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Evaluating Used Farm Machinery and Assessing the Sustainability of Tile Drainage Installation

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EVALUATING USED FARM MACHINERY AND ASSESSING THE SUSTAINABILITY OF TILE DRAINAGE INSTALLATION

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Agriculture, Food, and Environment
at the University of Kentucky

By

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Lexington, Kentucky

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Lexington, Kentucky

2024

ABSTRACT OF DISSERTATION

EVALUATING USED FARM MACHINERY AND ASSESSING THE SUSTAINABILITY OF TILE DRAINAGE INSTALLATION

This dissertation comprises three essays regarding the impacts of tile drainage implementation in row crop production and the evaluation of the farm machinery markets of combine harvesters and tractors. The second chapter focuses on tile drainage in traditional row crop agricultural systems. Although tile drain systems have been used for many years, recently, their popularity has increased. This increase has led to questions about these systems' costs and environmental impacts. These concerns have left many operations and individuals questioning if the system’s benefits outweigh the costs. This dissertation presents a life cycle cost (LCC) and carbon footprint (CF) Analysis for implementing a new tile drain system into a traditional row crop operation. This model presents an LCC and CF for a tile drain system and will provide the needed baseline to compare different system designs and materials for implementing a tile drain system.

Chapters three and four focus on used farm machinery markets for combine harvesters and tractors. Despite previous research evaluating the cost of farm machinery, much of the research is outdated or lacks a comprehensive view of the market, including limitations in evaluating newer machinery technologies. Couple these gaps with recent market shifts from the pandemic and supply chain shortages, and the literary work related to farm machinery falls short. Chapter three addresses the limitations of new machinery technologies by evaluating factors related to precision technologies and their effect on used combined prices. This chapter uses a hedonic pricing model with historical auction data to estimate used combined values. The full results from this chapter will provide a comprehensive evaluation of both precision agriculture technologies and brands and will assist in further understanding the factors and impacts of precision agriculture on combine harvesters.

The fourth chapter addresses the issue of evaluating machinery prices after a major market shift. Similar to the third chapter, a hedonic model was developed to assess the impacts of the Covid-19 pandemic on the used tractor market. The model included various control variables for the industry, including age, auction specifies, use, horsepower, and machinery specifics. Results suggest that a 16.3% increase in tractor prices can be attributed to the pandemic. Overall, this study will evaluate the pandemic's impact on the farm machinery sector and produce valuable estimations to assist operators in valuing machinery for both buying and selling.

KEYWORDS: Farm Machinery, Tile Drainage Systems, Life Cycle Cost, Hedonic Model, COVID-19, Precision Agriculture Technologies

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08/22/2024

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EVALUATING USED FARM MACHINERY AND ASSESSING THE SUSTAINABILITY OF TILE DRAINAGE INSTALLATION

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DEDICATION

To my family, friends, colleagues, and mentors.

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CHAPTER 1. INTRODUCTION

Net farm income in the United States hit an all-time high at $185 billion in 2022 even with declining production for corn and soybeans (Munch, 2023; *USDA/NASS QuickStats*, n.d.). Since then, a sharp decline is projected, 2023 is expected to see a decrease of almost 20%, with 2024 forecasting an additional decrease of 27% (Kassel, 2024). When factoring in the additional decrease of 4 billion in government payments, operations will likely have to optimize their decision-making for the farm (Munch, 2023). Farmed acres saw yet another decrease in 2022 for row crop operations specifically. Although yield per acre has increased over time, acres planted are at an all-time low (Shahbandeh, 2024), further complicating the situation for farmers who must grow more crops on fewer acres. Farmers aiming to increase their net farm income require either an increase in yields or a decrease in expense. This landscape requires producers to stay current with their knowledge and skills, as well as new trends and updating older ones. One possible option for increasing yields is implementing tile drainage systems on cropland.

Tile drainage systems are not new and have been used in row crop agriculture production for decades. Utilizing these systems, farmers can increase the number of acres farmed by moving excess water offsite after rainfall and allowing higher saturated areas to be farmable. Additionally, tile drains can allow soils to have higher water availability for crop intake and have been shown to increase yields by 20% or more in some cases (Geist, 2018). However, their popularity has not significantly increased in the past few years, remaining around 14% of cropland (Zulauf & Brown, 2019). Tile drains are not expected to be implemented on all cropland, but with the decrease in crop acres, farmers will likely have to push further into less suitable lands now more than ever.

Given the positives of implementing tile drain systems, the downside historically has been the installation cost. Numerous Extension publications have been published on the returns needed for the economic feasibility of tile drainage systems (Hofstrand et al., 2023; Schnitkey et al., 2022), but the methodology of how the cost of the system was determined is not included. Other works have provided guidance or principles for installing a system (Mahoney et al., 2010; Panuska, 2018) but fail to include how their per-acre costs were calculated. More recent concerns have focused around the environmental impact of system implementation (Bowman, 2020; Stika, 2019). Chapter 2 of this dissertation aims to address these concerns for farmers in the US by performing a carbon footprint analysis and life cycle cost analysis for a tile drainage system. The work not only aims to fill the gaps in the methodology of the installation cost but also provides a breakdown of the carbon footprint and system costs for various system designs and soil types. Additionally, a breakeven analysis was performed to provide a further understanding for farmers looking to add a system to their fields. Although farmers cannot control the field layout or soil type for installing a system, the results from this chapter provide guidelines and suggestions for the cost and emission estimates for implementing a system in various fields.

