjects' data were missing eye-tracking information. Thus, the usable data are from 28 subjects with 12 choice sets for each subject. Therefore, the total sample size is 336. Summary demographic statistics for the sample are reported in Table IV-2. In general, more women responded than men. The average age of participants is about 48 years, with 26 as the youngest age and 76 as the oldest age. Nine participants attended some college, while 17 participants hold bachelor's degree or higher. Among all respondents, four hold a degree in turf grass management; two hold a degree in plant and soil science, and the rest hold degrees other than the above two.

**Results and Discussion**

*Data Grouping*

Running regression models on choice basis could better indicate the pattern of learning effect and/or fatigue effect. However, the sample size for each regression may be too small to obtain reliable estimates. Thus, we group the data into three stages, early, middle, and late. The regression models are run based on stage. By grouping the data, we may not only identify the pattern of learning and/or fatigue effect, but also have a larger sample size to insure the reliability of regression results. As eye movements are good indicators of respondents' behavior, we may identify the pattern of eye fixation data for data-grouping purpose. Figure V-2 gives some insights on how to do preliminary grouping. When looking at the total visit duration, we identify an overall decreasing trend along the sequential choice tasks. However, there are some specific trends for different choice-task ranges. Between choice tasks one to five, there is a simple decreasing trend for total visit duration. For the rest of choice tasks, six to twelve, we can identify

[11] Each experiment took over an hour including time for calibration. Relatively small sample size is a common problem faced by eye tracking researches.

two similar cycles that indicate a "first-up-then-down" trend. The sixth to the eighth choice tasks represent the first cycle, while the rest four choice tasks represent the second cycle. Based on the trend of changes in total visit duration, our preliminary grouping is as following: choice tasks one to five as early stage, choice tasks six to eight as middle stage, and the rest four choice tasks as late stage.

In order to verify the preliminary grouping results, we estimate two breakpoints so the entire data is divided into three stages. In the generic regression model, the function of response variable contains linear part and non-linear part. Following Muggeo (2003), let $g(z;\ \theta)$ be the non-linear term for variable Z with parameter $\theta$ in the generic regression model

$$f(E[Y]) = \omega(X) + \gamma g(z;\ \theta) \tag{2}$$

where $f(E[Y])$ is the response variable in a regression model with a linear parameter, and $\omega(X)$ includes any variable with a linear parameter. As linear parts do not change, both the response and predictor are omitted. We focus on the non-linear part in the following.

The generic non-linear term around an initial known value of $\theta^{(0)}$ is estimated using First-order Tyler expansion:

$$g(z;\ \theta) \approx g\left(z;\ \theta^{(0)}\right) + (\theta - \theta^{(0)})g'(z;\ \theta^{(0)}) \tag{3}$$

where $g'(z;\ \theta^{(0)})$ is the first derivative of $g(\cdot)$ in $\theta^{(0)}$ (Muggeo, 2003).

With parameter $\gamma$, the non-linear parts of the generic model is

$$\gamma g\left(z;\ \theta^{(0)}\right) + \gamma(\theta - \theta^{(0)})g'(z;\ \theta^{(0)}) \tag{4}$$

which all depends on $\theta^{(0)}$. Let $\eta = \gamma(\gamma - \gamma^{(0)})$, fitting model (3) yields maximum likelihood estimates at each cycle for all parameters including $\hat{\gamma}$ and $\hat{\theta}$. Thus,

$$\theta = \frac{\hat{\eta}}{\hat{\gamma}} + \theta^{(0)} \quad (5)$$

updates estimate for the non-linear parameter $\theta$. When $\hat{\eta}$ is approximately zero, or not statistically different from zero, the estimated breakpoint equals to the previously known value $\theta^{(s)}$, meaning that there are no more improvements in the breakpoint estimation. Thus, the model converges when $\hat{\eta}$ is approximately zero, or insignificant.

