IDENTIFYING, QUANTIFYING, AND FORTIFYING THE RISK OF THE US CULL SOW MARKETING CHANNEL, THROUGH THE USE OF ANALYTICS

BY

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DISSERTATION

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ABSTRACT

Plagued by endemic disease and under the constant threat of novel pathogen introduction, potential losses in the profitability of the U.S. swine industry from disease are staggering. As a result, the industry has continued to place a spotlight on identifying, quantifying, and fortifying potential routes of pathogen entry into farms. While the industry has made great strides regarding the threat that supplies, animals, feed, vehicles, and aerosols pose to pathogen spread, research regarding numerous high-risk avenues remain uncultivated. Gaps within the collective knowledge of the industry regarding the threat of animal markets, namely the cull sow marketing channel, still exist.

The cull sow marketing channel moves 3.2 million animals annually. This significant segment of the industry poses an extensive threat to farms nationwide. The movement of animals within this market channel allows pathogens to spread within the channel and back to farms through the various indirect connections with transport vechicles and facilities. The complexity of these movements and the extended time animals spend within the channel after leaving the farm and before harvest creates an efficient means for untraced pathogen dissemination throughout the industry. These results suggest further quantification of the transmission potential of the cull sow marketing channel is necessary to prepare the swine industry for a novel pathogen introduction.

Regulators have proposed to limit the risk of slaughter market channels during a disease outbreak through the standstill of movements either regionally or nationally. While intuitively reasonable, the impact of a standstill on trade patterns and pathogen dissemination potential is

unquantified. Implementing an augmented gravity model facilitates the quantification of effects that a standstill may have on trade patterns based on the population size and standstill imposition location. The trade variation induced by the closure of or standstill around individual processing facilities (slaughter plants) increases the potential indirect contact between sows within the market and various farm populations. These models suggest that identification of infected farms prior to animal shipment is essential before the implemention of a regionalized standstill if the spread of a pathogen within the U.S. is to be limited.

The tools for syndromic surveillance within sow farms are limited. Available mechanisms, derived and adapted from industrial engineering and originally intended to improve physical manufacturing processes, are based on detecting increased variation levels induced by changes in the production process. Due to biological and process implementation variation, the inherent variability of swine production severely limits their effectiveness. The analytical robustness of machine learning can potentially combat the limitations imposed by a highly variable system. The development of a machine learning tool to monitor unexpected reproductive failure within a single farm identifies the introduction of a novel Porcine Reproductive and Respiratory Syndrome virus (PRRSv) approximately two weeks before diagnostic confirmation, which was initiated by human observation of clinical signs. This tool identifies production changes within a farm 2.5 weeks before the previously described EWMA method. While further validation is required, this machine learning tool may serve as an efficient means to quickly and accurately detect production disruptions, commonly disease.

This work is the first to identify, quantify, and fortify the risk posed by the cull sow marketing channel. While much information is still unknown, these studies increase the base knowledge of the industry regarding this significant sector. These results will allow regulators and producers alike to make better decisions in ensuring a secure pork supply as continual evaluation of such a dynamic system is needed to ensure a consensus about the risk and potential avenues of mitigation for this marketing network.

To my grandparents,

my biggest supporters in life

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CHAPTER 1: GENERAL INTRODUCTION

1.1 INTRODUCTION

Disease is the most extensive negative influence on productivity and profitability within the swine industry. (Bevins et al., 2018; Haden et al., 2012) Plagued by endemic diseases and under the constant threat of novel pathogen introduction, potential losses in profitability for the U.S. swine industry are staggering. (Holtkamp et al., 2013; Schulz & Tonsor, 2015) Endemic diseases such as porcine respiratory and reproductive syndrome virus (PRRSv), porcine epidemic diarrhea virus (PEDV), and influenza A virus (IAV) are estimated to cost the industry 640, 400, and 300 million dollars per year respectively. (Bevins et al., 2018; Haden et al., 2012; Holtkamp et al., 2013) While significant, the financial impact of endemic disease pales in comparison to the potential damage caused by an introduction and dissemination of a foreign animal disease such as African swine fever virus (ASFv) or foot and mouth disease (FMD). (Carriquiry et al., 2020; Ekboir et al., 2002) While these diseases impact the health and production of swine, an introduction in the US industry would result in a temporary cessation of foreign exports. These exports compose upwards of $7 billion (United States Department of Agriculture, 2012) of all annual swine sales. Such a disruption could lead to market collapse and financial ruin for many U.S. swine producers as the value of pork dimishes immediately.

Fortunately, the introduction of such a disease possessing the potential to damage both production efficiency and export markets has not occurred within the United States within recent history. (United States Government Accountability Office, 2019) However, novel diseases with similar clinical pictures have recently appeared within the swine industry. (Zhang et al., 2018) Senecavirus type A (SVA) of the Picornaviradae family (the same family as FMD) was first identified within the United States in 2002 but is believed to have enteredthe country as early as 1988. (Amass et al., 2004; Knowles et al., 2006) The clinical signs of SVA are indistinguishable from FMD and other vesicle-producing diseases, causing the mandated reporting of the disease within the United States. (California Department of Food and Agriculture, 2020) While the industry had previously diagnosed SVA, case numbers remained relatively low.(Zhang et al., 2018) However, during the summer of 2015, a significant spike in the number of cases occurred. (Hause et al., 2016) Antemortem and postmortem inspection of animals at terminal processing facilities identified a substantial proportion of these cases. While SVA was present in high numbers (Hause et al., 2016) disease traceback from terminal market cases was generally ineffective. Traceback routinely found origin farms free of SVA, even if an animal from the premise had a positive test for SVA within the marketing channel. Unfortunately, the basis for the increase in the number of cases and transmission routes remains poorly understood. This lack of understanding has fueled growing concerns (Lichoti et al., 2016; Maes et al., 2018; Sassu et al., 2018; Zhang et al., 2018) about gaps in the knowledge and preparedness of the indsutry for all routes of pathogen transmission and dissemination.

The industry realized these fears when PEDv, a virus novel to the U.S. swine herd at the time of its introduction, spread rapidly through the industry. (Bowman et al., 2015) First identified in May of 2013 (Stevenson et al., 2013), PEDv quickly spread across the United States, causing the death of 8 million pigs within the first year. (Mole, 2013; Stevenson et al., 2013) Because of its significant impact, the loss of nearly $1.4 billion industry-wide (Schulz & Tonsor, 2015), numerous research dollars have been dedicated to identifying and understanding its most likely transmission routes. While no one primary contributor has been pinpointed as the cause of PEDv's dissemination throughout the industry, ongoing research continues to garner a greater understanding as to illuminate the numerous routes that pathogens may spread.

Unfortunately, while research has made great strides, many untraced or unexplored routes of transmission still exist. With the ongoing risk of FAD introduction, the U.S. swine industry continues to place a spotlight on identifying, quantifying, and fortifying these potential routes to thwart the entry of a devastating pathogen into farms. (Amaku et al., 2015; S. A. Dee et al., 2004; S. A. Dee, Batista, et al., 2006; Eisenlöffel et al., 2019; Lowe et al., 2014) The following literature review investigates the numerous pathogen introduction and dissemination pathways that have been studied and fortified and attempts to indentify potential gaps in the literature. While pathways such as supplies, animals, feed, vehicles, and aerosols (Amaku et al., 2015; S. A. Dee et al., 2004; S. A. Dee, Batista, et al., 2006; Eisenlöffel et al., 2019; Lowe et al., 2014; VanderWaal et al., 2018) have been explored, research regarding numerous high-risk avenues remain uncultivated.

1.2 LITERATURE REVIEW

1.2.1 The Risk of Supply Entry

Producers commonly view entry or movement of supplies into a farm as a primary cause of disease transmission. While the relative risk of supplies arriving at a farm from distributors is mostly unknown, the percentage of boxes contaminated during shipment, the risk of shared tools, and semen are well documented. (Amass et al., 1999; Levis & Baker, 2011; Silva et al., 2018) Research has shown that the introduction of semen into farms can act as a means of transmission for PRRSv, PEDv, SVA, and many more potentially harmful pathogens. (Gallien et al., 2018; Vannucii, 2015; Yaeger et al., 1993) The conceivable threat that the entry of supplies poses has initiated a rise in research articles over the last several years.

Much of the work has focused on fortifying farms from the potential risk during inanimate item entry. Various routes of disinfection remain the staple of many biosecurity programs and have become the subject of many investigations. (Kordas et al., 2020; Leuck et al., 2020; Pieper et al., 2020; Ruston et al., 2019, 2020; Schultz et al., 2020) Research suggests that exposure to UV-C, chemical disinfectant, or extended times and temperatures may eliminate supply entry risk. (Dee et al., 2006; Leuck et al., 2020; Pieper et al., 2020; Schultz et al., 2020) While the success of these disinfection methods under farm conditions is debateable, all methods produce varying levels of risk reduction by decreasing pathogen load. So, while the relative risk of supply entry is largely unknown, implementing these methods may reduce the risk of such a hypothetical pathogen introduction.

1.2.2 Pathogen Spread Through the Movement of Animals

The contact between infected and susceptible animals remains one of the most consistent means of introducing and spreading pathogens to naïve herds. (Amaku et al., 2015; Blair & Lowe, 2019a; Lentz et al., 2016) This placement of infected animals into a naïve herd may occur due to the complexity of movements required by modern intensive farming practices. With the continual movement of replacement breeding females (gilts), newly weaned pigs, and growing pigs within a production system, the chance of transferring disease via animal movement exists. Every animal movement possesses the potential to move pathogens along with it. (Lentz et al., 2016; Moon et al., 2019) Because of this, producers have implemented management practices such as all-in all-out pig flow, closed herd (internal multiplication of replacement breeding females), and test/quarantine strategies to mitigate this risk. (Baker, 1987; Torremorell et al., 2002) While these practices are effective, surveillance remains the primary pillar of prevention. (Engle, 2003; Snelson, 2010) Because of the complex movements within these systems, the disease status of a herd or production system is of the utmost importance when attempting to limit susceptible and infected interactions. (Engle, 2003)

1.2.3 Aerosol Pathogen Transmission

Researchers have investigated aerosol pathogen transmission between pigs and barns in dense animal regions of the United States as a potential source of risk. (Amass et al., 1999; Corzo et al., 2013; Desrosiers, 2011) For example, PRRSv, PEDv, and influenza, and other small viral particles can move within wind currents and potentially spread disease. (Cho et al., 2007; Corzo et al., 2013; Kim et al., 2017) PRRSv has a documented potential to move up to 10.2 km (Cho et al., 2007; S. Dee et al., 2005, 2009; Otake et al., 2010) with wind currents, depending on the specific strain. (Cho et al., 2007) IAV can travel as far as 2.1 km, (Corzo et al., 2013) while PEDv can travel much greater distances of as far as 10 miles downwind of an infected farm. (Kim et al., 2017) While some of these viruses are known to travel varying distances, research quantifying the viral infectivity of these particles is inconsistent. (Dee et al., 2009; Otake et al., 2010)

Regardless of the information yet to be uncovered about the potential of aerosol transmission, the threat still exists. Due to this, some producers have resorted to placing filters at the air inlets of barns. Researchers have since demonstrated that this practice may decrease or eliminate viral detection at inlets. (Dee et al., 2005; Dee et al., 2006; Eisenlöffel et al., 2019) While further quantification of this risk is still needed, the addition of filters at the inlet may significantly reduce the risk.

1.2.4 Introduction of Pathogens in Feed and Feed Ingredients

The introduction of feed and feed ingredients into farms pose a risk as various pathogens can harbor in feed for extended periods. (Dee et al., 2016) In conjunction with studies satisfying

Koch's postulate by infecting pigs through the consumption of contaminated feed (Dee et al., 2014), feed is a well-documented pathway for disseminating pathogens. Because of this risk, various researchers have attempted to understand the risk of feed harboring pathogens. (Jones et al., 2020) One of the biggest fears regarding feed is the possibility of introducing a novel pathogen through the importation of feed ingredients from an infected country. One study modeling the trans-pacific shipment of feed and feed ingredients observed that pathogens such as SVA, FMDv, and ASFv were stable in most feed ingredients for up to 37 days. (Stoian et al., 2020) However, many common swine pathogens also can survive in at least one feed ingredient over that period.

Numerous techniques exist to minimize the potential of feed-based pathogen transmission. One method is to remove high-risk ingredients from diets. (Jones et al., 2020) At the same time, other mitigation strategies include the mandated storage of ingredients in bins before animal consumption. (Dee et al., 2019) Research has shown that soybean meal storage for at least 78 days before use is likely to inactivate the pathogen within its ingredients. (Dee et al., 2019) Feed additives may also potentially mitigate the risk of viral infection through the consumption of feed ingredients. The addition of formaldehyde increased the degradation of PEDv within contaminated feed. (Cochrane et al., 2016) So, while the threat of pathogen introduction through the movement and consumption of feed is real and present, multiple avenues exist to effectively eliminate this risk to swine farms.

1.2.5 Mechanical Transmission of Pathogens Through Vehicles

Not only can feed and animals introduce and disseminate disease, but the vehicles used to transport these items can also. Several retrospective studies investigating the role of animal transportation have indicted transport vehicles as the source of the pathogen. (McCluskey et al., 2016; Porphyre et al., 2020; Thompson, 1999) Observations of shared connections between infected and naïve herds have revealed that trucks are a likely link. Researchers have followed up these observations with inquiries regarding the risk of contamination of trailers and the minimum viral load within a trailer needed to infect swine during transport. Lowe et al. (2014) show that the act of unloading swine at a processing terminal processing facility can contaminate that trailer. The study reveals that for every trailer arriving positive, 0.7 additional trailers leave contaminated. (Lowe et al., 2017) Other research has shown that pigs within a trailer contaminated with as little as 10^3 TCID50 of PRRSv can infect swine within as little as two hours of contact. (Dee et al., 2004) Combining the findings of these two projects suggests that animal movement on contaminated trailers may exacerbate disease spread through indirect contact between farms. When these trailers are shared, as some terminal market trailers are, these indirect contacts between farms have been shown to increase by over 50%. (Porphyre et al., 2020) Research has also implicated shared contact of vehicle tires between premises as a potential route of mechanical transmission of pathogens. (Thompson, 1999) It is because of this that the disinfection of vehicles and trailers have become a common practice amongst swine producers to reduce the risk of pathogen transmission. (Patterson et al., 2011)

1.3 REVIEW OF THE CULL SOW MARKET LITERATURE

The US swine industry is the third largest in the world generating of 27.1 billion pounds of pork per year, equating to approximately 34 billion dollars of product. (Knight, 2022) This production is the result of an industry wide population of 72.2 million swine composed of 66.1 million market hogs and 6.1 million breeding animals. (Hamer, 2016) The swine population within the US is not centered in one location but instead spread across several US states such as

Iowa, North Carolina, Minnesota and Illinois, with inventories of 20.2, 8.7, 7.95 and 5.1 million head respectively. (Hamer, 2016)

When thinking about pork production people commonly think about the primary pork production chain, the lean hog market. Responsible for 94% of pork production within the US (Knight, 2022), this market is relatively understood as when swine leave grow finish farms after reaching a desired weight and are moved by trailer directly to slaughter. While concerns regarding welfare and deteriorating animal condition exist during transport in this market, (McGee et al., 2016; Rioja-Lang et al., 2019) the expedient movement from a limited number of sources eases a lot of fears. (Blair & Lowe, 2019a) However, the segment often forgotten about is the contributor of the other 6% of pork production, the cull sow market. (Knight, 2022)

A cull sow is a breeding female that has reached the end of its reproductive life cycle and is removed from the sow farm. (Fogsgaard et al., 2018) Approximately 50%, or 3.1 million animals, are culled from the US breeding population each year. (Blair & Lowe, 2019a) While only a small fraction of total pork production, this salvage slaughter network creates tremendous value to the swine industry as it generates value from discarded animals and is an important source of revenue generated by sow farms annually. (Gruhot, 2017)

The size of the cull sow marketing channel is not the only thing differentiating it from the lean hog market. USDA reports suggest that over 95% of the lean hog market pigs are sold directly by the producer to the slaughter plant. (Blair & Lowe, 2019a) This type of business arrangement allows for movement of lean hogs directly from the farm to the slaughter plant. Conversely, the sows are sold through more traditional marketing channels where intermediaries purchase sows at local markets, regroup sows according to size and type from multiple sources, and resell the animals to slaughter plants. (Sutherland, n.d.) Despite the increasing size and integration of the industry, the traditional market structure has remained since sow farms do not cull enough animals to make full trailer loads of sows at routine intervals to minimize the cost of transportation to slaughter.

This traditional market structure is composed of three main types of facilities that are interconnected by movements within this channel. Sows begin their journey at a sow farm from which they are culled. They are then sent to a collection point where market intermediaries purchase sows in small batches from farms to fill orders to slaughter plants (the final point in the network). Cull sows from farms across the US ultimately are moved in a select number of collection points and then consolidated into just 17 different federally inspected cull sow slaughter plants. (Blair & Lowe, 2019a)

1.3.1 Reasons for culling

The cull sow marketing network is composed of animals that have been removed from the breeding herd. While the exact reason for herd removal varies, ultimately the decision to cull is made when the animal's current or expected future performance is assumed to decrease drastically. (Anil et al., 2005; Dagorn & Aumaitre, 1979; Grandin, 2016; Zhao et al., 2015) Lack of performance is the failure of a sow to conceive a litter, gestate a litter to term or raise and wean a litter of piglets. Industry average suggests that sows should produce approximately 2.3 litters a year with approximately 10.4 piglets weaned per litter, therefore producing 23.7 pigs each year. (PigCHAMP, 2021) When this production falls off and a sow is neither gestating nor lactating, the cost of maintenance of the sow quickly begins to cut into her profitability and replacement by a more productive breeding female, a gilt, is economically the most logical move. (Gruhot, 2017) The cost of these non-productive days for the sow equates to 1.3 times the cost of feed, thus farms try to limit the number of these days for the sow. (Fitzgerald et al., 2008)

For that reason if an event occurs that is a result of poor performance or suggest poor future performance, the sow is culled and replaced by a new breeding animal known as a gilt.

Culling can be the result of age-related reproductive changes, disease, or injury. Researchers have spent time looking into the main causes of removal of sows from sow farms. (Anil et al., 2005; Dagorn & Aumaitre, 1979; Grandin, 2016; Zhao et al., 2015) A survey of lesions at two midwestern US facilities found that sows have rear heel lesions 67.5% of the time and front foot heel lesions 32.9% of the time making them the most common lesion found. Shoulder abrasions (12.5%), acyclic ovaries (9.0%), and cystic ovaries (6.3%) were found commonly within sows as well. (Knauer et al., 2007) Another study (Wang et al., 2019) found that in sows in farms in southwest China reproductive disease and lameness were the most common cause of culling, while Zhao found that on farms in southern China that reproductive disorders followed by lameness and old age were the most common reasons. (Zhao et al., 2015) While the most common assumed reason of culling differs slightly between studies, both lameness and reproductive disorders commonly lead the reasons for culling in all studies. Interestingly, while the recorded reasons for culling in these studies were lameness and reproductive disorder, another study by Knauer found that the culling code(the recorded reason for culling) was inaccurate 23% of the time when compared to postmortem inspection. (Knauer et al., n.d.)