The third and fourth chapters focus on production expenses for row crop operations by evaluating the second-largest expense for grain farms, machinery (Ibendahl, 2015). Machinery for a farming operation is considered a long-term investment and is often spread across the operation to calculate the per-acre machinery cost. It is estimated that machinery costs comprise over 40% of the total per-acre production expense for row crop operations (Ibendahl, 2015). Utilizing these per-acre expenses allows operations to compare their current machinery and evaluate if they are over or under-capitalized. Given that each farming enterprise uses different machinery types, chapter three focuses on harvesting operations by estimating the values of used combines and the impact of various precision agriculture technologies on the value.

Although precision agriculture has been used for many years, recently, it seems to have developed into every component of a combine. With the advancements in technology, and connectability, newer combines now have to be compared with various precision agriculture technologies. Utilizing auction data from 2010 through 2022, the first model estimates the factors that impact the overall secondary combine market and provides results that allow producers to estimate their combine's value accurately. Building upon this model, the second model evaluates the impact of different precision agricultural technologies on the value of the secondary combine market. In this model, various technologies were grouped to represent the precision agriculture function and avoid any increase from branding. Additionally, variables were developed to represent technology brand to allow the model to estimate the value of these brands separately from the individual technology. The study estimates the value increase from different brands, provides new estimates for depreciation related variables, and suggests which technologies are more valuable. Results can be used by buyers and sellers as average guidelines for comparing used combine options.

Moving to a broader range of production practices, tractors are the most used machinery across all farm types. Recently, the Covid-19 pandemic impacted every industry sector in the world, and farming was no different. Tractor values skyrocketed during the shutdown and continued to rise after shutdown restrictions were lifted. Government assistance has also increased rapidly, allowing many farmers to use the extra income to combat the rise in prices. Moving forward, government payments are projected to decrease, leaving operations with higher prices and lower available funds. In order to prepare for the change, an outlook on the impacts of the pandemic is overdue for the tractor market. Chapter four utilizes an auction dataset for US used tractors sales between 2010 and 2022. Two models were developed, with the first aimed to estimate the total impact of the pandemic on used tractors, and the second using lead and lag variables to evaluate the impact change for the ten months before and after the pandemic started. Results illustrate the impacts of factors such as brand, usage, condition, sale location, sale timing, and sale type, along with the pandemic estimates. Altogether, producers can use the estimates from this model to assist in evaluating tractors used in their operations and more accurately estimate values when buying and selling machinery.

Farming continues to project tighter margins and less government assistance, with the projection of decreasing net farm income in the coming years. Farmers need to optimize their operations to remain profitable in the future. Addressing two possible options of either increasing yields or decreasing expenses, this work presents an evaluation for implementing tile drainage and provides an updated analysis for combine and tractor machinery. Overall, this is just a beginning step in solving the industry issues even so the results presented here should assist operators, industry experts, and decision-makers to make informed decisions about farmland and farm machinery.

CHAPTER 2. EVALUATING REAL-WORLD TILE DRAINAGE SYSTEMS USING LIFE CYCLE COST AND CARBON FOOTPRINT ANALYSIS

2.1 Introduction

A tile drainage system is a network of subsurface pipes that collects excess water from the soil and moves it offsite. These systems can benefit farming operations by allowing historically higher saturated acres to be placed into row crop production. In addition, they allow more flexibility for farmers with crop operation practice dates while potentially increasing crop yields and soil health. Along with these potential benefits, the innovation of new pipe materials provides a more cost-effective and environmentally friendly system than the traditional clay drain tiles previously used (Bowman, 2020; Stika, 2019). Despite these positive benefits, the use of tile drainage systems is still low, with only 14% of U.S. cropland utilizing tile drainage and most of that land is found in the Midwest states of Illinois, Indiana, Iowa, Michigan, Minnesota, Ohio, and Wisconsin (Zulauf & Brown, 2019).

Opportunities exist to replace older systems to minimize environmental concerns from leaching into the water system, soil erosion, and loss of wetland habitats. However, even with the lower risk compared to the older system, the newer tile systems present emission concerns from installation and material construction. Given the uncertainty, this project performed a carbon footprint and life cycle cost, along with a design analysis, to add a tile drainage system to an existing row crop field to address. The objectives for this study are to 1) establish the parameters for four representative row crop fields that are being considered for adding tile drainage, 2) design tile drainage systems for each field with the ability to change each design based on soil type, 3) evaluate the carbon footprint from installation of different system combinations of field and soil type, 4) estimate the costs of installation on the various systems, and 5) evaluate and compare the results between soil types to fields and provide comparison for the farming operations.

Tile drainage for agricultural use in the U.S. dates to 1838, when the systems were first brought over from England (Young, 2014). However, systems similar to the ones in use today were not introduced until the 1940s when polyethylene plastics were invented. The new material led to corrugated pipes, which further developed in the 1960s into perforated plastic pipes (Young, 2014). Additionally, the installation process is more efficient now with the use of GPS machinery, and computer models for system design. With the new evaluations of tile drainage and the rising concern for environmental impact, estimating the carbon footprint from implementation is a starting point in understanding the impacts of these systems. Furthermore, using the different soil types and system designs should allow for the model to estimate the carbon footprint differences between various regions of the country since tile systems are field-specific.

