MODELING ECONOMIC RESILIENCE AND ANIMAL DISEASE OUTBREAKS IN THE TEXAS HIGH PLAINS

A Dissertation

by

HEN-I LIN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2010

Major Subject: Agricultural Economics

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Approved by:

Chair of Committee,	Bruce A. McCarl
Committee Members,	David A. Bessler
	Victoria Salin
	H. Morgan Scott
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ABSTRACT

Modeling Economic Resilience and Animal Disease Outbreaks in the Texas High Plains.
(December 2010)
Hen-I Lin, B.A., National Taiwan University;
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Chair of Advisory Committee: Dr. Bruce A. McCarl

Foot and Mouth Disease (FMD) could have a significant impact on the U.S. agriculture industry and the welfare of U.S. producers and U.S. consumers. In order to address the potential impact from animal disease outbreaks, this project is designed to utilize a combined epidemic and economic modeling framework to evaluate animal disease management strategies which can be used to reduce the potential losses in an unusual event such as FMD outbreaks.

In this study, we compare the welfare changes among three different parties with different strategies using, 1) ANOVA analysis; 2) cost benefit analysis; and 3) Risk Aversion Coefficient (RAC) analysis. Four types of index feedlots are selected in the study including, Feedlot Type 1 (> 50,000 heads of animals), Feedlot Type 4 (backgrounder feedlot), Large Beef Grazing (>100 heads of animals), and Backyard (<10 heads of animals). Results suggest that early detection of FMD events has the advantage in reducing risk as shown in the epidemiological impacts. Enhanced surveillance is found to be a preferred mitigation strategy for U.S. consumers in the scenario of smaller feedlot disease introductions (e.g. Large Beef Grazing and Backyard) and for U.S. producers in the larger feedlot disease introduction scenarios (e.g. Feedlot Type 1 and Feedlot Type 4). Adequate vaccination is not cost effective when seeking to minimize average loss but becomes a preferred strategy when the risk aversion rises.

Risk modeling with stochastic programming adopted in this study also confirms the importance of incorporating risk evaluation into decision making process. It offers another option for us to evaluate the mitigation strategies. Two portfolio models are adopted in this study including, E-V model (mean variance portfolio choice model) and Unified model. The results show that the preference for control strategies depends on risk attitude. Early detection proves to be preferable for U.S. consumers and is also preferred by U.S. processors and producers as Risk Aversion Parameters (RAP) rises. Adequate vaccination strategy can benefit U.S. consumers but does not give U.S. processors a better outcome. Adequate vaccination provides a better choice for U.S. producers when the RAP rises. Enhanced surveillance is preferred for U.S. consumers. For U.S. processors, enhanced surveillance does not give a better risk/return outcome. U.S. producers are likely to switch their preferences from regular surveillance to enhanced surveillance as their RAP rises.

DEDICATION

To My Dearest Father, Mr. R.S. Lin, who supports me all the way to pursue this common dream in his and my mind.

To My Dearest Mother, Mrs. S. M. Tsai, who always gives me courage and love when I face many difficulties.

To My Dearest Sister, Ms. Joyce Lin, who stands up for me and takes care for the family while I am away from home.

To My Dearest Love, Ms. Chris Hung, who always encourages me to move forward and gave me strength when I studied for my doctoral program at Texas A&M University.

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I would also like to show my appreciation to my committee members, Dr. David A. Bessler, Dr. Victoria Salin, and Dr. H. Morgan Scott, for their great and valuable comments on my dissertation. I also want to thank Dr. Chi-Chung Chen for his advice on my research when he visited Texas A&M University as a visiting scholar in 2009.

I would like to thank many friends, colleagues, and classmates in College Station during the past seven years. Special thanks to Dr. J.C. Han and Mrs. Su Han. They always treat me like their son, and offered many help when I needed it. Tommy Chui, Yongxia Cai, Pedro Alviola were my best classmates when we studied hard together for our doctoral program courses. Dr. Amy D. Haggerman was my former colleague in the FAZD research project and I learned a lot from her.

Finally, I would like to show my great appreciation to my family. Their great love and endless support have been the most valuable things in my life. I will continue to move forward and strive to achieve every goal that makes them proud.

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1. INTRODUCTION

Stimulated by economic growth, the demand for livestock products has been growing rapidly. According to a 2009 United Nations, Food and Agriculture Organization (FAO) report, the consumption of livestock products has shown substantial growth in major developing and developed countries, excepting in Africa (United Nations 2009). Research finds that the consumption of livestock products is significantly influenced by income level and urbanization (Rae 1998). More advanced technology used in breeding, feeding, processing, transporting, and marketing of livestock products has resulted in structural change in agriculture. The change in both consumption and livestock production has increased the volume of international trade. The United Nations FAO report also shows an increase in international trade volume and share of total agricultural livestock production from 1980 to 2006 (United Nations 2009).

Because of technology use and increased livestock production, agricultural production has also gradually become more greatly geographically clustered (United Nations 2009).

Considering the concentration of animals and urbanization, plus the more recent greater incidence of disease outbreaks, the prevention and control of potential animal disease outbreaks has become a very critical issue. For example, in the United States the cattle industry is very highly concentrated in the Great Plains region (see Figure 1). Several disease outbreak events have shown that naturally occurring animal disease can cause not only extreme economic loss in the livestock industry in this country, but can

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*This dissertation follows the style of *The American Journal of Agricultural Economics*.

also be a potential threat to human health and security of the general public as discussed below.

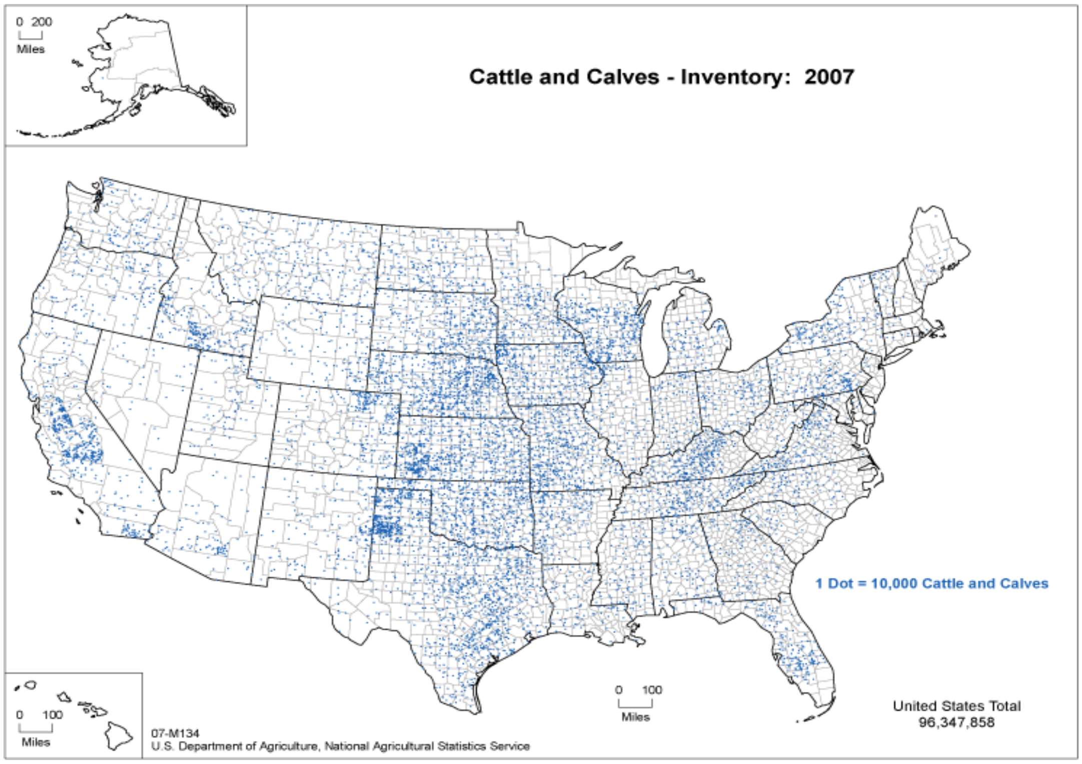


Figure 1: U.S. cattle and calves distribution

Source: US Department of Agriculture, National Agricultural Census Statistics Service, 2007. Cattles and Calve Inventory-2007.

In February 19, 2001, Donald Vidgeon, a British livestock transporter, noted a problem with sows he was to transport that morning, and alerted Mr. Craig Kirby, a resident veterinarian in Brentwood, United Kingdom (UK). This started the discovery of a Foot and Mouth Disease (FMD) outbreak in 2001, which was soon determined as the worst recorded epidemic outbreak (Anderson, 2002). Although FMD is not a direct danger to human health, this outbreak resulted in an extreme loss to the country. During the epidemic FMD outbreak in the UK, over 6 million animals were slaughtered and approximately £8 billion were lost (Donaldson et al. 2006).

FMD has traditionally been controlled by conventional strategies, including the slaughter of infected animals and the ‘stamping-out’ strategy (Anderson, 2002). Researchers also indicate that the non-vaccination policy was adopted in Europe from 1992 and the strategy of stamping-out was used under farmers’ or producers’ choices (Cohen, Van Asseldonk, and Stassen, 2007). These strategies were used in the FMD outbreak occurring in 1981 at the Isles of Wight, United Kingdom, and they were actually effective in preventing the disease from spreading in the regions where a small number of cases were found (Anderson, 2002).

However, conventional strategies were not able to stop the 2001 UK epidemic of FMD disease outbreak in most parts of the country (UK). Therefore, a culling strategy was adopted as an alternative to control the outbreak (Anderson, 2002). All infected and direct contact healthy animals were removed to ensure the elimination of FMD. As the UK exported meat to other countries, the impact reached many other traditional trade partners. Ex post estimates show that the damage to the UK economy is huge and the total estimated cost is between £7.6 to £8.5 billion (Mangen and Burrell 2003). The incident then led to increased public awareness and policy consideration relating ways to deal with threats from infectious animal diseases.

Recent bovine spongiform encephalopathy (BSE), avian influenza (AI), and classical swine flu events also raise similar concerns. In the United States, the 2003 BSE event resulted in immediate closure of beef overseas markets in several major U.S. beef importing countries, including Japan, Korea, Mexico, and Canada, stimulating lower prices and beef industry losses (Pendell et al. 2007).

During the 1997 Hong Kong avian influenza outbreak event, the AI virus was discovered among poultry handlers (WHO 2007). This event has started establishing evidence that AI can infect both animals and humans. Beginning in 2003, AI viruses caused animal disease outbreaks in poultry in several countries in southeastern Asia, including Bangladesh, Thailand, India, Indonesia, and Myanmar (WHO 2007). At the same time, China, Cambodia, Laos, and Vietnam also reported infections (WHO 2007). Approximately 250 million birds either died or were culled during the outbreak. The economic loss in Asia was also sizeable (WHO 2007).

The recent swine flu (influenza A H1N1) outbreak starting from Mexico in April 2009 has been reported to cause more than 18,114 deaths and affect more than 214 countries as of May 2010 (WHO 2010). The novel strand of influenza virus usually emerges from the exchange of viruses among different animals, humans, or wild birds (Narain, Kumar, and Bhatia 2009). Given that current agriculture production involving animals tend to be concentrated in populated areas because of the trend toward urbanization, the probability of having an epidemic infectious disease may be greater and will result in threats to potential economic loss and human health.

Research has suggested that movement of animals is an important risk factor influencing epidemic spread (Green, Kiss, and Kao 2006). Therefore, implementing effective prevention or response strategies at the local level to prevent the outbreak from happening has grown to be a critical issue in the area of animal disease control, particularly within the context of modern agricultural industry.

Because FMD is the most contagious animal disease of hoofed mammals and a potential massive animal health and economic threat, FMD is a priority area of concern within the United States Department of Agriculture (USDA) and the Department of Homeland Security (DHS). Many studies on the analysis of FMD-related decision-making have appeared mainly in veterinary journals (Bates et al. 2001, 2003; Berentsen, Dijkuizen, and Oskam 1992; Ferguson et al. 2001; Garner and Lack 1995; Keeling et al. 2001; Schoenbaum and Disney 2003). Most of those studies examine decision-making once an outbreak has occurred, largely addressing post-outbreak disease spread management with vaccination and slaughter as FMD disease spread management policies.

To further contribute to knowledge in this area, this dissertation is designed to research the effects of various mitigation strategies using combined Epidemic-Economic Simulation Modeling in an effort to provide information to reduce the cost and incidence of extreme disasters, and improve industry economic resiliency. This study is conducted in the face of a possible animal disease outbreak in the Texas High Plains.

1.1. Research Questions

FMD is a high risk disease facing the livestock industry. Research at the Center for Foreign Animal and Zoonotic Disease Defense (FAZD) has been examining the vulnerability of animal agriculture pertaining to this and other disease issues. In addressing the FMD issue one can approach it from several perspectives. First, one may address the fundamental issues inherent in the following questions:

1. How much of a threat is FMD?

2. Are there actions that if undertaken would limit vulnerability in terms of disease management alternatives during the course of an outbreak?

3. What are scientific developments that could accelerate detection or provide increased degrees of immunity?

4. What actions will be undertaken afterwards that could reduce further disease damage from different viewpoints of different parties?

Second, one could evaluate the risk consequences of mitigation actions by studying the welfare effects of various disease management strategies using stochastic modeling and economic risk-associated analytical approaches.

In this work a combination of these approaches will be used employing combined economic-epidemic simulation analysis, and a further risk based investigation.

1.2. Research Objectives and Methodology

This dissertation research investigates the effect of mitigation strategies on sectors' resiliency to potential animal disease outbreak. Addressing this problem requires a modeling formulation that depicts the resiliency response to decisions and sector characteristics. Two major modeling approaches will be taken to address this problem. The first modeling approach is an economic-epidemic framework that evaluates the consequences of a set of disease management strategies, and examining their effects on welfare, welfare distribution in turn making inferences about effects on resiliency.

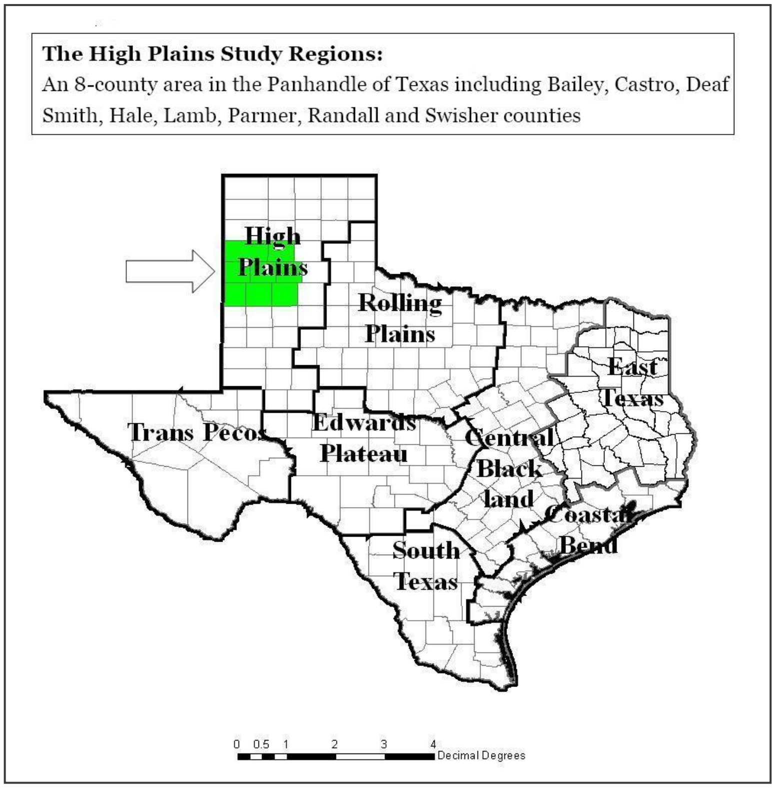
Disease outbreak will be simulated under a stochastic disease spread assumption. The second modeling approach involves determination of “optimal" resiliency responses with risk modeling through stochastic programming.

1.3. Case Study Region

Although the threat of animal disease outbreak on agricultural product supply in the United States is generally huge, Texas is one of the more vulnerable states. Texas has around 20 percent of the U.S. beef cattle production, and the total cattle industry sales value is estimated around $8 billion per year (Elbakidze et al. 2008). An FMD outbreak occurs in Texas, could well cause serious damage to the U.S. agricultural sector, and, consequently, to the whole economy. Therefore, Texas is an important region to target when researching resiliency responses of sector characteristics to animal disease outbreak.

In Texas, the major area for where beef cattle feedlots are located is in the Panhandle region. This study examines an 8-county area in the Panhandle of Texas (see Figure 2). According to the US Department of Agriculture (2007), those 8 counties contain 17.5 percent of the cattle and calves in the State of Texas, which is 2.5 percent of the U.S. total cattle and calf population. Moreover, in the category of cattle on feed, those regions contain 83.5 percent of Texas animals and 16.4 percent of U.S. animals. The initial motivation is to investigate a potential economic problem in modeling economic resilience for a possible animal disease outbreak in the Texas High Plains.

In addition, examining mitigation options on a local basis rather than a national scale can provide a better understanding of various components of developed optimal economic approaches used to prevent or detect disease outbreaks. Characteristics of developed economic models can be applied to a broader setting.



The High Plains Study Regions:
An 8-county area in the Panhandle of Texas including Bailey, Castro, Deaf Smith, Hale, Lamb, Parmer, Randall and Swisher counties

Figure 2: The Texas high plains project study regions

1.4. Organization of the Study

This dissertation is organized into five sections. Section 1 provides the introduction, research methodology, case study focus and objectives of the study. Section 2 gives an overview of the literature on the history of biosecurity within the context of animal disease management, the development of FMD disease control strategies, and the concept of economic resiliency, as well as its application in decision support tools. Section 3 applies an integrated epidemic-economic modeling to control strategies applied to an FMD disease outbreak in the Texas High Plains, and also employs stochastic dominance and risk aversion analysis to evaluate the effectiveness of mitigation strategies. Section 4 reports results of using a stochastic programming application of two risk portfolio choice formulations to evaluate optimal choice of mitigation strategies. Section 5 gives conclusions and discussion of future research.

1.5. Definition of Key Terms

Biosecurity: society's collective responsibility to safeguard the population from dangers presented by pathogenic microbes whether intentionally released or naturally occurring (Fidler and Gostin, 2008); it describes management practices preventing infectious disease from being introduced into a herd or flock.

Economic Resiliency: the ability of an agency/sector to recover from a severe incident (Rose, 2004). It includes two types of resilience: 1) inherent – the ability to recover under normal circumstances (eg. The ability to substitute inputs or allocate resources to respond to the price increase followed by the incident); 2) adaptive – the ability to recover under crisis (eg. Expanding the possibilities for input substitutions or providing more information to match suppliers' or customers' needs.) (Rose, 2004)

2. LITERATURE REVIEW

2.1. History and Origins of Agricultural Biosecurity

The history of agricultural resources considered to be potential targets of bioterrorism can be traced back to World War I (Monterey Institute of International Studies 2009). In 1925, the Geneva Protocol was initiated to prohibit chemical or biological weapons, since many countries such as Germany, Japan, and Russia (Former Soviet Union) used viruses to kill people or contaminate the food supply during the war (Geneva Protocol 1925; MIIS 2009). The concept of biosecurity emerged shortly thereafter and covers both deliberate and unintentional event origins. Whether the virus is released intentionally or occurs naturally, the threat to human health is clearly immense.

As a result, biosecurity has developed into the concept that is defined as a critical responsibility of the nation, which is to protect its citizens from dangers presented by pathogenic microbes (Fidler and Gostin 2008). It encompasses issues related to the use of biological weapons and the naturally or accidentally occurring infected disease. A consensus on the importance of addressing challenges of naturally infected disease outbreak has surfaced among researchers, policymakers, and international society. In 2006, the Bush Administration named fighting against naturally occurring disease epidemics as one of the prioritized national security topics (White House 2006), reflecting how massive the impact of a disease outbreak could be on the nation.

Foot and Mouth Disease (FMD) is one of the most highly infectious animal diseases. Although human health will not be impacted by FMD, it can cause significant economic damage because of the high likelihood of infecting animals exposed to the virus (GAO 2009). The United States has been FMD free since 1929; however, the possibility of accidentally introducing FMD into the country through international agricultural trading is still there, considering the fact that FMD has continued to happen in many countries in the world (U.S. Department of Agriculture 2007). FMD spread and outbreak cases have occurred in Europe, Asia, South America, and Africa since 2005 (see Figure 3).

Research has suggested that movement of animals is a large risk factor for many infectious diseases (Green et al. 2006). As a result, it is important to focus on the topic of risk management within the context of animal disease outbreak such as FMD in disease-free regions to provide involved governmental bodies and industry greater knowledge for effectively carrying out the diseased-related decision-making process, while facing an unexpected outbreak.

Therefore, this literature review will focus on various strategies used in FMD control management, and the relationship between selected strategy options and economic resiliency, and the development of epidemic economic simulation model selected to apply in this study.

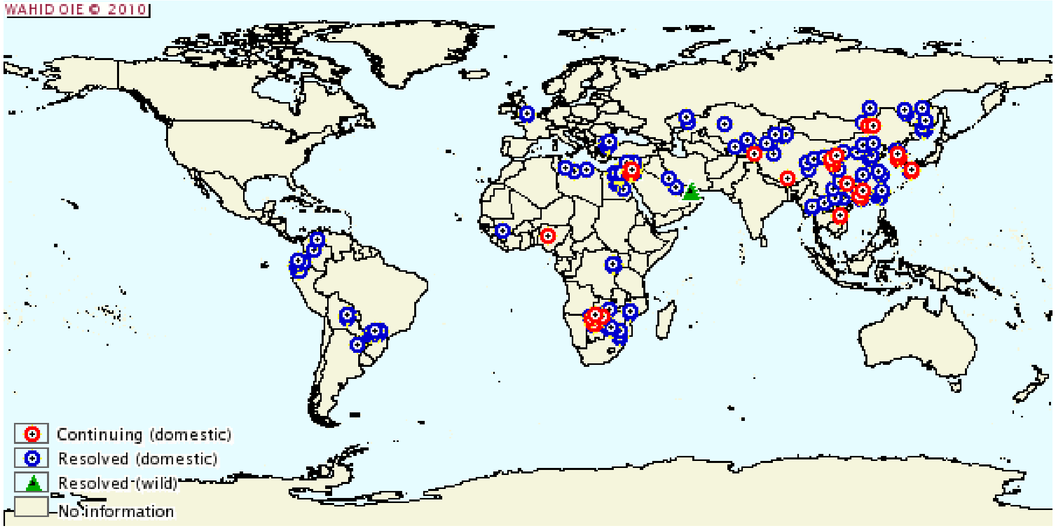


Figure 3: Global map of Foot and Mouth Disease (FMD) outbreak since 2005
Source: World Organization for Animal Health (OIE), *Global map of Foot and Mouth Disease (FMD) outbreak since 2005*, 2010. World Animal Health Information Database. (Accessed Aug 14, 2010)

2.2. FMD Control Measures

The "best" control measure to prevent an FMD epidemic from happening still remains controversial. Research conducted in the UK and Netherlands suggests that most stakeholders of the study prefer to adopt a preventive strategy to reduce risk of the outbreak, and then to eradicate the disease (Cohen, Van Asseldonk, and Stassen 2007). An effective early warning system to monitor animal health and vaccination can be used to prevent the outbreak from happening and/or reduce its magnitude. Control strategies introduced in this review include a) vaccination, b) slaughter control, and c) culling strategies.

Vaccination has been used to control FMD effectively in three settings (1) as prophylactic protection prior to an outbreak, (2) as an action to limit spread during the outbreak, or (3) as a strategy combined with slaughter control (Kitching and Hutber

2003). Hutber et al. (2010) conduct a review of previous vaccination programs and divides all into three major categories based on where vaccinations are used. That includes vaccinations applied in areas where the disease is endemic, semi-endemic, or disease-free. Due to the cost and possible entry of animal disease from vaccine administration plus international trade concerns, disease-free regions are not likely to take control of measures of regular vaccinations (Hutber et al. 2010). Therefore, vaccinations can be used as an effective measure, combined with other strategies when an unexpected disease outbreak occurs. However, whether vaccinations or slaughter control are more effective in controlling an epidemic remains controversial.

Ferguson et al. (2001) called for cost-benefit analysis of mass vaccination options versus slaughter-based control of infrequent outbreaks. Schoenbaum and Disney (2003) investigated the effectiveness of four slaughter and three vaccination strategies under varying conditions of herd sizes and rates of disease spread in the United States. Four slaughter options include slaughtering: a) only infected herds, b) herds with direct contact with infected herds, c) herds within 3km distance of infected herds, and d) herds with both direct and indirect contact with infected herds. Three vaccination options include: a) no vaccination, b) vaccination of all herds within 10km of infected herds after two infected cases were detected, and c) vaccination of all herds within 10km after 50 were detected. Although they generally found that ring slaughter control based on herd demographics and the rate of contact among herds is the best option as opposed to other slaughter strategies. They also found that early ring vaccination helps to control the outbreak duration. The finding is also supported by Keeling et al. (2001). They suggest that both ring slaughtering and ring vaccination were effective strategies if implemented rigorously, although ring slaughtering was more effective. A neighborhood cull option was found to be more effective than neighborhood vaccination. They also argue that spatial distribution, size, and species composition of farms all influence the pattern and regional variability of outbreaks.