The segmentation results indicate that the fifth and ninth choice tasks are the estimated break points. Thus, the choice tasks one to four are early stage, while choice tasks five to eight and choice tasks nine to twelve are middle and late stages, respectively. Even though the grouping results from eye fixation data and segmentation model are not exactly the same, they are very similar. Since the choice is most uncertain in the first task (Campbell et al., 2015; Carlsson et al., 2012; Hess et al., 2012; Kingsley & Brown, 2010), we leave out the data of the first choice task from analysis. In order to make sure that there are large enough data in the early stage, we take the preliminary grouping results for the following analyses.

*Analyses on Eye Fixation Data*

For each area of interest (hereafter shortened as "AOI"), several measurements were calculated, including time to first fixation, total fixation duration, fixation counts, and total visit duration. Time to first fixation is the time in seconds that an AOI first gets fixated on (Behe et al., 2015). It indicates respondents' first eye stop on the image. Total fixation duration is the total length of time in seconds that an AOI gets fixated on. Fixation count is the number of fixation received by an AOI. Total visit duration is the total length of time in seconds spent viewing an AOI. It indirectly indicates the measure of cognitive processing (Behe et al., 2015). According to Behe et al. (2015), total visit duration is the strongest predictor of product choice.

Figure IV-2 shows that there is an overall decreasing trend of all of the four fixation measurements from the first choice task to the last choice task. We have done pairwise comparisons on time to first fixation, total fixation duration, fixation count, and total visit duration between stages. Table IV-3 summarizes simple statistics of the eye fixation measurements. Between early and middle stages, respondents' time-to-first-fixation do not vary significantly. Similarly, between middle stage and late stage, we do not identify a significant change in time to first fixation. However, average time-to-first-fixation in the early stage is significantly longer than that in the late stage. In another word, it takes respondents longer time to first-fixate on one area of interest when they first begin the conjoint analysis. However, when they approached the last four choice tasks, they fixate on an AOI more quickly. The rest three fixation measurements, total fixation duration, fixation count, and total visit duration, have similar trends among the stages. All the three measurements in the early stage are significantly longer/larger than that in the middle stage and in the late stage, indicating that options in the early stage received more attention from respondents than in those in the middle and late stages. However, between middle stage and late stage, the eye fixation measurements do not vary significantly. From the middle stage to the late stage, respondents' attention stays the same.

*Effects of respondents' attention on estimates of attribute WTPs*

Table IV-4 reports parameter and willingness-to-pay estimates from the conditional analysis. According to Behe et al. (2015), total visit duration has the strongest relationship with product choice. Thus, we include it as the eye fixation variable in the regression model. When eye fixation variable is not included in the model, the price coefficient is negative and significant, implying that respondents prefer turfgrass products that are less expensive. Four out of the five turfgrass attributes ("winter kill reduction", "shade tolerance", "drought tolerance", and "salinity tolerance") have positive and statistically significant coefficients, indicating that respondents prefer turfgrass products with the four attributes. However, the coefficient of "10% maintenance reduction" is positive but not statistically significant. Since all attributes are effects-coded, the marginal utility of status quo could be calculated as the negative summation of mean coefficients of all five turfgrass attributes, which results to -1.3242 (excluding the mean coefficient of "10% maintenance reduction" as it is insignificant). The negative sign of status quo indicates that respondents dislike turfgrass products with none of the four attributes ("winter kill reduction", "shade tolerance", "drought tolerance", and "salinity tolerance").

Since respondents' visit durations vary widely by choice task, we unitize each respondent's total visit duration to one for 12 choice tasks in total. In another word, we assume that each respondent spends one unit of time on the entire 12 choice tasks, and calculate the proportion of total visit duration for each alternative as $\frac{tvd_{ka}}{\sum_{k=1}^{12} tvd_k}$ (where *k* represent the order of choice tasks, and *a* represents the order of alternatives in single choice task). The calculated proportion is included as the fixation variable in the logit model. Including the proportion of fixation can eliminate possible errors caused by different reading speeds and habits of respondents. When eye fixation variable (percentage of total visit duration) is included, the fitness of model is improved, as indicated by likelihood ratio test. The test result indicates that the model including eye fixation variable is superior to the one without eye fixation data. Coefficients of price and three turfgrass attributes ("winter kill reduction", "shade tolerance", and "drought tolerance") have the same sign and significance level as in the previous model that does not include fixation variable. The estimated coefficient of "salinity tolerance" is still positive, but turns insignificant at the 5% significance level. Estimated coefficient of "10% maintenance reduction" remains insignificant. Thus, when including the eye fixation variable, the marginal utility of the status quo changes to -0.9862. The estimated parameter of eye fixation variable is positive (0.1753) and statistically significant at the 5% level, suggesting that the probability of one alternative be chosen increases as respondents pay a longer visit to that alternative.