With better materials, installation equipment, and dual wall piping being introduced, there is potential for older systems to be replaced and the new modern tile drainage system’s use to increase. For farmers wanting to either add or replace tile drainage, the economics can be unclear, with most of the cost estimates not providing clear reasoning for the estimate (Hofstrand et al., 2023; Mahoney et al., 2010; Panuska, 2018; Schnitkey et al., 2022). Additionally, these publications do not illustrate the known differences in system cost based on the soil type of the field. Utilizing the life cycle cost approach, this chapter presents a model that can estimate various soil types on each field and provide insight into the cost impact of each soil type. Since, in real-life practice, a farmer cannot change the soil type of the field, the estimates are not directly compared but instead are guidelines for farmers from various regions, unlike the previous estimates that do not discuss soil type estimates. To provide an even further understanding of system cost, a breakeven analysis was performed to calculate the net present value for various systems.

2.2 Field Description and System Design

2.2.1 Field Design

A tile drainage system's design is based on the topography, soil type, location, and desired farming practices (McCain, 2022; Panuska, 2018; Wright & Sands, 2018) of the specific field. Given the goal of this study to provide real-world suggestions, an industry expert supplied information about four fields suitable for tile drainage systems (McCain, 2022). The selection of the four fields is to represent a typical row crop field in the southern Indiana, Kentucky, and Tennessee region as determined by the industry expert (McCain, 2022). Additionally, the study was set up to consider a scenario in which two fields have obstructions present, such as tree lines or waterways, to represent typical obstructions seen when installing a system (Easton et al., 2016; Sands, 2015). Tile drainage systems have three common system layouts: parallel, herringbone, or double main, while many fields can require a mix of the three (Panuska, 2018; Wright & Sands, 2018). The type of layout is often chosen based on considerations of field obstructions. It should be noted that often when implementing on an entire field, if possible, a parallel design is used due to its simplicity and economic efficiency. However, often a system is designed using the mixed type if any obstructions are present (McCain, 2022). Locations, field perimeters, obstruction perimeters, and system outlet locations for the four specific fields were provided by McCain (2022). Field descriptions for each of the four fields can be found in Table 2.1, and overhead pictures with field and obstruction perimeters outlined for each field can be found in Figures 2.1, 2.2, 2.3, and 2.4.

Field 1 (Figure 2.1) represents a field with an obstruction, thus preventing a parallel tile drain system from running the entire field width. For this field, a mixed design system of parallel and herringbone is used to cover the entire area. Furthermore, a second main line is introduced to move the water into the outlet from the opposite side of the obstruction. Field 2 (Figure 2.2) also provided the need for a mixed system type of a double main, parallel, and herringbone system. This field has a waterway that splits the field into two sections. Since the waterway runs through the entire field, a double main line is required for both field sections. Additionally, the perimeter of the field does not allow for a parallel system to cover all areas of the field adequately. Therefore, a mix of parallel and herringbone is used to drain the entire field. Field 2 also provides the largest area among the four fields presented. Field 3 (Figure 2.3) provided a rectangular field shape similar to a field in the Midwest, this field was a perfect fit for implementing a parallel system since no obstructions are present, and the field perimeter allows for proper runoff. Lastly, field 4 (Figure 2.4) evaluated a field with only perimeter issues. This field did not have any field obstructions, but due to the perimeter of the field, a parallel system would not reach all areas of the field. A mixed parallel and herringbone system was used to design this field. It should be noted upon mapping field 4 that there was a waterway along the field's parameter, which required two outlets for proper drainage. This change was confirmed by McCain (2022) for accuracy.

2.2.2 Mapping Tile Drainage System onto Fields

Given the provided field information, the next step was to digitally map the four fields to extract latitude and longitude coordinates to design each tile drainage system. Each field was individually added to Map Maker© (*Map Maker*, 2008), an online mapping system that calculated digital areas based on Google Maps© images. This software allowed for the recreation of each field and provided longitude and latitude coordinates for field obstructions, perimeters, and outlets. Utilizing the information from McCain (2022), additional points were added to divide each field into sections to allow each system design to change when the soil type changes (Section 2.2.3). The additional dividing of each field maintained a consistent outlet location, field coverage, and pipe slope throughout all system designs. Lateral pipelines were plotted by starting at the outlet end of the mainline, half of the lateral spacing distance from the edge of the field to maintain proper draining coverage (Ghane, n.d.). Then a new lateral was plotted at the lateral spacing distance from the previous lateral line. This process continued until a final lateral was plotted within half of the lateral spacing distance from the opposite edge of the field. Lastly, the elevation of outlets and laterals were checked using the Bulk Point Query Service (V 2.0) (*The National Map*, 2023), which provides elevation measurements based on longitude and latitude coordinates uploaded into the software. The corresponding elevation measure for each point was added to the model to ensure each pipeline maintained a downward slope of 1-2% while remaining within the proper lateral pipeline depth range for each soil type (Table 2.2)