A recent review article argues that the effectiveness of vaccination and slaughter control also differ on the infection status of the location (Hutber et al. 2010). It further indicates that the benefits of ring and targeted vaccination is not greater than slaughter control in disease-free regions and indicates that it is unclear that emergent blanket vaccination has economic benefits over slaughter control. They also found that blanket vaccination proved to be an effective measure in disease-free and semi-endemic regions.

Some other research investigates the relationship between the speed of slaughter control and FMD spread (Morris et al. 2001). They found that delaying the slaughter of animals at the infected farms beyond 24 hours would have slightly increased the size of the FMD epidemic during the UK 2001 FMD outbreak. Failure to carry out pre-emptive slaughter of animals at the susceptible farms would have substantially increased the size of the epidemic. Honhold et al. (2004) also suggest that there is a correlation between the speed of slaughter control and disease transmission among cattle with lower innate immunity. This research investigates the relationship among the rate of disease spread, average time from the first lesion to slaughter on infected premises, and the intensity of contagious and non-contagious premises. They found that the average time from the first lesion to slaughter control and the intensity of culling on non-contagious premises has a significant relationship (Honhold, et al., 2004).

Hutber et al. (2010) indicate that it takes approximately 5 days to achieve the immunity of vaccinated animals and finding the matched type of vaccines to the strain may also influence the effectiveness of this strategy. Morris et al. (2001) suggest that vaccination of up to three of the most outbreak dense areas, in addition to an adopted control policy, such as slaughter, would have slightly decreased the number of infected farms. However, relying solely on vaccination and disregarding other control policies would have significantly increased the size of an outbreak.

Garner and Lack (1995) investigated the effectiveness of four control options for FMD, including a) "stamping out" of infected herds only, b) stamping out of infected and dangerous contact herds, c) stamping out of infected herds plus early ring vaccination, and d) stamping out of infected herds plus late ring vaccination. They found that if FMD is likely to spread rapidly then slaughter of dangerous contacts and infected herds would reduce the economic impact of the FMD outbreak. Early ring vaccination turned out to reduce the size and duration of an outbreak, but was uneconomic when compared to stamping-out alone.

In general, slaughter control and vaccination are both more effective options among all control measures. Several studies suggest that slaughter control is an effective strategy; however, the combination of slaughter control and vaccination can help to reduce an epidemic in a more efficient way.

2.3. Surveillance and Detection

Surveillance programs developed at the local level provide protection from possible animal disease spread. However, surveillance programs usually are more costly than detection as the investment in disease control and management itself is expensive. Research has indicated that the United States is under-investing in a surveillance program for FMD (Kompas, Che, and Ha, 2006). Early detection of an animal outbreak such as FMD usually will reduce production and tourism consequences, as well as disease management costs during and after the spread. However, less attention has been devoted to pre-event decision-making.

Although some researchers have focused on surveillance system investigation, less attention has been devoted to pre-event decision-making. Attention to surveillance program (Bates et al. 2003; Akhtar and White 2003; Ekboir 1999), limited empirical investigation has addressed the issue of finding the optimal economic balance between pre-event preparedness and post-event response actions. Elbakidze and McCarl (2006) address this issue by investigating the economic balance between the pre-event installation/operation of surveillance and detection systems and post-event slaughter actions. They also examine the reliance within an optimal cost minimizing plan on pre-event periodic animal health testing, versus sole reliance on post-event response measures. They found that there is a positive correlation between pre-event investment and the probability and severity of the potential event, as well as costs and effectiveness of response options. Specifically, theoretical and empirical investigations suggest that the optimal level of investment in pre-event preparedness is increased when disease spread rate gets larger; response strategy is less effective or more costly; the probability of disease introduction increases; the costs of the pre-event activity fall; and the cobenefits of the strategy outside of an event increase.

Elbakidze et al. (2009) developed an integrated epidemiologic economic model to simulate the spread of disease across the region under various combinations of disease control options. The purpose of this integrated model is to estimate economic loss within the local cattle industry and associated costs of using corresponding disease management options based on the data obtained from epidemiologic output.

They use the AusSpread model (Garner and Beckett 2005) as the epidemiological model to simulate disease spread in this study. AusSpread is a state transition model, which builds a geographic information system (GIS) framework into the model design. This model is modified to include stochastic elements to include probabilistic factors in simulating disease spread (Garner and Beckett 2005). The spread of the disease is based on a susceptible, latent, infectious, recovered state transition specification where herds fall into one of the four categories at any given time period (Garner and Beckett 2005). The probabilities of transition from susceptible to latent states depend on the rate of direct and indirect contacts between herds and the probability of infection given contact. Elbakidze et al.’s (2009) simulations suggest that, on average, an epidemic might cost up to about $1 billion in local high-intensive cattle industry losses alone.

Based on the assumptions and results of epidemiologic disease spread simulations, Elbakidze et al. (2009) found that generally early detection was the most economically effective control option of those considered in the study. The payoff for detecting an incursion earlier was substantial: in the case of an epidemic originating in a large feedlot, the cost saving on average was $150 million. Although the costs of early detection programs were not modeled in this study, the findings suggested that, if an outbreak was to originate in a large feedlot, an early detection program, which would cost up to $150 million, would likely pass the benefit cost test. Adequate vaccine availability and enhanced surveillance were not economically effective in minimizing overall costs of disease outbreak, compared to delayed vaccine availability and the default surveillance strategy, respectively.

In addition, Elbakidze et al. (2009) used Generalized Stochastic Dominance methodology (McCarl 1990) to make inferences on the scenarios for which the cumulative distribution functions crossed. They found that for large feedlot introduction scenarios of all 16 considered mitigation strategies, the strategy of slaughter of infected, slaughter of dangerous contacts combined with regular surveillance and early detection was dominant if the risk aversion coefficient (RAC) is below 0.01 or above 0.099, while for RAC between those values the strategy of slaughtering infected and dangerous contact herds combined with early detection and enhanced surveillance was dominant. For backgrounder feedlot introduction scenarios, if RAC is lower than -0.099 then slaughtering infected and dangerous contact herds, combined with early detection and enhanced surveillance, is dominant. If RAC is greater than -0.099 then the strategy with slaughtering infected and dangerous contact herd, combined with early detection and regular surveillance, is dominant. For large grazing herd introduction scenarios, if RAC is below 0.13 then the dominant strategy is to slaughter infected and dangerous contact herds combined with regular surveillance and early detection. Otherwise dominant strategy is slaughter of infected and dangerous contact herds combined with early detection and enhanced surveillance. For backyard herd introduction scenarios the strategy of slaughtering infected and dangerous contact herds, combined with enhanced surveillance and early detection, is dominant at all values of RAC.

It does not look so certain that early detection will pass the cost benefit test in the results of the epidemiologic model; even the costs of early detection programs was not considered in the modeling. All the numbers and estimates in the study of Elbakidze et al. (2009) are reported as an average value, which might neglect the severity of infrequent outbreak. However, in most catastrophic outbreak cases, the related impact to the industry and the society can be significantly large so that a prevention measure may be necessary.

Due to limited research targeted on this area, this dissertation study will extend knowledge relative to finding the optimal mitigation strategy of improving economic resiliency in the face of a potential FMD outbreak. The details of the development of integrated epidemic/economic model will be described in the next section.

2.4. The Development of Integrated Epidemic/Economic Simulation Model

For the purpose of evaluating alternative control practices, a linked economic/epidemic model will be used.

Two major components are included in such a model: epidemic simulation and economic simulation. In an epidemic simulation, the focus is on simulating the disease spread under various control strategies and introduction scenarios. This means the epidemic model simulates the disease spread from multiple time periods, from the period of disease introduction, of restocking and recovering trade relationships to the time period of the full recovery from the outbreak. The result will be output distributions on disease spread characteristics under the control strategy used and the disease introduction characteristics. The economic model then uses output from the epidemiologic model to simulate the economic cost when facing a potential FMD outbreak. The key economic model output will be the economic loss incurred by producers within the cattle industry, and the government-borne costs of implementing disease control strategies.

The utilization of this integrated epidemic/economic model is divided into four phases: a) develop scenarios; b) epidemic simulation; c) economic simulation; and d) Analysis/Feedback Loop. A comprehensive research process procedure will be presented in Figure 4 below:

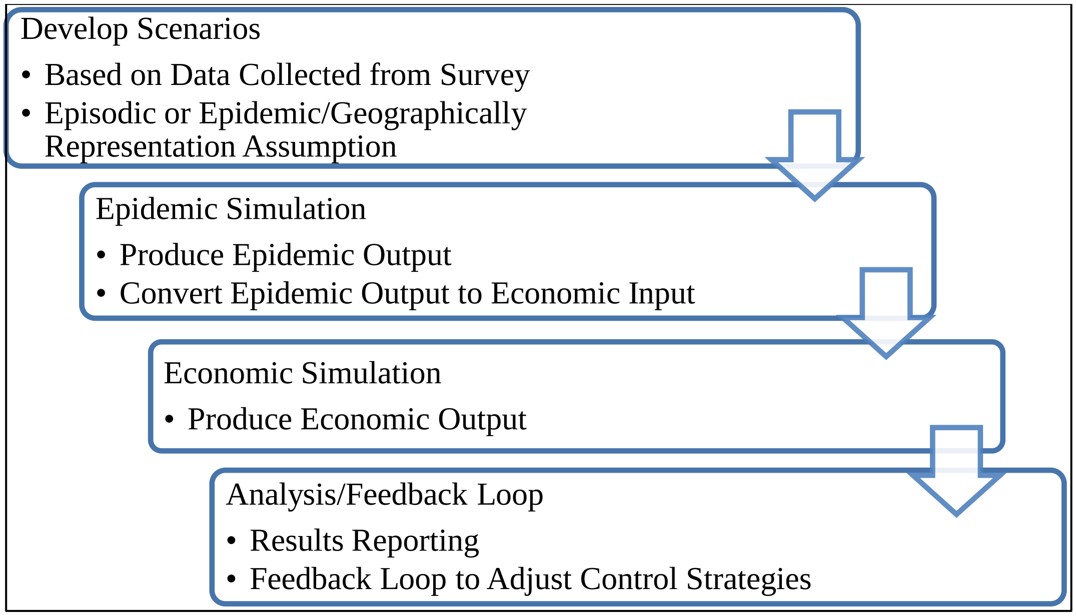


Figure 4: Comprehensive integrated economic/epidemic modeling procedure

2.4.1. Develop Scenarios

In terms of developing scenarios, there are several factors to be considered. The first is to determine the type of disease spread. The disease spread can be either episodic or epidemic. The second factor is where the disease spread occurs, which will be the geographic spread assumption. The third factor will be what control strategies to use and how they will be implemented. The last factor to be taken into account will be the assumption related to the potential impact on the international trade market.

2.4.2. Epidemic Models

Before building an integrated model, it is important to choose what control measures will be adopted during the simulation. In general, herd demographics and contact rates among herds in the region to be simulated should be collected beforehand. Epidemic modeling includes two different types of simulation: episodic modeling, which is to simulate until the disease is eradicated totally, and endemic modeling, which is to have disease spread reach a stable state. Two essential ways to model epidemics include spatial and non-spatially based approaches. Spatial modeling will be used to collect data on actual locations of infected herds and contact rates among them to simulate the disease spread. Non-spatially based models will use algorithms for disease spread to estimate the cost of a disease spread. For capturing the full distribution of disease spread accurately, a spatial stochastic model will be used in this study (Hagerman, 2009).

In the epidemic model, the investigation usually will target on the state of the animal health, which follows the Texas High Plains Report (Elbakidze et al. 2008), and generally includes four states: susceptible, latent, infectious, and recovered/removed.

Susceptible state refers to herds that could be susceptible to the disease. Latent state usually implies that animals have contracted the disease, but have not shown any clinical signs yet. When the clinical signs of infection are apparent, animals are at the infectious state. At this stage, the disease is being diagnosed and the treatment or response strategies are being taken. Recovered state usually refers to animals that either develop antibodies during the disease outbreak or are immune to the disease. Removed state implies that animals may have died because of the disease or other taken control measures such as slaughter control. Therefore, the disease spread is simulated based on whether a herd falls into one of these four states at any given time period. The probabilities of changing from susceptible to latent state rely on the rate of direct and indirect contacts among herds and the probability of infection given contact (Elbakidze et al. 2009).

2.4.3. AusSpread Model

In this study, the epidemic model employed will be the AusSpread model (Gardner and Beckett 2005), which is a stochastic, state transition susceptible-latent-infected-recovered (SLIR) model operating within the GIS framework. This model is appropriate for modeling activities in this integrated model. The AusSpread model also operates at different scales including the farm level, regional level, and national level (Gardner and Beckett 2005). Region usually refers to an area that is delimited by natural or geopolitical boundaries, and where homogenous animal production industry is located (Gardner and Beckett 2005). Considering characteristics of the Texas High Plains Region, the AusSpread model is an appropriate model to select in simulating a potential disease spread at the region scale.

AusSpread simulates disease spread on a daily basis. Therefore, contacts among different animal species are considered in the modeling process. Animal movements are included as well. Although the simulation is limited within a certain region, animal movements out of that region are recorded and tracked. The AusSpread model uses spatial distributions of livestock species including: feedlots, dairies, large and small beef operations, swine, small ruminants (sheep and goats), and backyard herds and their predicted contact structure to simulate the spread of FMD within the region.

There are three options available in the AusSpread model for modeling the predicted spread of disease: a spread rate parameter, which is analogous to the basic reproductive ratio (Ro), direct and indirect contact pathways, and a mixed (Ro and pathways) approach. The current version of AusSpread uses direct and indirect contact pathways to model disease spread. In addition to modeling contacts between herds, the model also incorporates disease spread due to sale barns, order buyers, and windborne spread from large feedlots and swine facilities.

In this study, a version of this model was used that was adapted to fit characteristics of Texas High Plains Cattle Industry (Ward, Highfield, and Garner, 2007; Ward et al., 2009; Elbakidze et al., 2009; Hagerman, 2009). Detection, vaccination, and surveillance strategies were simulated for the purposes of this study. The effectiveness of early detection versus late detection, adequate availability of vaccination versus limited availability of vaccination, and enhanced surveillance versus regular surveillance will be compared.

2.4.4. Economic Modeling

The economic model will use the outcome obtained from simulating a FMD spread using the epidemic model to calculate the associated economic impact of the potential outbreak. The impact calculated will include lost gross value of animals, lost gross income due to temporary business inactivity, consumer loss, trade loss, and cost of implementing mitigation strategies (Elbakidze et al. 2009). Therefore, the economic model needs to reflect the model generated disease spread and control characteristics. Four types of economic models could be used: simple cost calculating cost benefit analysis, input-output analysis, partial equilibrium, and computable general equilibrium models.

As this study intends to evaluate local region impact, cost of utilizing a certain control strategy, consumer losses, trade losses, and the general economic impact of the disease outbreak, the model equipped with great flexibility is appropriate for this type of examination. The Agricultural Sector Model (ASM) of the Forestry and Agricultural Sector Optimization Model (FASOM) is the model that is capable of examining all items we intend to evaluate. Therefore, this model is chosen for this study.

2.4.5. FASOM

The Agricultural Sector Model (ASM), which is part of the Forestry and Agricultural Sector Optimization Model (FASOM), was described in studies (Adams et al. 1993; McCarl 1990) and has a long history. The driving force of creating FASOM is to model intertemporal optimizing behavior of the economic agents that would be affected by carbon sequestration policies. Private timberland owners' decisions usually are influenced by tree farmers who plant millions of acres of potentially harvestable timber. By linking forest and agricultural sector in a dynamic framework, producers in both sectors can predict the consequences of their decisions and the impact of tree planting policies. This newly created model in a dynamic framework also allows for the land price equilibration in the sectors and for the transfer of lands based on the land's marginal profitability in all alternative forest and agricultural lands.

Therefore, FASOM is a mathematical programming model which is characterized by dynamic, nonlinear, and price-endogenous features (Adams et al. 1996). The model can simulate the multimarket, multi-period equilibrium for each product market. The need for maximizing the sum of producers' and consumers' surpluses in the market is also satisfied. Product prices in the two sectors are simulated in the model as well. In general, FASOM uses an optimizing technique to simulate the economic markets, which characterize transformation of resources into products over time, initial and terminal conditions, availability of fixed resources, and policy constraints (Adam et al. 1996), presenting the estimates of total social welfare in the form of consumer's and producer's surpluses. Due to the fact that this model is equipped with these characteristics, it is a good mathematical programming tool to utilize in this study, while the purpose is to evaluate the economic impact of a potential animal outbreak considering the welfare of producer's surplus and consumer's surplus.

2.4.6. Agricultural Sector Model (ASM)

The Agricultural Sector Model (ASM) is a subcomponent of FASOM (Chang et al. 1992; Adam et al. 1996) and is the particular part of FASOM that will be used herein.

ASM is a price-endogenous model designed to be simulated in the agricultural sector. It simulates 36 primary crop and livestock commodities and 39 secondary or processed commodities. There are more than 2,000 production possibilities (budgets) included in the model. Budgets for beef, dairy, hogs, sheep, broilers, turkeys, egg layers, and horses are included in this model, although the last category is treated in a very cursory fashion. Within the beef and hog operations, a number of intermediate budgets are represented to separate out important stages of production. The four budgets impacted by FMD, beef, dairy, hogs, and sheep, are discussed in detail below (Adams et al. 2005):

- Beef: Fed and non-fed beef are generated with intermediate goods of heifer and steer calves, heifer and steer yearlings, and cull cows. The simulation focus will be on modeling production at the cow-calf, stocker, and feedlot stages, plus an infusion of calves, and cull cows from the dairy herd.
- Dairy: Milk and calves are generated, along with cull cows.
- Hogs: Fed hogs are generated with intermediate outputs of feeder pigs and cull sows. Simulation is performing on the period of farrowing, finishing, and farrowing to finishing stages.
- Sheep: Wool, lambs, and cull ewes are generated.

When an animal disease occurs, the main focus will be on how to stop the disease spread and reduce the economic loss of all involved industries. Export losses are usually the major consequence to a country’s economy due to a disease outbreak (Schoenbaum and Disney, 2003). Because of possible trade bans imposed on a country undergoing a disease outbreak, the cost of processing industry usually increases (Wilson and Kinsella, 2004). Therefore, an issue will be how producers can make optimal production decisions to reduce the economic loss of such a “disease shock.”

According to Niemi et al (2008), disease shock can be measured through the realized demand and supply shocks. The simulation is conducted in a manner of evaluating the optimal value considering the percentage of production that is removed from the market and the loss in export demand, plus the duration of the shock. Within the ASM model, budgets in ASM are adjusted in the outbreak region to simulate the ‘disease shock.’ Epidemic data regarding head slaughtered, vaccinated, or restricted will be normalized on one animal basis. The ‘disease shock’ is simulated to calculate the optimal economic balanced cost under various control strategies.

As a result, FASOM/ASM modeling can provide detailed information regarding the number of dead animals, number or percentage price and quantity impact in the meat market, and the economic loss during the recovery from facing a disease break. Trade impacts can also be estimated by using the FASOM model.

2.4.7. Integrated Epidemic/Economic Modeling Process

This section will introduce details of a modeling process using step-by-step analysis performed in an AusSpread-ASM integrated model. The general structure and assumptions will be discussed in details.

2.4.8. Theoretical Assumptions

The first assumption refers to types of disease spread. Two types of disease spread are possible. Episodic disease means a single outbreak event, which can usually be eradicated in a short time period. Endemic disease means that it could not be eradicated once it is introduced into the region.

The second assumption refers to disease management options. These control options should be realistic and reflect what actually happens in a real outbreak event. Some strategies may be quite costly. Therefore, information gathered about control implementation cost should be comprehensive and as accurate as possible.

The third assumption includes alternative factors influencing the modeling results that should be considered. For example, export trade ban imposed on the country to cause the economic loss should be taken into account when performing analysis within the economic model. The key to making this assumption is to identify important issues that cannot be answered during the epidemic simulation stage.

2.4.9. Data Requirements

For the purpose of matching up data obtained from epidemic simulation with input parameters in the ASM Model, a set of standardized inputs should be defined before performing economic model simulation. They are summarized in Hagerman (2009) and re-organized in Table 1:

Table 1: Standardized Input Parameters

Inputs	Definition/Explanation
Altrun	The names of the set of alternative scenarios that are being considered. This will be each unique identifier for each scenario name if the model is being run on average epidemic results, or it could be a unique identifier for every iteration within each scenario if the full distribution of economic losses is desired.
Iter	The number of stochastic replications runs in the epidemic model. This must be at least 1 if the averages from the stochastic epidemic model are being run through the economic model, but may go up to the maximum number of iterations run in the stochastic epidemic model. For the two epidemic models considered here, the standard number of iterations was 100.
Id	A unique identifier for every premise in the affected region. This will vary by region and perhaps epidemic model.
Type	For each premises in the region, the type of that premises should be indicated so the appropriate budgets can be adjusted. At a minimum, these should indicate operation type on a premises (beef grazing, beef feeding, dairy, sheep, or swine operation). Ideally, more detail would be provided as will be discussed later.
All_stock	The total number of animals on each premises.
Status	The herd status at the end of the run for each unique premises id. This will generally be limited to the statuses corresponding to the states of the epidemic model: susceptible, infected, dead, and vaccinated. Adult animals that contract FMD rarely die from the disease, but the current U.S. response policy is to "stamp out" all of the infected and dangerous contact animals combined with vaccinate-to-die if vaccination is used. So the status of each premises should be categorized as either susceptible or dead at the end of the outbreak. This is because all sub-clinically infectious, infectious, and immune animals are slaughtered.
Restricted	This is an indicator variable used to identify herds in the quarantine zone (0 = not restricted, 1 = restricted). This variable may need to be conditioned on later so that only restricted premises that were not slaughtered for infection or vaccination are in a separate group. This allows an estimate of the animals that would need to be maintained while the movement restriction is in place, but will still be alive at the end of that period.
When_res	The number of days that the herd is under quarantine.

Table 1 Continued.

Inputs	Definition/Explanation
Days_left_res	The number of days that the herd will remain under quarantine at the end of the epidemic. Some models do not have this number, rather a standardized assumption can be made. For example, a 90-day period in which no new cases are identified may be the standard policy before movement restrictions are lifted.
Surv	An indicator variable used to identify herds that will be under surveillance.
N_visits	The number of times the herd is visited before surveillance ceases. This may be two visits in which no signs of FMD are observed, or may be weekly for the entirety of the outbreak. This is an assumption of the modeler or defined by policy generally.
Vacc	Indicator variable for herds that are vaccinated (0=no vacc, 1=vacc). If a vaccinate to live strategy has been employed, these animals will only be subject to the increased cost of the vaccination process and potentially a decline in the value of the animal after the movement restriction ban has been lifted. If a vaccinate to die strategy has been employed these animals must be added to the death loss from the disease. If vaccination is used, under current U.S. policy those animals must also be slaughtered.

Source: Hagerman, A. D., 2009. “Essays on modeling the economic impacts of a foreign animal disease on the United States agricultural sector” PhD dissertation, Texas A&M University.

2.4.10. Data Conversion

Data from the AusSpread model are reported in terms of animal populations in different scenario settings. Integration of two models includes the work of converting the epidemiologic data to economic data that can be adjusted and change the budget in the ASM model. A simple example is illustrated in Hagerman (2009):

For the animals slaughtered:

$$\%Dead_{i,t} = \sum_p Dead_{i,t,p} \Big/ \sum_p All\_Stock_{i,t,p} \qquad (1)$$

For the sum over all scenarios indicated by ids (p) where the status is "dead" is divided by the sum of all stock in all statuses for premises' ids. Each stochastic replication (i) and each type of herd (t) can be calculated and the data are transformed from individual premises impacts to regional impacts where, for each type of herd (e.g., cow/calf or dairy), the percentage of that particular herd type population in the diseased region that is susceptible, dead, vaccinated, or quarantined are calculated for each iteration (Hagerman, 2009).

2.4.11. Scenarios and Adjustments in ASM Model

The High Plains Study examines 64 scenarios, which include 4 infection index herd types (a large feedlot, a backgrounder feedlot, a large beef grazing operation, and a backyard operation) and 16 sets of combinations of disease mitigation strategies. The mitigation strategies include early versus late detection, adequate versus inadequate vaccination, ring and targeted vaccination, and regular versus enhanced surveillance.