1.3.2 Post culling considerations on farm

Once the animal is marked for culling, the sow rarely leaves the farm immediately. Because the number of sows culled daily is relatively small, sows are typically held on farm until shipment to the collection point can be made. (Blair & Lowe, 2019a; Fitzgerald et al., 2008) These extra days on the sow farm for the cull sows increase the farm’s cost and decrease the sows’s body condition leads to potential animal welfare concerns.

The holding sows from the time the decicion to cull until she is removed from the farm results in costs assocated with feeding that do not result in an increase in the amout of weight sold. (Fitzgerald et al., 2008) Sowsthat were recently lactating are held prior to culling to allow the udder to regress and cease milk prodcution to aviod a reduction in value of up to 5% when compared to non-lactating sows. (Fitzgerald & Stalder, 1999) While holding times are unavoidable on many farms, an economic analysis looking into the cost of feeding cull sows to increase body weight found that feeding culls between 1996 and 2005 was only justified when feed was extremely cheap and no to little labor was used. (Fitzgerald et al., 2008) Another industry article stressed that on top of feed cost, increased feeding/holding times equate to potential increases in mortality and loss of revenue for the farm. (Fitzgerald & Stalder, 1999) The author of the article suggested that sows that are ill, lame, or extremely thin made poor candidates for extended holding times. (Fitzgerald & Stalder, 1999) Both of these articles suggest that from an economic point of view, extended holding times on farms of cull sows are likely unfruitful, unless farms can feed well conditioned sows extremely cheap feed.

Concerns regarding the sow’s welfare is an unintended consequence of holding animals on the farm prior to shipment. Herskin found that on farm mixing of cull sows prior to transport can decrease transport fitness as quickly as 24 hours after mixing. (Herskin et al., 2020) Another study that examined the spread of Salmonella enterica within cull sows through preharvest transportation and holding practices found significant increases of the pathogen in sows at the time of slaughter. (Larsen et al., 2003) This may suggest that like Salmonella, other pathogens can move between cull sows as they are held for extended periods of time on farm. With the potential disease spread within a population of animals that have pre-existing conditions such as lameness, increased holding times become a welfare concern as sows remain untreated and their condition deteriorates. (Grandin, 2016; Herskin et al., 2017, 2020)

1.3.3 The purpose of collection points

Within the marketing network, when sows are removed from the breeding farm, they typically move to a collection point. Historically collection points serve as a location to sort and mix sows with sows from other breeding herds to fill specfic orders of indivdual slaughter facilities based on thier prefefed specfications. (Sutherland, n.d.) Sows are transported from the collection point to either another collection point or directly to a slaughter facility. Cleaning and disinfection of the collection point is uncommon due to their design and construction, and many have animals present from previous deliveries when new sows arrive.(Blair & Lowe, 2019a) Cull sows remain at the collection point until being sorted into a load heading to a terminal collection point. While this holding time should be no longer than 120hr (the maximum under federal law) anecdotal reports exist of individual sows remaining in this segment of the industry for up to 30 days. (Blair & Lowe, 2019a)

1.3.4 Holding of Cull Sows in collection points

Holding of cull sows within collection points does not differ drastically from holding of sows on farm. A recent study by McGee found that 16% of sows arriving at collection point were fatigued and 5% were lame. (McGee et al., 2016) This study evaluated 7105 animals on arrival at the collection point with three dead on arrival. Of all of the animals, 119 sows were separated due to poor condition of which 79 where eventually euthanized prior to shipment to the slaughter facility.(McGee et al., 2016) Another study investigated the number of fatigued animals by evaluating the behavior of cull sows in abattoirs prior to shipment ffinding an increase in aggressive behavior and a decrease in animals laying down. (Herskin et al., 2017) The stress of mixing and a decrease in fitness due to holding creates serious welfare concerns with extended holding times in collection points. Unfortunately, this segment of the cull sow marketing network is poorly understood and little is known about its impact on the condition of cull sows, disease spread and welfare.

1.3.5 The movement of cull sows

Because of the current structure of the swine industry, rarely can an animal live its life without moving on a trailer at least once. Various types of vehicles are used for transportation ranging from single-deck trailers to three-deck punch-hole trailers. Three-deck trailers are popular as they can transport large loads up to 230 slaughter weight pigs at once. (Rioja-Lang et al., 2019) However, while the tools used to move swine are common and understood, the impact of transport of sows in not.

1.3.6 Disease dissemination and transmission from transport

One concern when moving batches of cull sows from collection points to other collection points or slaughter facilities is the risk of disease dissemination and transmission back to sow farms. Several retrospective studies investigating the role of animal transportation have indicted transport vehicles. (McCluskey et al., 2016; Porphyre et al., 2020;Thompson, 1999) Researchers have investigated the risk of trailer contamination and the minimum viral load within a trailer needed to infect swine during transport. Lowe et al. show that unloading swine at a processing terminal processing facility has the potential to contaminate that trailer.(Lowe et al., 2014) Other research has shown that pigs within a trailer contaminated with as little as 10^3 TCID50 of PRRSv can infect swine within as little as two hours of contact.(Dee et al., 2004) This is futher supported by the work of Larsen et al who found that Salmonella enterica prevalence increased from 3% to 41% after holding and transportation to the slaughter facility. (Larsen et al., 2003) When these trailers are shared, as some terminal market trailers are, these indirect contacts between farms have been shown to increase by over 50%. (Porphyre et al., 2020) T

Transportation of mixed batches of cull sows may allow for disease to move between animals within the marketing channel and potentially back to sow farms through a fomite such as a imporperly disinfected trailer.

1.3.7 Impact of transportation on a cull sow's fitness

As previously discussed, disease dissemnation in the cull sow population undergoing transport is a real possibility and clearly impacts the health and wellbeing of the animals within this marketing segment. However, the impact of transport on a sow's wellbeing and fitness is deeper than infectious disease. Thodburg et al. suggest that cull sows may be more vulernable to decreases in condition than any other class of swine. (Thodberg et al., 2019) In the study, clincal scores regarding lesions and gait were taken before and after transport. After transport of a median time of 232 minutes, over half of the clincal scores significantly increased, bringing to light the stress of travel on this group of animals. (Thodberg et al., 2019) Another study by Peterson et al. found that not only was transport stressful but the temperature at the time of travel influenced the risk of death in transit or just prior to slaughter. (Peterson et al., 2017) When temperatures were between 85 and 92F the risk of death was 1.93 times greater than that of the risk of an average temperature between 54 to 79F. (Peterson et al., 2017) While it is clear that transportation impacts the health and well-being of cull sows, authors (Peterson et al., 2017; Thodberg et al., 2019) suggest that further research into risk factors such as distance traveled are needed to fully understand a cull sows fitness for transport to the slaughter facility.

1.3.8 Impact arriving at the slaughter facility on cull sows

While there are numerous lean hog slaughter facilities who generally have homogenous specifications for incomming animals within the cull sow marketing network, there are only a few cull sow specific slaughter facilites which tend to have more diversity of specfications for incomming animals. (Grandin, 2016) This leads to longer transport times and more mixing of animals prior to arrival at slaughter facilites. Both increase the time for disease to spread and impact the health of sows within the market channel. A recent case of Streptococcus equi within cull sows at a slaughter facility resulted in a 30-40% mortality over 5-7 days. (Sitthicharoenchai et al., 2020) Because of the large number of sows effected and the incubation period for Streptococcus, spread of the disease prior to arrival must have occured. Additionally, epidemiological investigations looking into incidences of Senacavirus A in breeding herds found that cull sow removal and interaction with this marketing network was the third highest risk interaction for disease introduction. (Baker et al., 2017) Because of the structure of the market and limited number of slaughter facilities, massive consolidation of animals from numerous farms to a few locations allows for increased disease prevalence within the market channel. (Grandin, 2016)

Numerous investigations have focused on the risk of disease, economics, health and well-being of animals within the cull sow market, but further work is requried to fully explore the risk of pahthgoen desimination and to the public's perception of the industry's mangment of animal welfare. (Grandin, 2016) Within all segments of the cull sow market, threats to animal health and well-being exist and while reasearch brings alot of these areas to light, no solutions have been researched to address the concerns brought foward. This is potentially due to the lack of transparancy and collective industry knowledge regarding the impact of standards and solutions within this market segement to the overall business continuity of the market and swine industy. Because of this, more data needs to be generated to increase the transparancy of the practices within this segment and further studies need to investigate the impact changes to the marke have on economics and animal health and well-being.

1.4 STATEMENT OF PROBLEM

The extensive work of the industry reveals the multiple potential avenues for pathogen dissemination and introduction to farms. This collective body of research has generated significant amounts of knowledge. It is responsible for vast improvements in the way decisions are made as the industry prepares for and attempts to limit the risk of introducing and transmitting a novel pathogen. However, gaps within the collective knowledge of the industry regarding all potential avenues still exist. This thesis will address the problem regarding the identification, quantification, and fortification of the U.S. cull sow marketing network.

The role of animal markets, namely the cull sow marketing channel, has been implicated as a route of disease spread and introduction in several epidemiological investigations. (McCluskey et al., 2016) These studies show that contact between farms and the cull sow marketing network is a high-risk interaction. While known and accepted throughout the industry as real, large amounts of information remain unknown regarding how and why animals move through the marketing channel. With nearly 3.2 million cull sows (Hamer, 2016) moving through the channel annually, the threat this unmanaged population poses, through indirect contacts with sow farms, remains too large to remain uninvestigated.

1.5 PURPOSE OF THE BODY OF WORK

The purpose of this dissertation is to generate an exhaustive body of knowledge regarding the cull sow marketing network in the U.S.. This work will convey the potential for pathogen transmission within the system, the dynamic risk it poses to swine breeding herds, and how current intervention strategies alter transmission patterns while offering an innovative method to limit this potential threat. This work includes data from sows that have traveled through the marketing channel and data collected from operational sow farms. This work uses the information collected to develop a comprehensive description of cull sow movements. Investigating these movements allows for a better understanding of sow movement dynamics when influenced by policy change or disruptions. Finally, this work develops an advanced analytical tool to minimize the risk posed by this marketing channel fortifying the swine industry. This dissertation is the only body of work exploring the threat that the U.S. cull marketing channel poses. This research provides the swine industry with a more extensive body of information to aid in better decisions as we attempt to ensure a secure pork supply.

1.6 IMPORTANCE OF THE BODY OF WORK

The spread of endemic diseases and introduction of novel diseases remain a serious threat to the U.S. swine industry. (Bevins et al., 2018; Haden et al., 2012; Holtkamp et al., 2013) The impact that diseases can have is two-fold, damaging both the health and profitability of individual swine farms and the entire industry, due to reductions in exports to foreign markets. Because of this understanding, the potential routes of disease spread and introduction is of utmost importance.

Research has explored many of these various routes, yet little knowledge exists regarding the risk posed by the marketing of cull sows. While the industry thinks of the cull sow marketing network as a high-risk contact within the daily operation of sow farms, no concrete evidence is available to quantify the risk. This body of work takes the first look at the marketing channel and how policy or other external changes may change that network. Moreover, it demonstrates how advanced analytics can mitigate the risk that the cull sow marketing network poses to the viability of the U.S. pork supply.

This research provides the industry with information necessary to re-evaluate current strategic and tactical plans during a FAD introduction. The information presented will also allow farm owners to make informed decisions regarding the protection of their assets from potential threats. This research focuses on disease impacts to the industry as a whole, but the results also have implications for animal welfare. A collaborative reevaluation of the U.S. cull sow marketing channel is needed to minimize the total risk of the industry, ensuring a functional and profitable system for all parties. The importance of this work lies in its capacity to delve into a known risk point and uncover the unknown magnitude of potential risk posed by the U.S. cull sow marketing network.

1.7 THEORETICAL FRAMEWORK

An investigation into how and why sows move within the marketing channel has become increasingly important with the undetected movement of disease through the swine industry. A retrospective epidemiological evaluation revealed that in PRRSv positive farms, the act of marketing sows was the second most likely event resulting in the pathogen introduction. (Haden et al., 2012) Initial theories about the introduction of PEDv into Canada implicated market trailers returning from the U.S. processing facilities as a potential source. (Pasma et al., 2016) While these risks are primarily due to indirect contact between farms and collection points or terminal processing facilities, the threat still exists. Moreover, if biosecurity practices concerning truck washing or animal loading fail, the risk posed to a farm is greatly exacerbated.

Researchers have investigated the potential of livestock transport trailers in harboring potential infectious doses of a virus. Research has shown that swine on a trailer contaminated with as little as 10^3 TCID50 of PEDV are likely to become infected after two hours of contact (Dee et al., 2004) Further studies then worked to quantify the risk of a trailer becoming contaminated. (Lowe et al., 2014) The study found that for every ten trailers testing PEDv positive at the arrival time, seven additional trailers became contaminated while unloading swine. (Lowe et al., 2014) Due to the possibility of contaminating and possessing the ability to harbor enough pathogen to infect swine, the movement of animals on trailers within the marketing channel can result in pathogen dissemination within the swine industry. With the possibility of pathogen spread, combined with current industry structure resulting in the massive consolidation of animals into a limited number of processing facilities (Blair & Lowe, 2019a), numerous unknown indirect connections exist between large segments of the U.S. swine industry. (Blair & Lowe, 2019a)

1.8 RESEARCH QUESTIONS

In an attempt to complete a thorough investigation to identify, quantify, and fortify the risk of the U.S. cull sow marketing network, this research focuses on three direct research questions to narrow the scope of this work. The research questions of these studies are:

RQ1: How are sows currently moving from the farm of origin to their terminal processing facility? What potential risks do these movements create for the U.S. swine industry?

RQ2: What are the effects of policy or outside influences on sow movement dynamics within this market channel?

RQ3: How can the risks of the cull sow marketing network be mitigated?

As there are little previous work and available data regarding the cull sow marketing network, the quantification of risk posed at an individual farm level is currently impossible. Thus, as the first study within this subject area, this research focuses on the broader conceptual identification of risk points within the network and how industry changes can impact these points. This work supplies general knowledge about the potential risk that this market poses and sets the stage for further research into each of those individual areas.

1.9 OVERVIEW OF RESEARCH DESIGN

This research is composed of three individual studies to answer the questions raised above. The initial research focuses on generating and describing a sizeable multi-terminal processing facility dataset created through a USDA-APHIS-VS partnership. Then, through the application of numerous descriptive statistics, knowledge is generated regarding the movement of sows within the marketing channel, followed by a discussion of how these results apply to the risk of pathogen dissemination through the cull sow marketing channel.

The second study builds off of the data collected in the previous work. In this study, an augmented gravity model, a method commonly used to understand trade policy, is applied to understand the complicated relationship between terminal processing facilities and a state's swine population. The model was employed to understand the effects of stop movement orders within a region on the cull sow marketing channel. Additional data collected during terminal processing facility closures due to the SARS-CoV2 pandemic during quarter two of 2020 allowed for evaluating the model using disruption data.

The final study utilized the conclusions of the previous work, that early disease detection was the critical control point in the current cull sow marketing network, to develop an enhanced syndromic surveillance tool. A novel method of syndromic surveillance, a production-disruption indicator that utilizes machine learning techniques, was created. Multiple farms of both high and conventional health status with well-defined clinical disease outbreaks were employed to validate the tool.

Overall, the completion of this body of work was through the collaboration of federal agency and swine producers. Their willingness to share data and provide guidance has shaped these projects into what they are today. The willingness of all parties to participate within this investigation of this complex and poorly understood subject matter has allowed for an impactful body of work that will enable the industry to prepare and reassess the potential introduction of a devastating pathogen.

1.10 DEFINITION OF TERMS

The following terms are defined to help the reader understand the context of each in these studies.

Cull Sow: A mature female animal removed from the herd because she has reached the end of her reproductive life. Removal can be the result of one of many potential reasons. The most common of these reasons include a lack of performance, illness, and injury. (Dagorn & Aumaitre, 1979) When removed, these animals are marketed to a terminal processing facility then converted into meat products for human consumption. (Dagorn & Aumaitre, 1979)

Farm of origin: The farm where a sow spends her productive life. The location is assumed to be the same location as where the sow was before culling. These farms correlate to the premise I.D. present on theI.D. tag of sows.

Terminal processing facility: This is the final point within the cull sow marketing network. It is responsible for slaughter and processing sows into pork products. Currently, 17 terminal processing facilities dominate this market with > 90% of the daily slaughter capacity. (*U.S. Packing Sector - Pork Checkoff*, n.d.)

Collection Point: A local premise that purchases cull sows from swine producers. An individual farm often chooses it because of convenience within the marketing network. At the collection point, the small batches from each farm are combined into full trailer loads to move onto the terminal processing facility.

1.11 ASSUMPTIONS AND LIMITATIONS

The central assumption of this work is that the data of the federal brucellosis surveillance program is of the highest quality. While this may be difficult to quantify, USDA-APHIS collects this data in the same randomized fashion used to surveil the national swineherd for brucellosis. Furthermore, the random sample used within these studies does not differ significantly from the complete dataset used within the pilot project, attesting to the validity of these samples.

This data represents the most extensive dataset ever collected to research the potential risks of the swine marketing network. These data represent seven different terminal processing facilities, representing 33% of the daily slaughter capacity. This body of works assumes that the samples collected from these seven facilities accurately represent the entire industry. While the possibility of bias exists, the risk present in this significant portion of the sector still conveys risk to the rest of the industry. The United States also uses this same sampling for the surveillance of brucellosis and pseudorabies. For these reasons, this body of work assumes that these datasets adequately and accurately represent the industry sector as a whole.

1.12 SUMMARY

This body of work sought to understand the potential risk of disease acquisition and transmission within the cull sow marketing network. It also proposes a potential tool that may be effective at minimizing these risks. While a wide variety of research investigating the possible avenues of disease introduction or transmission exist, there is a knowledge gap regarding information about the animal markets within the United States, namely the cull sow marketing network. The results of this body of work serve as the base for policy, management, and preparedness discussions and decisions for all parties within the swine industry nationwide.

Four more chapters follow: chapter II is a descriptive look at the current state of the U.S. cull sow marketing network, chapter III discusses the use of an augmented gravity model as a means of understanding the dynamics and impacts of policy or disruptions on sow movements, chapter

IV deals with the application of machine learning in the syndromic surveillance within a sow farm and how such a tool may impact risk, and chapter V provides a general conclusion to all chapters previous. This chapter interprets the findings of each chapter and discusses what it means to the swine industry as a whole.

CHAPTER 2: A DESCRIPTIVE EXPLORATION OF ANIMAL MOVEMENTS WITHIN THE UNITED STATES CULL SOW MARKETING NETWORK

2.1 ABSTRACT

More than 3.2 million cull sows enter the marketing channel annually in the U.S.. This combined with the limited number of federally inspected cull plants, each preferring to buy a specific type of sow, the channel experiences extensive commingling of sows from varying sources before harvest. This consolidation poses a threat to the U.S. swine industry, as diseases harbored across many different farms are now present at a few select locations, providing an opportunity for pathogens to replicate and spread throughout the marketing channel.