*Complete Combinational Comparisons*

In order to identify preference consistency, we compare WTPs from different regression models. Since the distributions of WTPs are not identifiable, we refer to complete combinational resampling approach, as described by Poe et al. (2005), following the steps as shown in below.

First, 1,000 sets of parameters, including price coefficient and turfgrass attribute coefficients, are bootstrapped from covariance matrices, for each model run. Then we calculate the WTPs from the simulated parameters. Let $D_{l,(m,n)}$ stands for the differences in WTPs of all possible combinations (1,000*1,000) between the two sets:

$$D_{l,(m,n)} = wtp_{l,(m)} - wtp_{l,(n)}; l = 1, \dots 5; m, n = 1, \dots, 1000 \quad (6)$$

where $wtp_{l,(m)}$ and $wtp_{l,(n)}$ are the wtp for the *l*-th attribute calculated from the *m*-th and *n*-th bootstrapped values, from two different groups.

As described above, we derived 1,000,000 different pairs of WTP differences and rounded them into two decimals[12]. For the two-sided tests, if the proportion, complete combinational test p-value (CC-test p-value), of $D_{l,(m,n)} = 0$ is smaller than 2.5%, the null hypothesis of equality is rejected at 5% confidence level[13].

1. *The Impact of Including Eye-Tracking on WTP Estimates*

We compared the WTPs between the model without eye fixation variable and the model considering eye fixation variable. Our first objective is to identify that whether WTPs from the model excluding eye fixation variable is the same with WTPs from the model including eye fixation variable.

[12] As WTPs are dollar values, with the smallest unit in the U.S. is one cent, rounding WTPs to 2 decimals is reasonable.
[13] In order to avoid confusion, for the flowing analyses, we doubled the calculated proportion, so if CC-test p-value is smaller than 5%, the null hypothesis of equality is rejected.

The null hypothesis is that WTP from model excluding eye fixation variable equals WTP from the model including eye fixation variable, for the same attribute. After obtaining the parameter estimations and covariance matrices from the models, we simulate two sets of data that containing turfgrass attribute coefficients and price coefficient. Each set of data has a sample size of 1,000 for each column. Then we calculate the complete combination of differences in WTPs each attribute between two models. If the CC-test p-value is smaller than 5% for an attribute, we reject the null hypothesis of equality and conclude that there is a change in WTPs between two models excluding and including eye fixation variable. As shown in Table IV-4, the CC-test p-values for the first four turfgrass attributes are smaller than 5%. Thus, We reject the null hypotheses rejected at 5% level and conclude that including eye fixation variable in the regression changes the WTPs for all turfgrass attributes except for "10% maintenance reduction" (as it is insignificant), compared to excluding eye fixation variable in the regression.

2. *Identifying Change in Preferences/WTPs*

Table IV-5 summarizes the estimated parameters and calculated WTPs for three stages. According to Table IV-5, we identify some changes in the significance level of estimated parameters. However, this may be due to the small sample size. Thus, we do not comment on the change of significance levels for models based on stage. We assume the same significance levels as in previous two models that based on entire data. The estimated parameters of attributes "winter kill reduction", "shade tolerance", "drought tolerance", and "salinity tolerance" are positive for all stages, while price coefficient is negative.