Because of 'stamp out' and slaughter of infected animals policy, numbers of adult cows are adjusted to reflect the death of those who are directly infected and fall into the category of having contact with infected animals. The equation of general budget adjustment is as follows:

$$LB\_Cattle_{\mathrm{Re}g,Type,Animal} = LB\_Cattle_{\mathrm{Re}g,Type,Animal} * (1 - Perc\_Change) \qquad (2)$$

where *LB_Cattle* is the pounds of calves produced by a single cow

Reg: the region of infection

Type: the type of budget being adjusted

Animal: the output of the budget being adjusted

Perc_Change: the percentage of disease loss in the infection region

The adjustment is made in cow-calf production, stocker operations, and feedlot operations as illustrated in Figure 5:

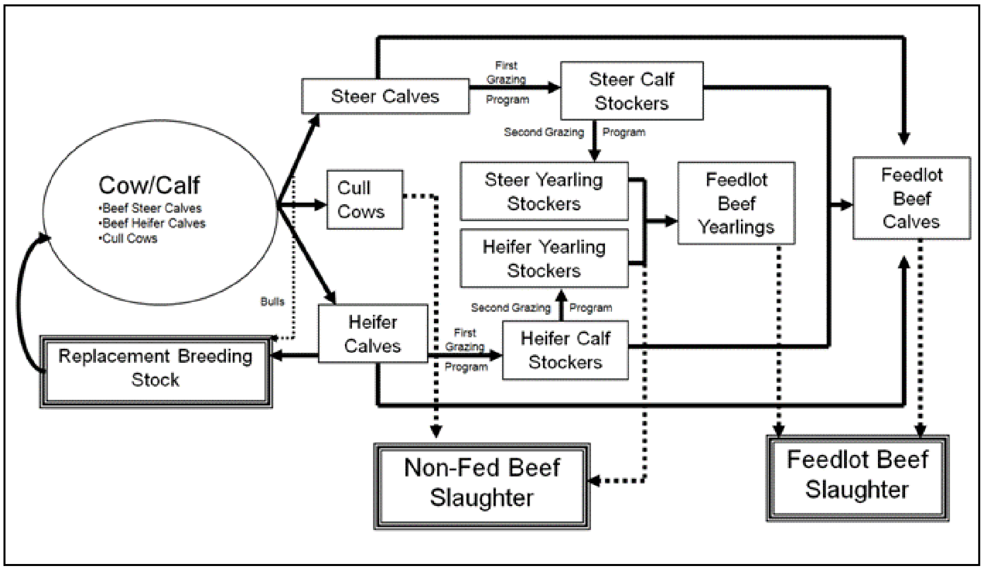


Figure 5: ASM beef cattle flow chart
Source: A. Hagerman, PhD dissertation, Chapter 3, p. 68, 2009.

2.4.12. Economic Simulation Output

The output of the ASM Model can be divided into many categories. The major output data we use for this study are welfare changes. In the category of welfare change, ASM gives us the changes in many categories from the base scenario (no disease outbreak) to a simulated scenario (after a possible simulated outbreak). The output reflects the welfare changes by U.S. consumers, U.S. processors, U.S. producers, U.S. total welfare, foreign consumers, foreign processors, foreign producers, and foreign total welfare.

3. EVALUATION OF WELFARE CHANGES BY A POTENTIAL FMD OUTBREAK IN THE TEXAS HIGH PLAINS[*]

3.1. Background

Researchers at the Center for Foreign Animal and Zoonotic Disease Defense (FAZD) at Texas A&M University (TAMU) conducted a simulation study of the animal and economical impact of FMD issues in the Panhandle of Texas based on regional livestock industry characteristics and animal movements. A High Plains specific version of the AusSpread epidemic simulation model (created by the Australian Department of Forestry, Fisheries, and Agriculture) was developed with assistance from the Texas Cattle Feeders Association (TCFA) and researchers at West Texas A&M University (WTAMU). The model was used to simulate decision and outbreak alternatives. Economic analysis of modeling results was conducted to evaluate the disease mitigation cost of various outbreak scenarios and mitigation strategies. This analysis was later expanded to account for the welfare impacts of not only the High Plains region, but the entire U.S. economy.

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[*] This section is a collaborative work with my former colleague, Dr. Amy D. Hagerman, under the Texas High Plains Project funded by the FAZD center. The materials in this section are also discussed in the PhD dissertation written by Hagerman in 2009.

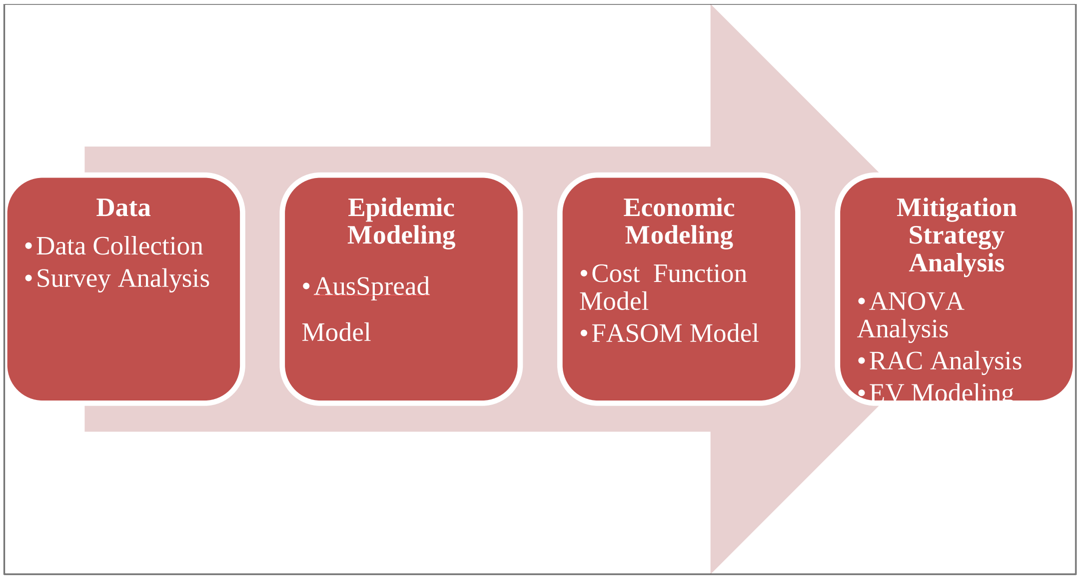

Figure 6: Texas high plains study - integrated modeling process

The High Plains region is representative of a high density livestock area. The study (Ward et al. 2007) proceeded in several stages (see Figure 6).The first phase involved a survey and interview data gathering component by Dr. Bo Norby at Texas A&M University. Initially, interviews with industry representatives were used to establish important 'points of contact' for livestock. Subsequently, quantitative surveys of livestock producers were used to determine the densities and distributions of farmed animals in the study area. The surveys were used to assess direct (animal-to-animal) and indirect (animal-to-vector/fomite-to-animal) contacts. The survey also gathered data on differences in the density, within-herd distributions, contact rates, and distances of movements of the various livestock species included in the study. Results from the producer survey indicated that there was little seasonal variation in contact rates for feedlots and dairies in this study area, but swine farms, which tended to be smaller in size, did have some seasonal changes in animal movements. Livestock arrived to the study area from 29 states, Mexico, and Canada. Animals were sent from the study area to 14 other states. Distances traveled by livestock in the area ranged from 10 miles to over 1,000 miles. Information was obtained on the size, composition, borders, and distribution of premises.

In the second phase, the AusSpread model was used to examine the potential impact of FMD introduction into an intensive agricultural setting; various disease introduction and mitigation strategies were simulated. There were a wide number of strategies simulated, which are summarized in the following content.

In the third phase, we bridge the models between epidemic and economic models. In this study, epidemic modeling is the AusSpread model while Cost function model was built by Elbakidze and McCarl (2005). The FASOM model was first incorporated in the economic modeling setting in this study, followed with further mitigation strategy analysis, which includes ANOVA analysis, welfare analysis, and RAC analysis (Elbakidze et al., 2009).

3.1.1. ASM Model Results

In this section, the welfare changes output data from the ASM model will be used to provide the experimental simulation results in the two major methods of basic descriptive statistics and risk aversion analysis. The welfare changes with and without the three designed mitigation strategies are categorized in three parties including U.S. consumer’s surplus, U.S. processor’s surplus, and U.S. producers’ surplus. Another specific strategy scenario design is conducted to avoid the possible correlated impacts between strategies in the original experimental design. A local impact in producers' surplus in the High Plains area will also present the severity of the welfare changes to the local economy due to the FMD outbreak.

The choice of accepting a disease control strategy can be determined by the risk aversion level of the decision makers. Elbakidze et al. (2009) find that a potential FMD outbreak can cost up to $1 billion in the local cattle industry in the Texas High Plains area. From their cost comparison methods, early detection is considered to be the best effective mitigation strategies among the three major strategies we have in our original experimental design. In addition, the vaccination strategy failed to pass their economic cost test due to the cost itself, and enhanced surveillance strategy is not effective either. The economic cost models have been well developed and become the initial and fundamental framework after this study begins.

The following content will be organized as follows. Section 1 provides the simulated data from the ASM model with basic statistics analysis. Section 2 presents an alternative scenario design comparison and results. Section 3 introduces the welfare changes data and that includes a stochastic dominance analysis and a risk aversion coefficient analysis. The latter analysis will give us BRAC point values if there is a crossing situation in the strategy preference comparisons. Local producers' welfare comparison and results are presented in Section 4. The overall conclusion and policy implications are provided in Section 5.

3.1.2. Data of the Experimental Simulation Scenario

Based on the High Plains Report Version I by Ward et al. (2007), the AusSpread model contains 13 types of herds in the study. Those are listed as follows:

1: Feedlot1: Company owned feedlot (>50,000 head).

2: Feedlot2: Stockholder feedlot (20,000 – 50,000 head).

3: Feedlot3: Custom feedlot (5,000 – 20,000 head).

4: Feedlot4: Backgrounder feedlot.

5: Feedlot5: Yearling-pasture feedlot.

6: Feedlot6: Dairy Calf-raiser feedlot.

7: Small beef: < 100 cattle.

8: Large beef: >100 cattle.

9: Small dairy: < 1000 number dairy cows.

10: Large dairy: >1000 number dairy cows.

11: Backyard: < 10 cattle.

12: Swine: pig concentrated animal feeding operations.

13: Small ruminant: sheep and goats.

Four types of herds out of the 13 were chosen as points where the initial infection begins. They were categorized as: 1) Feedlot Type 1 (large feedlots); 2) Feedlot Type 4 (small feedlots); 3) Large Beef operation (large beef grazing); and 4) Backyard operation. Sixteen different scenarios were designed with different simulated disease management settings including the three major mitigation strategies (e.g., early detection, adequate vaccination, enhanced surveillance). A total of 64 scenarios were simulated and are summarized in Table 2 (Elbakidze et al. 2008). Three sets of experimental design focusing on variables of interest with respect to three different mitigation strategies are shown in Table 3, Table 4, and Table 5.

Table 2: Original Experimental Design for Epidemic Modeling Scenarios

Mitigation Strategies (M)	Types of Herds (T)			
	Feedlot Type 1	Feedlot Type 4	Large Beef	Backyard
SR; Surv-R; SI; Sdc; DE	1	2	3	4
SR; Surv-R; SI; Sdc; DL	5	6	7	8
SR; R-Surv; SI; Sdc; DL; VT; VA	9	10	11	12
SR; Surv-R; SI; Sdc; DL; VT; VI	13	14	15	16
Surv-E; SI; Sdc; DE	17	18	19	20
Surv-E; SI; Sdc; DL	21	22	23	24
Surv-E; SI; Sdc; DL; VT; VA	25	26	27	28
Surv-E; SI; Sdc; DL; VT; VI	29	30	31	32
SI; Sdc; Surv-R; VR; DE; VI	33	34	35	36
SI; Sdc; Surv-R; DE	37	38	39	40
SI; Sdc; Surv-R; DL; VR; VA	41	42	43	44
SI; Sdc; Surv-R; DL; VR; VI	45	46	47	48
SI; Sdc; Surv-R; DE; VT; VA	49	50	51	52
SI; Sdc; Surv-R; DL	53	54	55	56
SI; Sdc; Surv-R; DL; VT	57	58	59	60
SI; Sdc; Surv-R; DE; VR; VA	61	62	63	64

Source: Elbakidze, L., A. Hagerman, L. Highfield, H. Lin, S. Loneragan, M. Ward, B. McCarl, B. Norby, J. Jacobs, R. Srinivasan, L.,. The High Plains Project Report: Version II. Center for Foreign Animal and Zoonotic Disease Defense (FAZD), 2008

*Notes: In this table, abbreviations and various terms are used. They are explained as follows:
Abbreviation:
Ring Slaughter: SR; Slaughter of infected: SI; Slaughter of dc's: Sdc; Regular Surveillance: Surv-R; Enhanced Surveillance: Surv-E; Early Detection: DE; Late Detection: DL; Target Vaccination: VT; Adequate Vaccination: VA; Inadequate Vaccination: VI; Ring Vaccination: VR
Type of randomization: Complete Randomized Design (CRD)
Type of treatment structure: Mitigation strategy (M) (with 16 levels) crossed with type of herds (T) (with 4 levels)
Type of the factors: M - fixed and T - fixed
Experimental Units (EU) and/or Measurement Units (MU): EU = MU = Individual simulation run
Sources of variation: M, T, and stochastic simulation runs 8,502 simulation points with 100 runs are given from the AusSpread model. With the integrated epidemiologic-economic modeling addressed in the previous section, welfare change data gives the results with 100 simulation points for each of the original 64 scenarios. We sort the 64 scenarios with the three mitigation strategies as the variables of interests.

Table 3: Experimental Design Focusing on Variables of Interest – Early versus Late Detection

Mitigation Strategy (M)	**Type of Herds (T)**				
Time of Detection	Pair Comparison	Feedlot Type 1	Feedlot Type 4	Large Beef	Backyard
Early Detection	A1E	1	2	3	4
	A2E	17	18	19	20
	A3E	33	34	35	36
	A4E	37	38	39	40
	A5E	49	50	51	52
	A6E	61	62	63	64
Late Detection	A1L	5	6	7	8
	A2L	21	22	23	24
	A3L	45	46	47	48
	A4L	53	54	55	56
	A5L	57	58	59	60
	A6L	41	42	43	44

*Notes: This table explains the scenarios we pick from the overall 64 experimental scenarios in Table1 in order to focus on the variable of interest (e.g. early detection in this case). The pair comparison codes are designed to distinguish the scenario which is selected for a certain variable of interest. For example, A1E represents the first focus scenario group with early detection. A1L is the control scenario group with late detection.

Table 4: Experimental Design Focusing on Variables of Interest – Adequate versus Inadequate Vaccine

Mitigation Strategy (M)	**Type of Herds (T)**				
Availability of Vaccine	Pair Comparison	Feedlot Type 1	Feedlot Type 4	Large Beef	Backyard
Adequate Vaccine	B1A	9	10	11	12
	B2A	25	26	27	28
	B3A	41	42	43	44
	B4A	61	62	63	64
Inadequate Vaccine	B1I	13	14	15	16
	B2I	29	30	31	32
	B3I	45	46	47	48
	B4I	33	34	35	36

Table 5: Experimental Design Focusing on Variables of Interest – Enhanced Surveillance versus Regular Surveillance

Mitigation Strategy (M)	**Type of Herds (T)**				
Types of Surveillance	Pair Comparison	Feedlot Type 1	Feedlot Type 4	Large Beef	Backyard
Adequate Vaccine	C1E	17	18	19	20
	C2E	21	22	23	24
	C3E	25	26	27	28
Inadequate Vaccine	C1R	37	38	39	40
	C2R	53	54	55	56
	C3R	57	58	59	60

3.1.2.1. Early vs. Late Detection

For comparing effects of early detection and late detection, we use descriptive statistics measures in Table 6, including Standard Deviation (SD), Coefficient of Variation (CV), and distribution percentile (10%, 75%, and 90%) to evaluate the welfare change effect of each mitigation strategy on consumers, processors, and producers at a national level. Analysis results are presented as follows:

- For U.S. consumers, early detection management strategy brings greater and better welfare changes in average under the scenario of initial infection from the first two larger operations (large feedlot and small feedlot). However, for the other two smaller operations (large beef grazing and backyard), when comparing early detection with late detection under the initial disease introduction, there is no significant improvement in the average welfare changes.

- For U.S. processors, early detection has less average welfare loss in the scenario of small feedlot and backyard operation. However, it shows greater welfare loss in the scenario of large feedlot and large grazing operation.
- For U.S. producers, early detection causes more damage on welfare in average for the first two larger operations. In the scenario of large beef grazing and backyard, early detection reduces extent in the loss of welfare.
- Regarding CV values, when using the measure of early detection strategy, their absolute values in the scenario of the first two larger operations are less in the welfare changes in all three parties. That means early detection provides a less risky alternative. On the other hand, in the scenario of disease introduction from the other two smaller operations, the bigger absolute CV value in the early detection measure implies that early detection strategy does not offer a riskless option.

The percentile of the distribution also indicates that the welfare change is deviating from the mean. In the large feedlot introduction scenario, early detection has a significantly positive welfare gains when observing U.S. customers ranged from the 10th and 75th percentile. Meanwhile, for U.S. producers, early detection has greater welfare loss in the 90th percentile. Under the small feedlot introduction scenario, the U.S. consumers and processors have greater welfare gain and less welfare loss when comparing to the 10th percentile. In both 75 and 90 percentiles of the U.S. producers' welfare comparison, early detection causes greater loss in welfare.

Table 6: Descriptive Statistics for the Welfare Changes in Millions 2000 – Early vs. Late Detection

Type of Herds	**Early Detection**			**Late Detection**		
Feedlot Type 1	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	166.61	-14.61	-952.86	157.26	-13.64	-943.73
SD	29.53	8.21	-56.19	42.57	12.61	41.43
CV	17.72	-56.19	-3.32	27.07	-92.46	-4.39
10th Percentile	133.41	-15.20	-992.40	84.21	-15.20	-992.40
75th Percentile	177.04	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-924.88	200.41	0.01	-882.06
Feedlot Type 4	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	158386	-12.23	-946.55	151.54	-13.13	-937.80
SD	36.05	8.32	-68.03	-13.13	12.19	-92.79
CV	22.70	-68.03	-3.89	-937.80	45.34	-4.83
10th Percentile	107.57	-15.20	-992.40	84.21	-16.55	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-922.13
90th Percentile	200.41	0.01	-906.93	200.41	0.01	-866.34
Large Beef	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	156.35	-14.70	-941.64	159.72	-11.99	-947.93
SD	41.98	13.18	41.90	38.71	7.92	38.58
CV	26.85	-89.69	-4.45	-947.93	38.58	-4.07
10th Percentile	84.21	-44.88	-992.40	107.57	-15.20	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-882.06	200.41	0.01	-906.93
Backyard	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	153.26	-13.77	-939.19	158.49	-16.02	-942.57
SD	40.75	12.16	41.65	36.10	11.30	39.32
CV	26.59	-88.31	-4.43	22.78	-70.58	-4.17
10th Percentile	84.21	-29.67	-992.40	107.57	-29.67	-992.40
75th Percentile	174.57	-15.20	-922.13	174.57	-15.20	-925.42
90th Percentile	200.41	0.01	-877.25	200.41	0.01	-891.50

*Notes: The numbers represent the welfare change in million dollars. CS represents the consumer's surplus, PR represents processors' surplus, and PS represents, producers' surplus.

- In the smaller operation introduction scenarios, the U.S. consumers have less welfare gains in the large beef grazing and backyard cases. The U.S. processors suffer a much greater welfare loss in the case of large beef grazing at the 10th percentile of the simulated distributions. The U.S. producers have reduced welfare loss with early detection strategy in both large beef and backyard scenarios.
- The same group in different settings may have shown the same number. We interpret this situation as the best or worst scenario which may occur under the same simulation scenario.
- Generally, early detection strategy can bring better average welfare improvement and have higher welfare gains even at the 10th percentile of the distribution to the U.S. consumers in the large feedlot and small feedlot scenarios. The finding is mixed for the U.S. processors. For U.S. producers, early detection helps in reducing the average welfare loss when there is a disease introduction in smaller operations (large beef grazing and backyard), and it also can prevent the possible greater welfare loss at the 90th percentile distribution comparison.

3.1.2.2. Adequate Vaccine vs. Inadequate Vaccine

The results of comparison of adequate vaccine versus inadequate vaccine are presented in Table 7. The findings are presented as follows:

- For U.S. consumers, adequate vaccination management strategy brings greater welfare gains in average under the scenario of infection introduction in small feedlot, large beef grazing, and backyard operations. There is a very small difference in welfare gains in the large feedlot introduction scenario.

- For U.S. processors, adequate vaccination has greater average welfare loss in the scenario of large feedlot, large beef grazing, and backyard operations; however, welfare loss is reduced in the scenario of small feedlot introduction.
- For U.S. producers, adequate vaccination reduces the extent of average welfare loss in the large feedlot introduction scenario, but it causes more damages in average on the welfare in the other three operations.
- Regarding CV values, their absolute values in the scenarios of large feedlot operations are greater in terms of welfare changes in all three parties with the enforcement of adequate vaccination. That means adequate vaccination could provide a more risky alternative. On the other hand, in the scenario of disease introduction for the other three operations, it shows the smaller value under the adequate vaccination measure, which implies that the early detection strategy offers a less risky option.
- In the large feedlot introduction scenario, adequate vaccination is less likely to have great welfare loss at the 90th percentile of the simulation distribution for U.S. producers. However, in the large beef grazing and backyard introduction scenario, U.S. producers have greater welfare loss with adequate vaccination at the 90th percentile. Meanwhile, for U.S. consumers, adequate vaccination gives greater welfare gains at the 10th percentile of the distribution in the small feedlot, large beef, and backyard scenarios.
- Generally, adequate vaccination strategy in the small feedlot, large beef grazing, and backyard scenarios can bring better welfare improvement on average and have

higher welfare gains at the 10th percentile of the distribution of the U.S. consumers. The result is very mixed for the U.S. processors. For U.S. producers, adequate vaccination helps in reducing the average welfare loss only when there is a disease introduction in the large feedlot. The possible greater welfare loss at the 90 percentile distribution may occur when the infection introduction point starts from large beef grazing and backyard operations.

Table 7: Descriptive Statistics for the Welfare Changes in Millions 2000 – Adequate vs. Inadequate Vaccine

Type of Herds	**Adequate Vaccine**			**Inadequate Vaccine**		
Feedlot Type	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	158.5229	-13.3789	-945.384	158.7029	-11.817	-947.094
SD	41.21846	11.5389	40.26023	38.28704	7.776123	38.28721
CV	26.00158	-86.2473	-4.25861	24.12498	-65.8046	-4.0426
10th Percentile	107.57	-15.20	-992.40	107.57	-15.20	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-892.55	200.41	0.01	-906.93
Feedlot Type	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	154.6311	-13.5513	-940.974	152.852	-14.5683	-937.826
SD	40.29592	10.78084	41.93706	40.9716	12.95539	41.91755
CV	26.05939	-79.556	-4.45677	26.80475	-88.9285	-4.46965
10th Percentile	107.52	-15.20	-992.40	84.21	-29.67	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-906.93
90th Percentile	200.41	0.01	-877.25	200.41	0.01	-877.17
Large Beef	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	160.4835	-17.2703	-943.559	154.9946	-12.5618	-942.229
SD	37.98871	13.72091	39.70676	44.92158	12.33488	43.39142
CV	23.67142	-79.4481	-4.20819	28.98268	-98.1938	-4.60519
10th Percentile	107.57	-44.88	-992.40	75.66	-15.20	-992.40
75th Percentile	176.56	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-895.92	200.41	0.01	-866.34
Backyard	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	155.0495	-14.5462	-940.393	153.1546	-14.3865	-938.239
SD	39.21775	12.20159	40.97698	44.10193	12.00962	45.96905
CV	25.2937	-83.8817	-4.35743	28.79569	-83.4784	-4.8995
10th Percentile	107.52	-29.67	-992.40	84.21	-29.67	-992.40
75th Percentile	174.57	-15.20	-906.93	174.57	-15.20	-924.88
90th Percentile	200.41	0.01	-877.25	200.41	0.01	-866.34

*Notes: The numbers represent the welfare change in million dollars. CS represents the consumer's surplus, PR represents processor's surplus, and PS represents, producer's surplus. Total welfare is the summation of the consumers', processors', and producers' surpluses.

3.1.2.3. Enhanced vs. Regular Surveillance

Data pertaining to the comparison of enhanced versus regular surveillance strategies in terms of welfare change is presented in Table 8. The findings of the analysis are presented as follows:

- For U.S. consumers, enhanced surveillance management strategy has greater average welfare gains under the scenarios of initial infection in two smaller operations (large beef grazing and backyard). However, the average welfare in the larger operations (large feedlot and small feedlot) do not show improvement by comparing enhanced surveillance to the outcomes of regular surveillance strategy.
- For U.S. processors, enhanced surveillance strategy has less average welfare loss in the scenario of large feedlot and backyard operation; however, it shows greater welfare loss in the scenario of small feedlot and large grazing operations.
- For U.S. producers, enhanced surveillance has less average damages on welfare in the first two larger operation disease introduction scenarios. In the scenarios of large beef grazing and backyard, enhanced surveillance increases the welfare losses in extents.
- While examining CV values, the absolute values in the scenarios of the two smaller operations are lower in the welfare changes in all three parties when using the measure of enhanced surveillance strategy. That indicates that enhanced surveillance strategy provides a less risky alternative. On the other hand, under the scenario of disease introduction in the other two larger operations, the larger absolute CV values in the enhanced surveillance measure implies that enhanced

surveillance strategy does not offer a riskless option.

- In the two smaller feedlot (large beef grazing and backyard) introduction scenarios, enhanced surveillance has significantly better welfare gains at the 10th percentile of the distribution for U.S. consumers. For U.S. producers, enhanced surveillance has greater welfare loss at the 90th percentile. In the other two larger feedlot (large feedlot and small feedlot) introduction scenarios, the U.S. consumers have less welfare gains at the 10th percentile; however, enhanced surveillance could make less welfare loss at the 90th percentile for the U.S. producers.
- Generally, in the large beef grazing and backyard operation scenarios, enhanced surveillance strategy can bring better average welfare gains and have higher welfare gains at the 10th percentile of the distribution for the U.S. consumers. However, in the same scenarios, the U.S. producers suffer larger welfare loss, and could have more severe welfare loss at the 90th percentile. When there is a disease introduction in larger operations (large feedlot and small feedlot), the phenomenon is presented in an opposite way. For U.S. producers, enhanced surveillance helps in reducing the average welfare loss and preventing the possible greater welfare loss at the 90th percentile of the simulated distribution. On the other hand, for the U.S. consumers, there are less average welfare gains and smaller welfare gains at the 10th percentile.