Premise identification tags (PIT) were collected with the help of the US Department of Agriculture's Animal and Plant Health Inspection Service-Veterinary Services Brucellosis Laboratory. Collection occurred for a total of 6 months. From each PIT the management/sow identification (ID), premises ID, state, facility, and slaughter date were recorded. Participating production systems identified the cull dates of individual sows from their system.

A total of 17,493 PITs were collected. This study collected PITs from 32 states and 1211 unique premises IDs. Facilities received sows from a median (IQR) of 9.5 (12.5) states and 71 (79.25) unique premises each week.

This chapter has appeared as an in part in 2 publications. The original citation is: Blair, B., & Lowe, J. (2019). Describing the cull sow market network in the US: A pilot project. *Preventive Veterinary Medicine*, *162*, 107–109. https://doi.org/10.1016/j.prevetmed.2018.11.005; Blair, B., & Lowe, J. (2022). A descriptive exploration of animal movements within the United States cull sow marketing network. *Journal of Swine Health and Production*, *30*(2), 72–78. https://doi.org/10.54846/jshap/1245

Sows traveled a median (IQR) distance of 472.7 (453.6) km with a maximum of 2812.8 km. A single premises delivered sows to 1, 2, or 3 or more slaughter facilities 59.7%, 33.4%, and 6.9%, respectively. Removal date from the farm of origin was available for 2886 (16.5%) individual sows. Of these, 66.1% were in the market channel for ≤ 3 days, 25% for 4 to 5 days, and 8.9% for > 5 days.

These data suggest movement between multiple collection points before harvest for sows with extended time in the channel because regulations prohibit sows from remaining at one location for more than 120 hours. While this data is not a complete view of the cull marketing channel, this is believed to be the most comprehensive review of the U.S. cull sow marketing channel to date. This data confirm previous work that a small, but significant number of sows move between collection points. These results suggest that the cull sow marketing channel provides an independent, but interconnected swine population that can maintain, expand, and transmit pathogens to the U.S. swine breeding herd. Control and elimination plans for the novel, transboundary, and foreign animal diseases should include this population.

2.2 INTRODUCTION

The threat of pathogen dissemination posed by the US cull sow market is one of the most significant knowledge gaps within the swine industry today. While the general purpose of the cull sow market is well understood by the industry, transparency (ie, current available data) of the movements that occur within the channel and the resulting risk of disease transmission is limited. With more than 3.2 million cull sows expected to enter the market channel annually (Hamer, 2016), uncontrolled management of this industry segment may lead to negative impacts on the health and production of both breeding and growing herds. (Blair & Lowe, 2019a) With significant concerns about foreign animal disease (FAD) introduction, the swine industry's limited comprehension of the potential for the cull sow marketing channel to both disseminate and serve as a reservoir for pathogens suggests further elucidation of those risks is needed as an essential part of US FAD preparedness.

The US cull sow market is structurally different than the lean hog market. A limited number of centrally located slaughter facilities (*U.S. Packing Sector - Pork Checkoff*, n.d.) are fed by a network of local collection points (buying stations) where sows are delivered from the farm. In contrast, the slaughter facilities for the lean hog market, the primary source of pork products in the United States, are predominantly located in pig dense regions resulting in > 95% of lean hogs moving directly from farm of origin to the slaughter facility. The structure of the cull sow marketing network results in the opposite effect where > 90% pass through an intermediary collection point before arriving at slaughter. (Blair & Lowe, 2019a) This structure promotes extensive commingling of sows as they move from the farm through buying stations to the slaughter facility.

Collection points located in sow dense regions allow farms to cull a small number of sows routinely while minimizing trucking cost. Frequently removing sows from the farm spares the added expense of holding sows until full truck load lots can be created and increased number of sows in inventory on the farm. The collection points serve to add value to these animals. Collection points facilitate the creation of truckload lots of a specific type of cull sow (weight, body condition) to meet the preferences of individual slaughter facilities. While complex, this market structure has benefited all parties involved, but drawbacks exist.

Within the United States, the welfare of cull sows has received little scientific attention, however, concerns regarding the fitness of animals at the time of transport have been raised. (Grandin, 2016) The pre-transport mixing of cull sows on farm can result in the clinical deterioration of sows in as little as 24 hours. (Thodberg et al., 2019) This deterioration is present in animals at the time of arrival at buying stations. Cull sows and boars comprised the majority of swine arriving fatigued, thin, and lame. (McGee et al., 2016) While there are still significant knowledge gaps regarding fitness during transport, the extended time that some cull sows remain within the marketing channel raises concerns that the current market structure may negatively impact the welfare of cull sows prior to harvest. (Blair & Lowe, 2019a)

The potential for pathogen dissemination though the cull sow marketing network is known but unquantified. The risk for pathogen dissemination originates from three factors: comingling sows from many sources, multiple movements from farm to harvest, and extended time in the market channel. Commingling of sows from many farms allows for uninfected sows from one farm to come in contact with pathogens from other farms in the market channel. The impact of transmission is increased during the movement of sows between multiple, nonterminal points in the marketing channel creating the opportunity for dissemination of disease across broad geographies. It has been estimated that up to 14% of all cull sows make 3 or more stops as they move between different collection points prior to slaughter. (Blair & Lowe, 2019a) The current cull sow marketing channel creates an "off-farm cull sow population" that can both transfer and serve as a reservoir population for pathogens.

While all the sows in the market channel are destined for slaughter, this reservoir population can serve as a source of pathogens for domestic swine herds. During the 2014 US porcine epidemic diarrhea virus (PEDV) outbreak, the lean hog network served as a means of expanding the outbreak when trailers were contaminated at the slaughter facility and returned back to production sites unwashed. (Lowe et al., 2014) The probability of contamination increased with both the temporal proximity of a trailer unloading after a contaminated trailer at the same dock and the viral load present at the slaughter facility. (Lowe et al., 2014) Even with the implementation of biosecurity practices, compliance failure is common at truck washes or during the loading or unloading of animals creating a route for pathogen introduction into the domestic swine industry. (Amass et al., 1999; Patterson et al., 2011)

The national scope, structure, and hypothesized complexity of the cull sow market creates a significant opportunity for pathogen transmission, including FADs throughout the US swine industry. (Blair & Lowe, 2019a) This study compiles data from a previously untapped source to generate a dataset capable of describing cull sow movements both spatially and temporally within the United States. By doing so, this study strives to provide a robust descriptive analysis of the US cull sow marketing network to date, serving as a reference to the swine industry in future endeavors.

2.3 MATERIALS AND METHODS

2.3.1 Data Collection

Data collection was in partnership with the USDA Animal and Plant Health Inspection Service-Veterinary Services (APHIS-VS) Brucellosis Laboratory located in Frankfort, Kentucky. The laboratory collected all PITs affiliated with samples submitted for brucellosis surveillance. (National Pork Board, n.d.) The samples represent sows randomly sampled from US slaughter facilities as part of the national brucellosis and pseudorabies monitoring program administered by USDA APHIS-VS.

Premises identification number tags serve as the traceability method for sows in the Swine Identification (ID) Plan established by the industry in 2004. (Celko, 2010) The industry compliance with the Swine ID Plan is high as PITs are present in greater than 90% of sows at the time of slaughter. (Blair & Lowe, 2019a) Samples collected by the laboratory originate from 7

US slaughter facilities. To maintain the confidentiality of the slaughter facilities, this study will refer to them as F1 through F7. Daily slaughter capacities of these slaughter facilities ranged from 20 to over 2800 pigs/day.

Collection of PITs occurred one week per month in May, June, and July of 2018 and February, March, and April of 2019. These dates were selected for ease of collection for the laboratory and to monitor movements in two different calendar quarters. For each PIT the management/sow ID, premises ID, state, facility, and slaughter date were recorded in a database. The geolocation for each unique premises ID was obtained using the premises verification tool from Pork Checkoff (National Pork Board, n.d.) which provides the street address of the farm and was visually confirmed and converted to geocoordinates in Google Maps.

For a subset of PITs, the date of removal from the farm of origin was obtained through the participation of 9 privately-owned swine production systems and 2 veterinary management companies. These systems have a collective one-time inventory of > 2.4 million sows representing more than 40% of the US swine breeding herd. Premises IDs for each production system were used to match the management ID to the farm removal date in their production record systems.

2.3.2 Data Analysis

The Euclidean distance between the farm of origin and the slaughter facility was calculated using the geospatial coordinates for each location. For each slaughter facility, the number of unique premises, the median distance traveled to the slaughter facility, and the number of states animals originated from were determined. For a subset of animals that originated at participating systems, the days in the slaughter market channel was defined as the difference between the farm removal date and the slaughter date. A box and whisker plot of distance traveled was created for each facility. In addition, dot plots of the number of weekly unique premises and states arriving to each facility were generated to elucidate any differences between facilities. All visualizations and statistics for this study were performed using R statistical software. (R Core Team, 2017)

2.4 RESULTS

A total of 17,493 individual PITs were collected, representing approximately 8.4% of the total number of sows slaughtered each week at the 7 slaughter facilities. These 7 facilities are responsible for 33% of the daily national cull sow slaughter. The collected data represents approximately 2.7% of the weekly national cull sow slaughter. The PITs represented 1211 unique premises and 32 states. Farm removal dates of 2886 individuals were recorded, representing 16.5% of all samples collected.

2.4.1 Description of Sows Present by Terminal Processing Facility

Sow PITs came from 7 different federally inspected slaughter facilities. The largest slaughter facility had a slaughter capacity of 2800 sows/day. (*U.S. Packing Sector - Pork Checkoff*, n.d.) The smallest slaughter facility capacity was believed to have been < 20 sows/day, as the surveillance sample submitted represented the entirety of their daily slaughter. In this study the slaughter facilities collected sows from a median (IQR) of 9.5 (12.5) states/day (Figure 2.1). Sows originated from a median (IQR) of 71 (79.25) premises/week (Figure 2.2).

The distance from farm of origin to slaughter facility for sows varied between facilities. Across all slaughter facilities, sows traveled a median (IQR) Euclidean distance of 472.7 (453.6) km (Figure 2.3). Sows entering F2 traveled the furthest with a median (IQR) of 706.2 (614.4) km while sows entering F6 traveled the least with a median (IQR) of 119.5 (173.1) km (Figure 2.4).

Some sows remained in the market channel for an extended time. Of the subset of 2886 sows from the seven study slaughter facilities, 66.1% remained in the marketing channel for 3 days, 25% for 4 to 5 days, and 8.9% for > 5 days. The median (IQR) time from removal to slaughter was found to be 3(3) days with a maximum of 40 days for 2 individuals.

2.4.2 Description of Premises

Of the 1211 premises in the dataset, 59.7% had cull sows arrive at a single slaughter facility. In comparison, 33.4% of the premises had animals arrive at two slaughter facilities and 6.9% of the farms were represented at three or more slaughter facilities across all tag collection dates.

2.5 CONCLUSION

This study is the first multiple slaughter facility dataset collected describing the US cull sow marketing network. With 17,493 individual PITs collected from sows representing 1211 unique farms, this dataset is nearly seven times as large as the previously published work. The size and temporal component of this dataset allows for exploration into why and how sows are moving within the marketing channel. These data should be used to facilitate improved policy and biosecurity decisions by the industry and regulators.

As previously hypothesized (Blair & Lowe, 2019a) and further supported by this work, the collection area for each slaughter facility is geographically vast and overlapping. The median distance between the farm of origin and terminal processing facility is 472.7 km, with 16% traveling more than 1000 km to reach their destination up to a maximum of 2812.8 km. This documents that sows consistently travel long distances. In addition to the distance traveled by sows, these are the first data to systemically describe the time animals spend within the cull sow marketing network. Some sows remain in the network for an extended amount of time, well beyond the incubation period of many important pathogens including foot-and-mouth disease, African swine fever, and classical swine fever. (Gabriel et al., 2011; Petrov et al., 2014; Stenfeldt et al., 2016) In combination with the routine mixing of sows, this time within the marketing network is poorly defined and untraced resulting in a dynamic population capable of maintaining pathogens independent of the national on-farm herd. The cull sow marketing network can be considered a dynamic, independent herd capable of acting as a reservoir population for pathogens and could facilitate undetected and unmonitored pathogen movement over great distances. The geographic basin of each slaughter facility is, for all practical purposes, nationwide creating connections between farms from disparate regions of the United States as farms from all regions provide animals to the cull sow marketing herd. Similarly, a study of the animal marketing system in the United Kingdom (Porphyre et al., 2020) found movements within the UK network increased the number of indirect connections between farms by 50%. Our data, further supported by the UK study, bring to light the potential dangers of this marketing network model.

The cull sow market is both complex and obscure. As previously hypothesized, up to 14% of sows have an extended period from farm removal to slaughter. This study supports that idea, with 8.9% of sows remaining in the marketing channel for greater than 5 days. Current US guidelines prohibit animals from being at a single location in the marketing channel for more than 120 hours. (US Governement, 2011) Assuming that market participants are compliant with federal law, sows in the channel for more than 5 days have been at multiple collection points in the network. In the case where animals were in the marketing channel for 40 days, animals would have been in 8 or more collection points prior to slaughter. In addition to significant disease dissemination concerns, there are animal welfare concerns. The extended time sows spend within the marketing channel may result in a reduced quality of life due to various factors. (Grandin, 2016; Thodberg et al., 2019)

In both this study and prior work (Blair & Lowe, 2019a), data was unable to be located that would facilitate tracking the movement of sows between their entry into the marketing network and the slaughter facility. Tracing animals from farm to slaughter is important because sows from a single farm may be sent to multiple slaughter facilities. In this limited but representative data set, greater than 40% of premises had animals identified at two or more slaughter facilities. These data are congruent with known market practices, specifically one of the greatest value creation actions of sorting sows at local collection points to meet the specific sow quality preferences of a slaughter facility.

The results of this study suggest that the characteristics of the US cull sow marketing network holds the potential to transmit disease in an undetected manner prior to arrival at a slaughter facility. The mixing and distribution of sows within the dynamic cull sow market population may result in pathogens being maintained and distributed across large geographic regions. The population within the network is poorly defined, not tracked, and not monitored. Because of the lack of measurement, there is no direct evidence of disease transmission within the network. However, Senecavirus A (SVA) infections detected in sows at harvest suggest that infections within the network are common and was further supported by an investigation within the North Carolina swine industry. (Hause et al., 2016) The discordance between farm status and individual sow status at harvest strongly suggests that infection occurred within the marketing channel.

While these data provide a meaningful snapshot of the US cull sow marketing network, they strongly suggest that comprehensive tracking and monitoring of animals in the cull sow marketing network is necessary. To achieve a comprehensive understanding of the network to facilitate the design of systematic mitigation strategies, capturing and maintaining records of individual sow movements within and between collection points is necessary. Ideally these data would be captured and maintained in a manner that would give regulators and the industry quick and easy access in the face of a novel disease outbreak to limit the impact of the cull sow marketing network on US herd health. The current structure of US cull sow marketing network warrants a robust reevaluation of biosecurity practices by the industry to ensure business continuity if an FAD is introduced or other novel pathogen emerges in the United States.

2.6 FIGURES

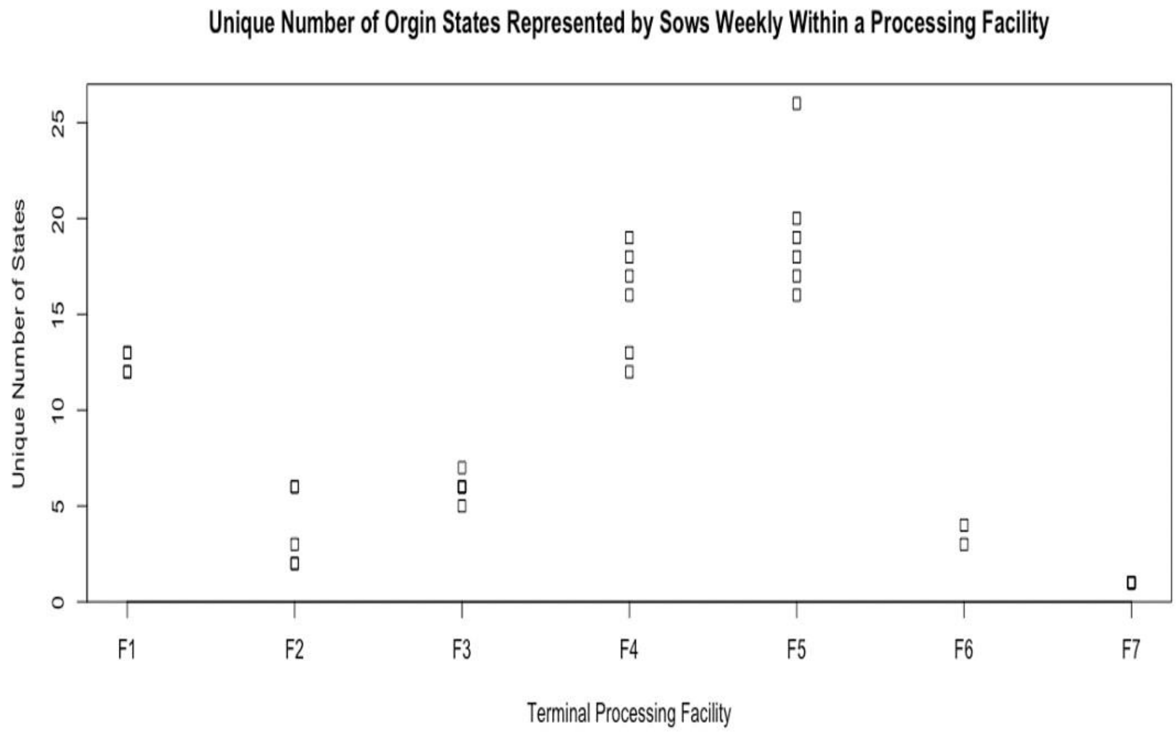

Figure 2.1 The number of unique states represented at the terminal processing facility weekly