2.2.3 Tile System Design Model

The points from mapping the fields, along with the respective latitude, longitude, and elevation measurements, were uploaded into the tile system design model to allow the model to design a tile system for each field, soil type, and pipe size combination. The tile system design model was developed in Excel to combine inputs of the digital layout of the fields from Map Maker (*Map Maker*, 2008), the elevation information from Bulk Point Query Service (V 2.0) (*The National Map*, 2023), and the required system design specifications. The design specifications required the pipe spacing and depth to be consistent throughout the field, the entire field to be covered, and all lateral pipes must allow water to flow through the main pipe by gravity. Pipe spacing and depth were updated based on the field's soil type and can be found in Table 2.2. The spacing and depths for the given soil type were based on the Hooghoudt Equation (Panuska, 2018) (Table 2.3). The equation uses a drainage coefficient, soil permeability, water table depth, and confining layer to calculate the appropriate drain spacing for a field. These variables will change not only with soil type but also with location. For this reason, some states have developed recommendations to assist with system installation (L. O. Anderson et al., 1984). However, Kentucky does not have recommendations for all soil types considered. To accomplish the goal of this study, required drain spacing and depths for each soil type were compiled from other state’s suggestions (Ghane, n.d.; Panuska, 2018; Sands, 2015), as well as calculated using the online software IGrow to reflect the soil characteristics of the southeast (*Drainage Calculators*, 2014). The suggested results from the four sources were compiled and presented to the industry expert McCain (2022), where they were adjusted to reflect realistic numbers to represent fields in Kentucky and the southeast (McCain, 2022). This approach allows for the results of this study to be used across the southeast region of the US instead of solely based in one state. All system design equations used a drainage coefficient of half an inch per day for consistency between the fields. The half an inch per day was based on a system providing "Excellent" drainage, as Wright & Sands (2018) defined. Precipitation history will differ by county within each state; for example, central Kentucky has not had a day that averages over 0.2 inches per day (National Weather Service, 2023).

The design specifications requiring the system to cover the entire field width were achieved by requiring that the end of each lateral pipe must be within half the length of the given pipe spacing for each design combination. The end measurement of half the length of the pipe spacing was used to allow for end drainage and is consistent with calculations from IGrow (Drainage Calculators, 2014) and Drainage Design Tool (Ghane, n.d.). Additionally, the tile system design model was developed to plot lateral lines based on the pipe spacing from the outlet point to within half of the lateral spacing of the edge of the field. This requirement ensured that the last two requirements for covering the entire field and maintaining the same outlet location were satisfied.

Combining the digital field layout with the previously mentioned specifications, the tile system design model developed different systems for each field and soil type pair. The model mapped each lateral pipe by calculating the distance from the outlet location and calculated the number of lateral pipelines needed for each combination. Then the length of each lateral pipeline was determined by taking the distance needed to cover the width of the field or section at that pipe's location. Once all lateral pipe lengths were calculated, the model totaled the pipe needed to implement the designed system for the entire field. The main pipelines were simple to calculate since the outlet location did not change between combinations. For the main pipelines, the model calculated the total length of pipe needed to drain all the laterals throughout the field back to the outlet point. Given the fields used in the study, the size of the main pipeline was not a limitation for drainage. All four fields were able to satisfy water runoff using an 8-inch main pipe. However, scenarios using a 10-inch main pipeline were calculated to provide estimates for fields that would need to use a larger main pipe size. The total pipe length needed for each system's lateral and main pipeline was then used to determine the associated life cycle cost and carbon footprint.

2.3 Methods

The goal of the carbon footprint and life cycle cost (LCC) analyses was to estimate the embedded carbon emissions and financial cost of implementing a tile drainage system on the previously mentioned four crop fields. The system boundaries for the carbon footprint and LCC included the construction of the system (e.g., excavating and backfilling) and manufacturing of the materials (e.g., piping) used. The study did not include operation, maintenance, or end-of-life within the system boundaries. Additionally, a breakeven analysis was performed to provide applicable results for farmers considering installing tile drainage systems (Section 2.3.4).

2.3.1 Design Options

In total, twelve combinations were evaluated; this included all combinations of pipe material (single-wall corrugated or dual-wall corrugated), lateral line pipe sizes (3-inch, 4-inch, or 6-inch), and mainline pipe sizes (8-inch or 10-inch). The results are presented across various soil types and system layout design types. The industry standard is a single-wall pipe with 4-inch lateral lines, and 8-inch mainlines when applicable due to the cheaper cost of the material (McCain, 2022; Panuska, 2018; Wright & Sands, 2018). In some cases, a dual-wall pipe is needed to maintain water flow in systems that require low pipe slopes or longer pipelines due to the installation field. Therefore, the decision to include both was made to provide comprehensive results for tile drainage system implementation. Pipe sizing will change based on the design and needs of a system, often increasing pipe size to handle additional water from longer laterals or heavier rain areas. During this study using the calculations described in Section 2.2, it was determined that a 4-inch lateral and 8-inch main pipe would satisfy the needs of each of the four fields presented. Therefore, the study's evaluation of the other pipe size options is to provide a comparison for fields that would need an increase in pipe sizing.

The inventory for analyzing construction and pipe manufacturing for tile drainage systems starts with the material. The material and installation equipment required was determined by Panuska (2018) and Wright et al. (2018). Since this study does not aim to implement a system in one specific location, transportation requirements assumed that materials would be transported fifteen miles using a commercial vehicle. The functional unit of one acre was used for comparison of the results presented in this study since it is the standard unit used across row crop agricultural work.

2.3.2 Carbon Footprint

Inventory data for each item for installation was acquired through Ecoinvent v3.5 (Wernet et al., 2016) database accessed through SimaPro v9.0.0.49. Additionally, the inventory of emissions from Ecoinvent was converted into climate change impacts (measured in kg CO_2 eq) using the Tool for the Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) v2.1 developed by the United States Environmental Protection Agency (Bare, 2012), accessed through SimaPro v9.0.0.49. A list of inventory items and their associated unit impacts can be found in Table 2.4.

The excavating process used a tile plow and tractor (McCain, 2022; Panuska, 2018; Wright & Sands, 2018). Given the assumption that a farm will have the appropriate tractor on hand to pull the tile plow, only the fuel required for the tractor to operate the tile plow was considered. For the tractor portion, the model calculated the amount of diesel needed per foot based on the tractor fuel consumption per hour of use (Laughlin & Spurlock, n.d.-a) divided by the distance covered per hour for operating a tile plow (Schmidt, 2013). The number of gallons needed per foot was then converted into the total kilograms per foot of the trench excavated. The tile plow implement was outside of the system boundaries since it is an attachment to the tractor during installation and does not require any additional fuel.