Table 8: Descriptive Statistics for the Welfare Changes in Millions 2000 – Enhanced vs. Regular Surveillance

Type of Herds	**Enhanced Surveillance**			**Regular Surveillance**		
Feedlot Type 1	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	158.4863	-13.896	-944.778	169.2103	-14.0851	-956.237
SD	41.97141	12.47851	40.91029	23.78367	3.966316	27.36572
CV	26.48268	-89.7995	-4.33015	14.05569	-28.1596	-2.86181
10th Percentile	84.24	-15.20	-992.40	151.20	-15.20	-992.40
75th Percentile	176.68	-15.20	-925.60	176.56	-15.20	-925.60
90th Percentile	200.41	0.01	-882.06	200.41	-15.20	-925.60
Feedlot Type 4	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	154.1941	-13.2799	-940.537	160.4158	-13.0808	-947.339
SD	42.85302	11.01377	44.26015	33.97603	8.8528	34.84645
CV	27.7916	-82.9355	-4.70584	21.17997	-67.6777	-3.67835
10th Percentile	84.21	-15.20	-992.40	107.57	-15.20	-992.40
75th Percentile	174.57	-15.20	-925.60	176.56	-15.20	-925.60
90th Percentile	200.41	0.01	-866.34	200.41	0.01	-906.93
Large Beef	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	165.8769	-13.4101	-953.354	155.9441	-11.2312	-944.648
SD	29.25653	5.498344	31.00046	42.26725	8.836043	41.06731
CV	17.63749	-41.0015	-3.25172	27.1041	-78.6739	-4.34737
10th Percentile	133.41	-15.20	-992.40	84.21	-15.20	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-924.88	200.41	0.01	-882.06
Backyard	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	159.0305	-13.8166	-945.325	157.8057	-16.2904	-941.76
SD	34.20128	9.955954	35.50975	36.74637	11.03961	40.22789
CV	21.50611	-72.0578	-3.75635	23.28583	-67.7676	-4.27156
10th Percentile	107.57	-15.20	-992.40	107.57	-29.67	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-906.86	200.41	0.01	-877.25

*Notes: The numbers represent the welfare change in million dollars. CS represents the consumer's surplus, PR represents processor's surplus, and PS represents, producer's surplus. Total welfare is the summation of the consumer's, processor's, and producer's surpluses.

3.1.3. An Alternative Scenario Comparison and Results

In this section, we have re-designed the original experimental design focusing on three different mitigation strategies as the variables of interest. In the original design, a correlation effect question is being raised because of a set of complicated combination settings under the 64 scenarios. In this alternative design, only a specific mitigation strategy will be in use in each scenario to avoid the correlation effect. All selected scenarios are summarized as in Table 9.

3.1.3.1. Early vs. Late Detection

In this section, a similar comparison to the one in the previous section will be conducted. Findings pertaining to differences between the original design and the alternative design will be presented. Whether a cross-strategy correlation effect exists in the original design will also be examined:

- With respect to the average welfare changes, all the trends are similar except in the case of the large beef grazing scenario. That is, U.S. consumers have higher average welfare gains with the implementation of the early detection strategy, and U.S. producers have larger average welfare losses. Compared to the original design, in the first two larger feedlot scenarios, less average welfare gains or losses are found in the first two larger feedlot scenarios. However, in the other two scenarios, the average welfare changes are larger in gains and losses.

Table 9: Alternative Experimental Design Focusing on Variables of Interest

Early Detection vs. Late Detection

Mitigation Strategy (M)	**Type of Herds (T)**				
Time of Detection	**Pair Comparison**	**Feedlot Type 1**	**Feedlot Type 4**	**Large Beef**	**Backyard**
Early Detection	A1E	1	2	3	4
	A4E	37	38	39	40
Late Detection	A1L	5	6	7	8
	A4L	53	54	55	56

Adequate vs. Inadequate Vaccine

Mitigation Strategy (M)	**Type of Herds (T)**				
Availability of Vaccine	**Pair Comparison**	**Feedlot Type 1**	**Feedlot Type 4**	**Large Beef**	**Backyard**
Adequate Vaccine	B1A	9	10	11	12
	B3A	41	42	43	44
Inadequate Vaccine	B1I	13	14	15	16
	B3I	45	46	47	48

Enhanced vs. Regular Surveillance

Mitigation Strategy (M)	**Type of Herds (T)**				
Types of Surveillance	**Pair Comparison**	**Feedlot Type 1**	**Feedlot Type 4**	**Large Beef**	**Backyard**
Enhanced Surveillance	C2E	21	22	23	24
Regular Surveillance	C2R	53	54	55	56

- With respect to the percentile comparison, in the first two introduction points scenarios, the basic results are similar to the ones above from the original design. However, in the last two smaller operation scenarios, results pertaining to U.S. producers are very different from the original one. Early detection gives a possible larger welfare loss at the 90th percentile, while there is less welfare loss in the original design. In addition, in the large beef grazing scenario, the U.S. consumers will get greater welfare gains at the 10th percentile.
- In general, there are similar responses when implementing mitigation strategies in different scenarios as shown in Table 10. With the early detection alone, in the backyard introduction scenario, U.S. producers would still suffer a possible greater loss even though the average welfare loss is reduced in this case.

3.1.3.2. Adequate vs. Inadequate Vaccination

Data concerning welfare changes are organized in Table 11 and the findings of the analysis will be presented as follows:

- With respect to the average welfare changes, the results are opposite to the ones of the original design in the large feedlot and backyard introduction scenarios. In the large feedlot scenario, U.S. consumers have higher average welfare gains with the implementation of adequate vaccination strategy, and U.S. producers have larger average welfare loss. In the backyard operation scenario, U.S. consumers have less welfare gains, while U.S. producers have smaller average welfare losses. Another finding in these two cases is that the gap or the average difference between adequate and inadequate vaccination mitigation strategies is much larger than in the original design.

- With respect to the percentile comparison, there are two findings. First, for U.S. producers, adequate vaccination gives a possible larger welfare loss at the 90th percentile in the large feedlot scenario, but a less welfare loss in the backyard scenario. Second, for U.S. consumers, adequate vaccination will get smaller welfare gains at the 10th percentile in the backyard scenario.
- In general, there are different responses regarding welfare changes for U.S. consumers and producers in the large feedlot and backyard scenarios. An important correlation problem may exist in the original design for the vaccination strategy as the variable of interest. Another noteworthy finding is that the impact of vaccination strategy on welfare changes is actually greater than the one measured in the original design.

Table 10: Descriptive Statistics for the Welfare Changes in Millions 2000: Early vs. Late Detection

Type of Herds	**Early Detection**			**Late Detection**		
Feedlot Type	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	165.47	-16.56	-949.87	154.42	-10.81	-943.32
SD	34.38	12.37	34.96	43.01	8.91	42.39
CV	20.77	-74.65	-3.68	27.85	-82.42	-4.49
10th Percentile	133.36	-44.88	-992.40	84.21	-15.20	-992.40
75th Percentile	177.04	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-909.05	200.41	0.01	-866.34
Feedlot Type	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	156.16	-11.07	-944.94	150.02	-15.10	-934.07
SD	40.24	8.27	40.33	44.91	14.14	45.84
CV	25.76	-74.75	-4.26	29.93	-93.61	-4.90
10th Percentile	104.80	-15.20	-992.40	84.21	-44.88	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-906.93
90th Percentile	200.41	0.01	-891.50	200.41	0.01	-866.34
Large Beef	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	162.99	-12.82	-950.87	158.09	-11.58	-946.46
SD	32.56	6.33	33.48	41.44	8.60	40.90
CV	19.97	-49.37	-3.52	26.21	-74.29	-4.32
10th Percentile	107.57	-15.20	-992.40	84.21	-15.20	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-906.93	200.41	0.01	-882.06
Backyard	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	155.68	-14.04	-941.58	158.00	-15.54	-942.28
SD	36.63	11.70	37.45	39.82	10.80	42.85
CV	23.52	-83.38	-3.97	25.20	-69.49	-4.54
10th Percentile	107.57	-16.65	-992.40	107.57	-29.67	-992.40
75th Percentile	174.57	-15.20	-924.19	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-895.92	200.41	0.01	-877.25

*Notes: The numbers represent the welfare change in million dollars. CS represents the consumer's surplus, PR represents processors' surplus, and PS represents, producers' surplus. Total welfare is the summation of the consumers', processors', and producers' surplus.

Table 11: Descriptive Statistics for the Welfare Changes in Millions 2000 - Adequate vs. Inadequate Vaccine

Type of Herds	**Adequate Vaccine**			**Inadequate Vaccine**		
Feedlot Type	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	160.47	-15.55	-945.55	154.42	-10.81	-943.32
SD	39.57	13.36	38.38	42.90	8.89	42.28
CV	24.66	-85.93	-4.06	27.78	-82.22	-4.48
10th Percentile	107.57	-44.88	-992.40	84.21	-15.20	-992.40
75th Percentile	177.04	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-906.93	200.41	0.01	-866.34
Feedlot Type	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	154.08	-12.17	-941.91	150.02	-15.10	-934.07
SD	40.19	10.16	40.88	44.79	14.10	45.72
CV	26.08	-83.50	-4.34	29.86	-93.38	-4.90
10th Percentile	105.24	-15.20	-992.40	84.21	-44.88	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	-15.20	-906.93
90th Percentile	200.41	0.01	-877.25	200.41	0.01	-866.34
Large Beef	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	161.80	-15.80	-946.74	158.09	-11.58	-946.46
SD	36.90	12.85	36.89	41.34	8.58	40.80
CV	22.81	-81.34	-3.90	26.15	-74.11	-4.31
10th Percentile	107.57	-44.88	-992.40	84.21	-15.20	-992.40
75th Percentile	176.68	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-906.93	200.41	0.01	-882.06
Backyard	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	148.18	-10.63	-936.73	157.88	-15.54	-942.08
SD	44.84	12.12	43.88	39.71	10.77	42.73
CV	30.26	-114.06	-4.68	25.15	-69.33	-4.54
10th Percentile	84.21	-15.20	-992.40	107.57	-29.67	-992.40
75th Percentile	174.57	0.01	-906.93	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-866.34	200.41	0.01	-877.25

*Notes: The numbers represent the welfare change in million dollars. CS represents the consumer's surplus, PR represents processor's surplus, and PS represents, producer's surplus. Total welfare is the summation of the consumers', processors', and producers' surpluses.

3.1.3.3. Enhanced vs. Regular Surveillance

Data concerning the comparison between enhanced surveillance and regular surveillance strategy will be presented in Table 12. Welfare results of the analysis will be presented as follows:

- With respect to the average welfare changes, there are two different results from the ones in the original design. First, in the small feedlot scenario, U.S. producers do not get any benefit from using the enhanced surveillance strategy in the situation of increasing welfare loss. Second, U.S. consumers have smaller welfare gains with enhanced surveillance in the introduction scenario of backyard operation.
- With respect to the percentile comparisons, a similar trend is shown from the trend of average welfare changes. In the large feedlot and small feedlot scenarios, the gap of consumers' welfare gain at the 10th percentile and producers' welfare loss at the 90th percentile between enhanced and regular surveillance is getting close to a much smaller extent. On the other hand, the same gap is expanded to a larger extent in the scenarios of large beef grazing and backyard introduction.
- In general, there are two major findings in this analysis. First, enhanced surveillance could be less effective in the measure of average welfare changes. From the analysis, we have found that less U.S. consumer's gains are shown in the backyard scenario and greater U.S. producer's welfare losses are presented in the small feedlot scenario. Second, from the analysis of percentile comparison, we have found that enhanced surveillance could have greater impacts on welfare changes

under the scenario of having disease introduction in smaller operations, and smaller impacts in the introduction scenario of larger feedlots.

Table 12: Descriptive Statistics for the Welfare Changes in Millions 2000: Enhanced vs. Regular Surveillance

Type of	**Enhanced Surveillance**			**Regular Surveillance**		
Feedlot Type	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	159.28	-18.54	-941.42	164.32	-13.07	-952.06
SD	43.20	16.96	40.93	29.06	5.28	31.47
CV	27.12	-91.50	-4.35	17.68	-40.39	-3.31
10th Percentile	105.24	-44.88	-992.40	107.57	-15.20	-992.40
75th Percentile	181.00	-15.20	-925.60	174.57	-15.20	-925.60
90th Percentile	200.41	0.01	-892.31	200.41	0.01	-906.93
Feedlot Type	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	146.59	-8.76	-937.06	149.78	-12.49	-936.40
SD	47.61	10.05	46.95	41.82	13.63	40.58
CV	32.48	-114.80	-5.01	27.92	-109.09	-4.33
10th Percentile	75.66	-15.20	-992.40	84.21	-18.17	-992.40
75th Percentile	174.57	0.01	-906.93	174.57	0.01	-906.93
90th Percentile	200.41	13.13	-866.27	200.41	0.01	-866.34
Large Beef	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	164.32	-13.07	-952.06	144.52	-8.56	-934.58
SD	29.06	5.28	31.47	51.39	10.96	49.32
CV	17.68	-40.39	-3.31	35.56	-128.04	-5.28
10th Percentile	107.57	-15.20	-992.40	49.82	-15.20	-992.40
75th Percentile	174.57	-15.20	-925.60	174.57	0.01	-906.93
90th Percentile	200.41	0.01	-906.93	200.41	13.13	-855.85
Backyard	**CS**	**PR**	**PS**	**CS**	**PR**	**PS**
Mean	149.78	-12.49	-936.40	150.26	-17.71	-931.74
SD	41.82	13.63	40.58	47.58	14.08	50.24
CV	27.92	-109.09	-4.33	31.66	-79.53	-5.39
10th Percentile	84.21	-18.17	-992.40	52.05	-44.88	-992.40
75th Percentile	174.57	0.01	-906.93	174.57	-15.20	-918.33
90th Percentile	200.41	0.01	-866.34	200.41	0.01	-855.85

*Notes: The numbers represent the welfare change in million dollars. CS represents the consumer’s surplus, PR represents processor’s surplus, and PS represents, producer’s surplus. Total welfare is the summation of the consumers’, processors’, and producers’ surpluses.

3.1.4. Stochastic Dominance and Risk Aversion Coefficient Analysis[*]

A risk analysis will be conducted by using the concept of stochastic dominance when a decision maker faces a choice of using the ex post mitigation strategies. Stochastic dominance will tell us which mitigation strategy is preferred to use. However, there is always a crossing situation when the choice is not dominant to the other. A Breakeven Risk Aversion Coefficient (BRAC) analysis will come along to solve this situation. In addition, we can find out the Risk Aversion Coefficient (RAC) points where the preference switches from one choice to the other.

3.1.4.1. Basic Theoretical Concept of Stochastic Dominance and BRAC[1]

Stochastic dominance (SD) can inform decision makers how to pick a choice under weak assumptions about risk attitudes. Three basic assumptions are made, including a) each individual is an expected utility maximizer, b) two alternatives can be used to compare and they are mutually exclusive, and c) the stochastic dominance analysis is based on the population probability distribution (McCarl 1996).

3.1.4.1.1. First Degree Stochastic Dominance

Assume x is the level of wealth, while f(x) and g(x) give the probability of each level of wealth for alternatives f and g. The difference in the expected utility between the prospects is as follows:

$$\int_{-\infty}^{+\infty} u(x)\, f(x)\, dx - \int_{-\infty}^{+\infty} u(x)\, g(x)\, dx \qquad (3)$$

The equation can be rewritten as:

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[*] This part adopts the materials from McCarl, B.A. "Choosing among Risky Alternatives Using Stochastic Dominance." Unpublished Manuscript, Texas A&M University, August 2008.

$$\int_{-\infty}^{+\infty} u(x)\,(\,f(x) - g(x)\,)\;dx \qquad (4)$$

If f is preferred to g, then the sign of the above equation would be positive. Conversely, if g is preferred to f, the sign of the above equation is negative.

Apply the integration by parts formula to

$$a = u(x) \qquad (5)$$

$$b = (F(x) - G(x)) \qquad (6)$$

where $F(X) = \int_{-\infty}^{X} f(x)\,dx$

$$G(X) = \int_{-\infty}^{X} g(x)\,dx \qquad da = u'(x)dx$$

$$db = (f(x) - g(x)\,)\,dx$$

Under this substitution, the integration of

$$\int_{-\infty}^{+\infty} u(x)\,(\,f(x) - g(x)\,)\;dx \;\text{ equals }\; [u(x)\,(\,F(x) - G(x))]_{-\infty}^{+\infty} - \int_{-\infty}^{+\infty} u'(x)\,(\,F(x) - G(x)\,)\;dx \qquad (7)$$

In the left part when F(x) and G(x) are evaluated at x equals -∞, both equal zero; x equals +∞. Both equal one and plus infinity where they equal one so the left part equals zero. Now let us look at the right part, which is:

$$-\int_{-\infty}^{+\infty} u'(x)\,(\,F(x) - G(x)\,)\;dx \qquad (8)$$

If the overall sign is positive, then f dominates g.

3.1.4.1.2. Second Degree Stochastic Dominance

The above FSD derivation says expected utility of f minus g can be expressed as

$$-\int_{-\infty}^{+\infty} u'(x)\,(\,F(x) - G(x)\,)\;dx \qquad (9)$$

Applying integration by parts

$$\begin{aligned} a &= u'(x) \\ db &= (F(x) - G(x))\,dx \end{aligned} \tag{10}$$

so that:

$$\begin{aligned} da &= u''(x)\,dx \\ b &= (F_2(x) - G_2(x)) \end{aligned} \tag{11}$$

where F_2 and G_2 are the second integral of the cdfs

$$F_2(X) = \int_{-\infty}^{X} F(x)\,dx \tag{12}$$

$$G_2(X) = \int_{-\infty}^{X} G(x)\,dx \tag{13}$$

Under these circumstances, if we plug in our integration by parts formula we get the equation

$$-[u'(x)\,(F_2(x) - G_2(x))]_{-\infty}^{+\infty} + \int_{-\infty}^{+\infty} u''(x)\,(F_2(x) - G_2(x))\,dx \tag{14}$$

The formula above has two parts. Let us address the right-hand part of it first.

$$-[u'(x)\,(F_2(x) - G_2(x))]_{-\infty}^{+\infty} + \int_{-\infty}^{+\infty} u''(x)\,(F_2(x) - G_2(x))\,dx \tag{15}$$

Right-hand part contains the second derivative of the utility function times the difference in the integrals of the cdf with a positive sign in front of it.

$$+\int_{-\infty}^{+\infty} u''(x)\,(F_2(x) - G_2(x))\,dx \tag{16}$$

To guarantee that f dominates g, the sign of this whole term must be positive. Two assumptions need to be added in the second stochastic dominance. First, the second derivative of the utility function with respect to x is negative everywhere. Second, $F_2(x)$ is less than or equal to $G_2(x)$ for all x with strict inequality for some x.

One extension of stochastic dominance that has been utilized is generalized stochastic dominance (GSD). One again starts from the variant of the expected utility function:

$$-\int_{-\infty}^{+\infty} u'(x)\,(\,F(x) - G(x)\,)\ dx \tag{17}$$

Meyer and Meyer (2005) investigated the magnitude of this expression under the conditions that the Pratt risk aversion coefficient falls into an interval:

$$r_1(x) \le \frac{u''(x)}{u'(x)} \le r_2(x) \tag{18}$$

Meyer and Meyer (2005) posed an optimal control format for this examination. where the variable is u(x)

$$\begin{aligned} & Max - \int_{-\infty}^{+\infty} u'(x)\,(\,F(x) - G(x)\,)\ dx \\ & s.t.\ \ (u'(x))' = (\frac{u''(x)}{u'(x)})\,u'(x) \\ & \qquad r_1(x) \le \frac{u''(x)}{u'(x)} \le r_2(x) \end{aligned} \tag{19}$$

When this problem is solved, it looks for the choice of utility function, which has r(x) constrained in the interval. The objective function is the expected utility difference, which if positive means f dominates g. When we maximize it, we find the greatest expected utility difference over all possible utility choices such that r(x) is in that interval. If the greatest utility difference is negative, then f must dominate g.

Meyer and Meyer (2005) recognized that this is a simple optimal control problem since it is linear in the control variables. The problem has what it is called a Bang-Bang solution.

$$r(x^*) = \begin{pmatrix} r_1(x^*) \text{ if } \int_{x^*}^{+\infty} u'(x)\,(F(x) - G(x))\, dx > 0 \\ r_2(x^*) \text{ if } \int_{x^*}^{+\infty} u'(x)\,(F(x) - G(x))\, dx \le 0 \end{pmatrix} \tag{20}$$

Meyer originally wrote a computer program to do this, but implements it with $u(x_i) = - e^{-rxi}$. Yet another approach has been used to deal with crossings. Hammond (1974) showed that, given two alternatives that cross once, under constant absolute risk aversion there is a break-even risk aversion coefficient (BRAC) that differentiates between those two alternatives.

Hammond (1974) also noted the expected utility problem given a constant absolute RAC (r) is

$$\int_{-\infty}^{+\infty} - e^{-rx} f(x)\, dx \tag{21}$$

Equation 21 is a form of the mathematical statistics moment generating function. This does not imply that the risk aversion parameter is a constant, rather it could be increasing, decreasing, or of any other form as long as it remains between the two bounds.

GSD generalizes the other stochastic dominance forms when $r_1 = 0$ and $r_2 = \infty$ we get second degree, while $r_1 = -\infty$ and $r_2 = \infty$ is the same as first degree. This has been a fairly heavily used technique in the 1990s. The biggest problem in using this technique is always concerning finding the r_1, r_2 values.

The moment generating function under normality, given the risk aversion parameter r for distribution f, is as follows:

$$m(r) = e^{-\left(r\bar{u}_f - \frac{\sigma_f r^2}{2}\right)} \tag{22}$$

If we solve this for the break-even risk aversion parameter, first thing we need to do is to set the expected utilities equal:

$$e^{-\left(r\bar{u}_f - \frac{\sigma_f^2 r^2}{2}\right)} = e^{-\left(r\bar{u}_g - \frac{\sigma_g^2 r^2}{2}\right)} \tag{23}$$

Or

$$r\bar{u}_f - \frac{\sigma_f^2 r^2}{2} = r\bar{u}_g - \frac{\sigma_g^2 r^2}{2} \tag{24}$$

This can be manipulated to

$$r^2\left(-\frac{\sigma_f^2}{2} + \frac{\sigma_g^2}{2}\right) + r(\bar{u}_f - \bar{u}_g) = 0 \tag{25}$$

which yields two roots

$$\begin{aligned} r &= 0 \\ r &= \frac{2(\bar{u}_f - \bar{u}_g)}{(\sigma_f^2 - \sigma_g^2)} \end{aligned} \tag{26}$$

Notice then for any two normally distributed prospects, we can find a break-even risk aversion parameter using this formula.

McCarl wrote a program (RISKROOT) to implement Hammond's approach with an empirical discrete distribution of unknown form. RISKROOT takes data for two alternatives and searches for the break-even risk aversion parameters between those two alternatives by solving the following equation for all applicable values of r.

$$\sum_i -e^{-rx_i}\,(f_i(x) - g_i(x)) = 0 \tag{27}$$

RAC can show the degree of a particular decision maker's aversion to risk. Therefore, we can make further assumptions to distinguish from one choice to another choice, which is to a range where RAC falls. Generalized stochastic dominance or mean variance programming models are often employed in this type of analysis. McCarl (1988) developed an approach based on Hammond's study (1974), in which the dataset are explored to see what risk aversion coefficients differentiate among prospects under the assumption of a constant risk aversion. When using this method, one does not need to specify bounds of the RAC. It calculates given bounds of the RAC. The program is called RISKROOT. The RISKROOT program finds RACs in such a manner that, on each side of them, a given distribution dominates. However, there may be multiple values for these RACs with multiple preference shifts. Such RACs are hereafter called break-even risk aversion coefficients (BRACs) (McCarl 1996).

Another version of the BRAC analysis has been called Stochastic Efficiency with Respect to a Function (SERF). The advantage of using the SERF method in calculating BRAC points is that this method allows for an estimation of the utility-weighted risk premiums. The feature permits the payoffs comparing between risk alternatives (Hardaker et al. 2004). Instead of using RISKROOT, we use SERF as implemented in Simetar (Richardson 2007). We also employ the graphical display of BRAC points using SERF.

3.1.4.2. Early vs. Late Detection

The stochastic dominance and calculated BRACs can tell us how each mitigation strategy dominates and where one alternative has passed the other in the introduction scenario of four assumed cattle operations. The analysis is summarized as follows.

- In Figure 7, for U.S. consumers, early detection strategy dominates from risk neutral (RAC=0) to risk averse (RAC>0) in the first two larger operation (large feedlot and small feedlot) introduction scenarios. However, in the smaller operation (large beef grazing and backyard) introduction scenarios, early detection strategy is not preferred.