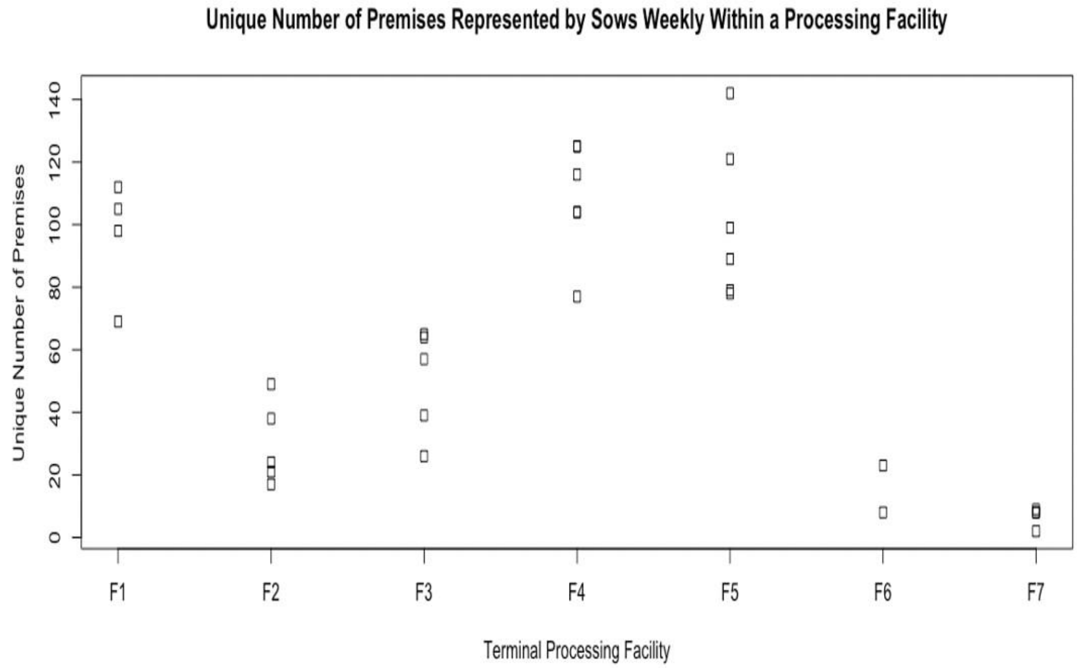

Figure 2.2. The unique number of premises represented by sows arriving to a terminal processing facility

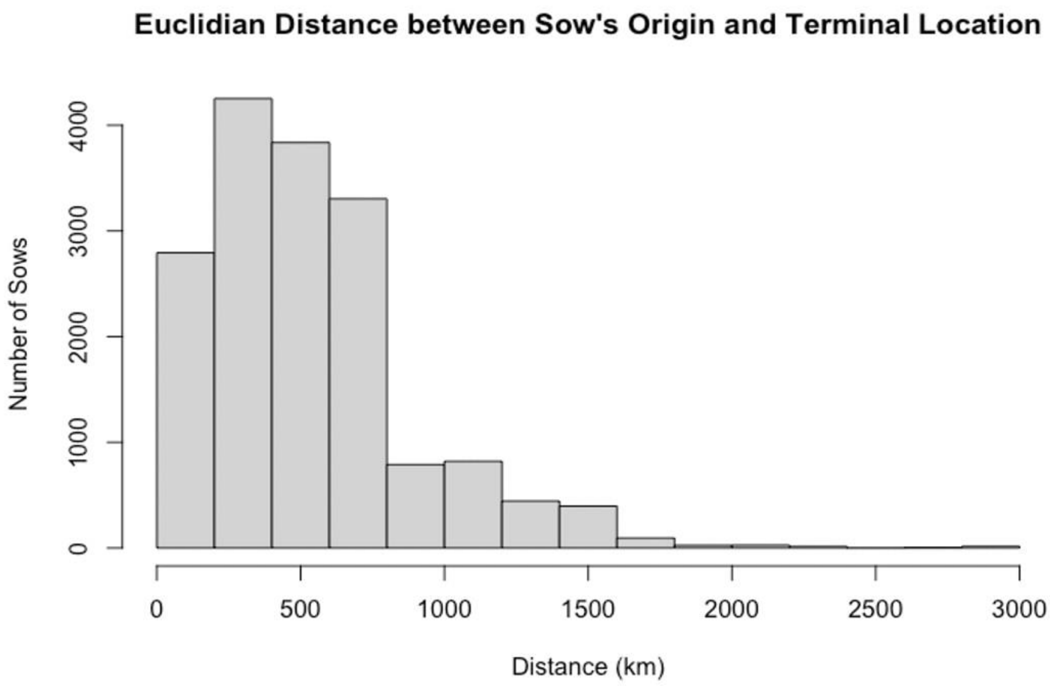

Figure 2.3. The distribution of the Euclidian distance between a sows' farm of orgin and terminal processing facility

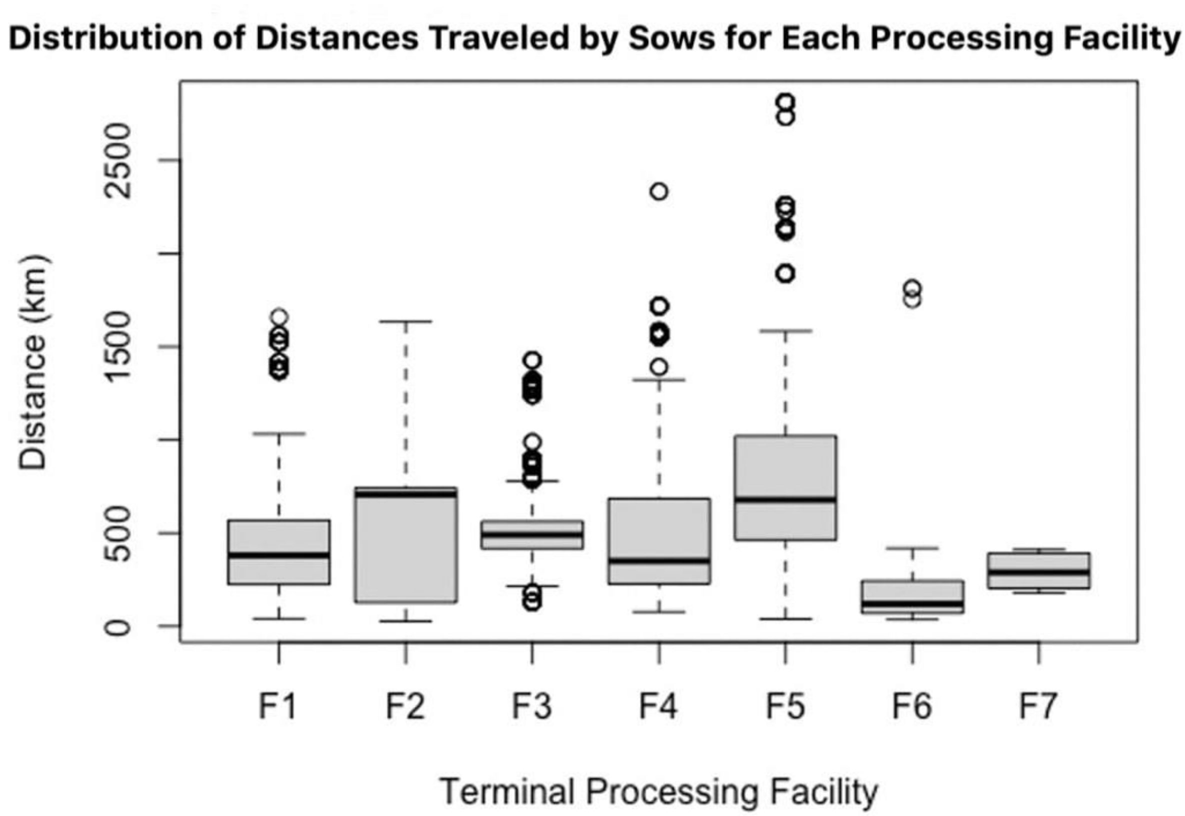

Figure 2.4. Box plots of the distance traveled by sow to each processing facility

CHAPTER 3: THE APPLICATION OF AN AUGMENTED GRAVITY MODEL TO MEASURE THE EFFECTS OF A REGIONALIZED STANDSTILL TO THE POTENTIAL RISK DISTRIBUTION OF THE US CULL SOW MARKET

3.1 ABSTRACT

The continuous threat of foreign animal disease (FAD) is real and present for the U.S. swine industry. Because of this, the industry has developed plans to ensure business continuity during a FAD outbreak. A core aspect of these plans is regional standstill orders of swine movements to prevent disease spread following a FAD introduction. Unfortunately, there is a dearth of information about the impact of such practices on animal movements throughout the remaining swine marketing channel. This study utilizes a simplified gravity model, to understand the effects of standstill orders on individual states. The effect of each closure on the established trade patterns is determined by monitoring changes in a PPML regression coefficients of the model. Model validation compared the predicted impact of the closure of a terminal processing facility against a real-life closure dataset collected during the SARS-CoV-2 pandemic. The analysis determined that both the population size and location of the closure affected the observed trade patterns. These findings suggest that using a regional stop movement order may complicate disease introduction preparation as each policy comes with its own potential outcome, shifting the geospatial distribution of area risk posed by these cull populations.

This chapter has appeared as an in part in 1 publications. The original citation is: Blair, B., & Lowe, J. (2022). The Application of an Augmented Gravity Model to Measure the Effects of a Regionalization of Potential Risk Distribution of the US Cull Sow Market. *Veterinary Sciences*, *9*(5). https://doi.org/10.3390/vetsci9050215.

3.2 INTRODUCTION

The size of the US swine industry, with more than six million breeding animals (Hamer, 2016), in conjunction with its diverse geographical distribution requires a complex set of movements to maintain the sustainability and continuity of the marketing channels. (Blair & Lowe, 2019b) The movement of cull sows (breeding females who are destined for slaughter) through the marketing channel and into the human food chain is exceptionally complex. (Blair & Lowe, 2021) Within the cull sow marketing channel, animals move from farms across the US and Canada to a limited number (17) of cull sow-specific slaughter facilities which are not geographically distributed proportionally to the location of the swine breeding herds. This requires a system where the mixing and movement of sows across the country is common. (Blair & Lowe, 2021) The cull sow system is different from the lean hog market (Sutherland, n.d.), the primary pork supply chain, where hogs move directly to terminal processing facilities, cull sows move through at least one or more additional points before slaughter. (Blair & Lowe, 2019b)

The cull sow marketing channel is composed of three unique components: farms of origin, collection points, and terminal processing facilities. (Sutherland, n.d.) The marketing channel's unique segment, intermediary collection points, exists for one reason, to generate additional value for the industry. Collection points continuously buy animals from farms, then sort sows by weight and body type to sell them to the proper slaughter facility based on preference. (Sutherland, n.d.) By allowing sow farms to remove small batches of cull animals at convenient times, collection points relieve the farm of the additional expense associated with retaining non-productive sows. (Abell, 2011; Fitzgerald et al., 2008)

Traditionally, the cull sow marketing channel was assumed to be transient, composed of a population of animals moving quickly from farm of origin to terminal processing facility. These assumed attributes were thought to have only a minor material impact on the amplification or transmission of disease within the US swine industry. However, recent disease outbreaks within the industry, such as PEDv (Huang et al., 2013) and Seneca Valley virus (Hause et al., 2016), have brought forward new questions regarding this marketing segment's role in disease transmission and dissemination. (Baker et al., 2017) During these outbreaks, spread within marketing populations and outward to the industry was observed (Baker et al., 2017), raising concerns regarding this marketing network's role in disease transmission.

Recent studies have hypothesized that this population is not transient, but instead a dynamic population capable of incubating and disseminating pathogens. (Blair & Lowe, 2021) This hypothesis is predicated partially on the extended time sows remain within the marketing channel. (Blair & Lowe, 2021) While this time varies, the median time spent within the marking channel is three days (Blair & Lowe, 2021), with more than 8.9% of sows remain within the market for more than five days prior to slaughter. (Blair & Lowe, 2021) Longer than the incubation period of many common swine diseases (Dixon et al., 2019; Moennig, 2000; Orsel et al., 2009), these extended interactions within the marketing population allows for pathogen amplification and transmission, allowing this population to serve as a disease reservoir for the entire industry. In addition to the extended transit times, the complexity of movements occurring within the marketing channel influences this population's inherent risk to the industry. (Blair & Lowe, 2021) The complexity of these movements generates an increase in the number of connections within the marketing channel and thus indirection connections between farms of vastly different regions. (Blair & Lowe, 2021) The act of selling into a marketing channel alone may increase the number of indirect connections to a farm by more than 50%. (Porphyre et al., 2020) Because these cull populations, associated with the terminal processing facilities, possess attributes common amongst all herds, a group of animals that interact for a period of time, they should be considered their own, independent herd. As such, these herds present risk to the industry just as any other swine herd would.

These herds, composed of cull animals, possess an associated disease status that impacts neighboring populations and the geographical region as the facility interacts with the industry. Populations, such as sow farms, are shown to significantly impact the disease risk of other swine populations within the same neighborhood or geographic vicinity. (Machado et al., 2019) The disease status of a sow farm's animal population was one of the significant predictors of disease outbreaks in neighboring farms. (Machado et al., 2019) Suppose this is true of all populations that interact with a region or population. In that case, this herd of cull sows likely influences the area disease risk both regional and nationally, depending on its interactions with the swine industry. These neighboring effects have been observed between herds with varying disease outbreaks, Classical Swine Fever, PEDV, and PRRSV. Because of this, understanding the interactions these terminal processing facilities associated herds have with the industry is of utmost importance when trying to mitigate the effects of these poorly managed cull populations.

While it can be assumed these herds, associated with terminal processing facilities, present area disease risk, the amount of risk posed by each is largely unknown and difficult to calculate. However, the geographical distribution of this risk, as defined by their interactions, is known and has been shown to remains relatively stagnant under normal market conditions. (Blair & Lowe, 2021) The consistency of this risk's distribution makes mitigation possible as disease traceback and targeted disease surveillance can be enacted. However, while currently stagnant, the impact of a disruption to the industry, such as foreign animal disease, policy change, or market disruptions, to these geospatial distributions remain largely unknown. Changes to this distribution of risk threaten the swine industry, as the complexity and the changing dynamic of the market channel would allow disease to move erratically through the US. These previously undescribed dynamics complicate preparations for a foreign animal disease introduction. Changing interactions may allow pathogens to spread across the industry in ways previously unobserved, making mitigation attempts impossible.

With the increasing threat of foreign animal disease introduction to the US swine industry, understanding these potential shifts of the market populations' geospatial risk distribution is of the utmost importance. This information may inform decisions regarding disease mitigation and control, ensuring the best outcome for the industry as a whole. As mentioned, the US swine industry has spent considerable effort safeguarding the country from ASF and preparing for its introduction. Across the globe, pork production has been devastated by African Swine Fever (ASF) and Foot and Mouth Disease (FMD). (Mathew & Menon, 2008; McLaws & Ribble, 2007; Rushton, 2012) The recent global outbreak of ASF was first identified in Georgia in 2009, spreading across Europe and eventually China by August 2018. (Ge et al., 2018) To combat this, the USDA released the "Disease Response Strategy African Swine Fever" in the spring of 2019 (Moon et al., 2019) to serve as strategic guidance in the event of an ASF outbreak. One of the critical pillars of response is the control and subsequent eradication of the disease. The goals of this process are three-fold:

1. Detect, control, and contain the disease in animals as quickly as possible;
2. Eradicate the disease using strategies that seek to stabilize animal agriculture, the food supply, and the economy and to protect public health and the environment;
3. Provide science- and risk-based approaches and systems to facilitate continuity of business for non-infected animals.

As stated in the report, "*Quarantine and movement control measures are fundamental to any ASF response effort*". (Moon et al., 2019) While a nationwide standstill on animal movements will ensure no disease transmission results, the effects of regionalized standstill orders are poorly understood. This is especially true concerning how a regionalized standstill will change the geospatial distribution of disease risk area posed by herds present within the cull sow marketing network. This study uses a simple gravitational model, a method commonly used within trade, to study the dynamic effects of regionalized stop movement practices. It will investigate how both known and unknown market influences on sow movements impact the distribution of area disease risk posed by these marketing populations.

Because the interactions within the cull sow marketing channel can be viewed as a form of trade, the use of the augmented gravity model makes sense when exploring system dynamics in the face of disruptions. Economists have long quantified dynamic trade patterns under the influence of behavior or policy through gravitational models. (Bajardi et al., 2011; De Benedictis & Vicarelli, 2005; Egger, 2001; Natale et al., 2009) Walter Isard first introduced the use of the augmented gravity theory in 1954 (Isard, 1954) as an empirical method to investigate the flow of commodities from different distances. While many doubted the theoretical justification for augmented gravity theory, its trade application continues to serve as an accurate method to understand the movement of goods.

As a standard method to study bilateral trade flows, researchers have implemented augmented gravity modeling for decades within international economics. (Battersby & Ewing, 2005; Carrère, 2006; De Benedictis & Vicarelli, 2005; Kucheryavyy & Rodríguez-clare, 2013; Özer, 2014) Traditionally studies have employed this method of econometric analysis to understand trade patterns. Within these models, weight is assigned based on the size of each parties' economy, while distances represent trade cost, commonly expressed as a combination of physical distance and obstacles to trade. The gravitational theory of trade assumes that the closer and more massive trade partners' economies are, the more trade between them. (Isard, 1954)

Many studies exist utilizing augmented gravity modeling to evaluate the effects of trade between two entities. One such study investigated the South Asian Free Trade Area (SAFTA) role and how it potentially impacts countries' exports. (Rahman et al., 2006) It found that while some countries, Pakistan and India, were expected to gain exports from joining the agreement, others, such as Sri Lanka, were not (Rahman et al., 2006). Another study empirically quantified the trade potential between India and 146 countries. (Batra, 2004) It found that the economy's size and cultural similarities impact bilateral trade. (Batra, 2004) It also proposed changes to policies allowing trade to double with China.

The application of the theory also includes animal movements. One such study focuses on the impact of EU-mandated country of origin labeling on Italy's cattle movement. (Natale et al., 2009) Through use of a gravity model it found that regions of the most extensive inventory are more likely to trade with each other, regardless of distance than those with small populations. (Natale et al., 2009) Researchers have also used augmented gravity modeling to assess the impact of disease outbreaks in the US on poultry and poultry product trade. (Thompson et al., 2019) Both studies show that the gravity model's use could quantify various impacts on an industry, such as disease, on bilateral trade.

While augmented gravity models have been used exhaustively for international and local trade agreements, their application to understanding animal marketing is limited and within swine nonexistent. While some work exists (Natale et al., 2009; Thompson et al., 2019), none have focused on movement within the US swine industry. This study implements the augmented gravity model to study the effects of regionalized standstills on animal movement in the cull sow marketing channel. Thus, the dynamic impact of policy changes on the geographical distribution of disease dissemination risk posed by the marketing channel.

3.3 MATERIALS AND METHODS

3.3.1 Data Collection

Data collection was in partnership with the USDA-APHIS-VS Federal Brucellosis Laboratory (Laboratory). This laboratory collected all premises identification number tags (PIN) (Celko, 2010) affiliated with samples submitted for surveillance of brucellosis, representing the sows randomly sampled from seven US terminal processing facilities as part of the national program for brucellosis and pseudorabies surveillance.

PIN currently serves as the traceability method of the “Swine ID Plan” established by the industry in 2004. The industry has a high PIN tag adoption rate, with PIN tags present in greater than 90% of sows at the time of slaughter. (Blair & Lowe, 2019b) Samples collected by APHIS originate from seven US processing facilities. This study refers to the terminal processing facilities as F1-F7 to protect the identity of the participating facilities.

PIN collection occurred over six weeks with collection one week per month in May, June, July of 2018, and February, March, April of 2019, with the recording of the management/sow ID, Premise ID, state, plant, and kill date from each PIN. Geolocations for Premise ID came from a pork checkoff premise lookup database allowing for the acquisition of the street address for each premise ID. Google Maps (*Google Maps*, 2019) was then used to confirm a swine facility at the corresponding street address and to convert the address into latitude and longitude coordinates.