2.3.3 Life Cycle Cost

The cost of materials and equipment for system installation were found using R.S. Means data (R.S.Means, 1997), except for the cost of excavation, which was calculated using MSBG (Laughlin & Spurlock, n.d.) since a tile plow estimate was not available through R.S. Means. The pipe cost estimates used the unit cost (per foot) of each pipe given that pipe's diameter (Table 2.5). These unit costs for the lateral and main pipelines were multiplied by the total length of the pipe calculated in the tile drain system design model previously mentioned (Section 2.2). The backfilling of the trenches used a per cubic yard estimate from RSMeans multiplied by the total volume of backfill in each system. The transportation costs were determined using the assumed distance of 15 miles to the field using a freight vehicle with a per mile cost of $0.67 (R.S.Means, 1997).

The cost of excavation considered the tractor's use for installation and the purchasing of a tile plow. The required use of the tractor for installation was determined by finding the average amount of pipe installed per hour (Schmidt, 2013) combined with the per-hour cost of using that tractor from MSBG (Laughlin & Spurlock, n.d.). The unit cost for the tractor was then converted to a per linear foot estimate for the LCC model. A 225-horsepower tractor was used for the estimate with a per-hour labor cost of \$20 per hour and a fuel cost of \$3.75 per gallon, all of which are suggested by MSBG (Laughlin & Spurlock, n.d.) It should be noted that tractor diesel is off-road fuel and will not be the same price as the fuel used for the freight transport vehicles. The tile plow cost per acre was calculated by combining information from MSBG (Laughlin & Spurlock, n.d.) and the tile plow online price (*AgToGo | Precision Ag | Crary Tile Plow | Crary PRO® Tile Plow – AG TO GO*, n.d.). Since the plow is an implement and connected to the tractor, all fuel and labor costs were captured in the tractor per acre cost. Using similar earth-moving type machinery, MSBG suggested a repairs and maintenance percentage of 65%, a useful life of 12 years, and an annual use of 150 hours per year (Laughlin & Spurlock, n.d.). These estimates were combined with the purchase price of \$37,000 for a new tile plow, resulting in a per-hour estimate of \$29.40. The tile plow cost per hour was added to the tractor's per hour cost of \$100.24 and then divided by the feet per hour installed, resulting in a per-foot cost estimate for the installation of the tile drain.

2.3.4 Breakeven Analysis

A breakeven analysis was performed to estimate what production changes would be needed for the system to be economically feasible. The breakeven model was constructed to compare each combination of soil type, system design, or field.

Additionally, an average for each soil type across all four fields in each system design combination was included to minimize the impact of “economies of scale” with field size on the results. To represent a realistic row crop operation, the model utilized a yearly corn-soybean crop rotation.

Given a combination, the model calculated the net present value (NPV), and payback period for a tile drainage system. The calculation is based on key variables that include the discount rate of 8%, estimated crop yield percentage increase of 20%, expected price and yield for corn and soybeans, and desired 50-year term of payback for NPV. Corn and soybean price and yield estimates for 2023 through 2033 were taken from FAPRI (*U.S. Agricultural Market Outlook*, 2023). However, no estimates are provided for years after 2033. Since crop yields have historically suggested a linear upward trend, a linear trendline was used to estimate crop yields after 2033. The trendline was based on actual crop yields from 2003 through 2021 and the estimated yields from 2022 through 2023 (*U.S. Agricultural Market Outlook*, 2023). As for crop prices, a linear relation has not been shown historically. Therefore, years after 2033 use a five-year price average based on prices observed between 2018 to 2022 (*U.S. Agricultural Market Outlook*, 2023). Previous literature suggests a potential yield increase for tile drainage acres of up to 25% compared to non-drainage acres (Kladivco, 2020; Schilling, 2022). Since these yield increases are field specific, the model uses a 20% increase for the break-even analysis.

In addition to the key variables, cost increase estimates for corn and soybeans were added to the model to account for the cost increases from the additional yields. The increased cost estimates are based on Kentucky located operations (Halich, 2023) and included costs for seed, fertilizer, drying, storage, transport, machinery, and labor. Each cost was calculated at the per bushel level to allow the model to accurately estimate the changes from the additional yield. The calculation was based on the per acre cost and then divided by the yield per acre estimate (Halich, 2023). Cost increase estimates for the break-even model are located in Table 2.6.

2.4 Results

Soil types and system design combinations cannot be directly compared to one another since each combination will depend on the field in which the tile drainage system is installed. Even though the systems cannot be compared across different soil types, this study generated an average carbon footprint and life cycle cost estimate for each soil type across all four fields to provide an additional estimate that limits the impact of "economies of scale" from larger fields. The functional unit for this study was one acre to reflect the common unit used in farming practice. As expected, the model suggested using the smallest pipe size possible for both the carbon footprint and LCC results. Since all four fields were able to properly remove the water with the smallest pipe option, the results suggested the use of the 3-inch lateral pipe with the 6-inch main pipe for all scenarios. Although the model found no issues with the 3-inch pipes' ability to handle the needed runoff amounts, due to years of perception within the industry, producers will often choose the 4-inch lateral pipe over the 3-inch pipe (McCain, 2022). As for the main pipelines, there were no issues with industry perception against using the 8-inch pipe size. To illustrate the results in terms of the industry practices, the study used the combination of a 4-inch lateral pipe and an 8-inch main pipe as the "base case" scenario. Additionally, the soil type for the "base case" scenario was Silt Loam to provide a consistency in results between fields and represents the majority of the soil in the four selected fields in this study.