- In Figure 8, for U.S. producers, opposite to the results for U.S. consumers, in the first two large operation introduction scenarios, early detection is not preferred from risk neutral (RAC=0) to risk averse (RAC>0). In the large beef grazing scenario, early detection dominates from risk neutral to risk adverse. In the backyard introduction scenario, early detection is preferred as the RAC is greater than 0, and less than 0.0607. When RAC is bigger than 0.0607, early detection strategy does not dominate in the U.S. producers' welfare changes.
- For the overall U.S. welfare changes, in the large feedlot introduction scenario, early detection is not preferred as seen in Figure 9. In the small feedlot introduction scenario, early detection becomes preferred strategy only when RAC is larger than 0.8333. In the larger beef grazing scenario, early detection dominated as RAC lies between 0 and 0.0607. In the smallest feedlot (backyard) scenario, the result also shows that early detection dominates as RAC is between 0 and 0.0722.
- In general, U.S. consumers economically prefer the early detection strategy when there is a larger operation introduction (e.g., large feedlot and small feedlot). U.S. producers can accept early detection strategy only in the scenario of large beef introduction or in the situation where the decision-makers are neutral and less risk adverse (RAC<0.0668) in the backyard introduction scenario. For the overall U.S. welfare changes, early detection will only be considered beneficial in three situations. One is at a high risk averse level (RAC>0.8333) in the small feedlot

scenario, and the other two are at similar low risk adverse levels, 0<RAC<0.0607 in the large feedlot introduction scenario, and 0<RAC<0.0722 in the backyard introduction scenario.

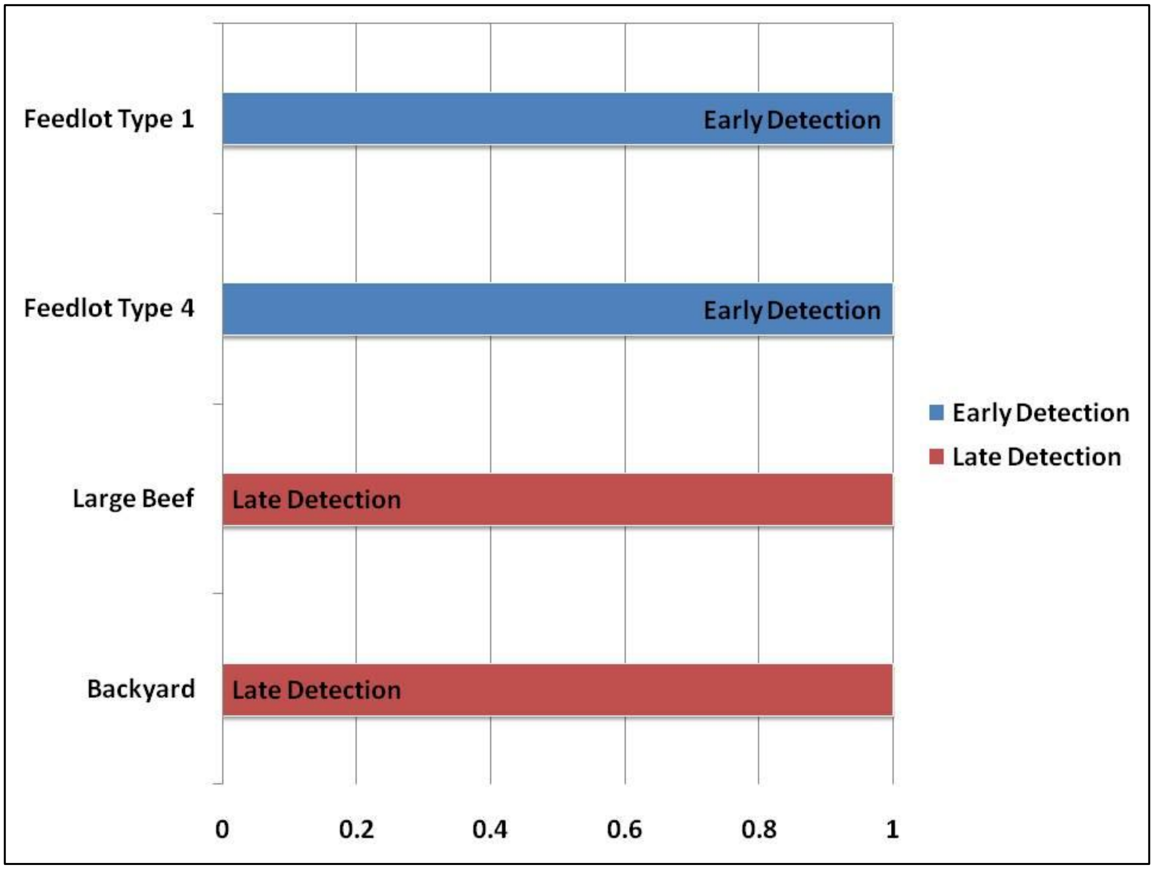


Figure 7: Early vs. late detection strategy dominance with respect to U.S. consumers' surplus

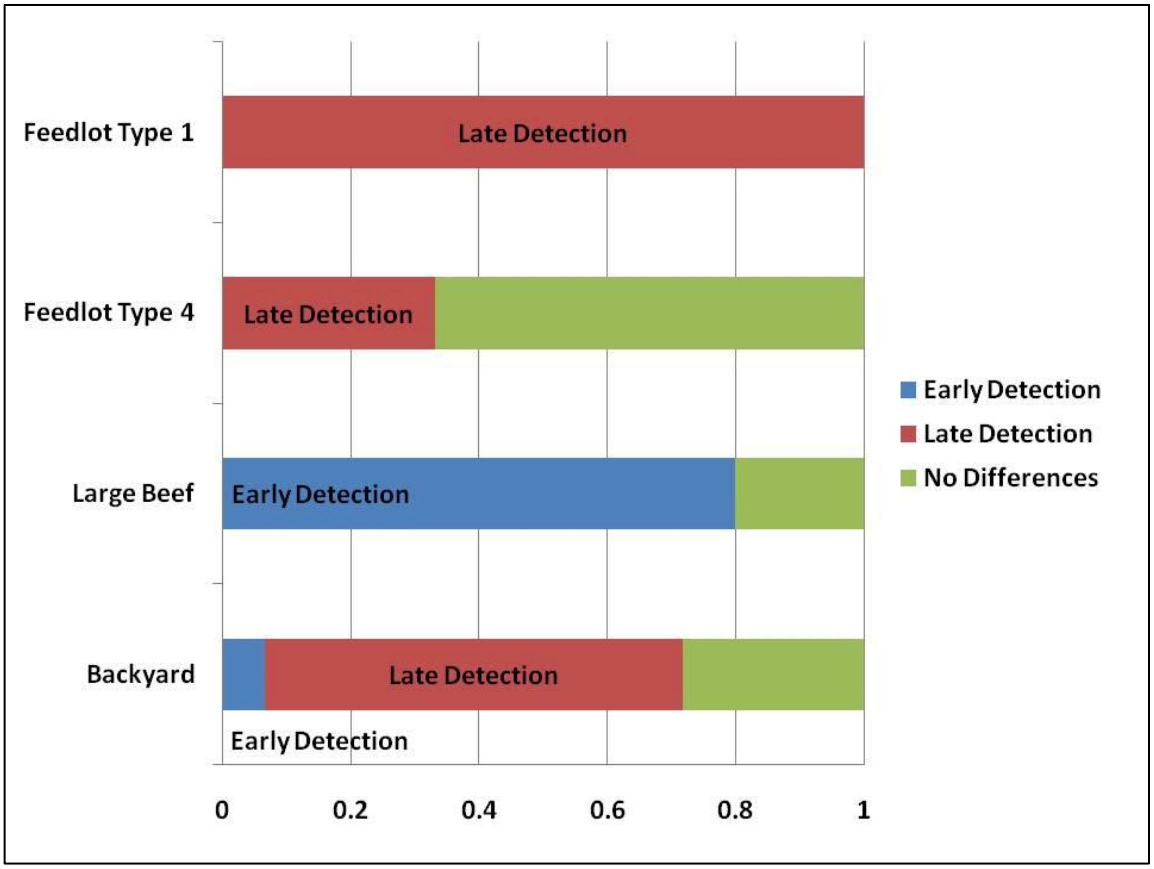


Figure 8: Early vs. late detection strategy dominance with respect to U.S. producers' surplus

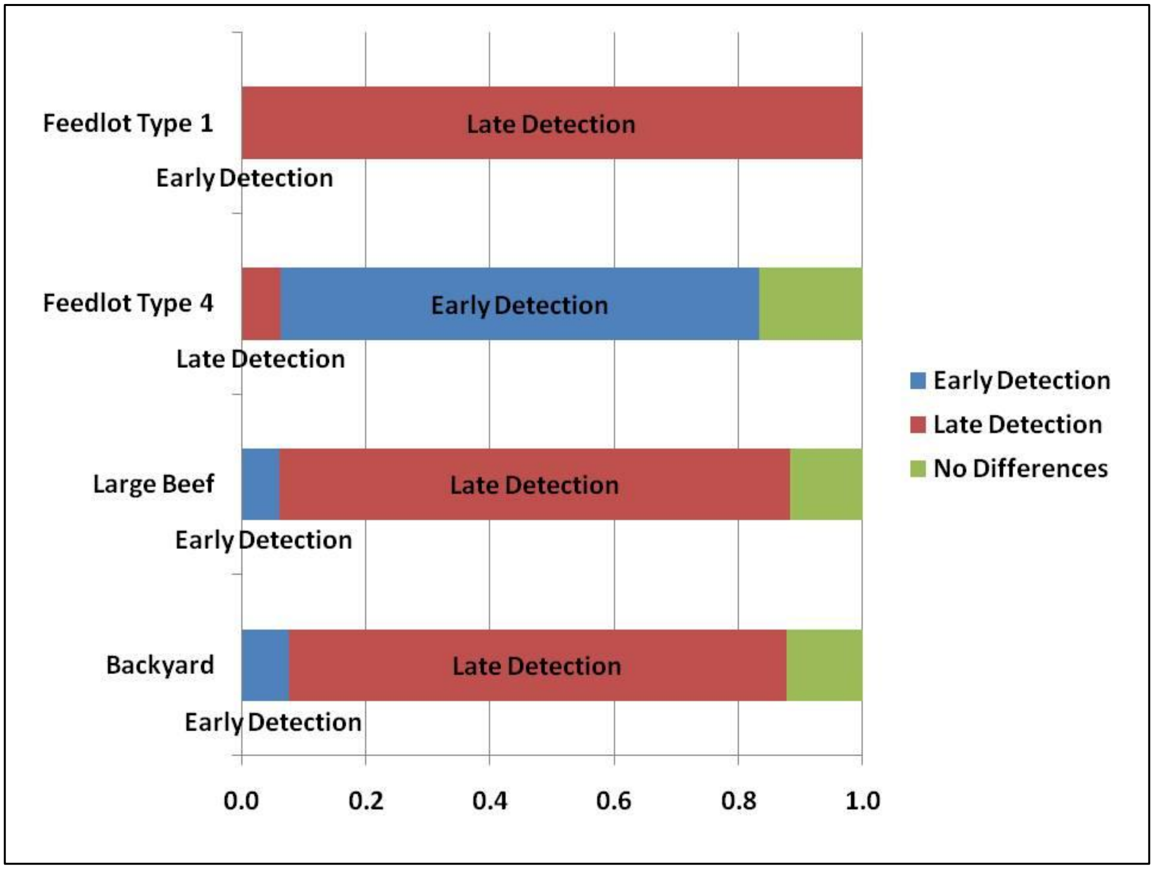


Figure 9: Early vs. late detection strategy dominance with respect to U.S. total welfare

3.1.4.3. Adequate vs. Inadequate Vaccines

Data concerning comparison of adequate versus inadequate vaccines is presented in Figure 10, Figure 11, and Figure 12 respectively. The analysis is summarized as follows:

- In Figure 10, for U.S. consumers, adequate vaccination strategy dominates from risk neutral (RAC=0) to risk averse (RAC>0) in the two smaller operations (large beef grazing and backyard). In the two larger operation (large feedlot and small feedlot) introduction scenarios, adequate vaccination strategy is not preferred.
- In Figure 11, for U.S. producers, in the large feedlot introduction scenario, adequate vaccination strategy is preferred. In the small feedlot scenario, the adequate vaccination strategy dominates at the higher risk aversion level (e.g. RAC> 0.0491). In the large beef grazing scenario, adequate vaccination is only accepted when the risk adverse level is between 0.011 and 0.2789. In the backyard scenario, adequate vaccination is not preferred.
- For the overall U.S. welfare changes, in the large feedlot introduction scenario, adequate vaccination is preferred from risk neutral to risk averse. In the small feedlot introduction scenario, adequate vaccination becomes the preferred strategy only when RAC is larger than 0.0741. In the larger beef grazing scenario, adequate vaccination does not dominate over other strategies. In the backyard scenario, the result also shows that adequate vaccination dominates when RAC is between 0.0571 and 0.8443.
- In general, U.S. consumers preferred adequate vaccination strategy when there was a disease introduction from smaller operations (e.g., large beef grazing and

backyard). U.S. producers can accept adequate vaccination strategy in the larger operation introduction scenarios. Adequate vaccination dominates in the following scenarios at different risk adverse level: from risk neutral to risk averse in the large feedlot scenario, RAC> 0.0491 in the small feedlot scenario, and 0.2789<RAC<0.7104 in the large beef grazing scenario. For overall U.S. welfare changes, adequate vaccination is preferred in the large feedlot scenario. This strategy will be useful at the risk averse level (RAC>0.0741) in the small feedlot scenario, and 0.0571<RAC<0.8443 in the backyard introduction scenario.

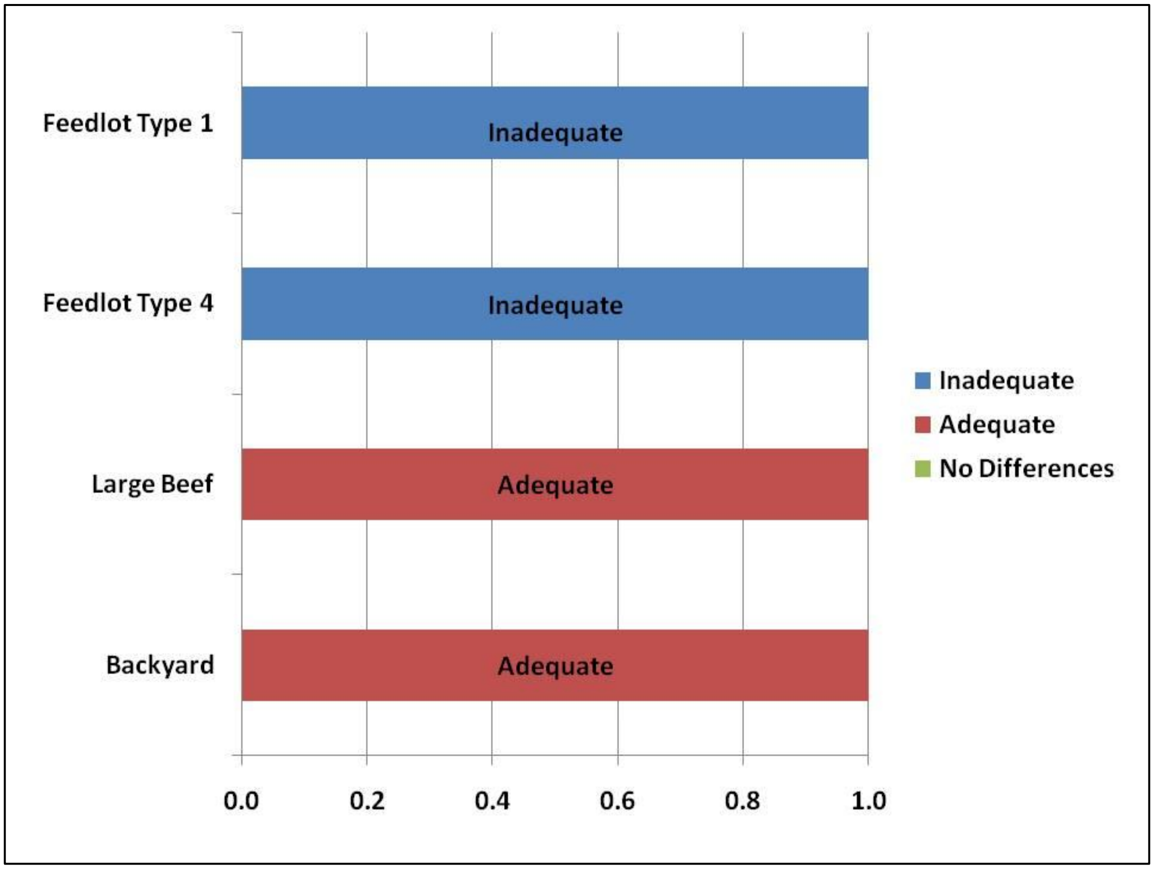


Figure 10: Adequate vs. inadequate vaccines strategy dominance with respect to consumer's surplus

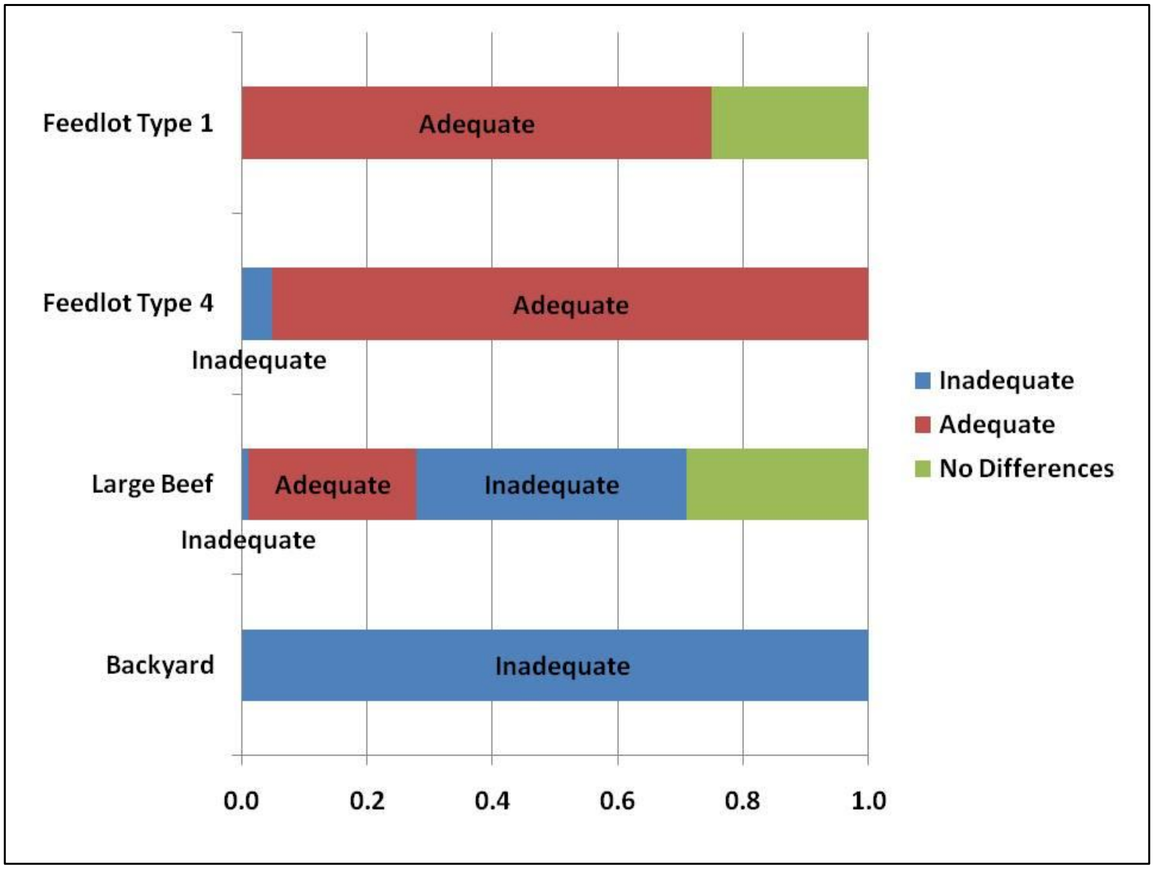


Figure 11: Adequate vs. inadequate vaccines strategy dominance with respect to producer's surplus

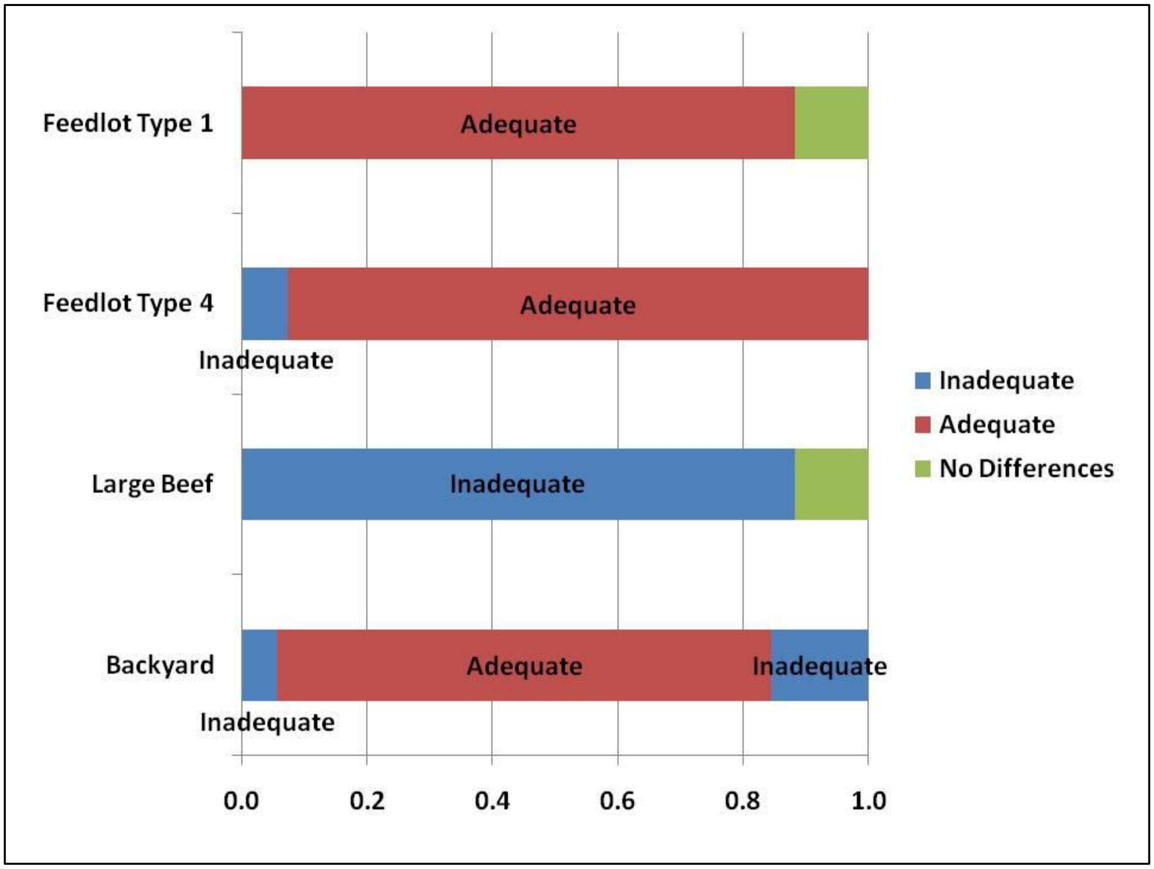


Figure 12: Adequate vs. inadequate vaccines strategy dominance with respect to U.S. total welfare

3.1.4.4. Enhanced vs. Regular Surveillance

Data concerning the comparison of enhanced surveillance and regular surveillance strategy will be presented in Figures 13, 14, and 15. The analysis is summarized as follows:

- In Figure 13, for U.S. consumers, enhanced surveillance strategy dominates from risk neutral (RAC=0) to risk averse (RAC>0) in the two smaller operations (large beef grazing and backyard). In the two larger operation (large feedlot and small feedlot) introduction scenarios, enhanced surveillance strategy is not preferred.

- In Figure 14, for U.S. producers, enhanced surveillance strategy is preferred in the two larger feedlot (large feedlot and small feedlot) introduction scenarios. In the two smaller operation (large beef grazing and backyard) scenarios, enhanced surveillance strategy does not show a better result.
- For the overall U.S. welfare changes, enhanced surveillance is preferred from risk neutral to risk averse in the large feedlot introduction scenario. In the small feedlot introduction scenario, adequate vaccination becomes preferred only when RAC is larger than 0.1118. In the larger beef grazing scenario, enhanced surveillance does not dominate over the other strategy. In the backyard scenario, the result also shows that adequate vaccination dominates as RAC is between 0 and 0.1301**.**
- In general, U.S. consumers preferred enhanced surveillance strategy when there is a disease introduction from smaller operations (e.g., large beef grazing and backyard). U.S. producers can accept enhanced surveillance strategy in the larger operation (e.g., large feedlot and small feedlot) introduction scenarios. For overall U.S. welfare changes, enhanced surveillance is good in the large feedlot scenario. This strategy is also preferred at the risk averse level (RAC>0.1118) in the small feedlot scenario, and 0<RAC<0.1301 in the backyard introduction scenario.