In order to verify whether there are changes in preferences along with stages, we made pairwise comparisons on the estimated coefficients for all five attributes among all the stages. The null hypothesis is that estimated parameter of one attribute in one stage equals its counterpart in another stage. The null hypotheses suggest that respondents' preferences are consistent among stages. The first panel of Table IV-6 summarizes the test results. We conclude that there are no differences in attribute parameters between every two stages. However, respondents' price coefficient changes. Thus, we conclude that as respondents go through the choice experiment, they have constant preferences over product attributes. However, the respondents change their price sensitivity between two stages. Increase in price causes more loss to respondents' utility in the late stage than in the early stage. This conclusion contradicts with Carlsson et al. (2012), as they indicated a decrease in price sensitivity in later sequences.

Similarly, we compared the estimated WTPs pairwise among three stages. The null hypothesis is that respondents' WTP for one attribute are stable along with stages. Results are as shown in the bottom panel of Table IV-6. As the CC-test p-values for all turfgrass attributes are all smaller than 0.05, the null hypothesis of no change in WTP for each attribute is rejected. We conclude that respondents' preferences changed when dealing with choice tasks among stages. However, the changes in WTPs are due to changes in price sensitivity. Respondents' preferences to turfgrass attributes stay consistent among stages.

*Identify Change in Scales*

As indicated above, respondents' preferences are consistent among the early, middle, and late stages. However, since the price sensitivity varies, respondents' WTPs for turfgrass attributes shift among stages. In order to identify the existence of learning and/or fatigue effect, we run scale heterogeneity models, first without fixation variable in the model, then with fixation variable in the model. Estimation results are shown in Table IV-7. According to Table IV-7, there is no individual heterogeneity identified in our study. This means that respondents act similarly and do not have individual-specific variances. The two scale-related coefficients, $\varphi_1$ and $\varphi_2$, are insignificant, indicating that there are no scale changes when respondents processed through choice tasks in early, middle, and late stages. Therefore, when the model does not include fixation information, we conclude that no scale change is identified. Thus, no learning effect or fatigue effect. We also test the model fit and compare the estimated WTPs between conditional logit model and this model. The test results indicate that there is no improvement in model fit from adding the two scale-related variables. The estimated WTPs are not affected as well.

Since Van Loo et al. (2015) mentioned that including fixation data in the model may have an impact on scales and estimated WTPs, we run another scale heterogeneity model with fixation variable included in the scale function. The second column in Table IV-7 represents the results. When fixation variable is included, there are some changes in values and significance levels of estimated parameters. The individual heterogeneity parameter is still insignificant at 5% level, indicating that there is no individual heterogeneity. The first two terms of scale function are insignificant, as in the previous model. However, the estimated parameter of fixation variable is negative and significant at 5% level. The significant and negative value of fixation variable indicates that as the total visit duration to one choice task increases, the scale parameter decrease. Thus, the error variance goes up. In another word, the fact that respondents pay more attention to one choice task indicates they are more uncertain about their choice. As reported previously, there is a decreasing trend in total visit duration from the early stage to the middle stage. Between the middle stage and the late stage, there is no significant change. Thus, we conclude that respondents have learning effect from the early stage to the middle stage. In addition, considering the impact of attention on scale change significantly improves the model fit. Even though visual attention has an impact on the scale, it does not influence the WTP estimates. When we compare the estimated WTPs between scale heterogeneity models without and with fixation variable, we do not obtain any significant change.

**Conclusions**

Conjoint analysis is in wide use in exploring consumers' buying decision. However, the nature of repeated choice tasks in the conjoint analysis may reduce the value of obtained information. The existence of ordering effects, especially learning effect and fatigue effect, challenges the usefulness of information obtained from the conjoint analysis. The fact that conjoint analysis does not reveal respondents' decision-making process is its limitation. In this study, we combined eye-tracking technology with conjoint analysis. Including eye-tracking technology, could overcome the limitation of conjoint analysis, as eye-tracking technology records and reports respondents' eye movements when they process information.