2.4.1 Carbon Footprint Results

The full carbon footprint results can be found in Tables 2.11, 2.12, 2.13, and 2.14. Carbon emissions from tile drainage installation were estimated as kg CO_2eq the standard unit of measurement for carbon footprints. For comparison, one gallon of diesel fuel would have a carbon footprint of 1.7 kg CO_2 eq (Table 2.4).

Sil loam soils averaged a carbon footprint of 551.3 kg CO_2 eq across the four fields, with field 2 holding the lowest estimate followed by fields 4, 3, and 1 for a base case of a 4-inch lateral pipe and 8-inch main pipe. When the model dropped to a 3-inch lateral pipe with an 8-inch main, the average emission was 401.5 kg CO_2 eq, with the field order from lowest to highest as field 2,3,4, then 1. For fields that would require larger pipe sizing for heavier water runoff, results from the combination of a 4-inch lateral and a 10-inch main pipe averaged an emission of 588 kg CO_2 eq with the lowest emission estimate held in field 2. Following field 2, field 3 was estimated at 686 kg CO_2 eq, followed by field 4 at 688 kg CO_2 eq, and field 1 at 713.6 kg CO_2 eq. The largest capacity option presented in this study was a 6-inch lateral and 10-inch main pipe and was estimated to have an average emission of 1149.1 kg CO_2 eq for silt loam soils with the field order of 2,3,4, and 1 from lowest to highest estimated carbon footprint. As mentioned previously, dual-wall piping estimates were calculated to provide comprehensive results, although it is unlikely a system would consist fully of dual-wall piping. Nevertheless, the results for dual-wall piping in silt loam soils for the base case piping size averaged an emission estimate of 767.6 kg CO_2 eq. Field 2 was again the lowest estimate, with fields 1,3, and 4 holding closer estimates to each other than field 2 with an order of field 4,3, then 1 from lowest to highest. Since dual-wall piping is not commonly used for an entire system, comparing the change from the base case pipe sizes to the other combinations is presented as a percent change in the discussion Section 2.5 below to illustrate the changes in a more effective way.

For all combinations, field 2 held the lowest carbon footprint among the four fields in the study due to the larger overall size of the field allowing for longer lateral pipelines which would decrease the per acre estimates presented. On average field 4 held the second lowest carbon footprint estimates, followed by field 3, and then field 1. Although the results for fields 1, 3, and 4 were relatively close to each other, the order between fields 3 and 4 did switch between different combinations. Soil types followed expectations due to the pipe spacing difference with lower carbon footprints for systems in sandy soils and higher for systems in clay soils.

2.4.2 Life Cycle Cost Results

The full life cycle cost results can be found in Tables 2.7, 2.8, 2.9, and 2.10. Results from the life cycle cost portion of the study were converted to a per-acre cost for all four fields since per-acre is the common unit of measurement within the industry. The base case scenario was estimated at $3,640.57 per-acre, much higher than previous studies (Mahoney et al., 2010; Schnitkey et al., 2022). Field 2 held a substantially lower estimate at just $1,599, while the other three fields were over double. A comparison and further investigation of the differences seen between the fields and soil types is discussed in the following Section 2.5.4. For the 4-inch lateral and 8-inch main pipe base case, Field 4 was estimated to have the second lowest cost, followed by Field 3, then Field 1. As expected, dropping lateral pipe size down to a 3-inch pipe resulted in lower cost estimates with an average of $1,912 per acre. Cost order remained the same for the four fields with Field 2 holding the lowest estimate for the 3-inch lateral piping at $852. Fields 4,3, and 1 again resulted in similar estimates to one another at $2,215, $2,263, and $2,319 respectively. On the other hand, when the model moved to a 4-inch lateral and 10-inch main pipe, the average cost was $3,788. Field 2 resulted in the lowest cost at $1,676, followed in order of lowest to highest Field 4, 3, and 1. For fields with larger amounts of water runoff, increasing the lateral pipe size to 6-inch, while maintaining the 10-inch main pipe, would result in the average cost of $5,940 per-acre, a 56% increase in the cost of the system. Similar to the carbon footprint results, the use of dual-wall piping drastically increased the cost. As mentioned previously, dual-wall piping is not likely to be used for an entire system and is mostly used in sections of a system where water flow needs to be increased to maintain flow rates of the system. Therefore, the cost of an entire system is not useful and results were converted to a percent change and presented in the discussion Section 2.5. For 8-inch main pipe systems, Field 2 held the lowest estimated cost followed by Field 4, 3, and 1. The order of fields remained the same for systems with a 10-inch main pipe and either a 4-inch or 6-inch lateral. However, systems that used a 3-inch lateral and 10-inch main pipe resulted in the order of Field 2, 3, 4, and 1 from lowest to highest average cost.

2.5 Discussion

In the agriculture setting, a system’s design will be based on the specific field of implementation. Tradeoffs between the carbon footprint and the cost of the system will be completely dependent on the individual farmer’s preferences and will likely be heavily weighted towards the lowest cost system (McCain, 2022). Instead of providing a recommended or “best” system, this section discusses the differences seen between designs investigated and aims to provide guidance for industry understanding of how carbon footprint and cost of tile drainage systems change based on the variables of a field.