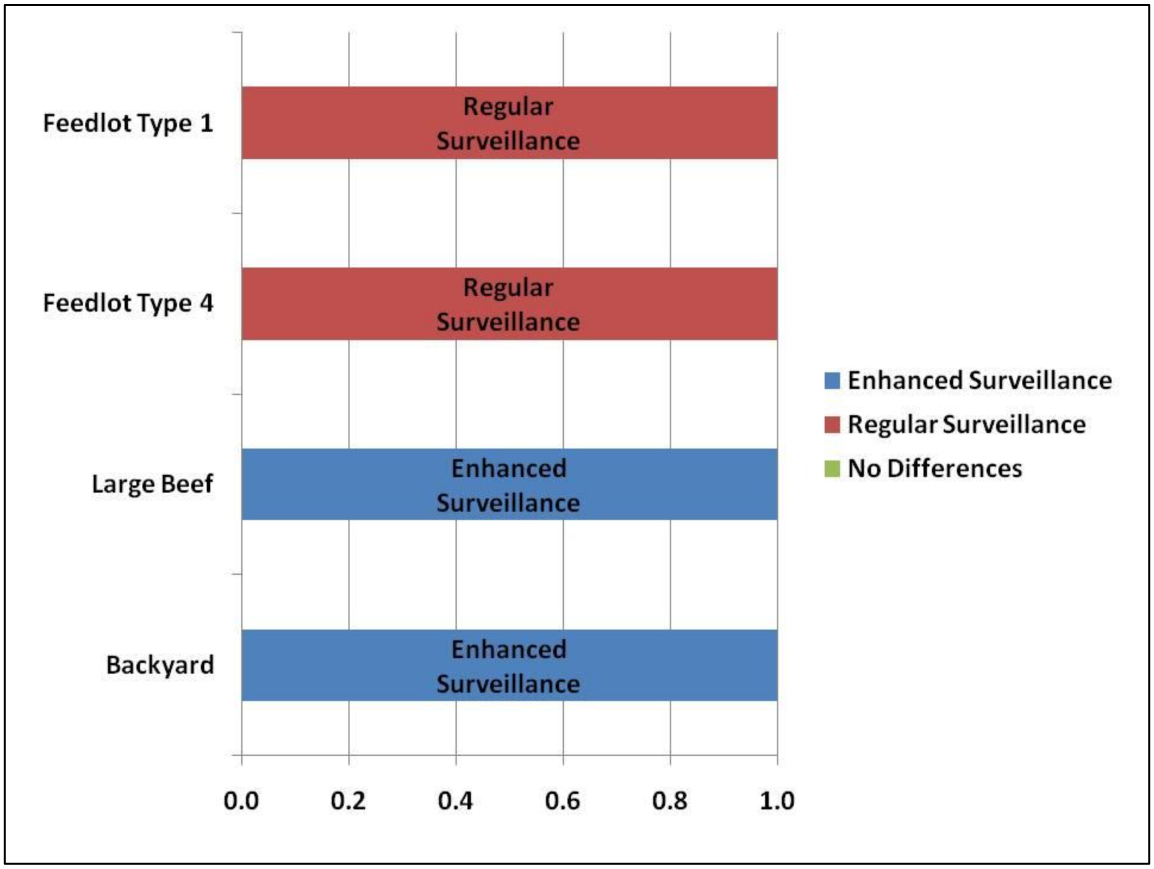


Figure 13: Enhanced vs. regular surveillance strategy dominance with respect to consumers’ surplus

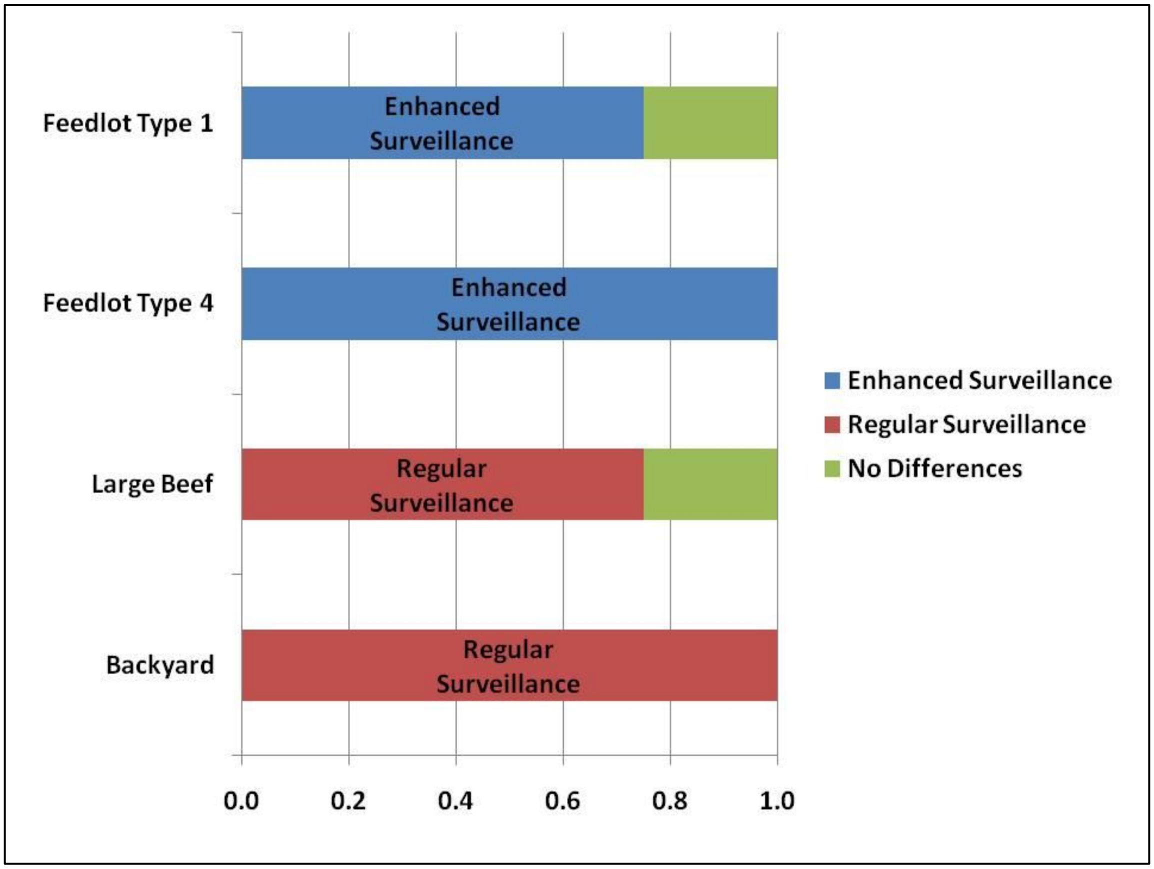


Figure 14: Enhanced vs. regular surveillance strategy dominance with respect to producers' surplus

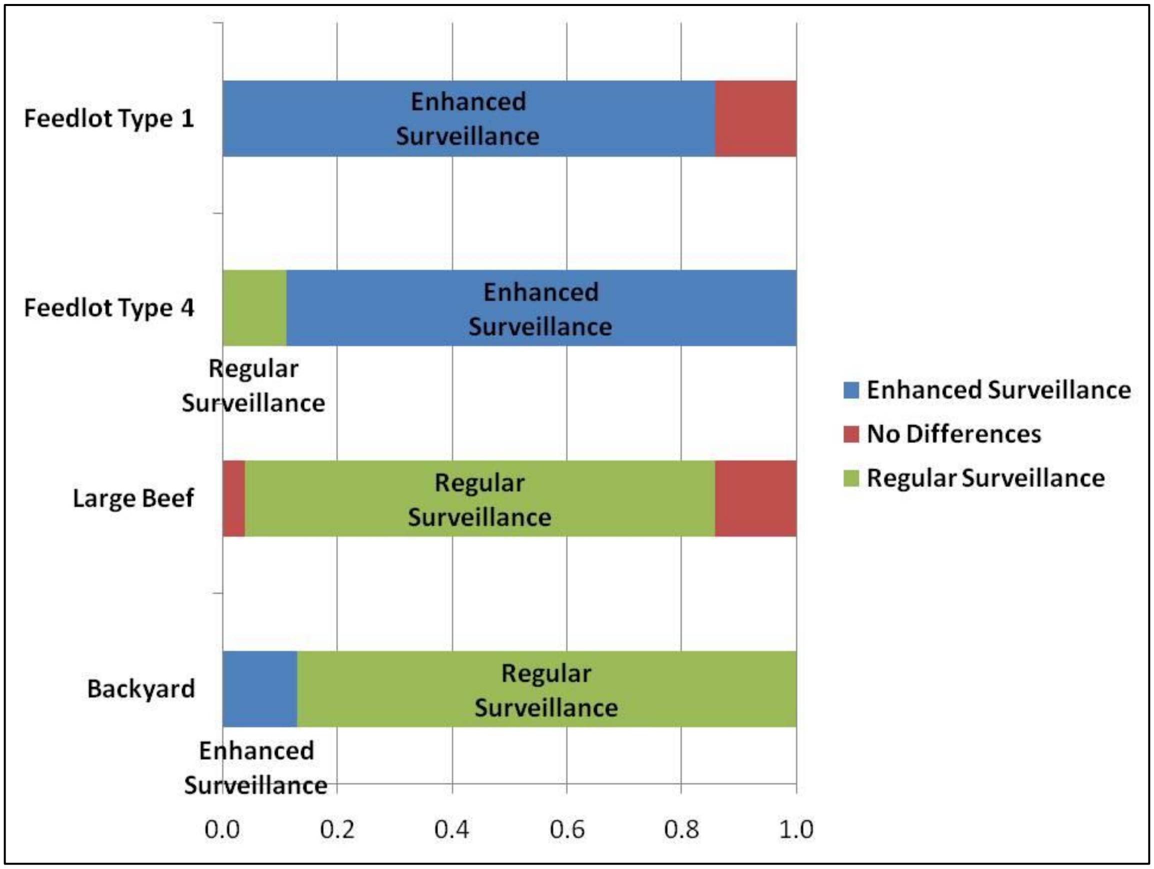


Figure 15: Enhanced vs. regular surveillance strategy dominance with respect to U.S. total welfare

3.1.4.5. BRAC Results from Alternative Design for the Mitigation Strategies

From the alternative designs, we want to find out whether this setting could give a reasonable result from the BRAC analysis compared to the outputs from the original design. Findings of major differences will be summarized as follows:

- Early Detection: In the small feedlot scenario, U.S. producers could get better results by using the early detection strategy if RAC is greater than 0.0703. In the large beef grazing scenario, this strategy will benefit U.S. consumers. In the backyard scenario, early detection is preferred for U.S. consumers if RAC>0.0104. For overall U.S. welfare changes, early detection is acceptable in the range of 0.04<RAC<0.1167.

- Adequate Vaccination: In the large feedlot scenario, U.S. consumers prefer the adequate vaccination strategy. However, U.S. producers can only accept adequate vaccination in the range of 0.0227<RAC<0.171. For overall U.S. welfare changes, adequate vaccination is not preferred. In the small feedlot scenario, U.S. consumers also prefer adequate vaccination. In the backyard scenario, U.S. consumers do not prefer early detection, while U.S. producers could accept the strategy in the range of RAC<0.06. For U.S. welfare changes, it is acceptable if RAC<0.1444.
- Enhanced Surveillance: For this strategy, when compared to the original design, most of the characteristics are very similar. However, in several scenarios, a range of enhanced surveillance strategies exists. For example, in the large feedlot scenario, enhanced surveillance is preferred for U.S. producers if RAC<0.152 and for U.S. welfare changes if RAC<0.0348. In the small feedlot introduction case, enhanced surveillance becomes acceptable for U.S. producers when RAC is greater than 0.0439. In the backyard scenario, U.S. consumers prefer the mitigation strategy when RAC is greater than 0.0017.
- In general, this alternative design gives us another look at the stochastic dominance and BRAC situation with three major mitigation strategies. Among these strategies, there are no further correlated effects. When U.S. producers change their preferences in implementing early detection strategies in the large beef grazing

scenario, they can begin adopting early detection strategy with higher risk aversion attitudes in the small feedlot and large beef scenarios. The result suggests that U.S. consumers change their preferences in adopting adequate vaccination in the large feedlot and small feedlot scenarios. U.S. producers also change from late detection to early detection in large feedlot and backyard scenarios within a range of specific RAC. For enhanced surveillance, there exists a certain range of RAC in several scenarios when enhanced surveillance is accepted.

3.1.5. Overall Concluding Remarks and Policy Implications

A number of analyses in previous sections present whether different mitigation strategies are preferred in the standpoint of welfare changes comparisons. The three mitigation strategies have different impacts on U.S. consumers and U.S. producers.

Early detection has the advantage as a strategy in reducing risks. In large and small feedlots index herds, it helps consumers to have higher lower bound welfare gains, as well as outbreaks starting in large beef grazing and backyard operations. The variability of the change in the range of producer’s losses is reduced. In addition, disease infection starting from small feedlots and large beef grazing operations lead to a preferred decision for using early detection strategy as risk aversion rises. Early detection is preferred for the risk neutral and risk adverse for U.S. consumers in the large feedlot, small feedlot, and large beef grazing index herd case, while it is preferred in the backyard case when risk aversion rises. Meanwhile, U.S. producers could prefer early detection in the small feedlot, large beef grazing, and backyard as the risk aversion level rises.

Vaccine availability results suggest that improving vaccine availability during an incursion is not a cost effective mitigation option when seeking to minimize the average loss. Adequate vaccination does not show effectiveness at a national welfare level. However, as risk aversion rises for U.S. consumers in the large feedlot, small feedlot, and large beef grazing index herds, it shows the preference toward adequate vaccine availability. U.S. producers could prefer adequate vaccine strategy in the small feedlot index herd as the risk aversion rises.

Enhanced surveillance has proved to be a great strategy to reduce U.S. producer’s welfare losses for outbreaks starting in large feedlots and small feedlot operations. This strategy also helps to increase U.S. consumer’s welfare gains in large beef grazing and backyard operation index herds. Both large feedlot and small feedlot introductions lead to a preference toward enhanced surveillance as risk aversion rises. However, there is a preference toward regular surveillance as risk aversion rises for large beef index herds and backyard index herds. This implies that this strategy is to reduce risk in areas with larger feedlots. For U.S. consumers, regular surveillance strategy dominates in the situation of larger feedlot introduction, while enhanced surveillance dominates in the smaller feedlot introduction. U.S. producers have a preference for enhanced surveillance strategy when there are larger feedlot introductions.

Further research that includes a more comprehensive and detailed analysis for each individual type of feedlot can be conducted. We might find reasons that can contribute to differences among the index feedlots. The analysis from this study can help to develop Agricultural policies for FMD prevention and mitigation, which can be enforced with considerations of other scenarios, varied reactions in different types of feedlot operations, and diverse perspectives from all parties involved in the national welfare composition.

4. RISK MODELING FOR EVALUATION OF MITIGATION STRATEGIES

An FMD outbreak poses a potential threat for the United States. This raises serious concerns and a number of parties are considering how to reduce the possible huge loss. Risk is a major factor across major control strategies. In this study, we evaluate the economic consequences of a number of control strategies considering both their average welfare and their risk implications.

Many risk modeling approaches have been developed to evaluate possible decision choices. Stochastic modeling is not used to yield the best beneficial option for decision makers; however, it is utilized to assist them to find a robust position across all possible events (McCarl and Spreen 1997). There are two major types of stochastic programming risk models (McCarl and Spreen 1997). In the first type, all decisions must be made when the event occurs and all the possible outcomes are taken into account when decisions are made. However, in the second type decisions can be made when the event occurs, but subsequent decisions may be made to change or complement the initial decision adapting to the realized uncertainty.

The modeling approach used in this Section is the first type, which is stochastic modeling programming without recourse (McCarl and Spreen 1997). All decisions must be made when the event occurs and no other decision will be made after any uncertainty is resolved. In this Section, we will use the welfare results derived from ASM Modeling in the previous Section to evaluate the ‘optimal’ solution under all circumstances in a risk modeling analysis. The factor of what risk attitude is chosen by decision makers will be incorporated into this risk modeling analysis as well. According to McCarl and

Spreen (1997), risks may arise in different ways including objective function coefficients, technical coefficients, or right-hand side coefficients. They may contribute to the overall risk level separately or collectively. As the previous Section targets using welfare comparison to determine the ‘optimal’ solution for decision makers, this Section will include the factor of risk variable to analyze whether the ‘optimal’ solution will be influenced by taking this variable into account.

This Section will include three parts. Two risk models will be introduced in Part 1. The first risk model is mean-variance (EV) portfolio choice formulation under objective coefficient risk modeling analysis, and the second model is the unified model (McCarl and Spreen 1997). Results of these two risk modeling analyses will be presented in Part 2. Part 3 will include a comprehensive discussion based on results of risk modeling analysis. All findings will be summarized in the last Part of this Section, and concluding remarks will be presented.

4.1. E-V Model

When there is a portfolio choice problem, decision makers have to set a criterion to develop an optimal strategy to reach their goal. The Linear Programming (LP) formulation was criticized by Markowitz for the drawback of investing all funds in the highest return option. An expected value variance (E-V) model, first formulated and exploited by Markowitz (1959), takes divergence between observed and modeled behaviors into consideration (McCarl and Spreen 1997).

Usually, this modeling approach applies to investment in order to make the high returns less a risk adjustment. In this study, we introduce this risk modeling concept and apply it to the mitigation strategy choice decision to reach an ideal goal of reducing the mean and risk aspects of welfare loss from a potential FMD outbreak in the Texas High Plains. A state of nature (k) refers to each of the 100 simulated welfare runs performing under a chosen scenario with four types of disease introduction index herd. The welfare levels in the 16 designed strategy combinations are treated as the objective value of X_k.

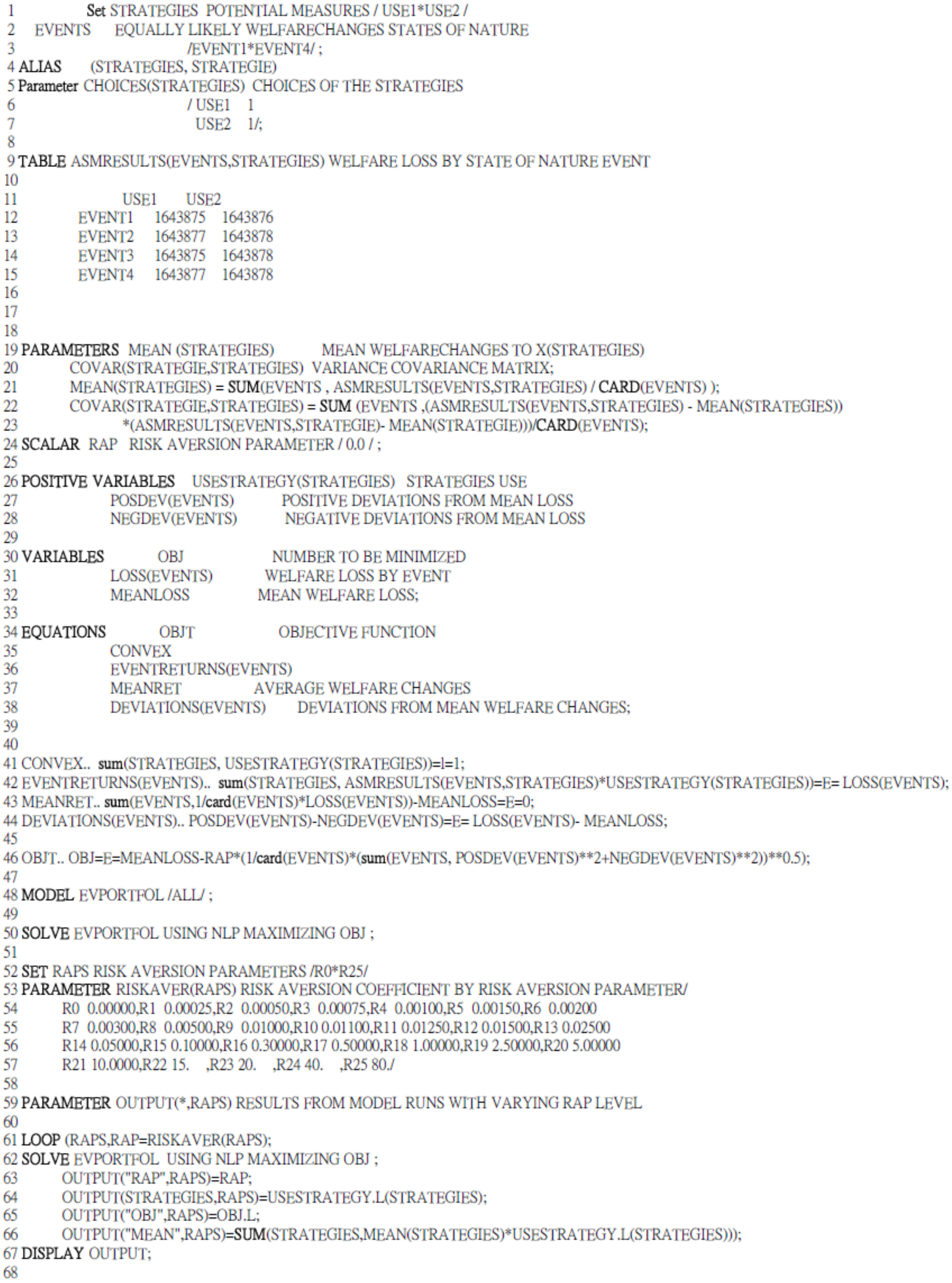
4.1.1. E-V Model Formulation

The following formulations are referred to McCarl and Spreen (1997):

A general formulation of the E-V problem is

$$\begin{array}{llcll} Max & \bar{C}X & - & \Phi & X'SX \\ s.t. & AX & & & \leq \; b \\ & X & & & \geq \; 0 \end{array} \tag{28}$$

In this study, the formula above defines the mean and variance of a LP objective function with a risky parameter, which also represents the welfare level in this case. The objective function maximizes expected welfare ($\bar{C}$X) less a "risk aversion coefficient" ($\emptyset$) times the variance of total welfare (X'SX). C represents the welfare level, and X is the proportion of choice when facing either using a specific mitigation strategy or not using it at all. In our case, we are looking for a portfolio of mitigation strategies subject to a proportion constraint in pursuit of expected welfare maximization. Therefore, b is equal to 1. The model assumes that decision makers will trade expected welfare for reduced variance. The GAMS formulation of E-V model is shown in Figure 16.