Respondents total visit duration was included to reflect respondents' real attendance to attributes in model estimations. Along with the sequential choice tasks, respondents' attention decreases from the first choice task to the last choice task. This conclusion keeps with the statements from Krajbich et al. (2010), Meißner and Decker (2010), and Orquin and Loose (2013). We also find that respondents' attention to an alternative positively affects the probability of choice. That is, the higher weight respondents put on an alternative when processing information, the higher probability that this alternative is chosen within a given choice task.

Including eye fixation data in regression significantly improve the model fit. Meanwhile, including fixation variable changes the estimated value of respondents' WTPs. This indicates that when respondents' attention is not considered in a logit model, the estimated WTPs are biased, thus unreliable. Estimation of WTPs is important in terms of identifying consumers' real preference on product attributes. To some extent, considering attention uncovers respondents' information acquisition and processing in the choice experiment, thus improves the interpretation of results from the conjoint analysis.

We also analyze the learning and/or fatigue effects in conjoint analysis. The existence of learning and/or fatigue effect can be confirmed by preference change and scale change. The inconsistency in preferences may due to learning effect or fatigue effect, or both. If respondents' choices are consistent, the scale parameter does not change, so respondents are with constant error variance. If respondents learn during the choice experiment, they are more certain about their choices along with the sequence of choice tasks. Thus, the error variance becomes smaller. On the contrary, if respondents get fatigued, their choice consistency decreases, thus resulting in a larger error variance. We do not identify preference change among the early, middle, and late stages. However, respondents' price sensitivity vary among stages, thus causes a change in estimated WTPs. We run scale heterogeneity model, aiming at identifying scale change and distinguish between learning and/or fatigue effect. The results indicate that there is no scale change when fixation variable is included in the scale function. Running scale heterogeneity model without eye fixation variable does not improve model fit or change the estimated WTPs, compared to the original conditional logit model. We also scale heterogeneity model with eye fixation in the scale function. The results confirmed that eye fixation has a significant impact on the scale, which contradicts with Balcombe, Fraser, and McSorley (2015). The estimated parameter of fixation variable is negative, meaning that the variance increases as attention increases. Since we discover a decreasing trend of visual attention from the early stage to the middle stage, we conclude that respondents learn when they process choice tasks in the early stage to those in the middle stage. However, we do not identify a significant decrease in visual attention between the middle stage and late stage. Thus, we cannot conclude that there is learning effect or fatigue effect between the last two stages.

There are several limitations of our study. One limitation is small sample size. With eye-tracking device installed, it took approximately one hour for one respondent to finish one set of 12 choice tasks. Also, our respondents were recruited during international turfgrass conference, thus have a small demographic range. Due to the time and expense constraint, we were not possible to enlarge the sample size for this study. Another limitation is that aligning with the eye-tracking device may have an impact on respondents' behavior (Balcombe, Fraser, and McSorley, 2015).We need to pay further attention to this issue. For further research, we may enlarge the sample size and widen the demographic range of respondents.

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**Table IV-1. Conjoint analysis experimental attributes and attributes levels**

| Attribute | Definition | 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 IV-2. Summary Statistics of Participants**

| Attribute | Description | Mean (Std. Error) |
|---|---|---|
| Gender | 1=male;<br>0=female | 0.16 (0.374) |
| Age | Age in years | 47.56 (12.484) |
| Education | Highest level of education completed<br>1=<$12^{th}$ grade<br>2=high school diploma<br>3=some college<br>4=bachelor's degree or higher graduate | 3.654 (0.485)<br>65.4% hold Bachelor's degree or higher |
| Ethnicity/Race | 1=White<br>2=African American<br>3=Native American<br>4=Asian | 1.12 (0.600)<br>96% are White |
| Degree Area | 1=turf grass management<br>2=horticulture<br>3=landscape architecture<br>4=plant and soil science<br>5=other | 3.91 (1.640) |
| Sales | Amount of sales in 2014<br>1=<$100,000<br>2=$100,000 - $249,999<br>3=$250,000 - $499,999<br>4=$500,000 - $999,999<br>5=$1,000,000 - $1,999,999<br>6=$2,000,000 - $3,999,999<br>7=$4,000,000 - $5,999,999<br>8=$6,000,000 - $7,999,999<br>9=$8,000,000 - $9,999,999<br>10=>$10,000,000 | 5.81 (2.899) |