From the 16 states with the largest sow populations, an annual cull population was estimated at 50% of the sow inventory, as reported by the National Agriculture Statistics Service in the national hogs and pigs report (Hamer, 2016). US pork checkoff reports provided capacity estimates for five of the seven terminal processing facilities. (*U.S. Packing Sector - Pork Checkoff*, n.d.) The capacities of two plants, F6 and F7, are unknown, resulting in their exclusion from the dataset. The geolocation for each state was denoted by the state's capitol, while the terminal processing facilities' geolocation reflects the business's physical location.

3.3.2 Mathematical description of the cull marketing network

The relationships that exist within the cull sow marketing network are complex and challenging to understand. Terminal processing facility populations attract sows from many states at varying rates. Describing this phenomenon through the use of analogies helps us make sense of such complex relationships. The use of gravitational theory is one such analogy. This analogy has long been used within trade and policy discussions to understand bilateral trade relationships between different countries:

$$F = G\,(M_1 \times M_2)/d$$

The above equation has been used to describe the force of attraction (gravity) one body has on another. It describes the complicated relationship, Force (F), that objects exert on each other as a function of the product of their masses (M1 and M2); this is inversely proportional to the distance between them (d) and the constraints of the system or universe represented by the gravitational constant (G). This equation also works intuitively to describe trade networks, as trade (X_{ij}) is dependent on the size of economies (Y_i, Y_j) and distance or trade cost between trading partners (t_{ij}), with C serving as a constant, as described in this simplified equation:

$$X_{ij} = C\,(Y_i\, Y_j)/t_{ij}$$

The equation was modified to improve the empirical application of this equation. Modifications allow variables to impact trade at varying degrees:

$$X_{ij} = C\,(Y_i^{b1}\,Y_j^{b2})/(t_{ij}^{b3})$$

This relationship is commonly represented empirically as:

$$\ln(X_{ij}) = C + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + e_{ij} \ldots.$$

This study uses this empirical equation combined with the data collected to understand the complicated relationship between a state's sow population and terminal processing facilities. For this study's simple gravity model, X_{ij} is equal to the total trade between a state and terminal processing facilities. Y_i and Y_j represent the economy's size or the weekly cull sow population or slaughter capacity for the states and terminal processing facilities, respectively. This model's trade cost (t_{ij}) represents the Euclidian distance between the state's capitol and terminal processing facilities and the reported price difference, between regions reported by the Daily Direct Prior Day Sow and Boar report (Agriculture Marketing Service, 2020):

$$\ln(Trade_{ij}) = C + b_1 \ln(Pop_i) + b_2 \ln(Pop_j) + b_3 \ln(Distance_{ij}) + b_4 \ln(Basis_{ij}) + e_{ij} \ldots.$$

Due to the multiple zero trade values, this study employs Poisson regression by pseudo maximum likelihood (PPML) to fit the linear model for b_1, b_2, b_3, and b_4 through the use of the gravity package (Wölwer et al., 2018) within R. (R Core Team, 2017)

Once the initial gravity model was complete, the potential trade index between each state and terminal processing facility was calculated for each week, as previously described. (Egger, 2001) The potential trade index is simply the proportion of actual to predicted trade. This is done by taking the observed trade frequency over the fitted trade frequency of the PPML model:

$$\text{Potential Trade Index} = \frac{\text{Trade}_{ij}}{\text{Trade}_{\hat{i}\hat{j}}}$$

$Trade_{ij}$ represents the observed trade between state and processing facility and $\widehat{Trade_{ij}}$ represents the fitted trade frequency.

Trade potential, or the frequency of trades that can still be made to maximize current trading conditions can then be calculated by multiplying the observed trade frequency by one minus the trade index. Trade potential acts as a metric of potential trade creation between entities. (De Benedictis & Vicarelli, 2005)

$$\text{Trade Potential} = \text{Trade}_{ij} \times (1 - \text{Potential Trade Index})$$

Trade Potential and Potential Trade Index values were calculated for each state-processing facility interaction.

3.3.3 Model Validation

Because this type of methodology has not previously been performed on swine trade networks, validation is key to further valid results. Disruptions within the cull sow marketing network resulted from the SARS-CoV-2 pandemic, allowing the opportunity to validate a model creation method by comparing observed data to theoretical simulation data after a terminal processing facility's closure (F1). Disruption trade observations were collected in the same manner as previously described, occurring during the first three weeks of May 2020.

To create the simulation of a single processing facility's closure, three weeks of data from the previous dataset were adjusted so that the trade to F1 was equal to zero. Then, by utilizing the previously calculated trade potential indices, reductions in demand were made. Reductions in trade were made equally amongst all relationships with a negative trade potential to account for an increase in supply or decrease in processing facility space. A PPML model, as previously described, then utilized both the observed disruption data and simulated data to generate the coefficient and standard error of each significant variable for comparison. Comparisons of the two models were made using Chow's test to determine if the models were significantly different statistically. Statistical difference was concluded if the p-value was less than 0.05.

3.3.4 Stop Movement Scenarios

Using the mathematical relationship previously described, the PPML model was subject to two stop-movement scenarios; a stop-movement of North Carolina and Missouri populations. For each scenario, the trade from the standstill population to processing facilities was set to zero. Then, utilizing the potential trade index, adjustments were made to trade between remaining populations and terminal processing facilities by equaling the increase in demand between available potential trade. The study then uses the PPML of each unique scenario to quantify the value of each significant coefficient. The North Carolina swine population's closure allows for the effects of a large population a great distance away from the centroid of the industry to be compared to a moderate-sized population near the centroid of the industry.

To better understand the impact of these model disruptions on the industry, heat maps of the 16 reported states were generated. A map showing the proportion of each state's population entering the terminal processing facility's population was then calculated by dividing the fitted outcome of the PPML model and each state's population. In addition, for both the Missouri and North Carolina scenarios, a heat map representing the percent change to these proportions was generated for each of the five terminal processing facilities. These graphs better allow the reader to understand the impact of shifting coefficients within the PPML.

3.4 RESULTS

3.4.1 Mathematical Description of the Cull Sow Marketing Network

The baseline empirical gravity model formed from the trade data collected between 2018 and 2019 fits all variable coefficients, with distance and populations remaining significant (Table

3.1). For the cull sow market during normal operating conditions, the distance between the terminal processing facility and state population, terminal processing capacity, state population all impact the observed trade (Table 3.1). A 1% increase in the distance between trade partners results in a decrease of 1.15% in trade, where increases in terminal processing facilities and state populations result in increased trade (Table 3.1).

Under normal marketing conditions the maximum potential trade index observed was 1.12 between Colorado and F4. This suggest that the opportunity F4 has increased demand of sows from Colorado. While the minimum index observed was −1.59 between Nebraska and F3, representing a surplus of sows in Nebraska to enter the F3 facility. To better compare the supply/demand situation between states and facilities, the proportion of each state's cull population entering the terminal processing facility population, as estimated by the fitted outcomes of the PPML, can be found in Figure 3.1.

3.4.2 Model Validation Results

The SARS-CoV-2 pandemic allowed for a unique insight into market dynamics in the wake of disruption. F1, a terminal processing facility within Kansas, closed for three weeks in May 2020. The closure of this terminal processing facility resulted in a mean increase of 4.66% of trade pattern variation. In comparison, the associated simulation based on the previous data resulted in a mean decrease in trade patterns of 1.02%.

3.4.3 Processing Facility Closure Scenario

The removal of 5500 sows weekly or the estimated cull sow capacity of F1, a terminal processing facility, allows for the validation of the model by comparing the real-life data set to the described disruption scenario creation method. The results of both models are present in Table 3.2.

The closure of the F1 processing facility decreased the impact of distance between the state population to terminal processing facilities. This impact increased by 33.7% and 22.4% for the simulation and actual data, respectively. A small impact was also observed within the terminal processing facility population's impact on trade, as both the real scenario and simulation decreased by 5.06% and 9.78%, respectively. Finally, the impact of the state's cull sow population on trade has decreased by 58.48% for the created simulation. The state population of cull sows falls out of the actual scenario's completed model as it is no longer significant.

A comparison of both models reveals that the generalized change in coefficients is similar. While the fitted coefficients differ slightly from each other, the direction of change is the same within all coefficients. For the two coefficients that remain significant within both models, they lie within the standard error of each. Chow's test also reveals that the regression models do not significantly differ with a *p*-value of 0.8396. This indicates that the gravity model of trade of the cull sow market is an adequate predictor of the impact of policy change or trade disruption.

3.4.4 North Carolina Scenario

With the removal of 450,000 sows annually or the estimated cull sow population of North Carolina, changes to trade within the cull sow marketing network result in a mean decrease of terminal processing facilities purchasing variation of 12.69% with the simulated data. The simulated reduction in trade variation causes changes in the variable coefficients. A slight decrease in the coefficient associated with distance and facility capacity is present (Table 3.1). These changes result in an 11.16% decrease in the impact of distance on trade (Table 3.1). The effect of a processing facility capacity on the number of trades increases, while the state population's impact decreased (Table 3.1) These results reveal that removing a large population a great distance from the center of the industry results in processing facilities purchasing animals close to their location, as seen with all terminal processing facilities (Figure 3.2).

Facilities with higher capacity also increase their activity as they try to buy sows to fill the standstill's demand gaps, as seen especially with F5 (Figure 3.2). However, the state population's size is less critical in determining potential trade partnerships in this scenario (Figure 3.2). Ultimately, during a disruption resulting in a loss of a major source of cull sows, large processing facilities must become more active in trying to fill the open spaces left by those removed animals. As a comparison between Figures 3.1 and 3.2 shows, large terminal processing facilities, like F5, increase trading with states geographically near regardless of size and seek out fewer sows from states at greater distances.

3.4.5 Missouri Scenario

With the removal of 235,000 sows annually or the estimated cull sow population of Missouri, changes to trade within the cull sow marketing network result in a mean decrease in terminal processing facilities purchasing variation of 30.03% with the simulated data. With the simulated reduction in trade variation, massive changes in variable coefficients are present. An increase of the coefficient associated with distance and facility capacity is present (Table 3.1). These changes result in a 32.44% increase in the impact of distance on trade (Table 3.1). The effect of processing facilities' capacity on the amount of trade decreased by 61.74%, while the state population's impact is no longer significant within the model (Table 3.1).

These results reveal that removing a moderate-sized population within the center of the industry results in a substantial impact on trade such as removing a large population. The difference in scenarios show that location is just as influential on trade dynamics as the shutdown population's size. As seen within Figure 3.3, the impact of distance from the terminal processing facility decreases as trade increases are observed in many states. Interestingly, especially compared to the North Carolina closure, removing the Missouri population causes the majority of the processing facilities to become more active in acquiring sows from many locations regardless of distance (Figure 3.3).

3.5 DISCUSSION

To better describe the cull sow market's network dynamics, a simple gravitational model was used to evaluate potential changes within the marketing system and how they may affect trade patterns between states and terminal processing facilities. The advantage of such a model is that it can provide empirical predictions of the system, as changes impact current system constraints. These impacts allow policymakers to evaluate how potential strategies, such as regional stop-movements or standstills, are related to disease spread implications regarding the geospatial distribution of area disease risk.

The SARS-CoV-2 pandemic has allowed the unique opportunity to validate using a gravitational model to predict the impact of a disruption to the cull sow marketing channel. During the pandemic, the closure of a terminal processing facility created the opportunity for the collection of a unique real-life disruption dataset. This unique dataset allows for the comparison of a simulated model to the real-life dataset's results. The comparison results reveal that while some minor differences exist between the two models' coefficients, overall, the models do not significantly differ. These results suggest that a gravitational model, simulated from previously collected data, serves as an effective means of understanding dynamic trade and distribution of interactions within this system.

Understanding both the cull sow marketing channel's current dynamics and potential future dynamics is extremely important to quantify potential risk geographical distributions. Since most of the marketing risk is due to indirect contact within the channel and not directly from interactions between infected and susceptible animals, understanding the relative change in interactions between the terminal processing facilities' cull populations and state populations is crucial during a pathogen spread event.

The current market's trade dynamics are such that large populations within close proximity prefer to trade with each other. As shown, a 1% decrease in distance between entities results in a 1.15% increase in trade. However, as disruptions within the market occur, such as the potential closure of a region, these behaviors change. The scenario describing the closure of North Carolina allows for the impact that a large population lies a great distance from the industry's centroid to be quantified. With a population of greater than 450,000 sows, the removal of this population results in a decrease in the influence of distance and state population size on trade, with a mild increase in terminal processing facility capacity. The removal of such a large population results in terminal processing facilities, especially larger facilities, preferring to buy from states closer to them regardless of state population size. Processing facilities trade at higher levels to meet demand, creating a more uniform distribution of trade between facilities and states, including states not evaluated in this project. Because this population lies so far from the center of the industry, no one terminal processing facility relies soley on this population to compose a significant proportion of their capacity. Thus, this population's removal causes facilities to rely on previously well-defined local relationships to fill the gaps left by this closure. More extensive facilities such as F5 demand is slightly greater, due to size, and thus they most become more active across several states to fill that void.

The scenario describing the Missouri facility's closure allows the opportunity to compare a population near the industry center. Because of Missouri's proximity to the centroid of the marketing network, the simulation removing this population elucidates the location effect. The closure of Missouri results in a mean absolute change in coefficients of 45.81%. This scenario suggests an increase in the impact of distance. This means that terminal processing facilities are more likely to purchase sows from greater distances. The significant decrease observed in terminal processing facility population's influence suggests that removing Missouri's population would significantly increase demand in all terminal processing facilities regardless of capacity. This change in trade dynamics is so severe that the state population's influence on trade is no longer significant. Unlike the closure of North Carolina, all processing facilities are impacted by removing a centrally located population near the major of the facilities, which causes meaningful changes in multiple facilities trade preferences, resonating throughout the entire system. This increase in demand at terminal processing facilities results in trade preferences with large state populations and nearby regions to dissolve. Demand in the 34 states, not reported, is likely to increase significantly as new relationships will be explored to remedy the increase in demand.

These scenarios show that an individual state's closure can exacerbate the movement of pathogens as it may change the geospatial distribution of interactions and thus the distribution of risk to states. The changing geospatial distribution of interactions allows for unknown risk across the industry as the frequency of interactions between processing facility, and state populations become more uniform. This increasingly uniform distribution of interactions with states occurs as demand now outweighs supply, influencing facilities' purchasing preferences, as defined by location, population size, and regional price difference that previously existed.

While the quantitative risk present from these interactions is unknown, changes in normal operating conditions cause the geographical distribution, which was relatively stagnant, to change depending on the location and size of the standstill population. These findings suggest that using a regional stop movement order may complicate disease introduction preparation. Each policy iteration comes with its potential outcome, shifting the geospatial distribution of area risk posed by these cull populations.

The redistribution of interactions generates new indirect connections between state and processing facility populations, potentially allowing disease to spread in previously unimaginable ways. Suppose disease introduction triggers a regionalized standstill of movements, ensuring all infected animals are within the defined closure area and that no infected animals exist within the marketing populations is of extreme importance. Suppose unknown infected animal movement is allowed to happen and interacts with one of the many independent cull sow herds. In that case, this work suggests that the stop movement order is likely to increase the probability of an indirect connection between that infected population and numerous states, as previous relationships now change, allowing a disease to move seemingly randomly throughout the industry.

3.6 FIGURES AND TABLES

Variable	Normal Function	North Carolina Closure	Missouri Closure
Distance	−1.158 (0.091) ***	−1.302 (0.088) ***	−0.783 (0.120) ***
Facility's Weekly Slaughter Capacity	1.053 (0.080) ***	1.124 (0.084) ***	0.4299 (0.125) ***
State's Weekly Slaughter Capacity	0.803 (0.081) ***	0.550 (0.081) ***	-
Regional Basis	-	-	-

Table 3.1. Results of the fitted PPML models for all four scenarios. Results reported as regression coefficient (Standard Error) $p<0.05^{*}$, $p<0.01^{**}$, $p<0.001^{***}$

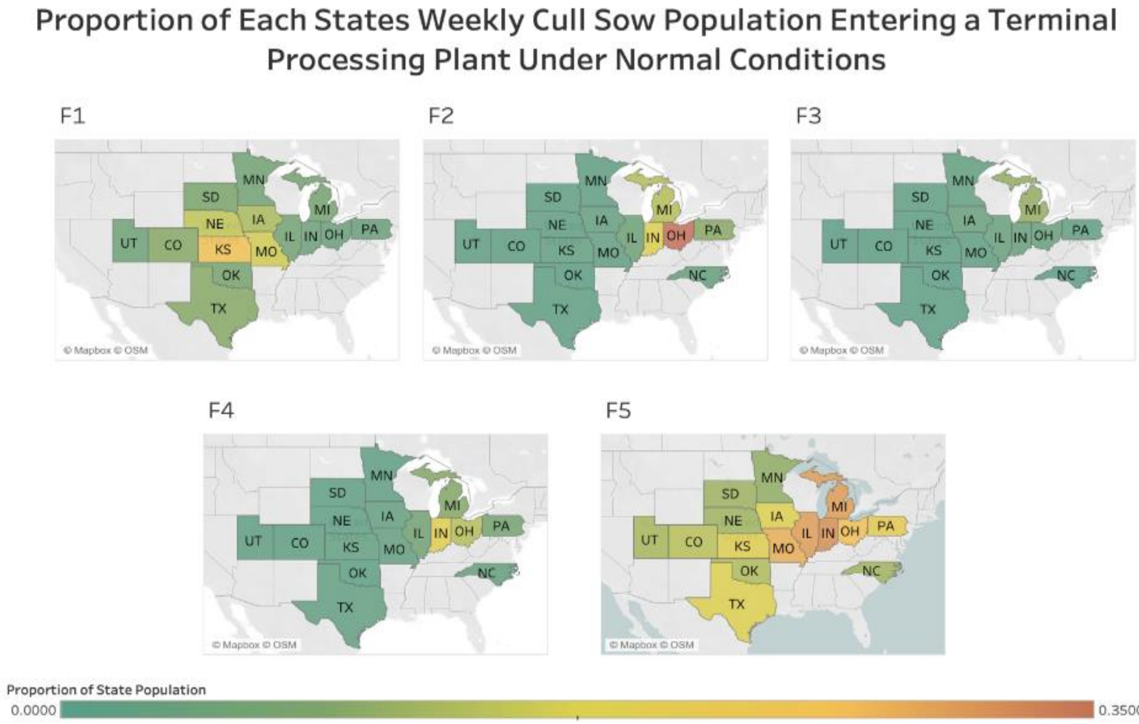

Figure 3.1. The proportion of a state's cull sow population that enters each terminal processing facility F1–F5, under normal operating conditions. Each pane labeled F1, F2, F3, F4, F5 represents a different processing facility.