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            Set STRATEGIES  POTENTIAL MEASURES / USE1*USE2 /
  EVENTS      EQUALLY LIKELY WELFARECHANGES STATES OF NATURE
                              /EVENT1*EVENT4/ ;
ALIAS       (STRATEGIES, STRATEGIE)
Parameter CHOICES(STRATEGIES)  CHOICES OF THE STRATEGIES
                              / USE1    1
                                USE2    1/;

TABLE ASMRESULTS(EVENTS,STRATEGIES) WELFARE LOSS BY STATE OF NATURE EVENT

                  USE1      USE2
          EVENT1    1643875   1643876
          EVENT2    1643877   1643878
          EVENT3    1643875   1643878
          EVENT4    1643877   1643878



PARAMETERS  MEAN (STRATEGIES)           MEAN WELFARECHANGES TO X(STRATEGIES)
          COVAR(STRATEGIE,STRATEGIES)  VARIANCE COVARIANCE MATRIX;
          MEAN(STRATEGIES) = SUM(EVENTS , ASMRESULTS(EVENTS,STRATEGIES) / CARD(EVENTS) );
          COVAR(STRATEGIE,STRATEGIES) = SUM (EVENTS ,(ASMRESULTS(EVENTS,STRATEGIES) - MEAN(STRATEGIES))
                  *(ASMRESULTS(EVENTS,STRATEGIE)- MEAN(STRATEGIE)))/CARD(EVENTS);
SCALAR  RAP   RISK AVERSION PARAMETER / 0.0 / ;

POSITIVE VARIABLES    USESTRATEGY(STRATEGIES)   STRATEGIES USE
                POSDEV(EVENTS)          POSITIVE DEVIATIONS FROM MEAN LOSS
                NEGDEV(EVENTS)          NEGATIVE DEVIATIONS FROM MEAN LOSS

VARIABLES         OBJ                 NUMBER TO BE MINIMIZED
                LOSS(EVENTS)          WELFARE LOSS BY EVENT
                MEANLOSS              MEAN WELFARE LOSS;

EQUATIONS         OBJT                OBJECTIVE FUNCTION
                CONVEX
                EVENTRETURNS(EVENTS)
                MEANRET               AVERAGE WELFARE CHANGES
                DEVIATIONS(EVENTS)       DEVIATIONS FROM MEAN WELFARE CHANGES;


CONVEX..  sum(STRATEGIES, USESTRATEGY(STRATEGIES))=l=1;
EVENTRETURNS(EVENTS)..  sum(STRATEGIES, ASMRESULTS(EVENTS,STRATEGIES)*USESTRATEGY(STRATEGIES))=E= LOSS(EVENTS);
MEANRET.. sum(EVENTS,1/card(EVENTS)*LOSS(EVENTS))-MEANLOSS=E=0;
DEVIATIONS(EVENTS).. POSDEV(EVENTS)-NEGDEV(EVENTS)=E= LOSS(EVENTS)- MEANLOSS;

OBJT.. OBJ=E=MEANLOSS-RAP*(1/card(EVENTS)*(sum(EVENTS, POSDEV(EVENTS)**2+NEGDEV(EVENTS)**2))**0.5);

MODEL EVPORTFOL /ALL/ ;

SOLVE EVPORTFOL USING NLP MAXIMIZING OBJ ;

SET RAPS RISK AVERSION PARAMETERS /R0*R25/
PARAMETER RISKAVER(RAPS) RISK AVERSION COEFFICIENT BY RISK AVERSION PARAMETER/
        R0  0.00000,R1  0.00025,R2  0.00050,R3  0.00075,R4  0.00100,R5  0.00150,R6  0.00200
        R7  0.00300,R8  0.00500,R9  0.01000,R10 0.01100,R11 0.01250,R12 0.01500,R13 0.02500
        R14 0.05000,R15 0.10000,R16 0.30000,R17 0.50000,R18 1.00000,R19 2.50000,R20 5.00000
        R21 10.0000,R22 15.    ,R23 20.    ,R24 40.    ,R25 80./

PARAMETER OUTPUT(*,RAPS) RESULTS FROM MODEL RUNS WITH VARYING RAP LEVEL

LOOP (RAPS,RAP=RISKAVER(RAPS);
SOLVE EVPORTFOL  USING NLP MAXIMIZING OBJ ;
        OUTPUT("RAP",RAPS)=RAP;
        OUTPUT(STRATEGIES,RAPS)=USESTRATEGY.L(STRATEGIES);
        OUTPUT("OBJ",RAPS)=OBJ.L;
        OUTPUT("MEAN",RAPS)=SUM(STRATEGIES,MEAN(STRATEGIES)*USESTRATEGY.L(STRATEGIES)));
DISPLAY OUTPUT;

```

Figure 16: GAMS formulation sample – E-V Model

Properties of optimal E-V solution can be calculated by the Kuhn-Tucker condition. The Lagrangian function is

$$\ell(X,\mu) = \bar{C}X - \Phi X'SX - \mu(AX - b) \tag{29}$$

And the Kuhn-Tucker conditions are

$$\begin{array}{rcll}
\partial\ell/\partial X & = & \bar{C} - 2\Phi X'S - \mu A & \leq 0 \\
(\partial\ell/\partial X)X & = & (\bar{C} - 2\Phi X'S - \mu A)X & = 0 \\
X & & & \geq 0 \\
\partial\ell/\partial\mu & = & -(AX - b) & \geq 0 \\
\mu(\partial\ell/\partial\mu) & = & \mu(AX - b) & = 0 \\
\mu & & & \geq 0
\end{array}$$

,

where μ is the vector of dual variables (Lagrangian multipliers) associated with the primal constraint $\sum X_1 \leq 1$.

Two major indications come from the Kuhn-Tucker conditions. First, the solution allows more variables to be nonzero than a LP basic solution. This occurs since variables can be nonzero to satisfy the n potential conditions $\partial\ell// \partial X = 0$ and the m conditions, where AX = b or μ = 0. Thus, the solution can have more nonzero variables than constraints. Second, the $\partial\ell/ \partial X$ equation relates resource cost (μ) with marginal revenue ($\bar{C}$) and a marginal cost of bearing risk (-2ΦX'S). The optimal shadow prices are risk adjusted as are the optimal decision variable values (McCarl and Spreen 1997).

4.1.2. Unified Modeling and Stochastic Programming

A unified model formulation is illustrated as follows:

$$\textbf{Max} \quad \overline{\boldsymbol{Welfare}} - \square\{\textstyle\sum_{\mathbf{k}} \mathbf{P_k}[(\mathbf{d_k^+})^2 + (\mathbf{d_k^-})^2]\}^{\mathbf{0.5}} \tag{30}$$

$$\begin{array}{llll}
\textbf{S.t.} & \sum_j X_j & \leq 1 & for\ all\ j \\
& \sum_j C_{k_j} X_j \quad - \quad welfare_k & = 0 & for\ all\ k
\end{array}$$

$$\sum_k P_k \, welfare_k \; - \; welfare_k \qquad = 0$$

$$welfare_k - \overline{welfare} - d_k^+ + d_k^- \;\; = 0$$

$$X_j \,, \; d_k^+, d_k^- \quad \geq 0 \quad for \, all \, j,k$$

$$\boldsymbol{welfare_k} \,, \quad \boldsymbol{\overline{welfare}} \qquad \boldsymbol{\geq 0 \quad for \, all \, k}$$

A new variable (*welfare*) is introduced as the welfare level under the state of nature *k*, which is reflecting the simulated welfare level with the addition of welfare gain or welfare loss after a hypothetical FMD outbreak. A variable is entered for average welfare ($\overline{welfare}$) which is equated to the probabilities (P_k) times the welfare levels. We treat all the simulation points with the same probability. All P_k values are equally weighted. This term also reflects the expected welfare maximization. Deviations between the average and state of nature dependent welfare level are treated in the constraint formulation as d_k^+ is welfare above the average level and d_k^- shows welfare below the average level. The objective function includes the expected welfare value, the probabilities, and deviation variables. Figure 17 shows the GAMS formulation.

```
              Set STRATEGIES  POTENTIAL MEASURES / USE1*USE2 /
  EVENTS      EQUALLY LIKELY WELFARECHANGES STATES OF NATURE
                              /EVENT1*EVENT4/ ;
ALIAS      (STRATEGIES, STRATEGIE)
Parameter CHOICES(STRATEGIES)  CHOICES OF THE STRATEGIES
                              / USE1    1
                                USE2    1/;

TABLE ASMRESULTS(EVENTS,STRATEGIES) WELFARE LOSS BY STATE OF NATURE EVENT

                  USE1      USE2
           EVENT1     1643875   1643876
           EVENT2     1643877   1643878
           EVENT3     1643875   1643878
           EVENT4     1643877   1643878



PARAMETERS  MEAN (STRATEGIES)          MEAN WELFARECHANGES TO X(STRATEGIES)
          COVAR(STRATEGIE,STRATEGIES)  VARIANCE COVARIANCE MATRIX;
          MEAN(STRATEGIES) = SUM(EVENTS , ASMRESULTS(EVENTS,STRATEGIES) / CARD(EVENTS) );
          COVAR(STRATEGIE,STRATEGIES) = SUM (EVENTS ,(ASMRESULTS(EVENTS,STRATEGIES) - MEAN(STRATEGIES))
                  *(ASMRESULTS(EVENTS,STRATEGIE)- MEAN(STRATEGIE)))/CARD(EVENTS);
SCALAR  RAP   RISK AVERSION PARAMETER / 0.0 / ;

POSITIVE VARIABLES    USESTRATEGY(STRATEGIES)   STRATEGIES USE
                 POSDEV(EVENTS)          POSITIVE DEVIATIONS FROM MEAN LOSS
                 NEGDEV(EVENTS)          NEGATIVE DEVIATIONS FROM MEAN LOSS

VARIABLES          OBJ                  NUMBER TO BE MINIMIZED
                 LOSS(EVENTS)          WELFARE LOSS BY EVENT
                 MEANLOSS              MEAN WELFARE LOSS;

EQUATIONS          OBJT                  OBJECTIVE FUNCTION
                 CONVEX
                 EVENTRETURNS(EVENTS)
                 MEANRET               AVERAGE WELFARE CHANGES
                 DEVIATIONS(EVENTS)       DEVIATIONS FROM MEAN WELFARE CHANGES;


CONVEX..  sum(STRATEGIES, USESTRATEGY(STRATEGIES))=l=1;
EVENTRETURNS(EVENTS)..  sum(STRATEGIES, ASMRESULTS(EVENTS,STRATEGIES)*USESTRATEGY(STRATEGIES))=E= LOSS(EVENTS);
MEANRET.. sum(EVENTS,1/card(EVENTS)*LOSS(EVENTS))-MEANLOSS=E=0;
DEVIATIONS(EVENTS).. POSDEV(EVENTS)-NEGDEV(EVENTS)=E= LOSS(EVENTS)- MEANLOSS;

OBJT.. OBJ=E=MEANLOSS-RAP*(1/card(EVENTS)*(sum(EVENTS, POSDEV(EVENTS)**2+NEGDEV(EVENTS)**2))**0.5);

MODEL EVPORTFOL /ALL/ ;

SOLVE EVPORTFOL USING NLP MAXIMIZING OBJ ;

SET RAPS RISK AVERSION PARAMETERS /R0*R25/
PARAMETER RISKAVER(RAPS) RISK AVERSION COEFFICIENT BY RISK AVERSION PARAMETER/
         R0  0.00000,R1  0.00025,R2  0.00050,R3  0.00075,R4  0.00100,R5  0.00150,R6  0.00200
         R7  0.00300,R8  0.00500,R9  0.01000,R10 0.01100,R11 0.01250,R12 0.01500,R13 0.02500
         R14 0.05000,R15 0.10000,R16 0.30000,R17 0.50000,R18 1.00000,R19 2.50000,R20 5.00000
         R21 10.0000,R22 15.    ,R23 20.    ,R24 40.    ,R25 80./

PARAMETER OUTPUT(*,RAPS) RESULTS FROM MODEL RUNS WITH VARYING RAP LEVEL

LOOP (RAPS,RAP=RISKAVER(RAPS));
SOLVE EVPORTFOL  USING NLP MAXIMIZING OBJ ;
         OUTPUT("RAP",RAPS)=RAP;
         OUTPUT(STRATEGIES,RAPS)=USESTRATEGY.L(STRATEGIES);
         OUTPUT("OBJ",RAPS)=OBJ.L;
         OUTPUT("MEAN",RAPS)=SUM(STRATEGIES,MEAN(STRATEGIES)*USESTRATEGY.L(STRATEGIES)));
DISPLAY OUTPUT;

```

Figure 17: GAMS formulation sample – unified model

4.1.3. Theoretical Concerns of EV Model Use

From the 1970s, the Expected Utility Theory (von Neumann and Morgenstern) gives the main theoretical basis for choice under uncertainty. The major concentration in the EU model is mainly on how a change in the random parameter, x, affects the decision made by an economic agent (Rothechild and Stiglitz 1971). McCarl and Spreen (1997) argue that there is a general agreement that maximizing the E-V problem is equivalent to maximizing expected utility when one of two conditions holds. First, the underlying income distribution is normal - which requires a normal distribution of the cj, and the utility function is exponential (Freund 1956). Second, the underlying distributions satisfy Meyer's location and scale restrictions. In addition, Tsiang (1972) has shown that E-V analysis provides an acceptable approximation of the expected utility choices when the risk taken is small relative to total initial wealth.

4.2. Results

In this section, a sorted ASM welfare data set from the previous section is used, and welfare changes are transferred to the total welfare values for each party and a U.S. total as the variable for each state of nature after the addition of the base welfare value. The base welfare level is the welfare level before the outbreak is initiated. The welfare value becomes the c in the objective function of the EV model. There are four types of disease introduction index herds for each of the 16 strategy combinations. In each combination for each index herd, there are 100 ASM simulation runs that are treated as states of nature.

In this analysis, mitigation strategies are the variables of interest as selected in both original and alternative designs for the EV modeling and Unified modeling portfolio analysis. This risk modeling methodology is used to test the effectiveness of each focus mitigation strategy in the aspect of U.S. consumers' surplus, U.S. processors' surplus, U.S. producers' surplus, and total U.S. welfare. A switch point of RAP can help us to realize the response of decision makers to a selected mitigation strategy at certain levels of risk aversion. Moreover, those two portfolio models can provide us suggestions in possible investment on either a single mitigation strategy or a mixed set of strategies.

However, since we can only pick one as a preferred option, the choice with more investment share units will be viewed as a preferred strategy in the situation when there exists an optimal portfolio selection for both using the targeted mitigation strategy and the opposite mitigation strategy.

4.2.1. Overall Results for All Strategies with Respect to U.S. Total Welfare

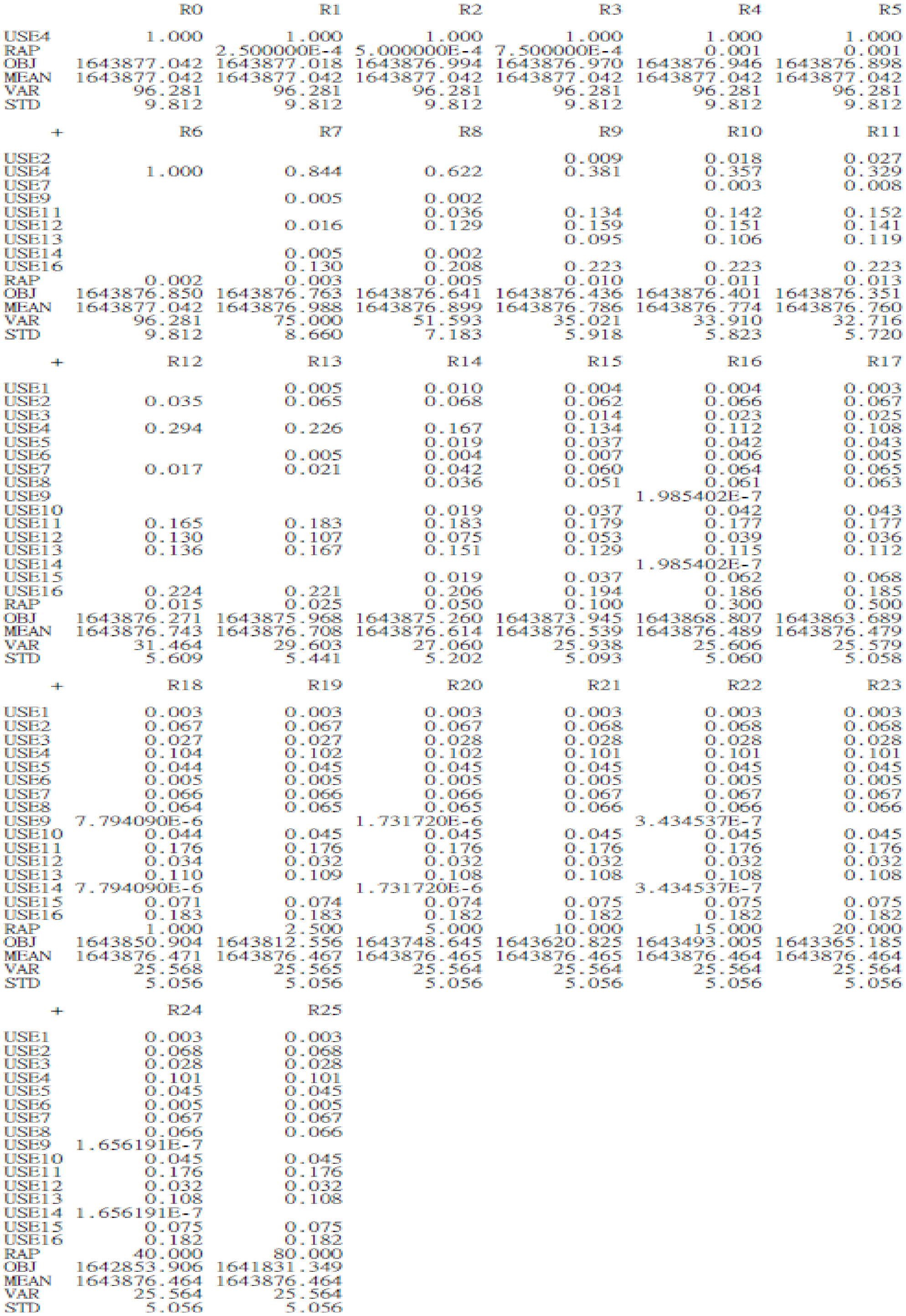
First, we check the U.S. total welfare levels from all 64 scenarios after the addition of welfare changes assuming an FMD outbreak occurring in the Texas High Plains. We treat the four types of disease introduction index herds as events in our formulations, and the 16 different strategy combinations as variables (see Table 13). For each type of introduction index herd, there are 100 simulated welfare change runs in each strategy combination. With the addition of base welfare level, those 6,400 runs are viewed as states of nature given a potential FMD outbreak.

The EV portfolio modeling runs with varying Risk Aversion Parameter (RAP), which is presented in Figure 18, show us that there is only one solution (use4) dominating all the other strategy combination designs in the RAP range between 0 and

0.002 with respect to the U.S. total welfare. The use4 strategy that includes ring slaughter, regular surveillance, slaughters of infecteds, slaugher of dc's, late detection, targeted vaccination, and inadequate vaccines. As the RAP rises to between 0.002 and 0.003, other strategies (use9, use14, use16) are being introduced into the optimal mixed portfolio result. The use4 strategy still has the laregest proportion in the mixed results and remains a preferred strategy as the RAP is equal to or less than 0.025.

Table 13: Use of Mitigation Strategy Combination in GAMS Formulation

Mitigation Strategy (M)	**USE**
Ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, early detection	1
Ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, late detection	2
Ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, late detection, targeted vaccination, adequate vaccine	3
Ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, late detection, targeted vaccination, inadequate vaccine	4
Enhanced surveillance, slaughter of infecteds, slaughter of dc's, early detection	5
Enhanced surveillance, slaughter of infecteds, slaughter of dc's, late detection	6
Enhanced surveillance, slaughter of infecteds, slaughter of dc's, late detection, targeted vaccination, adequate vaccine	7
Enhanced surveillance, slaughter of infecteds, slaughter of dc's, late detection, targeted vaccination, inadequate vaccine	8
Slaughter of infecteds, slaughter of dc's, regular surveillance, ring vaccination, early detection, inadequate vaccine	9
Slaughter of infecteds, slaughter of dc's, regular surveillance, early detection	10
Slaughter of infecteds, slaughter of dc's, regular surveillance, late detection, ring vaccination, adequate vaccine	11
Slaughter of infecteds, slaughter of dc's, regular surveillance, late detection, ring vaccination, inadequate vaccine	12
Slaughter of infecteds, slaughter of dc's, regular surveillance, early detection, targeted vaccination, adequate vaccine	13
Slaughter of infecteds, slaughter of dc's, regular surveillance, late detection	14
Slaughter of infecteds, slaughter of dc's, regular surveillance, late detection, targeted vaccination, adequate vaccine	15
Slaughter of infecteds, slaughter of dc's, regular surveillance, early detection, ring vaccination, adequate vaccine	16



```
               R0          R1          R2          R3          R4          R5

USE4        1.000       1.000       1.000       1.000       1.000       1.000
RAP               2.500000E-4 5.000000E-4 7.500000E-4       0.001       0.001
OBJ   1643877.042 1643877.018 1643876.994 1643876.970 1643876.946 1643876.898
MEAN  1643877.042 1643877.042 1643877.042 1643877.042 1643877.042 1643877.042
VAR        96.281      96.281      96.281      96.281      96.281      96.281
STD         9.812       9.812       9.812       9.812       9.812       9.812

    +          R6          R7          R8          R9         R10         R11

USE2                                            0.009       0.018       0.027
USE4        1.000       0.844       0.622       0.381       0.357       0.329
USE7                                                        0.003       0.008
USE9                    0.005       0.002
USE11                               0.036       0.134       0.142       0.152
USE12                   0.016       0.129       0.159       0.151       0.141
USE13                                           0.095       0.106       0.119
USE14                   0.005       0.002
USE16                   0.130       0.208       0.223       0.223       0.223
RAP         0.002       0.003       0.005       0.010       0.011       0.013
OBJ   1643876.850 1643876.763 1643876.641 1643876.436 1643876.401 1643876.351
MEAN  1643877.042 1643876.988 1643876.899 1643876.786 1643876.774 1643876.760
VAR        96.281      75.000      51.593      35.021      33.910      32.716
STD         9.812       8.660       7.183       5.918       5.823       5.720

    +         R12         R13         R14         R15         R16         R17

USE1                    0.005       0.010       0.004       0.004       0.003
USE2        0.035       0.065       0.068       0.062       0.066       0.067
USE3                                            0.014       0.023       0.025
USE4        0.294       0.226       0.167       0.134       0.112       0.108
USE5                                0.019       0.037       0.042       0.043
USE6                    0.005       0.004       0.007       0.006       0.005
USE7        0.017       0.021       0.042       0.060       0.064       0.065
USE8                                0.036       0.051       0.061       0.063
USE9                                                  1.985402E-7
USE10                               0.019       0.037       0.042       0.043
USE11       0.165       0.183       0.183       0.179       0.177       0.177
USE12       0.130       0.107       0.075       0.053       0.039       0.036
USE13       0.136       0.167       0.151       0.129       0.115       0.112
USE14                                                 1.985402E-7
USE15                               0.019       0.037       0.062       0.068
USE16       0.224       0.221       0.206       0.194       0.186       0.185
RAP         0.015       0.025       0.050       0.100       0.300       0.500
OBJ   1643876.271 1643875.968 1643875.260 1643873.945 1643868.807 1643863.689
MEAN  1643876.743 1643876.708 1643876.614 1643876.539 1643876.489 1643876.479
VAR        31.464      29.603      27.060      25.938      25.606      25.579
STD         5.609       5.441       5.202       5.093       5.060       5.058

    +         R18         R19         R20         R21         R22         R23

USE1        0.003       0.003       0.003       0.003       0.003       0.003
USE2        0.067       0.067       0.067       0.068       0.068       0.068
USE3        0.027       0.027       0.028       0.028       0.028       0.028
USE4        0.104       0.102       0.102       0.101       0.101       0.101
USE5        0.044       0.045       0.045       0.045       0.045       0.045
USE6        0.005       0.005       0.005       0.005       0.005       0.005
USE7        0.066       0.066       0.066       0.067       0.067       0.067
USE8        0.064       0.065       0.065       0.066       0.066       0.066
USE9  7.794090E-6             1.731720E-6             3.434537E-7
USE10       0.044       0.045       0.045       0.045       0.045       0.045
USE11       0.176       0.176       0.176       0.176       0.176       0.176
USE12       0.034       0.032       0.032       0.032       0.032       0.032
USE13       0.110       0.109       0.108       0.108       0.108       0.108
USE14 7.794090E-6             1.731720E-6             3.434537E-7
USE15       0.071       0.074       0.074       0.075       0.075       0.075
USE16       0.183       0.183       0.182       0.182       0.182       0.182
RAP         1.000       2.500       5.000      10.000      15.000      20.000
OBJ   1643850.904 1643812.556 1643748.645 1643620.825 1643493.005 1643365.185
MEAN  1643876.471 1643876.467 1643876.465 1643876.465 1643876.464 1643876.464
VAR        25.568      25.565      25.564      25.564      25.564      25.564
STD         5.056       5.056       5.056       5.056       5.056       5.056

    +         R24         R25

USE1        0.003       0.003
USE2        0.068       0.068
USE3        0.028       0.028
USE4        0.101       0.101
USE5        0.045       0.045
USE6        0.005       0.005
USE7        0.067       0.067
USE8        0.066       0.066
USE9  1.656191E-7
USE10       0.045       0.045
USE11       0.176       0.176
USE12       0.032       0.032
USE13       0.108       0.108
USE14 1.656191E-7
USE15       0.075       0.075
USE16       0.182       0.182
RAP        40.000      80.000
OBJ   1642853.906 1641831.349
MEAN  1643876.464 1643876.464
VAR        25.564      25.564
STD         5.056       5.056
```

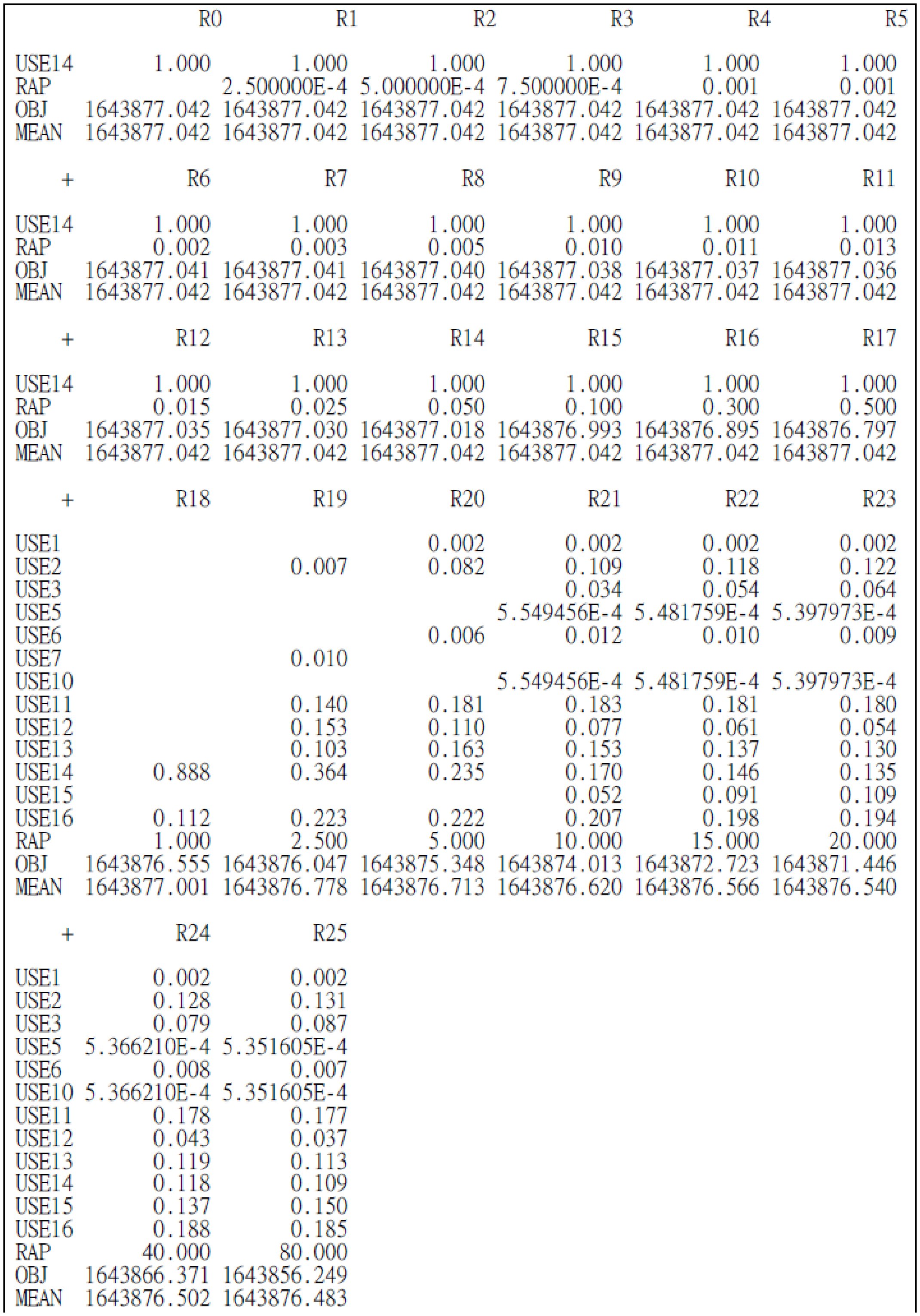
Figure 18: Results from E-V model runs with varying RAPs for all strategies with respect to U.S. total welfare

The preferred strategy switches from the use4 strategy to the use16 strategy as the RAP rises to between 0.025 and 0.05. The use16 strategy includes slaughter of infecteds, slaughter of dc's, regular surveillance, early detection, ring vaccination, and adequate vaccination. As the RAP rises to 0.05 and higher, most of the 16 strategy combinations are selected in the optimal portfolio results. In the RAP range between 0.05 and 80, the maximum in our EV modeling outputs, the strategies with a significant portfolio proportion result that is higher than 0.1 are use4, use11, use13, and use16. The use11 strategy is the combination of slaughter of infected slaughter of dc's, regular surveillance, late detection, ring vaccination, and adequate vaccine. The use13 strategy includes slaughter of infecteds, slaughter of dc's, regular surveillance, early detection, targeted vaccination, and adequate vaccine. We find that adequate vaccination has great advantages, because it is part of the use4, use11, use13, and use16 strategy combinations.

The overall portfolio result indicates that if decision makers are more risk averse if the RAC is greater than 0.05, then they might consider mitigation strategies that employ early detection and adequate vaccination. As risk aversion rises to a even higher level, the three mitigation strategies might offer certain helps to maximize the obejective function in the EV modeling with the various strategy combinations in the optimal portflio outcome. However, McCarl and Bessler (1989) suggest that RAC should fall within the reasonable bounds, and using an unreasonably large maximum RAC value is always seen in the literatures. In addition, how to identify the preferred strategy becomes difficult as RAP rises among most of the 16 mixed strategy usages in the output table.

From the results shown in the previous section, we have known that there are siginificant welfare distributions among U.S. consumers, U.S. processors, and U.S. producers. U.S. producers suffer a possible welfare loss when there is a FMD outbreak occurring in the Texas High Plains. Therefore, further investigation with a specific design for treating mitigation strategies as the variable of interests researching the effects on the welfare of different parties should be conducted, which is designed to prevent a huge loss in the welfare of any specific party in the nation.

Based on the optimal portfolio result of Unified model runs in Figure 19, we have found that the strategy combination (use14) is the only selected strategy within the RAP range between 0 and 0.5. The use14 strategy includes slaughter of infecteds, slaughter of dc's, regular surveillance, and late detection. This strategy is very similar to the use4 strategy combination in the previous EV model runs. An optimal solution of a