**Table IV-3. Summarized Eye-Tracking Measures for Three Stages (n=336)**

| Stages | Time to First Fixation (seconds) | | Fixation Duration (seconds) | | Fixation Count (times) | | Total Visit Duration (seconds) | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std Dev. | Mean | Std Dev. | Mean | Std Dev. | Mean | Std Dev. |
| Early | 0.83 | 1.54 | 11.82 | 7.28 | 51 | 29 | 12.82 | 7.93 |
| Middle | 0.61 | 1.19 | 9.84 | 7.94 | 42 | 32 | 10.59 | 8.50 |
| Late | 0.46 | 0.50 | 8.65 | 5.85 | 37 | 23 | 9.31 | 6.30 |

**Table IV-4. Parameter and WTP Estimates from Conditional Logit Models**

| Variable | Estimates | | |
|---|---|---|---|
| | w/o eye-tracking data | w. eye-tracking data | $\overline{\Delta WTP} = E[WTP_{w/o} - WTP_{w/}]$ |
| Price | -1.5065***<br>(0.4640) | -2.1934***<br>(0.5202) | -- |
| Winter Kill Reduction | 0.2543***<br>(0.0720)<br>[0.34] | 0.2079***<br>(0.0743)<br>[0.18] | 0.19** |
| Shade Tolerance | 0.4175***<br>(0.0712)<br>[0.56] | 0.3488***<br>(0.0742)<br>[0.32] | 0.34** |
| Drought Tolerance | 0.4694***<br>(0.0729)<br>[0.62] | 0.4295***<br>(0.0748)<br>[0.40] | 0.36** |
| Salinity Tolerance | 0.1830**<br>(0.0719)<br>[0.24] | 0.1406*<br>(0.0741)<br>[0.12] | 0.15** |
| 10% Maintenance Reduction | 0.0618<br>(0.0728)<br>[0.08] | -0.0187<br>(0.0.0777)<br>[0.00] | 0.14 |
| Percentage of Total Visit Duration | -- | 0.1753***<br>(0.0505) | -- |
| -2 log likelihood | -233.85 | -227.03 | -- |

*, **, and *** indicate statistical significance at 90%, 95%, and 99% confidence level, respectively.
Numbers in parentheses are standard errors.
Numbers in brackets are WTPs.
Attributes are effect-coded.

**Table IV-5. Parameter and WTP Estimates from Conditional Logit Models for Three Stages**

| Variable | Estimates | | | |
|---|---|---|---|---|
| | Early Stage | Middle Stage | Late Stage | $\overline{\Delta WTP} = E[WTP_1 - WTP_3]$ |
| Price | -0.9695<br>(0.7024) | -1.0748<br>(0.9074) | -3.4205***<br>(1.2105) | -- |
| Winter Kill Reduction | 0.1995*<br>(0.1159)<br>[0.42] | 0.4110***<br>(0.1491)<br>[0.76] | 0.2207<br>(0.1447)<br>[0.13] | 0.90*** |
| Shade Tolerance | 0.4873***<br>(0.1338)<br>[1.04] | 0.3289**<br>(0.1382)<br>[0.62] | 0..5516***<br>(0.1582)<br>[0.32] | 1.33*** |
| Drought Tolerance | 0.4646***<br>(0.1489)<br>[0.96] | 0.5470***<br>(0.1459)<br>[1.02] | 0.5833***<br>(0.1620)<br>[0.34] | 1.06*** |
| Salinity Tolerance | 0.0169<br>(0.1643)<br>[0.03] | 0.1756<br>(0.0.1683)<br>[0.31] | 0.2582*<br>(0.1562)<br>[0.15] | 0.06** |
| 10% Maintenance Reduction | -0.0668<br>(0.1670)<br>[0.00] | -0.0020<br>(0.1568)<br>[0.00] | 0.1414<br>(0.1542)<br>[0.08] | -0.33 |

*, **, and *** indicate statistical significance at 90%, 95%, and 99% confidence level, respectively.
Numbers in parentheses are standard errors.
Numbers in brackets are WTPs.
Attributes are effect-coded.