2.5.1 Carbon Footprint Discussion

Starting with the base case scenario of 4-inch lateral and 8-inch main piping on a silt loam soil, the carbon footprint was estimated at an average of 551 kg CO_2 eq per acre. When looking at the average across all fields and all soil types, the average system would produce 554 kg CO_2 eq for the 4-inch lateral and 8-inch main piping system. Similar to the base case, Field 2 held the lowest carbon footprint with an average of 325 kg CO_2 eq, followed by Field 4 at 612 kg CO_2 eq, Field 3 at 625 kg CO_2 eq, and Field 1 at 652 kg CO_2 eq. When the lateral pipe size decreased to 3 inches, an average decrease of 26% across all fields and soil types was found. Comparing the decrease in cost by field illustrated a closer grouping of the results with all four Fields estimating a change within 3% of one another across all soil types. On the other hand, increasing to a 6-in lateral pipe drastically increased the cost of the system by nearly double at an average of 97%. Although the carbon footprint changed for all inventory groups, the largest portion of the change was in the pipe material. For the single-wall piping, the increase in material was over double for the 6-inch pipe compared to the 4-inch. Similarly, the transportation of the material is also based on the weight of the pipe resulting in over double the emissions for the 6-inch pipe. However, the carbon emissions for transportation were significantly lower than the material. Therefore, the results suggest that the major driving factor of the carbon emissions is the pipe. An increase to a 10-inch main pipe did not increase the carbon footprint as much as the change in lateral due lower distance of mainline pipes in the system. On average an increase of 7%

was estimated for implementing a 10-inch pipe instead of the 8-inch. Like the increase in emissions with the lateral piping, the major increase was seen with emissions related to the piping material. When the model required the use of a dual-wall pipe, carbon footprint increased by 48% on average across all combinations of fields and soil types. Although the increase was smaller than expected compared to the increase seen in piping sizing changes, the magnitude of the increase was heavily variable depending on the lateral pipe size, ranging from 77% in the 3-inch later systems to 28% in the 6-inch systems. Nevertheless, the percent increase seen for the use of a dual-wall pipe should be used for producers to estimate the emission increases for portions of a system that will require high flow rates. When results were discussed with an industry expert, producers will only utilize dual-wall piping in specific cases where flow rate is an issue and will only use dual-wall pipes for the specific section of the system (McCain, 2022).

2.5.2 Carbon Footprint Comparing Fields

Carbon footprint per-acre estimates varied across the four fields, with a close grouping for fields 1,3 and 4; while field 2 consistently held a lower estimate. Although the fields presented different combinations of the common tile drainage system layout, the size of field 2 was able to outweigh the obstruction challenges within the field. Since each field design was specific to the actual field, it is not possible to determine if an estimated increase was due to the system design or field parameters. The middle obstruction presented in field 1, estimated results were 2.2% to 4.9% higher in the base case than fields 3 and 4. By definition of the system design, the presence of a middle obstruction would increase a field’s carbon footprint from incorporating a tile drain system, this comparison suggests that the magnitude could be fairly small if all other variables are equal. When moving to the smaller lateral pipe size of 3-inch the difference for field 1 compared to Fields 3 and 4 is between 3.8% and 3.9%, while moving to the larger 6-inch lateral pipe results in a larger range of –0.1% and 6.5%. Although these comparisons are only suggestions of estimate changes from a field with a middle obstruction, the ranges and differences shown from changing the pipe size illustrates the magnitude difference of the additional material needed for the larger pipe and the change in impact for larger sized pipe systems will have because of the obstruction.

Field 4 was the closest system layout to field 2 with the presence of a waterway though the entire field. On the other hand, field 3 presented the simplest layout with the entire field having a lateral system design and one main pipeline. Although a comparison of field estimates cannot determine the exact reason for an increase, comparing fields 2 and 4 provides a suggestion for an increase from a middle of the field waterway. Across all soil types and 8-inch main pipe systems, an average change of 2.4% was observed for moving from field 4 to field 3. Further investigation illustrated a similar change in the magnitude of comparisons as field 1. For the 4-inch and 6-inch lateral piping, all combinations found that field 4 would hold a lower carbon footprint than field 3. However, for the 3-inch lateral piping, field 3 was estimated to have lower estimates than field 4 on average across all soil types. The model estimated that field 4 is lower than field 3 in soils with higher permeability, but field 3 estimates a lower carbon footprint in soils with lower lateral spacing for the 3-inch piping resulting in the lower average for field 3 over all soil types. Although this result is troubling at first, the change in the order of fields 3 and 4 was due to the scale differences of the emissions estimate of the 3-inch piping compared to the other two options. In each case field 3 required less main piping than field 4 due to the lack of field obstructions and lateral system design. For the lateral piping needed, field 4 required less than field 3 due to field layout having the main line run though the center of the field. The amount of piping for the lateral and main lines does not change when pipe sizing is changed since it is solely based on the soil type. Therefore, the estimated carbon footprint for 3-inch piping is low enough to outweigh the additional piping amount used in field 3 in the lower permeable soils resulting in a lower emission estimate than the mainline pipe carbon footprint difference between the two fields. The carbon footprint estimate for the 4-inch and 6-inch piping was not low enough to shift the order of the two fields but did estimate a lower difference between the fields in lower permeable soils.