Variable	F1 Closure Scenario	F1 Closure Actual
Distance	−0.744 (0.108) ***	−0.899 (0.214) ***
Facility's Weekly Slaughter Capacity	0.950 (0.092) ***	1.00 (0.186) ***
State's Weekly Slaughter Capacity	0.334 (0.089) ***	-
Regional Basis	-	-

Table 3.2. Results of model validation for F1 closure. Results reported as regression coefficient (Standard Error) $p < 0.05$ *, $p < 0.01$ **, $p < 0.001$ ***.

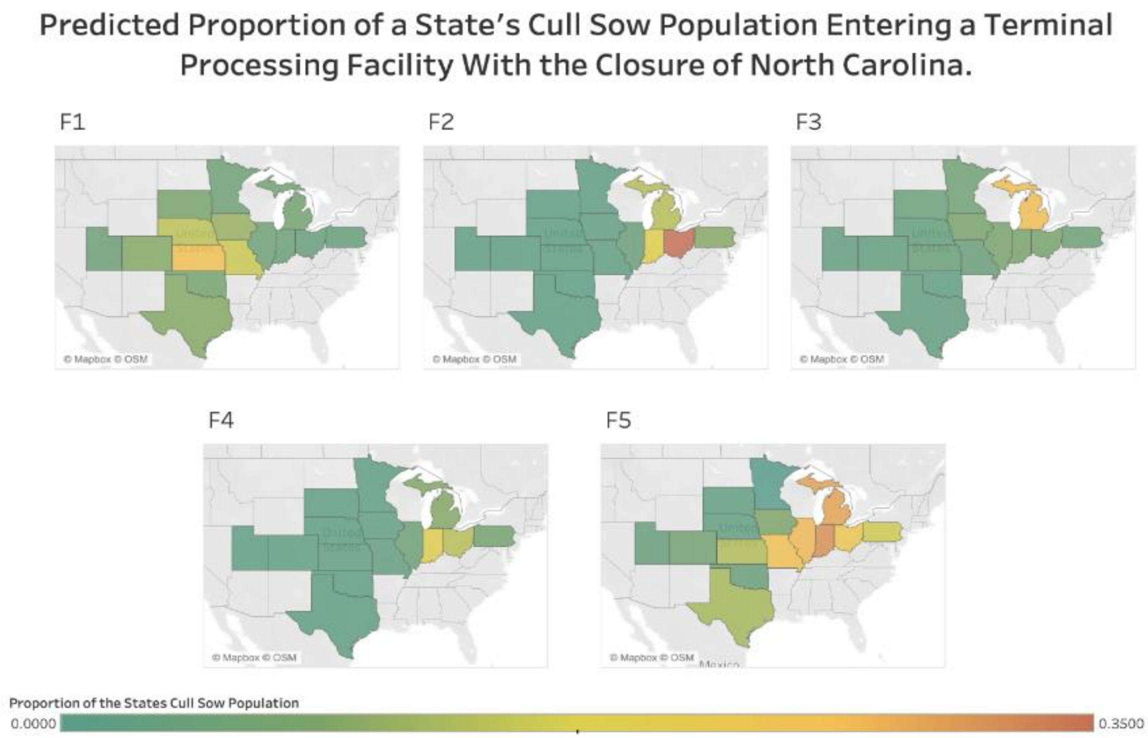

Figure 3.2. The predicted proportion of a state's cull sow population that enters each terminal processing facility F1–F5, with a closure of movements to and from North Carolina. Each pane labeled F1, F2, F3, F4, F5 represents a different processing facility.

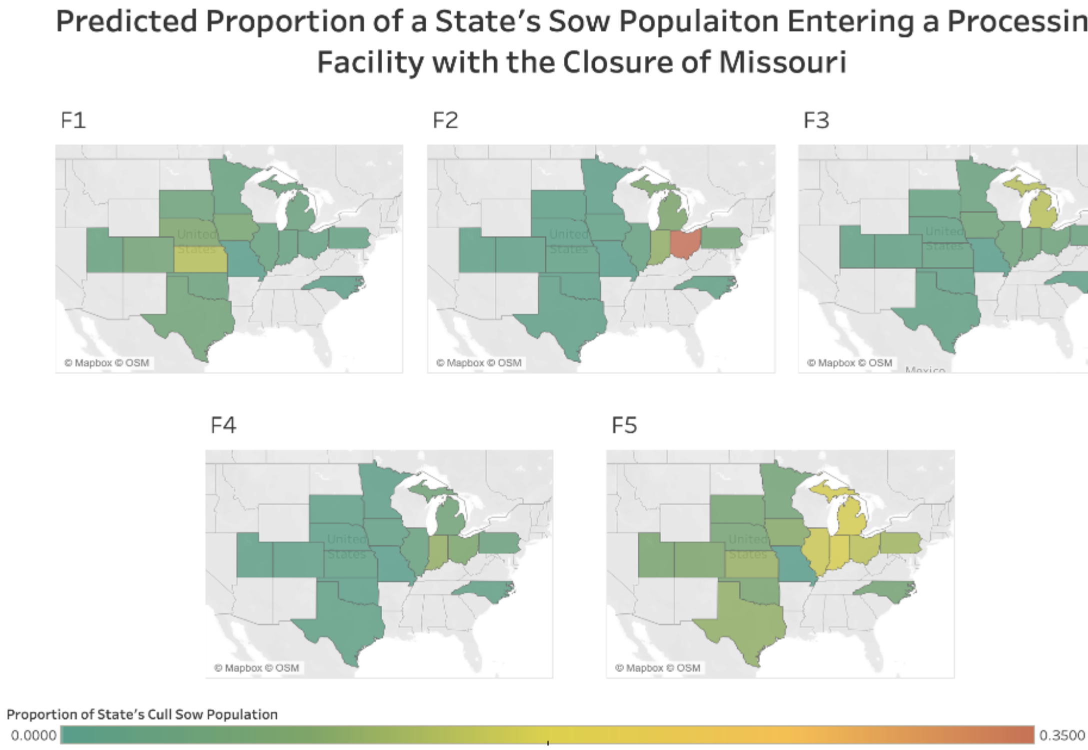

Figure 3.3. The predicted proportion of a state's cull sow population that enters each terminal processing facility F1–F5, with a closure of movements to and from Missouri. Each pane labeled F1, F2, F3, F4, F5 represents a different processing facility.

CHAPTER 4: A CASE STUDY OF THE APPLICATION OF ARTIFICAL INTELLIGENCE TO AID IN THE CLINICAL DETECTION OF PORCINE REPRODUCTIVE AND RESPIRATORY SYNDROME VIRUS IN SOW FARMS

4.1 ABSTRACT

The introduction of a pathogen into a livestock population is the cause of some of the most devastating losses by swine farms. The early detection of disease plays an essential role in limiting the effects of a pathogen introduction on a population. While the use of routine lab-based molecular testing for antigens can aid in rapid pathogen detection, the number of samples statistically required, and the associated expense make its frequent use unrealistic. For these reasons, researchers continue to develop additional tools to aid in disease detection. Statistical process control, one such tool, utilizes production data to detect disruptions in farm performance as a signal of disease. However, the sensitivity of this method is low because of the inherent biological variation present in swine production. This project proposes a predictive tool that overcomes the limitations of inherent biological variation by utilizing current machine learning advancements to detect disease quickly and accurately within a population.

The early identification of a pathogen on a sow farm facilitates timely management decisions to slow pathogen transmission and reduce the severity of disease within a single farm, a production system, and regionally. Producers' decisions encompass a broad range of tactics to limit spread through the feed, people, supply, or animal movements. Prompt implementation of

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these tactics is essential for minimizing both the individual producer's and the industry's short- and long-term financial losses.

Here we describe a tool that facilities sensitive syndromic surveillance for sow farms by applying machine learning to historical individual sow production records to predict of the outcome of an individual breeding event. The tool predicts which sow breeding events will yield piglets (farrow) and subsequently monitors the outcome of the breeding event. If more services result in failure (sows that did not farrow but were predicted to) than expected, as defined by the model's error, the model signals a disruption (presence of disease). To compare the sensitivity of our tool to the established Statistical process control approach (SPC), retrospective data from two sow farms that experienced a Porcine reproductive and respiratory syndrome virus (PRRSv) introduction were assessed.

While both our machine learning based tool and SPC detected PRRSv introduction on each farm, the average detection was 1 and 3 weeks before the farm reported a disease event using our novel machine learning-based method and 2 weeks after and 1 week before using SPC. In addition to identifying the PRRSv introduction, the machine learning approach identified production disruption resulting from changes to the electronic sow feeding system on the farm SPC failed to identify this disruption. These two test cases demonstrate that our novel machine learning-based method maybe more sensitive for the surveillance of swine farms for pathogen and non-pathogen related disruptions to average production compared to previously described SPC based approach. While both test cases involved the detection of a novel PRRSv introduction, the machine learning based technique is broadly applicable to economically important diseases, and most importantly can serve as an early alert for novel pathogens where industry level monitoring is not conducted routinely.

4.2 INTRODUCTION

The timely and sensitive detection of a novel pathogen is the foundation any infectious disease control and management plan for the infected population, be it human or animal. For global pig production, early detection of infectious diseases in commercial swine herds facilitates timely management decisions to limit the spread of a disease outbreak within a specific farm or production system and, more broadly, at a regional or industrial level. (Herholz et al., 2006; McLaws & Ribble, 2007) In modern swine production systems, a single farm site typically specializes in only one phase of production (breeding or growing) with many of the support services (feed, semen, supplies, transportation, and maintenance) shared between farms. Growing pigs from a single breeding herd are often raised on multiple farms that are separate from the breeding herd source and from each other. The growing pigs arrive at the farm after being weaned from their dams, at approximately three weeks of age, and remain there until they are sold for harvest at a pork processing facility. The total time between weaning and harvest is typically 26 weeks. Therefore, at these growing farms, there may be pigs on site that arrived from the breeding herd any time from one to 26 weeks prior. This farming structure results in the frequent movement of feed, people, supplies, and pigs between farms. As the time between pathogen entry and detection increases in a breeding herd, the number of movements that occurred also increases, resulting in additional primary and secondary transmission events due to contact with the infected, but undetected, breeding farm. These contact transmission events can serve as means of pathogen introduction directly with pig movement or indirectly with fomites between farms, increasing the probability of additional disease outbreaks. (Dorjee et al., 2013)

Disease outbreaks in swine herds lead to morbidity and mortality which are costly to the pig farmer. Financial losses suffered from infectious diseases are substantial in the US swine industry. Porcine Reproductive and Respiratory Syndrome (PRRS), a viral disease that results in abortions and pneumonia, results in a loss of $664 million per year to the US swine industry. (Holtkamp et al., 2013) While remarkable, these financial losses from PRRS alone are a fraction of the forecasted potential losses associated with a foreign animal disease introduction. (Brown et al., 2020) Early pathogen identification for rapid control and eradication of an outbreak is pivotal for limiting both the economic losses on farms and those financial losses associated with the inability to access foreign export markets. (Paarlberg et al., 2008) Therefore, to reduce loss of income and market access, accurate surveillance protocols for early detection of disease to prevent outbreak spread are needed. Unfortunately, the practical and economic constraints associated with the large sample size required to ensure accurate surveillance for an infectious disease via diagnostic, i.e., laboratory assays forces veterinarians and farmers overseeing the herds to rely on clinical observation as a method for identifying a novel infectious disease in a herd. (Richt & Webby, 2013) Regrettably, this approach is fraught with challenges due to non-specific clinical signs and the difficulty associated with intense, repeated, individual observation in large populations. Combined, this makes the rapid and accurate identification of novel and clinically significant pathogens practically difficult. (Elbers et al., 1999; Fritzemeier et al., 2000) To address this challenge, veterinarians and scientists are adapting the technical and analytical tools broadly applied to detect system-level changes in other industries, such as statistical process control, for the rapid and accurate detection of infectious disease in swine populations.

Statistical process control (SPC) monitors a system for disruptions to a process, i.e., a production cycle. (Woodall, 2000) SPC compares current process outcomes to historical variation around the mean. If the current data indicates a shift from the historical mean that is greater than the expected normal variation, an “SPC signal” is generated. This signal implies the existence of a production disruption, which the operator can then investigate further. (Vries & Reneau, 2009) This use of structured, objective assessment employing the statistical concept of the mean (average) and variance (variation around a mean) is also applicable to swine production systems. The presence of stringent controls over farm management, nutrition, and environment can be used to keep the herd's production outcomes within steady and predictable boundaries. A common cause of disruption of production outcomes in agricultural animal systems is the physiological disorders within the population due to disease outbreaks. The resulting morbidity and mortality from a disease incursion results in production outcomes that deviate from predicted boundaries. (Vries & Reneau, 2009) The ability to systemically identify the deviation of a production outcome from the historical average can thus serve as a useful indicator of the introduction of a novel pathogen into the population. Indeed, SPC has been implemented for use in animal agricultural industries, such as within swine farms and pork production, to both monitor production outcomes and as an indirect method to detect disease. (Vries & Reneau, 2009) Examples within the swine industry include the use of SPC to monitor changes in abortion rate and frequency within sow farms which enabled detection of PRRSv infection one to four weeks before conventional diagnostic methods. (Silva et al., 2017) In addition, SPC monitoring of water intake data detected disease in young piglets one day prior to clincal observation of a change in drinking behavior. (Madsen & Kristensen, 2005)

For these reasons, research into additional modalities to monitor outcomes that can function in systems with a high degree of variation is needed. Machine learning (ML) is one such modality that can create accurate predictions of the outcome parameters of a process. (Michie & Donald, 1968) The robustness of ML algorithms in predicting outcomes within variable processes (Deo, 2015) creates the opportunity to compare a predicted outcome to the actual result. The comparison of an outcome to the predicted outcome from ML better represents current system performance than comparison to historical averages which, by definition, do not take the current system performance into consideration but rely heavily on previous performance to inform the parameters. Many industries, such as crop agriculture (Díaz et al., 2017; Shakoor et al., 2017), forestry (Diamantopoulou & Özçelik, 2018), energy (Fischetti & Fraccaro, 2018), and manufacturing (Li, 2016; Meredig, 2017) have adopted ML approaches to monitor changes in productivity. However, the adoption of ML-driven techniques in animal agriculture (Cihan et al., 2017), while possible, is limited.

This paper describes a machine learning based tool to monitor the production process within sow farms, namely pregnancy failure events, as a method of clinical sign detection and signal the need for further diagnostic confirmation during a disease outbreak. The goal of this analytical tool is to reduce the time between the introduction and detection of a new infectious disease in a swine breeding herd.

4.3 MATERIALS AND METHODS

This study creates a non-specific syndromic surveillance method for sow farms to monitor the normal production cycle's disruptions by comparing actual reproductive outcomes to predicted outcomes. The following sections outline the steps taken to develop the tool.

4.3.1 Data Collection

The data set consists of sow breeding records from two approximately 6000 female breeding herds located in the Midwestern United States and contains approximately thirteen years of retrospective production data. This data consisted of records from individual sow services exported from the farm's record management system. (Porcitec®, Agritec, Barcelona, Spain)

In addition, any major event with the potential of disrupting production was recorded during the study timeframe (2019-2020). This study refers to the farms as Farm 1 and Farm 2. Both farms experienced outbreaks of PRRS following the introduction of a novel, unrelated variant of the PRRS virus (PRRSv). Both farms are considered "high health" status and are free of *A. pleuropneumoniae* and swine dysentery. Each farm adheres to intensive biosecurity systems and practices, including shower in-shower out, dedicated supply delivery, dedicated, washed, and thermally assisted dried live animal transport. *M. hyopneumoniae* and Influenza A virus (IAV) infections are present in both herds. Both farms have common management, feed, and semen sources but independent external sources of replacement breeding females.

Farm 1 utilizes group-based housing for gestating sows after 40-45 days of pregnancy until farrowing. Sows are housed individually during lactation, the pre-breeding period and for the first 40-45 days of gestation. The farm made a change to the equipment used to feed sows in group housing with installation starting in January and ending in April 2019. This farm has been historically free from PRRSv infection. In week 12 of 2020 an IAV-H1N1 gamma cluster virus that had not been previously identified on the farm resulted in an outbreak of clinical respiratory disease typical of influenza. Two weeks later, week 14, 2020, an outbreak of PRRS was confirmed though standard molecular diagnostic methods, reverse transcription-polymerase chain reaction (rt-PCR), and clinical investigation by the herd veterinarian. 1 contains the complete history of Farm 1.

Farm 2, all sows are housed individually across all phases of production. There was significant maintenance activity on the farm during the late summer and early fall of 2019, resulting in the movement of sows at abnormal times during gestation. In week 2 of 2020 an IAV- H1N1 gamma cluster virus that had not been previously identified on the farm resulted in an outbreak of clinical respiratory disease typical of influenza. Historically the farm was endemically infected with PRRSv but was free from detectable clinical signs and PRRSv nucleic acids in routine sampling and testing of pigs during lactation from December 2018 until week 19 of 2020. In week 19 of 2020 an outbreak of PRRSv due to a new variant was confirmed though standard molecular diagnostic methods (rt-PCR, genomic sequencing) and clinical investigation by the herd veterinarian.

4.3.2 Data Cleaning

Once collected, the raw data is subject to data cleaning to address missing data, outliers, and errors. The goal of this exercise is to ensure that all entries are both valid, formatted and have adequate nonblank entries as required for the the prediction model. This data cleaning process utilized a standardized technique across all observation in both data frames. All duplicate observations were removed from the dataset. A duplicate observation was defined as any observations with an identical ID and service dates less the 21 days apart, the normal length of a reproductive cycle of a sow. Then variables with any structural errors, and formatting within the entries were addressed. Outliers within the dataset were identified when any when any numerical production variable was greater than three z scores from the mean of that production variable. Individual service records (observations) were censored if containing an outlier. For this analysis variables missing more than 60% of the entries were excluded for their limited predictive value to the problem. Finally records with biologically implausible outcomes, outside an appropriate range based on technical knowledge, were assumed to be errors and the observation was removed.

4.3.3 Feature Engineering

Following an initial round of cleaning, feature engineering generated additional variables and information to identify potential complex relationships to enhance the model's predictive value. Featuretools, a publicly available python library, was utilized to perform feature engineering on the datasets. Featuretools uses the deep feature synthesis algorithm (Kanter & Veeramachaneni, 2015) to automatically generate additional features from rational datasets. The deep feature synthesis algorithm is a method used to automate and standardize the feature creation process and uses various mathematical functions (e.g., transformations, aggregation) to calculate new variables.

Featuretools generates an entity set, or a master dataset where every variable, feature, is assigned a data type, such as categorical, numerical, or date-time index. Date-time indexes dictate when data becomes available to use within the engineering process, such as when a value can be used to calculate a historical mean. This allows Featuretools to calculate historical variables at the time of each observation, only including previously collected data. For example, the date that a sow gets bred would be the date-time index for that observation and the new features calculated based on past observations such as historical means would only include values collected prior to the date-time index. For this study, primary datetime index was defined as the service date, and the secondary date-time index, service result date. All variables become available for historical calculations at the time of the primary index except gestation length, lactation length, liveborn, total born, stillborn, mummies, weaning age, number of weaned pigs, and wean to first service interval. These become available for inclusion after the secondary date-time index.