**Table IV-6. Complete Combinational Test Results for Stage Comparisons**

| Parameters | CC-test p- value | | |
|---|---|---|---|
| | Early vs. Middle | Middle vs. Late | Early vs. Late |
| Price | 0.01 | 0.01 | 0.01 |
| Winter Kill Reduction | 0.88 | 0.18 | 0.55 |
| Shade Tolerance | 0.22 | 0.86 | 0.63 |
| Drought Tolerance | 0.66 | 0.57 | 0.71 |
| Salinity Tolerance | 0.75 | 0.66 | 0.86 |
| 10% Maintenance Reduction | 0.61 | 0.75 | 0.82 |
| **WTPs** | **CC-test p- value** | | |
| | Early vs. Middle | Middle vs. Late | Early vs. Late |
| Winter Kill Reduction | 0.04 | 0.01 | 0.03 |
| Shade Tolerance | 0.01 | 0.04 | 0.03 |
| Drought Tolerance | 0.03 | 0.03 | 0.04 |
| Salinity Tolerance | 0.04 | 0.03 | 0.04 |
| 10% Maintenance Reduction | 0.30 | 0.38 | 0.41 |

**Table IV-7. Stage-Base Scale Heterogeneity Model Estimates**

| | Excluding Fixation in Scale Parameter | Including Fixation in Scale Parameter | $\overline{\Delta WTP_1} = E[WTP_{cond} - WTP_{scale\ w/o}]$ | $\overline{\Delta WTP_2} = E[WTP_{cond} - WTP_{scale\ w/}]$ |
|---|---|---|---|---|
| Price | -1.6562*** (0.4935) | -2.9666*** (1.0935) | -- | -- |
| Winter Kill Reduction | 0.2603*** (0.0753) [0.31] | 0.4339*** (0.1606) [0.29] | 0.05 | 0.07 |
| Shade Tolerance | 0.4148*** (0.0720) [0.50] | 0.7978*** (0.2274) [0.54] | 0.11 | 0.07 |
| Drought Tolerance | 0.4810*** (0.0739) [0.58] | 0.9725*** (0.2688) [0.66] | 0.10 | 0.03 |
| Salinity Tolerance | 0.1751* (0.0736) [0.21] | 0.3286** (0.1541) [0.22] | 0.05 | 0.03 |
| 10% Maintenance Reduction | 0.0708 (0.0737) [0.09] | 0.0825 (0.1441) [0.06] | 0.00 | 0.03 |
| Individual Heterogeneity | -0.0042 (0.3514) | 0.0002 (0.3795) | -- | -- |
| Scale-Related Coefficient $\theta_1$ | 0.0115 (0.1539) | 0.0333 (0.1542) | -- | -- |
| Scale-Related Coefficient $\theta_2$ | 0.1501 (0.1406) | 0.1232 (0.1446) | -- | -- |
| Scale-Related Coefficient $\theta_3$ | -- | -0.6880*** (0.2541) | -- | -- |
| -2 Log Likelihood | -232.97 | -227.92 | | |

$^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at 90%, 95%, and 99% confidence level, respectively.
Numbers in parentheses are standard errors.
Numbers in brackets are WTPs.
Attributes are effect-coded.