```
                R0          R1          R2          R3          R4          R5

USE14        1.000       1.000       1.000       1.000       1.000       1.000
RAP                2.500000E-4 5.000000E-4 7.500000E-4       0.001       0.001
OBJ    1643877.042 1643877.042 1643877.042 1643877.042 1643877.042 1643877.042
MEAN   1643877.042 1643877.042 1643877.042 1643877.042 1643877.042 1643877.042

    +           R6          R7          R8          R9         R10         R11

USE14        1.000       1.000       1.000       1.000       1.000       1.000
RAP          0.002       0.003       0.005       0.010       0.011       0.013
OBJ    1643877.041 1643877.041 1643877.040 1643877.038 1643877.037 1643877.036
MEAN   1643877.042 1643877.042 1643877.042 1643877.042 1643877.042 1643877.042

    +          R12         R13         R14         R15         R16         R17

USE14        1.000       1.000       1.000       1.000       1.000       1.000
RAP          0.015       0.025       0.050       0.100       0.300       0.500
OBJ    1643877.035 1643877.030 1643877.018 1643876.993 1643876.895 1643876.797
MEAN   1643877.042 1643877.042 1643877.042 1643877.042 1643877.042 1643877.042

    +          R18         R19         R20         R21         R22         R23

USE1                                 0.002       0.002       0.002       0.002
USE2                     0.007       0.082       0.109       0.118       0.122
USE3                                             0.034       0.054       0.064
USE5                                       5.549456E-4 5.481759E-4 5.397973E-4
USE6                                 0.006       0.012       0.010       0.009
USE7                     0.010
USE10                                      5.549456E-4 5.481759E-4 5.397973E-4
USE11                    0.140       0.181       0.183       0.181       0.180
USE12                    0.153       0.110       0.077       0.061       0.054
USE13                    0.103       0.163       0.153       0.137       0.130
USE14        0.888       0.364       0.235       0.170       0.146       0.135
USE15                                            0.052       0.091       0.109
USE16        0.112       0.223       0.222       0.207       0.198       0.194
RAP          1.000       2.500       5.000      10.000      15.000      20.000
OBJ    1643876.555 1643876.047 1643875.348 1643874.013 1643872.723 1643871.446
MEAN   1643877.001 1643876.778 1643876.713 1643876.620 1643876.566 1643876.540

    +          R24         R25

USE1         0.002       0.002
USE2         0.128       0.131
USE3         0.079       0.087
USE5   5.366210E-4 5.351605E-4
USE6         0.008       0.007
USE10  5.366210E-4 5.351605E-4
USE11        0.178       0.177
USE12        0.043       0.037
USE13        0.119       0.113
USE14        0.118       0.109
USE15        0.137       0.150
USE16        0.188       0.185
RAP         40.000      80.000
OBJ    1643866.371 1643856.249
MEAN   1643876.502 1643876.483
```

Figure 19: Results from unified model runs with varying RAPs for all strategies with respect to U.S. total welfare

mixed strategy (use14 and use16) begins when the RAC is between 0.5 and 1. As the risk aversion level rises above 2.5, more strategy combinations are selected in the optimal mixed strategy portfolio. Meanwhile, the use14 strategy is the preferred strategy due to its largest proportion in the portfolio. The preferred strategy usage is switched from use14 strategy to use16 strategy when the RAC rises to between 5 and 10. The use16 strategy begins to serve as a preferred strategy to improve the overall welfare objective function in the face of a hypothetical FMD outbreak when RAP is equal to or higher than 10. The difference between use14 and use16 is that three more mitigation strategies, including early detection, ring vaccination, and adequate vaccine, are included in the use16 strategy combination. Two of them are our targeted strategies in this study.

Moreover, in the RAP range between 10 and 80, which is the maximum in our modeling, the strategies with a significant proportion in the optimal portfolio result that is higher than 0.1 are use2, use11, use13, use14, and use16. The use2 strategy combines with strategies of ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, and late detection; the use11 strategy is the combination of slaughter of infecteds, slaughter of dc's, regular surveillance, late detection, ring vaccination, and adequate vaccine; the use13 strategy includes slaughter of infecteds, slaughter of dc's, regular surveillance, early detection, targeted vaccination, and adequate vaccine. We are not able to prove any advantage of any targeted mitigation strategy by looking for similarities among those strategy combinations with a significant proportion under the given result.

From this overall effect evaluation for all strategies in the Unified modeling, we can conclude that early detection and adequate vaccination could both be good mitigation strategies as the decision makers become risk averse.

The contribution of the three targeted mitigation strategies to maximize the established objective function in both the EV model and the Unified model cannot be identified to provide strong enough evidence for the effectiveness of the overall effects on the U.S. total welfare. More efforts can be made with further investigation on the effects based on the design for the variables of interest for each mitigation strategy in the welfare comparisons of each different party and U.S. total welfare.

4.2.2. Results for Early Detection as a Mitigation Strategy

In this section, we continue to use the alternative design where mitigation strategies are treated as the variable of interest with a specific objective to avoid inter-strategy effects. The optimal portfolio results of both EV modeling and Unified modeling runs are shown in Table 14. The major findings are summarized as follows.

Table 14: Optimal Proportion Usage for Early Detection as a Mitigation Strategy

RAP	**EV Model**				**Unified Model**			
	PS	**PR**	**CS**	**Total**	**PS**	**PR**	**CS**	**Total**
0	0	0	***1***	0	0	0	***1***	0
0.0003	0	0	***1***	0	0	0	***1***	0
0.0005	0	0	***1***	0	0	0	***1***	0
0.0008	0	0	***1***	0	0	0	***1***	0
0.001	0	0	***1***	0	0	0	***1***	0
0.0015	0	0	***0.976***	0	0	0	***1***	0
0.002	0.079	0	***0.876***	0	0	0	***1***	0
0.003	0.247	0	***0.775***	0	0	0	***1***	0
0.005	0.381	0.003	***0.695***	0	0	0	***1***	0
0.01	0.482	0.269	***0.634***	0	0	0	***1***	0
0.011	0.491	0.293	***0.629***	0.037	0	0	***1***	0
0.013	***0.502***	0.322	***0.622***	0.094	0	0	***1***	0
0.015	***0.515***	0.358	***0.614***	0.164	0	0	***1***	0
0.025	***0.542***	0.429	***0.598***	0.305	0	0	***1***	0
0.05	***0.562***	0.482	***0.586***	0.411	0	0	***1***	0
0.1	***0.572***	***0.509***	***0.58***	0.463	0	0	***1***	0
0.3	***0.579***	***0.526***	***0.576***	0.499	0	0	***1***	0
0.5	***0.58***	***0.53***	***0.575***	***0.506***	0	0	***1***	0
1	***0.581***	***0.533***	***0.574***	***0.511***	0	0	***1***	0
2.5	***0.582***	***0.534***	***0.574***	***0.514***	0	0	***1***	0
5	***0.582***	***0.535***	***0.574***	***0.515***	0.164	0	***0.773***	0
10	***0.582***	***0.535***	***0.574***	***0.516***	0.412	0	***0.667***	0.284
15	***0.582***	***0.535***	***0.574***	***0.516***	0.472	0	***0.635***	0.368
20	***0.582***	***0.535***	***0.574***	***0.516***	***0.5***	0	***0.62***	0.407
40	0.488	0.374	***0.574***	***0.516***	***0.542***	0	***0.597***	0.462
80	0.244	0.187	***0.574***	***0.516***	***0.562***	0	***0.585***	0.489

*Note: PS -U.S. Producers, PR - U.S. Processors, CS - U.S. Consumers; the highlighted slots indicate early detection is a dominant or preferred strategy.

For U.S. consumers:

- Results indicate that early detection is a good option for disease control for risk neutral (RAP=0) to risk averse (RAP>0) decision making in both models. EV modeling results show that early detection is a dominant strategy as the RAP is between 0 and 0.001, while Unified modeling suggests that early detection is the only selected strategy for usage as the RAP is between 0 and 2.5. The optimal proportion outcome suggests a mixed strategy that includes both early detection and late detection starting when the RAP is equal to or greater than 0.0015 in the EV modeling case and 5 in the Unified modeling case, respectively. However, early detection has greater proportion and remains a preferred strategy in both modeling cases.

For U.S. processors:

- Early detection strategy is not a better choice for U.S. processors in the EV modeling runs as the RAP is between 0 and 0.05. However, early detection becomes a preferred strategy as its optimal proportion is greater than the proportion of the late detection strategy when the RAP is 0.1 or higher. However, early detection does not offer a better option for U.S. processors in the Unified modeling result.

For U.S. producers:

- Early detection strategy can be a good choice in both modeling runs. However, the switch RAP points in both modeling outcomes are very different. In the EV modeling case, early detection becomes a preferred strategy as RAP is equal to or greater than 0.013; in the Unified modeling case, the preference is the late detection strategy instead. The preference switches from late detection to a mixed strategy only when RAP is equal to or greater than 5. Early detection has the same or greater proportion in the optimal portfolio selection and becomes a preferred strategy as RAC rises up to 20 or higher.

For overall U.S. welfare:

- Early detection can be a preferred option to choose. EV modeling outcome indicates that its optimal proportion is equal to or greater than the proportion of the late detection strategy as the RAP is equal to or greater than 0.5. However, in the Unified modeling result, early detection can never become a preferred strategy even though the RAC reaches to a very high level.

4.2.3. Results for Adequate Vaccination as a Mitigation Strategy

The results are shown in Table 15. Major findings in both EV modeling and Unified modeling results are summarized as follows.

For U.S. consumers:

- Adequate vaccination provides a good option for disease control for risk neutral (RAP=0) to risk averse (RAP>0) decision making for U.S. consumers in both models. EV modeling results show adequate vaccination is a dominant strategy as the RAP is between 0 and 0.0003, while Unified modeling suggests that adequate vaccination is the only selected strategy for usage as the RAP is between 0 and 0.015. The optimal proportion outcome suggests a mixed strategy that includes both adequate vaccination and inadequate vaccination starting when the RAP is equal to or greater than 0.0003 in the EV modeling case and 0.025 in the Unified modeling case, respectively. However, adequate vaccination has greater proportion and remains a preferred strategy in both modeling cases.

Table 15: Optimal Proportion Usage for Adequate Vaccine

RAP	**EV Model**				**Unified Model**			
	PS	**PR**	**CS**	**Total**	**PS**	**PR**	**CS**	**Total**
0	0	0	***1***	0	0	0	***1***	0
0.0003	0	0	***0.533***	0	0	0	***1***	0
0.0005	0	0	***0.525***	0	0	0	***1***	0
0.0008	0.105	0	***0.522***	0	0	0	***1***	0
0.001	0.213	0	***0.521***	0	0	0	***1***	0
0.0015	0.32	0	***0.519***	0	0	0	***1***	0
0.002	0.373	0	***0.519***	0	0	0	***1***	0
0.003	0.427	0	***0.518***	0	0	0	***1***	0
0.005	0.47	0.073	***0.518***	0	0	0	***1***	0
0.01	***0.502***	0.263	***0.517***	0.037	0	0	***1***	0
0.011	***0.505***	0.28	***0.517***	0.079	0	0	***1***	0
0.013	***0.509***	0.301	***0.517***	0.13	0	0	***1***	0
0.015	***0.513***	0.326	***0.517***	0.191	0	0	***1***	0
0.025	***0.521***	0.376	***0.517***	0.315	0	0	***0.823***	0
0.05	***0.528***	0.414	***0.517***	0.407	0	0	***0.649***	0
0.1	***0.531***	0.433	***0.517***	0.453	0	0	***0.581***	0
0.3	***0.533***	0.446	***0.517***	0.484	0	0	***0.538***	0
0.5	***0.534***	0.449	***0.517***	0.49	0	0	***0.53***	0
1	***0.534***	0.45	***0.517***	0.495	0	0	***0.523***	0
2.5	***0.534***	0.452	***0.517***	0.498	0.297	0	***0.519***	0
5	***0.534***	0.452	***0.517***	0.499	0.425	0.284	***0.518***	0
10	***0.534***	0.452	***0.517***	0.499	0.48	0.373	***0.517***	0.293
15	***0.534***	0.452	***0.517***	0.499	0.499	0.4	***0.517***	0.367
20	***0.534***	0.452	***0.517***	0.499	***0.508***	0.413	***0.517***	0.401
40	***0.417***	0.289	***0.517***	0.499	***0.521***	0.433	***0.517***	0.451
80	***0.209***	0.144	***0.517***	***0.5***	***0.528***	0.433	***0.517***	0.475

*Note: PS -U.S. Producers, PR - U.S. Processors, CS - U.S. Consumers; the highlighted slots indicate adequate vaccination is a dominant or preferred strategy.

For U.S. processors:

- The adequate vaccination strategy does not offer a better choice for U.S. processors in both modeling results. Adequate vaccination has a proportion in an optimal mixed strategy solution as the RAP is equal to or greater than 0.005 in the EV modeling results. In the Unified modeling results, a mixed strategy happens only when the RAP is equal to or greater than 5. The proportion of the adequate vaccination strategy is always smaller than the proportion of inadequate vaccination in both modeling results. Therefore, the adequate vaccination strategy is not in the preference for U.S. processors.

For U.S. producers:

- The adequate vaccination strategy can be a good choice for U.S. producers in both modeling runs. However, the switch RAP points in both modeling outcomes are very different. In the EV modeling case, adequate vaccination becomes a preferred strategy as RAP is equal to or greater than 0.01; however, in the Unified modeling case, adequate vaccination is preferred only when there is a decision maker whose RAP level is equal to or greater than 20.

For overall U.S. welfare:

- Adequate vaccination becomes a preferred strategy in the EV modeling results only when the RAP is equal to or greater than 80, while it has a share of optimal usage as the RAP is equal to or greater than 0.005. In the Unified modeling results, adequate vaccination has the proportion of optimal usage as the RAC is equal to or greater than 5, and it never becomes a preferred strategy.

4.2.4. Results for Enhanced Surveillance as a Mitigation Strategy

The results for the enhanced surveillance as a mitigation strategy are shown in Table 16. Major findings in both EV modeling and Unified modeling results are summarized as follows.

For U.S. consumers:

- The enhanced surveillance strategy is a good option for U.S. consumers to invest within the range from risk neutral (RAC=0) to risk averse (RAC>0) in both modeling results. Enhanced strategy is the only preferred strategy when the RAP is between 0 and 0.0003 in the EV modeling results and the RAP is between 0 and 0.5 in the Unified modeling. Even though a mixed strategy solution exists at a higher RAP level, enhanced surveillance still gives a better outcome for U.S. consumers.

For U.S. processors:

- The enhanced surveillance strategy does not offer a better choice for U.S. processors in both the EV modeling and Unified modeling results. Enhanced surveillance has a proportion in an optimal mixed strategy solution as the RAP is equal to or greater than 0.005 in the EV modeling results. In the Unified modeling results, a mixed strategy exists only when the RAP is equal to or greater than 2.5. The proportion of enhanced surveillance strategy is always smaller than the proportion of regular surveillance in both modeling results. Generally, U.S. processors do not prefer this enhanced surveillance strategy in both of the modeling results.

For U.S. producers:

- Enhanced surveillance is a preferred option when the RAP is equal to or greater than 0.015 in the EV modeling results. In the Unified modeling, the preference switches from regular surveillance to enhanced surveillance when the RAP is equal to or greater than 20.

For overall U.S. welfare:

- Enhanced surveillance becomes a preferred strategy as its usage proportion in the optimal solution is equal to or greater than the proportion of regular surveillance in the EV modeling results as the RAP is equal to or greater than 5. In the Unified modeling results, enhanced surveillance does not become a preferred strategy because regular surveillance always has a greater usage proportion in all RAP ranges between 0 and 80.

Table 16: Optimal Proportion Usage for Enhanced Surveillance

RAP	EV Model				Unified Model			
	PS	**PR**	**CS**	**Total**	**PS**	**PR**	**CS**	**Total**
0	0	0	***1***	0	0	0	***1***	0
0.0003	0	0	***1***	0	0	0	***1***	0
0.0005	0	0	***1***	0	0	0	***1***	0
0.0008	0	0	***0.847***	0	0	0	***1***	0
0.001	0	0	***0.767***	0	0	0	***1***	0
0.0015	0.158	0	***0.687***	0	0	0	***1***	0
0.002	0.254	0	***0.647***	0	0	0	***1***	0
0.003	0.35	0	***0.607***	0	0	0	***1***	0
0.005	0.427	0.025	***0.575***	0	0	0	***1***	0
0.01	0.484	0.246	***0.551***	0.028	0	0	***1***	0
0.011	0.489	0.266	***0.548***	0.071	0	0	***1***	0
0.013	0.496	0.29	***0.546***	0.122	0	0	***1***	0
0.015	***0.503***	0.319	***0.543***	0.186	0	0	***1***	0
0.025	***0.519***	0.378	***0.536***	0.312	0	0	***1***	0
0.05	***0.53***	0.422	***0.531***	0.406	0	0	***1***	0
0.1	***0.536***	0.444	***0.529***	0.454	0	0	***1***	0
0.3	***0.54***	0.459	***0.527***	0.485	0	0	***1***	0
0.5	***0.541***	0.462	***0.527***	0.492	0	0	***1***	0
1	***0.541***	0.464	***0.527***	0.496	0	0	***0.883***	0
2.5	***0.541***	0.465	***0.527***	0.499	0.206	0.069	***0.646***	0
5	***0.542***	0.466	***0.527***	***0.5***	0.396	0.299	***0.585***	0.178
10	***0.542***	0.466	***0.527***	***0.501***	0.471	0.386	***0.556***	0.355
15	***0.542***	0.466	***0.527***	***0.501***	0.495	0.413	***0.546***	0.405
20	***0.542***	0.381	***0.527***	***0.501***	***0.506***	0.426	***0.541***	0.43
40	***0.393***	0.191	***0.527***	***0.501***	***0.524***	0.446	***0.534***	0.466
80	***0.196***	0.095	***0.527***	***0.501***	***0.533***	0.456	***0.53***	0.483

*Note: PS -U.S. Producers, PR - U.S. Processors, CS - U.S. Consumers; the highlighted slots indicate enhanced surveillance is a dominant or preferred strategy.

4.3. Summary

Through the two risk portfolio models, we find that preference for control strategies depends on risk attitude. For total U.S. welfare, adequate vaccination gains a greater share as with larger RAPs. In the Unified modeling, early detection and adequate vaccination increase as the RAP reaches a high level. However, additional information arises when other parties are considered.

Early detection proves to be preferable for U.S. consumers. The EV optimal portfolio solutions show that early detection brings benefits for U.S. processors and U.S. producers as RAP rises. However, in the Unified modeling result this takes a high RAP.

In the adequate vaccination strategy analysis shows that it benefits U.S. consumers, but does not give U.S. processors a better outcome. Adequate vaccination provides a better choice for U.S. producers as the RAP rises in the EV modeling solution, but it is only preferred with a high RAP in the Unified modeling framework.

Enhanced surveillance is preferred for U.S. consumers. For U.S. processors, enhanced surveillance does not give a better risk/return outcome. U.S. producers switch their preference from regular surveillance to enhanced surveillance as their RAP rises.

5. CONCLUSIONS, FUTURE RESEARCH, AND LIMITATIONS

5.1. Summary of Major Findings

In this dissertation, I examined the desirability of using three major mitigation strategies under a simulated FMD outbreak originating in the Texas High Plains. This was done using conventional cost benefit, welfare analysis and risk analysis. The welfare results come from an epidemic- economic analysis utilizing an agricultural sector model (ASM) operating over the results of the epidemiologic model (AusSpread). The analysis yields project the impact of possible outbreaks on animal slaughter, U.S. consumers' welfare, U.S. processors' welfare, U.S. producers' welfare, and overall U.S. welfare.

The main findings from this work are:

- Current literature suggests that early detection may be the most economically acceptable mitigation strategy. In this study, we have found that it is not preferable under risk neutrality, but becomes preferable as the decision maker becomes more risk averse (e.g., with a higher RAP).
- Current literature suggests that the adequate vaccine availability strategy may not be very cost effective. We also find that this vaccine availability strategy is never economic under expected value maximization but can become so under risk aversion. U.S. consumers are the main welfare beneficiary from the usage of this strategy, but U.S. producers suffer a large average welfare loss. The risk portfolio modeling shows that adequate vaccination reduces risk for U.S. consumers, but not for U.S. processors. For U.S. producers and overall U.S. welfare, adequate vaccination becomes preferred as the RAP rises.

- Enhanced surveillance measures are generally not preferred in the stochastic dominance comparison, but are preferred in the risk portfolio model as the RAP rises. The risk modeling results indicate that enhanced surveillance could help both U.S. consumers and producers in risk management.
- We find that U.S. consumers are the major beneficiary group from any of the three mitigation strategies, while U.S. producers outside the study area generally suffer a greater loss. A comprehensive compensation scheme might need to be developed to overcome those distributional differences with the corresponded welfare change estimates in this study.
- Risk is found to be an important factor indecision making. A number of mitigation strategies become more acceptable when risk management is considered.
- The results we have found above show implications for policy makers. It is important to examine vulnerability and possible mitigation strategies for a number of disease vulnerabilities. From an economic welfare analysis, the results from such evaluations can identify both absolute and distributional welfare results across different parties in the society. A compensation program could be established on the basis of that welfare evaluation in order to improve biosecurity strategy performance.

5.2. Limitations

Limitations of this study are associated with the treatment of correlation, case study specificity, and reliance on one epidemic model with limited cases.

- Identification of the desirability of possible strategies can be complicated by the experimental design used in the epidemic model simulations. The alternative design for the three mitigation strategies improved my ability to identify the effects and further efforts along that line may well be in order.

- Case study specificity is another limitation because the effort is concentrated in the Texas High Plains, but other regions may respond differently, and thus the results are not generalizable.
- Reliance on one epidemic model might also restrict the generalization of the findings in this study.

5.3. Future Research

More future research can be done in several ways:

- A two-stage *stochastic programming with recourse* study could be done to examine the decisions made stage by stage with alternative strategies pursued as the outbreak proceeds and consideration of any a priori costs that may be encountered,. In the first stage, the cattle production and fixed cost investment would be determined before an FMD outbreak. Then cattle production, disease management effort, production and market prices depend on whether a FMD outbreak occurs or not, and are reflected in the second stage.
- A case study on the UK outbreak could be conducted to investigate th risk attitudes for decision makers.
- A trade analysis with the framework of the two-stage stochastic programming could be further accomplished to examine the implications of meat trading bans.
- The study suffers from limitations in the use of a single epidemic model, a limited

set of mitigation strategies, and case study region specificity. The work could be extended to use more models over a wider geographic area with more strategies evaluated.

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