After the entity set was built, normalization occurred to create additional datasets for different subsets or groups. These subsets were individual sows, parities (number of recorded litters), and service groups (all the sows bred in one calendar week), allowing information to be grouped by subset to generate additional combinatory features, such as the mean of a category, to improve accuracy. Finally, a target entity, dataset, consisting of three objects: ID, cutoff time, and target was defined. Where ID is the unique service ID, cutoff time, or time in which the model will make a prediction is the service date, and the target for the model is the service result. After completing all entities, automated deep-feature synthesis on the data set, with max_depth = 3, finalized the feature engineering process. In total, 33 variables split into four entity sets entered automated feature engineering, resulting in 495 additional features. After feature engineering, the dataset underwent data quality analysis, as previously described.

These steps maximized the usefulness of the raw data to train a supervised classification model. Before training, standardization was performed on all numerical features so that features lie between -1 and 1. Dummy variables represent all categorical variables because the classification algorithm does not permit text data.

4.3.4 Exploratory Data Analytics

Multiple data visualization techniques in Python's Seaborn and Matplotlib libraries to investigate relationships were applied before creating the model. The detection of highly correlated variables employed correlation plots. Multicollinearity was defined as variables the have a Pearson’s correlation coefficient greater than 0.9. For highly correlated variables, the second variable was removed. This cut-off value (0.9) was only selected to ensure that nearly duplicate data did not exist, as multicollinearity do not affect decision trees and thus will not impact the selected algorithm.

4.3.5 Training a Machine-learning Model

When predicting the outcome of a service (farrow/not farrow), the target variable is categorical. Therefore, a supervised classification model, in this case gradient boosting algorithm, XGBoost, was employed. Supervised classification models allow the user to train an algorithm to predict group membership by providing historical data and known outcomes for the algorithm to train from.

XGBoost, allowed for accurate predictions on a large complex tabular data set without excessive computer processing requirements. Gradient boosting is a method wherein the final prediction model comprises multiple weak prediction models, usually decision trees. Combining multiple weak predictors creates a single strong predictor. Because of these attributes, gradient boosting is a reliable choice when trying to formulate a prediction model from the expected data. (Natekin & Knoll, 2013)

Model training utilized the SciKitLearn library within Python. (Pedregosa et al., 2011) Exclusion of the parity 0 animals in the dataset occurred before training. Gilts (Parity 0 animals) in these farms have no historical data recorded before breeding precluding analysis. For training, a randomized 80% of the instances comprised the training dataset, with the remaining 20% serving as the test dataset to measure the accuracy of the model's predictions. The model was trained to the default XGBoost classification algorithm to predict whether a sow will farrow at the time of breeding. All the parameter settings were set to the default settings within SciKitLearn. The features of the greatest importance to the model were parity, previous lactation length, previous gestation length, and previous number of liveborn piglets.

Assessment of the model for accuracy, precision, and recall followed model training. Accuracy is the percentage of predictions made correctly. Precision is the percentage of sows that farrowed of those that the model predicted to farrow (true positives of predicated positives). The recall is the percentage of sows that the model predicted to not farrow that actually failed to farrow (true negatives of actual negatives). The accuracy of the overall model was greater than 90% for both farms, precluding the need for model tuning.

Following the initial model's completion, a 5-fold cross validation was performed. From each training set, the mean and standard deviation of the algorithm's weekly error were used to generate an X bar SPC chart to monitor the model error fluctuations over time. Weekly error represents the number of incorrect predictions discovered during that calendar week divided by total number of sows with predictions. The arithmetic mean of the weekly error is then calculated by calculated the average of a weeks within the study timeframe. Standard deviation was calculated in a similar fashion. The workflow of the machine learning process can be seen in Figure 4.1.

4.3.6 Machine Learning Error Rate Technique for Process Disruption

The cumulative error of the predictions for each day over the most recent twelve months of data were plotted on an X bar chart for each farm to monitor potential production disruptions. Cumulative error was defined as the number of sows that failed to maintain pregnancy that were expected to complete a successful pregnancy to term (farrow) for sows that had a service event in the prior 115 days divided by the total number of sows that had a service event in the prior 115 days.

The plotted cumulative error was evaluated with a standardized set of rules to signal aa production disruption in the farm. The rules utilized to determine a signal were as follows:

1. anytime the weekly cumulative error stays above one standard deviation away from the mean for five or more weeks, a signal is triggered,

2. anytime the weekly cumulative error of the model remains two standard deviations above the mean for three or more weeks, a signal is activated,
3. anytime the cumulative weekly error of the model surpasses three standard deviations above the mean, a signal is triggered.

SPC chart creation employed the R statistical environment. (R Core Team, 2017)

4.3.7 Development of Statistical Process Control

On the available data, a previously described exponentially weighted moving average (EWMA) techniques was implemented based on the reported abortions from each farm. This analysis served as the "gold standard" for comparison of the Machine Learning Error Rate Technique's ability to detect process disruptions. Chart parameters followed those described (Silva et al., 2017), with sigma equal to 3 and the smoothing parameter equivalent to 0.40. The baseline average for abortions for the SPC chart used 21 weeks of data before the final 18 months of data. EWMA SPC chart creation employed the R statistical environment. (R Core Team, 2017)

4.3.8 Comparison of Detection Methods

An extensive history of disease outbreaks, major process changes (e.g. changes in feed, health program additions or removals, or management practices), major construction events, and unforeseen natural disasters for both farms. The detected signals on each farm were compared to the farm's histories to determine if the timing of signals were correlated with known changes on the farm. Both farms rely on detection of clinical signs followed by confirmatory diagnostic testing to detect the presence of PRRSv. Both the machine learning based model and the EWMA model were then compared to the date that diagnostic samples were taken. The days until clinical observations were compared for the two systems.

4.4 RESULTS

When comparing this novel approach and the previously described EMWA SPC chart for abortions as a syndromic surveillance method, the mean detection time was 2.5 weeks later for the EMWA SPC method for abortions than the Weekly Cumulative Error SPC generated from the machine learning approach, Table 4.1. Although slower the EMWA SPC method detected the same number of disruptions as the Weekly Cumulative Error SPC.

4.4.1 Results of Training an XGBoost Algorithm

4.4.1.1 Farm 1

Following data cleaning, processing, and feature engineering, the Farm 1 dataset contained 448 features and 151,451 instances, where each instance represented a service event. After five independent training runs of the algorithm, the maximum accuracy observed was 91.1%, and the minimum was 90.2%. The mean accuracy, precision of farrowing prediction, and recall of farrowing prediction, of all five trials was 90.4%, 90.2%, and 99%, respectively (Table 4.2). The mean weekly cumulative error of the model was 0.63%, with a mean-standard deviation of 0.58%.

4.4.1.2 Farm 2

After data cleaning, processing, and feature engineering, the Farm 2 dataset contained 459 features and 151,541 instances. After the five unique training runs of the algorithm, the maximum accuracy observed was 92.7%, and the minimum was 92.1%. The mean accuracy, precision of farrowing prediction, and recall of farrowing prediction, of all five trials was 92.5%, 92.3%, and 99.1%, respectively (Table 4.3). The mean weekly cumulative error of the model was 0.48%, with a mean-standard deviation of 0.46%.

4.4.2 Signal of Production Disruption

The Weekly Cumulative Error Xbar Chart for Farm 1 (Figure 4.2), with sigma equal to 0.58%, reveals one signal of production disruption in the 18-month timeframe. This signal occurred in week 13 of 2020. The farm's veterinarian detected a novel PRRSv infection in week 14, 2020. Casual observation of the Xbar chart revealed a continuous increase in model error starting in week 10, 2020. The Weekly Cumulative Error Xbar-R Chart for Farm 2 (Figure 4.3), with sigma equal 0.46%, revealed four production disruption signals over the 18-month timeframe. These signals of disruption occur in weeks 9-2019, 23-2019, 43-2019, and 16-2020—three of the four signals correlated to events in the farm history. Extensive on-farm maintenance (equipment repairs requiring the abnormal movement of sows between individual pens) potentially explain the signal during week 23-2019. The farm performed multiple vaccinations for IAV and PRRSv, potentially explaining the unexpected pregnancy failures in week 43-2019. Finally, the signal in week 16-2020 occurs three weeks before detecting a novel PRRSv infection on the farm.

4.4.3 SPC Chart of Abortions

The EWMA SPC chart of the farm's abortions, as previously described, was used to identify potential disruptions. Farm 1 had three signals (Figure 4.4). The first in week 5-2019 may correlate with the beginning of the change in electronic gestating sow feeding systems. The second signal in week 24-2019 does not correlate with any known events. The final signal during week 16 of 2020 occurs two weeks after PRRSv detection.

The EWMA chart for Farm 2 identifies two signals (Figure 4.5) during week 43-2020, which correlates with multiple mass vaccinations of the herd in weeks 40-2019 and 42-2019, and in week 18-2020, one week before the detection of a novel PRRSv.

4.5 DISCUSSION

Historically, producers and veterinarians have relied on clinical observation by farm staff to identify disease in a farm. More recently, producers and veterinarians have used more advanced approaches such as Statistical process control (SPC) to detect disease-related disruptions within a production system. While both methods can accurately detect disease within a population, their reliance on biological and clinical parameters with a high degree of intrinsic variation limits their effectiveness in signal detection. Further limiting SPC's value are the subtle clinical effects of endemic diseases such as PRRSv and Influenza, in the face of high intrinsic variation in production outcomes present in commercial production.

While SPC can be a useful tool for monitoring health and production in livestock systems, limitations of its use exist. SPC was initially developed to detect disruptions within tightly regulated processes; however, its capacity to recognize disturbances in systems with high intrinsic variability, i.e., biological systems like animal agriculture - especially in the area of reproduction, is limited. (Woodall, 2000) Furthermore, the use of SPC in livestock systems has been applied to several commonly measured production outcomes such as the percentage of pregnant animals that successful give birth (i.e., sow farrowing rate) or the number of abortions per day or week in a fixed population of pregnant animals. Changes in these outcomes are often multifactorial and include not only infectious diseases, but also nutrition, animal care, and environmental conditions. In addition, changes in production outcomes, e.g., an increase in the number of abortions, are not specific to a single infectious disease since most diseases have overlapping patterns of changes or clinical signs. Furthermore, in herds endemically infected with one or more pathogens, the clinical diseases present cause changes to measured production outcomes continuously but with varying degrees of severity. Since the production parameters vary as a direct result of variations in clinical disease prevalence, the sensitivity of SPC to detect disease within the population diminishes. (Woodall & Montgomery, 1999) This means that in populations endemically infected with one or more pathogens, subtle changes in production outcomes that occur shortly after a novel pathogen introduction may go undetected because the resulting impact is less than the variation in production outcomes already occurring from the preexisting, endemic pathogens. Since SPC relies on historical information to monitor a process for disruptions (Woodall, 2000), the SPC method is vulnerable to failure if a high degree of intrinsic variation is present within the system, such as occurs with endemic diseases or to the inherent variability in biological processes.

Applications of advanced data analytics, particularly machine learning, can facilitate the processing of large complex datasets to identify complex relationships quickly and accurately within a system. In this application, machine learning overcame the problems that a highly variable system creates for identifying production disruptions, such as those caused by novel pathogen entry. Development, training, and validation demonstrated that the trained machine learning algorithm could predict correctly 92.7% of the time if an individual sow will farrow at the time of breeding. Changes in the algorithm's accuracy facilitated monitoring sow populations for unexplained reproductive failure throughout gestation in herds with a known health and management history.

Overall, the Weekly Cumulative Error SPC performed well. For the two PRRSv outbreaks in the validation datasets, this method detected clinical disruptions, on average, 1.5 weeks before recorded diagnostic confirmation. While the accuracy of on farm detection is unknown, we believe both farms represent a typical trained farm staff within the US, this in combination with routine diagnostic surveillance ensure the identification of disease. In herds that experience fewer recent disruptions, the advantage in detection time compared to clinical signs observation may be more significant. The difference in model detection timing compared to clinical conformation between the two farms is most likely due to the farm's inherent variability before the outbreak's onset. That is that Farm 1’s event history is such that the target variable, service outcome, is more variable in nature, as events has impacted farrowing rates previously. Farm 1, with the shorter detection time advantage, was going through the remodeling of the gestation feeding system, resulting in error substantially larger than the historical mean during this period decreasing the sensitivity of the Weekly Cumulative Error SPC. Because of this increased variability, prediction of such a variable is made harder, resulting in a lower overall performance of the model. The effects of remodeling on top of the increased inherent variation in the production data from Farm 1, resulted in the farrowing prediction model only obtaining a mean accuracy of 90.4%

When comparing this novel approach and the previously described EMWA SPC chart for abortions as a syndromic surveillance method, the mean detection time was 2.5 weeks later for the EMWA SPC method for abortions than the Weekly Cumulative Error SPC generated from the machine learning approach. The EMWA SPC method detected the same number of disruptions as the Weekly Cumulative Error SPC. These results suggest the EMWA SPC for abortions is slower to detect disease outbreaks than the Weekly Cumulative Error SPC tool. While the EMWA SPC for abortions method may be a more specific tool in identifying abortion-inducing events, the Weekly Cumulative Error SPC tool has a faster detection time. However, the Weekly Cumulative Error SPC tool failed to identify an IAV introduction in one farm over this period.

Even with the Weekly Cumulative Error SPC tool performing well in this study further validation is needed, both on a larger number of farms and for a wider number of ailments, whether pathogen or management induced. This paper is meant to describe the potential use of a machine learning technique to drive diagnostic testing decision on farms, while larger studies are needed to calculate meaningful sensitivity and specificity of disease processes on farm. The presence of IAV on both farms prior to PRRSv could also potentially reduce vigilance of farm staff in clinical detection, again reinforcing the need of further validation. In addition, the use of a such a tool requires real-time access to farm data to ensure that a disruption is identified as early as possible. The number of farms currently able to enter farm data in real-time is limited, as many still use paper records on farm that get uploaded to an electronic form at a future date. This lag between paper and the electronic records system may negate the benefit noted on some farms. While currently a major limitation, such technologies the prove beneficial may entice farms to adopt faster alternative methods of data collection.

While Weekly Cumulative Error SPC tool comes with some limitations, it is believed ability to quickly identify production-related disturbances within farms holds tremendous promise. Although there are many potential causes for a signal, the Weekly Cumulative Error SPC may serves as a sensitive method to detect numerous production disruptions, including disease. While specificity is poor for a singular disease, due to the vague clinical signs monitored, reproductive failure, the ability to actively, passively from existing data, and accurately conduct syndromic surveillance on farms is a step rate change in the ability to mitigate the impact of disease in a herd, system, region, and country. This method has the potential to detect clinical disruptions that may impact conception or gestation of a litter on a farm, including but not limited to diseases that cause anorexia or pyrexia. The Weekly Cumulative Error SPC does not replace the skills and knowledge of a veterinarian, producer, or confirmatory diagnostic testing but serves alongside them to enhance their abilities and focus their efforts.

In addition to syndromic surveillance, there are multiple other applications of the Weekly Cumulative Error SPC. The ability to detect disruptions in production has significant value for both the rare occurrence of disease and common management challenges. The ability to quickly detect and investigate the cause of such a disruption allows swine producers to swiftly remedy potential issues and return the farm to optimal performance. Thus, it ensures the peak performance of a herd based on the constraints in each scenario.

While other methods currently exist to make predictions about the occurrence of PRRSv or PEDv on swine farms (Paploski et al., 2021; Shamsabardeh et al., 2019; Silva et al., 2019), this is the first described using existing production data that is routinely collected on sow farms. While other methods are able to detect disease accurately within a farm, the application of the Weekly Cumulative Error SPC may allow for easier adoption as it only relies on a singular farm's data, and not the neighborhood characteristics. While there are advantages and disadvantage of each method, the ability that machine learning shows when predicting disease from differing data types is impressive and shows the potential for such a technology within the industry. As the swine industry continues to collect more and more data, the combination of the many datasets used within each method may lead to a superior model as both individual farm performance and the regional risk profile are accounted for.

This project achieved its objective to develop a novel, data-driven approach to production record analytics that utilizes machine learning techniques to improve clinical disruption detection times shortening the time to diagnostic confirmation within a sow farm. While limited in scale, we believe that Weekly Cumulative Error SPC serves as a foundation for detecting changes in swine health/production at the farm, system, and industry level in the presence of normal production variation. With the ability to accurately predict an individual sow's breeding service outcome, unexpected variation (more than the model's expected error) serves as a quick and accurate process disruption signal which may help guide diagnostic surveillance on farm.

4.6 FIGURES AND TABLES

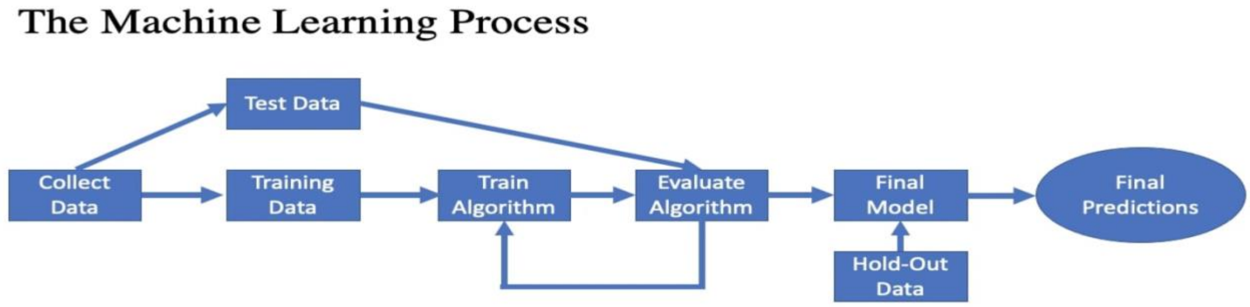

Figure 4.1 Workflow of the machine learning process.

	EWMA SPC	*Cumulative Error SPC*
Farm 1	-2 weeks	1 week
Farm 2	1 week	3 weeks

Table 4.1 Comparison of EMWA SPC to cumulative error SPC as weeks before clinical observation.

	Precision	*Recall*	*F1*
Farrow	90.2%	99.0%	94.6%
Failure	44.7%	51.3%	48.0%
Overall			94.0%

Table 4.2 Performance metrics of machine learning model on farm 1. F1 scores represent the harmonic mean of the precision and recall for the row.

	Precision	*Recall*	*F1*
Farrow	92.3%	99.1%	94.6%
Failure	66.3%	74.6%	70.5%
Overall			92.7%

Table 4.3 Performance metrics of machine learning model on farm 2. F1 scores represent the harmonic mean of the precision and recall for the row.