**Options A and B represent two different sets of sod/turfgrass 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 | YES | 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 | YES | NO | |
| Salinity Tolerance | NO | YES | |
| 10% maintenance reduction | YES | NO | |
| Farm gate Price per Square Foot | $0.15 | $0.25 | |
| I would choose | ☐ | ☐ | ☐ |

**Figure IV-1. Choice Task for Turfgrass Study**

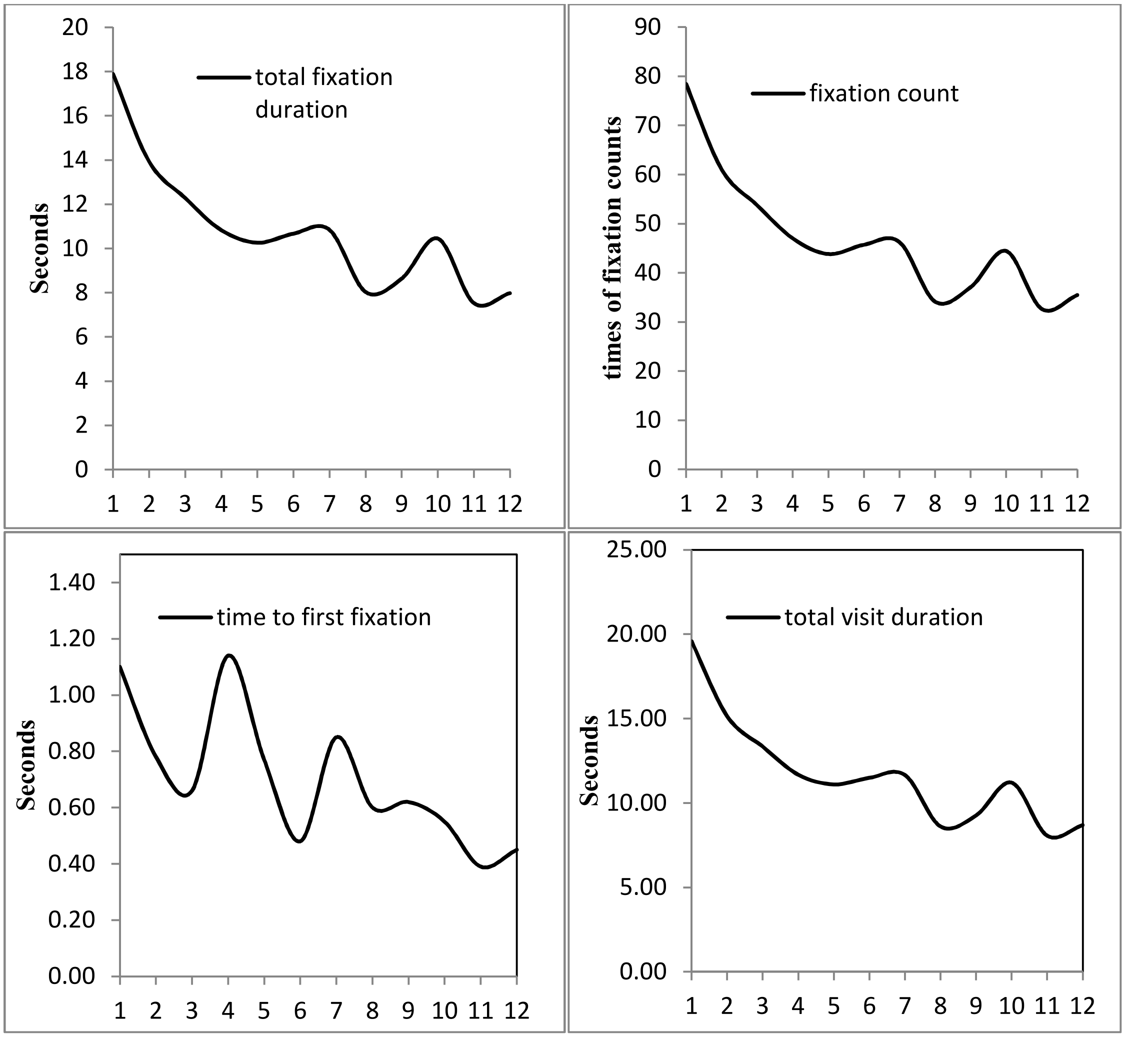


**Figure IV-2. Total Fixation Duration, Fixation Counts, Time to First Fixation, and Total Visit Duration over Choice Tasks**

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