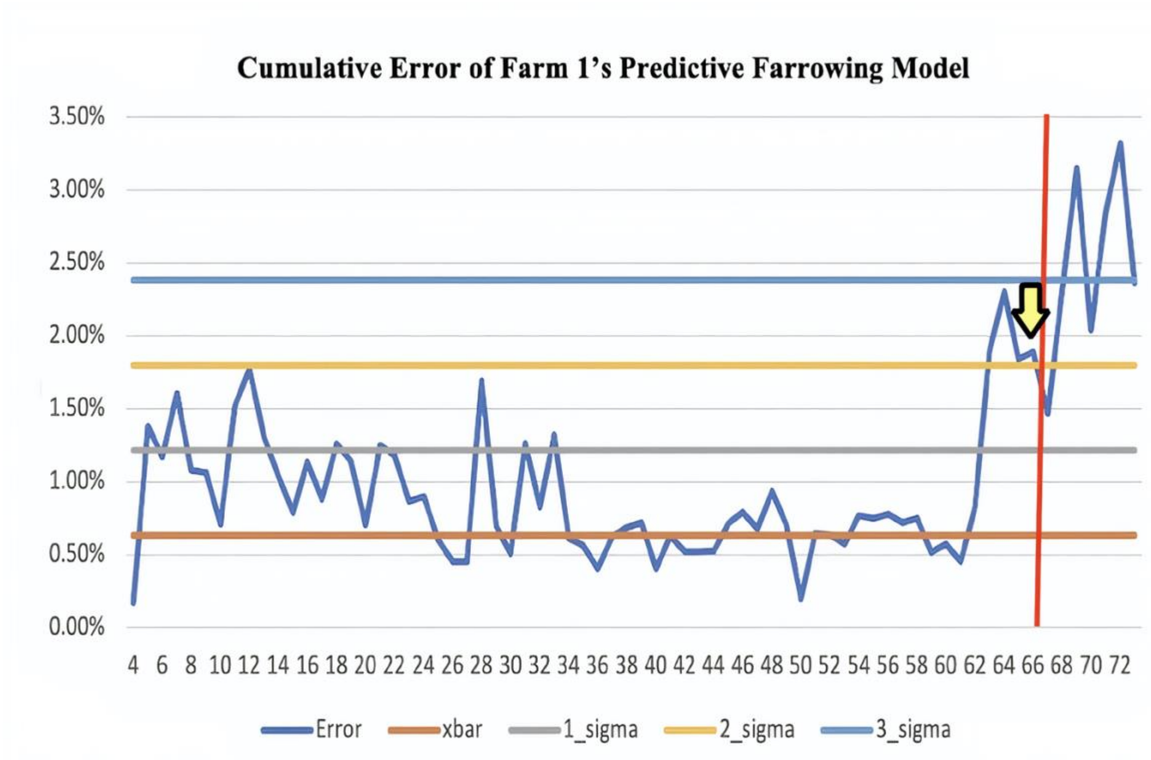

Figure 4.2. Weekly cumulative error of farm 1, as compared to 1, 2, and 3 sigmas from the mean error of the predictive model. Signal is highlighted by the yellow arrow. The solid red vertical line highlights the clinical observation of PRRSv.

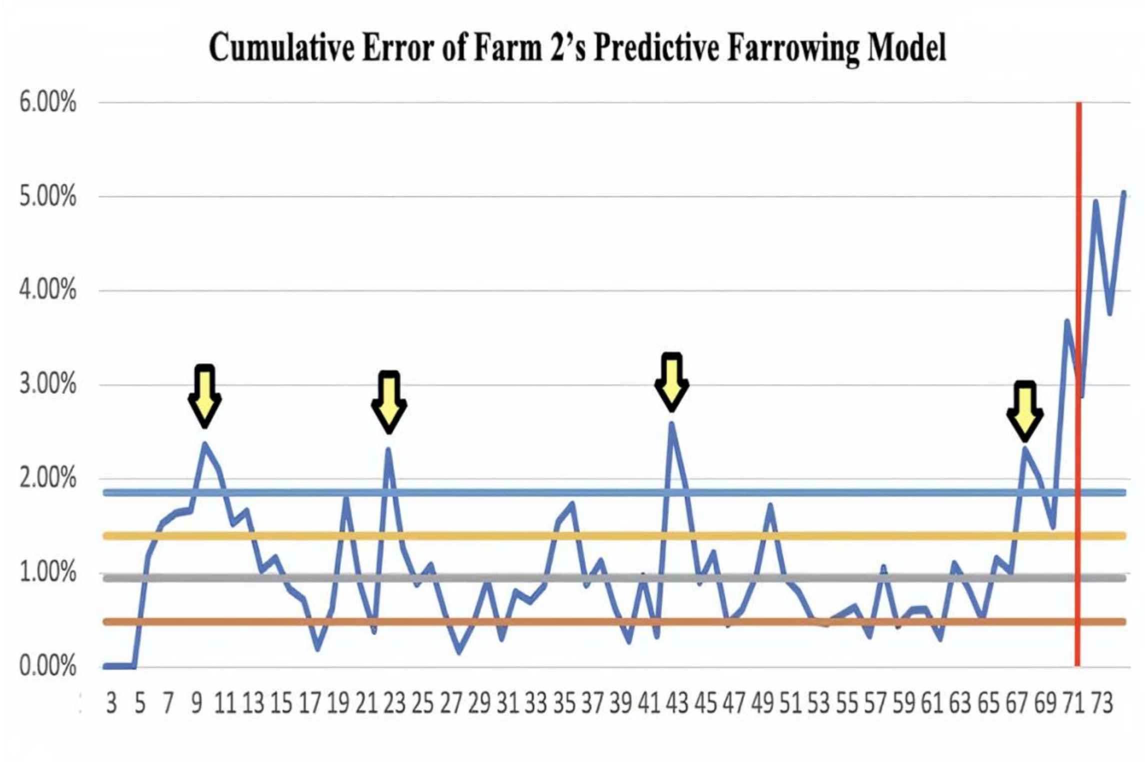

Figure 4.3 Weekly cumulative error of farm 2, as compared to 1, 2, and 3 sigmas from the mean error of the predictive model. Signal is highlighted by the yellow arrow. The solid red vertical line highlights the clinical observation of PRRSv.

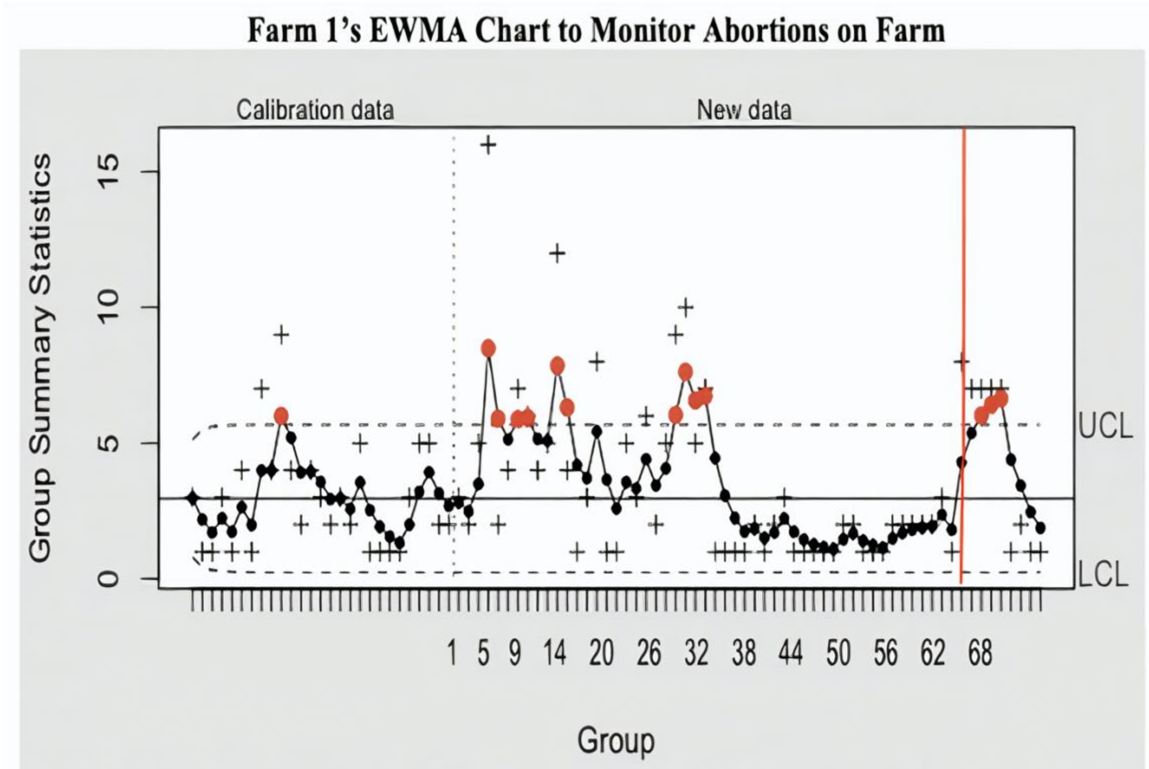

Figure 4.4 EWMA of number of weekly abortions occurring in farm 1. Red dots represent an EWMA outside of the control limit and the solid red line represents the week of PRRSv observation

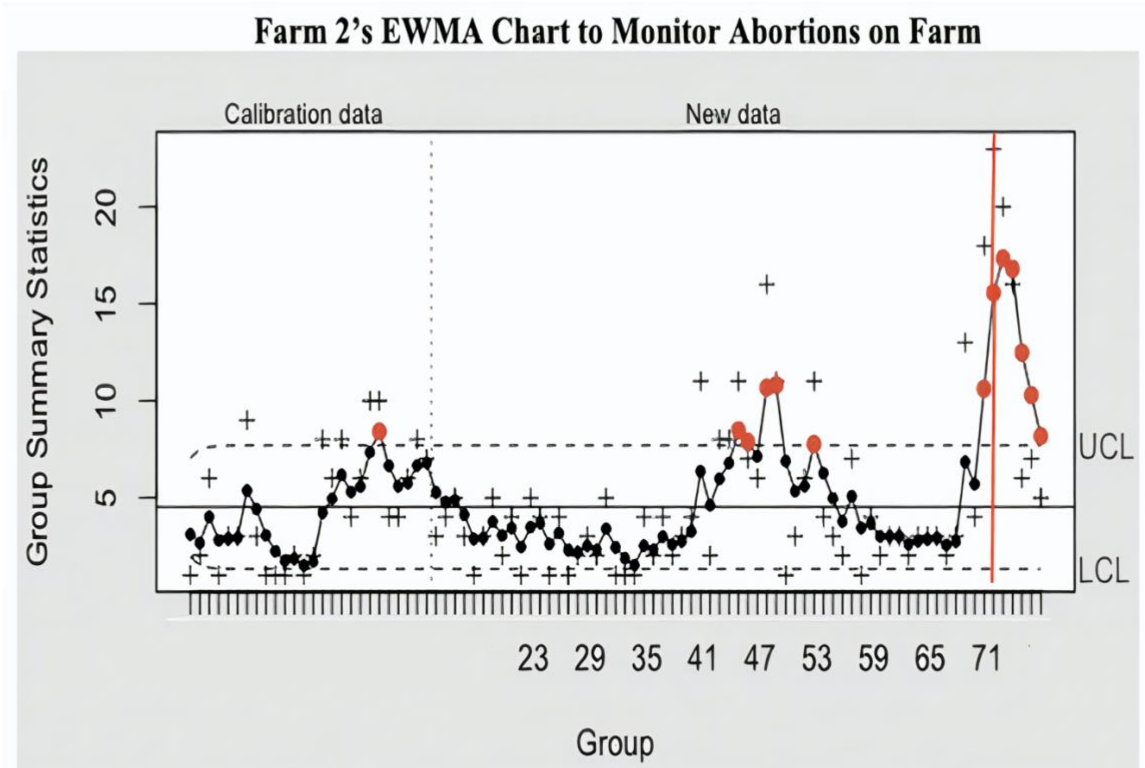

Figure 4.5 EWMA of number of weekly abortions occurring in farm 2. Red dots represent an EWMA outside of the control limit and the solid red line represents the week of PRRSv observation

CHAPTER 5: GENERAL CONCLUSION

The U.S. cull sow marketing network presents a threat to the national swine industry from both endemic and, more importantly, Foreign Animal Disease (FAD) because of its complexity and structure. However, adoption of advanced analytical tools may help diminish that risk.

Within the U.S. cull sow marketing network, animal movements are vast, complex, and non-transient, each creating their own inherent risk to the U.S. swine industry. The vast nature of animal movements allows contact between sows originating from geographically diverse origins creating indirect connections between farms across great distances. The large expanse of these contacts facilitate the dissemination of pathogens across the U.S.

The complexity of the market amplifies the issues created by its vastness. Sows move not only from long distances, but multiple times, between collection points, to meet the demands of market participants. This complexity increases the number of contacts between sows that originate in different regions. During a regional disease outbreak, these indirect connections may serve as an efficient means to disseminate pathogens throughout the U.S., moving seemingly unnoticed through the complex and undocumented interactions occurring within the channel. The complexity and absence of documentation of movements within the cull sow marketing channel impede traceback to identify the source of pathogens for disparate disease outbreaks.

The non-transient nature of sows within the marketing channel amplifies the effects of a single infected sow entering the marketing channel. A significant percentage (>8%) of sows remain within the channel longer than the incubation period of many common swine diseases, including FMD, ASF, and CSF. The retention of sows in the marketing channel creates an undocumented and unmanaged pathogen reservoir within this population because animals have the time necessary to acquire and replicate pathogens.

Unfortunately, the current policy to control and eliminate foreign animal disease fails to recognize the potential of the marketing channel to spread an undetected pathogen. The current USDA policy for a FAD introduction is a national or regional movement standstill to eliminate pathogen spread. A nationwide standstill may have the desired effect. However, regionalized standstills may enhance transmission through the disruption of normal market relationships. A regional standstill will remove cull sows from the market, forcing the remaining terminal processing facilities to adjust the trade patterns to maintain capacity and profitability. The resulting changes induce terminal processing facilities to lose their preference to purchase sows from large and nearby populations of cull sows. These effects suggest that the distribution of sows purchased by specific plants begins to normalize relative to the size, location, or slaughter capacity, of the closed region altering the normal trade relationships and, therefore, the indirect contacts between farms across the U.S..

While a regional standstill will minimize the risk for national transmission posed by the population in the standstill area, a failure to identify diseases within another region, not under a standstill order, may result in dire consequences due to the disruption of trade patterns between terminal processing facilities and states. Following a regional standstill order, the resulting proportion of sows from states in any packing plant becomes less variable, thus increasing the number of unique contacts between states through the marketing channel, causing a potential shotgun effect on pathogen spread following the introduction of an unidentified infected animal to the market channel. Because of this possibility, the accurate and early detection of disease at a farm level, most likely by syndromic surveillance, is a critical part of the U.S. FAD response plan.

Machine learning for detecting production disruptors within a sow farm is a promising avenue for syndromic surveillance. Boasting quick detection time and broader application than previous methods, the Weekly Cumulative Error SPC method may serve as a way to reduce the risk of unintended introductions of pathogens in the cull sow marketing channel. By monitoring reproductive failure, farms can quickly investigate the causes of atypical performance under current constraints. While not specific for detecting a single disease or problem, Weekly Cumulative Error SPC serves as an efficient means to monitor a farm holistically in combination with inquisitive veterinarians and producers.

Due to the constant threat of FAD introduction, there are significant concerns about the risk U.S. cull sow marketing channel poses to the U.S. industry. This work identifies threats within the system to guide future policies and decisions when managing an invasive pathogen. Also, it proposes using a novel syndromic surveillance tool, Weekly Cumulative Error SPC, at a farm level. Farm-level surveillance, given current diagnostic constraints, remains the best way to reduce the risk that the cull sow marketing network poses for FAD dissemination by reducing the chance of an undetected infected animal entering the system. The broad application of a sensitive farm-level surveillance tool utilizing data from existing systems will fortify the marketing network by identifying diseases on farms before animals enter the market channel.

Like the proposed surveillance method, other advanced analytical tools may be able to provide avenues to combat the market's complexity by improving transparency and traceability. Advances in computer vision have begun to allow for the recognition of animal identification (ear tags) by strategically placed cameras over a group of animals. Placement of sch a camera in conjunction with the already in place premise identification tags may allow sows to be traced as they journey through various locations within the channel. Sensors-driven computer algorithms, monitoring the health and production of swine on-farm in real-time, may also allow for early disease detection during an outbreak, limiting the spread outward to the markets and surrounding farms. The potential combination of traceability and early disease detection would be a tremendous step in the right direction when attempting to limit the impact of the marketing channels during a disease event.

While advances in technology and analytics hypothetically address some of the discovered concerns of the marketing channel, limitations exist regarding its implementation. The US swine industry has begun to prioritize data and data collection. However, this initiative is still in its infancy, and the amount and reliability of such data vastly vary across different segments. For example, sow farms routinely collect production data on an individual sow level, whereas grow-finish collects no individual records but collects data at a lot level. Because of these differences, implementing some advanced tools proves difficult as the amount of data required to deploy an accurate algorithm successfully does not exist. To improve this data collection issue, the industry continues to develop sensors to collect more granular data about swine in real-time, hoping to decrease case fatality rates while improving the animals' overall production. While sensors are likely an essential step in implementing analytical driving management, cost and durability continue to plague such attempts.

While it may be easy to demand changes to the cull sow marketing channel to reduce the risk, the system has benefited the industry. Implementing practices to reduce risk must be done in light of the financial benefits of the current system. While this analysis is outside the current scope of this project, this work opens the door for research on how changes to the cull sow marketing network impact the potential for disease movement and financial outcomes for producers and packers.

Some changes are possible with little impact on the market while still minimizing risk from the channel to the U.S. herd. The mandatory use of electronic ear tags (ePIN) to facilitate the automated collection of granular information concerning the entry and exit of individual sows at all collection points would allow for the enumeration of the relative risk present through the indirect contact of farms, systems, regions, and states. Transparency at all levels of the market would help improve business continuity in the event of a disruption.

Further evaluation of the non-transient nature of the marketing channel is necessary. The extended time that sows remain within the channel poses one of the greatest threats for pathogen dissemination. Not only does it pose a disease threat, but because of the time with little oversite, there is a potential welfare concern for the industry. While a reduction in time from farm to harvest is likely to impact the current business structure, reducing the overall time that animals can remain in the system may result in a net benefit to the industry. While outside this scope of this study, such a policy may be incredibly impactful for the industry.

Finally, the re-evaluation of regionalized standstill orders is necessary to ensure the FAD preparedness of the U.S. industry. While conceptually sound, the unintended entry of an infected animal into the marketing channel from a herd in a region not encompassed by the standstill area currently poses a significant threat based on the analysis. The use of syndromic surveillance tools at a farm level is one way to decrease that risk, but broad acceptance would be needed to protect the industry. Re-evaluation of the enactment of a standstill order, in light of these data and surveillance/testing capacity for both the commercial and show pig industries, is required to ensure that diseases are not present outside of the closed region.

Although this work makes great strides in understanding the complex system that is the cull sow marketing network, there is still a great deal to learn. Continual evaluation of such a dynamic system is needed to ensure a consensus among decision-makers about the threats and potential avenues of risk mitigation for this marketing network. This work sets forth a framework to identify, quantify, and fortify this swine industry sector. Moreover, while this is just a single step in a long journey to ensure a secure pork supply, this work is another step in the right direction.

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