2.5.3 Carbon Footprint Soil Type Differences

Soil types are also field specific and will depend on the location of where a tile drainage system is installed. Although producers do not have control over the soil type, the results of this study provide a better understanding of the carbon footprint of installing a system and its relationship with different soil types. As expected, sandy soils held the lowest carbon footprint estimate across all combinations and silty clay soils held the highest. Since both the tile depth and spacing are changing based on soil type using either as the sole explanation for the emissions differences would not be appropriate. Comparing changes between soil types, carbon footprints were higher in soils with low permeability on average.

2.5.4 Life Cycle Cost Discussion

The base case scenario was estimated to have an installation cost of $3,641 per acre on average across all four fields. Across all soil types, the 4-inch lateral and 8-inch main pipe system held an average cost of $3,661 per acre. As expected, due to the size of field 2 was less than half of the cost seen in the other three fields at $1,599 per-acre. fields 1,3, and 4 all held close estimates to each other, with the order from lowest to highest as field 4, field 3, then field 1. For the 3-inch lateral piping options, the cost of the system dropped immensely from the base case to an average cost of $1,912 on silt loam soils with field 2 estimated at $852 per-acre. On the other hand, the increase of moving to a 6-inch lateral pipe resulted in the average cost increasing by over $2,000 per-acre from the base case. The larger change seen with the 6-inch lateral systems is due to the piping material increase. Moving to the larger 10-inch main pipe had less of an impact of the cost as the change in lateral piping, on average the cost only increased by $148 per-acre in the base case scenario.

Similar to the carbon footprint results, fields 4 was the second lowest cost estimate except for a few soil types. For 3-inch lateral systems, field 3 estimated a lower cost than field 4 for soil types sandy clam loam, clay loam, silty clay loam, and sandy loam. The lower estimate is due to the field parameters and the system layout to satisfy those parameters. field 4’s parameters required the model to estimate a higher increase in the amount of piping used per-acre with these soil types compared to the other soil types. Since field 3 did not present the same parameters, the model did not estimate the large increase in pipe per acre, resulting in a slightly lower cost. When moving up to the 4-inch or 6-inch piping only clay loam and sandy clam soils illustrated a higher cost form field 4. In these cases, the increase in the amount of piping needed to satisfy the parameters, the additional cost of the piping was not enough to outweigh the increased cost. The cost increase from requiring a dual-wall pipe to be used was well above the change seen in the carbon footprint results, with an average increase of 449% across all combinations. Comparing the changes seen for the lateral pipe sizes, 6-inch lateral piping held a lower percent increase from the dual-wall, followed by 4-inch, then 3-inch piping. Since the use of a dual-wall pipe is not likely to be used across an entire system, the estimated change suggests farmers are expected to have 4.5 times more for the portion of a system that needs dual-wall piping.

2.5.5 Life Cycle Cost by Field

The initial expectation was that fields with no obstructions would hold cost estimates well below other layouts, followed by fields with waterways through the middle, then fields with obstructions. The per-acre findings of this study suggested otherwise with the lowest estimates coming from fields with waterways. As mentioned, the order of the fields was not consistent throughout all scenarios. The order change seen between fields 3 and 4 demonstrates the limitations of providing a comprehensive tile drain cost model for all fields. The increase in piping per-acre is not related to the soil permeability since field 4 is the second lowest cost for both clay and silty clay soil types. Due to the dimensions of field 4, the spacing of the few soil types resulted in the model having to place extra lateral piping to ensure drainage would reach the edge of the field.

2.5.6 Life Cycle Cost by Soil Type

Soil type results followed expectations due to the underlying design equations calculating the pipe amounts. Higher permeable soils were estimated to have lower per-acre cost suggesting that field design could not outweigh the cost savings from wider spacing requirements of soils such as sand.

2.5.7 Breakeven Analysis

Utilizing Kentucky crop budgets for 2023, the breakeven analysis estimated a negative NPV for all of the base case scenarios. Similarly, if the lateral pipe size was increased to 6-inch, all four fields were negative. Moving to a silt loam soil with a 3-inch lateral pipe suggested a NPV of $68.97 for Field 2, but was negative for the other three fields. Across all soil types and pipe sizes, only field 2 illustrated positive NPV with higher permeability soils. Investigating these results would suggest that the fields represented in this work are too small in size to be profitable at the given prices of the breakeven model. Therefore producers looking to install systems on smaller fields will either need higher crop prices or higher yields for installation to have a positive NPV.

2.6 Conclusion

Tile drainage systems have been used in agriculture for decades (Young, 2014); however, recent cost estimates are lacking from scientific literature (Hofstrand et al., 2023; Mahoney et al., 2010; Panuska, 2018; Schnitkey et al., 2022). Additionally, new materials and installation improvements along with the environmental concerns of modern-day agriculture, provide the need for a carbon footprint analysis to be performed for installing these systems. The model considers four different crop fields representing common layouts for a tile drain system. Those fields were digitally mapped using online mapping software to determine critical points, which were then fed into Excel to design tile systems for each field with the ability to redesign a layout when soil type changed. An LCC and carbon footprint model utilized the Excel outputs, R.S. Means database, and Ecoinvent database for each design and calculated each combination's cost and carbon emission. The results suggest that using a single-wall pipe will have the lowest cost and environmental impact. The base case scenario used a 4-inch lateral pipe, 8-inch main pipe on silt loam soils for consistency. For the fields used in the study, the use of a 3-inch lateral pipe showed no issues, while suggestions producers could save up to one-third of the cost compared to the 4-inch lateral pipe.

Given this study's objectives, parameters, and design, the base case tile system would average a cost of $3,641 per acre and have a carbon footprint of 551 kg CO_2 eq per acre across all four fields. Economies of scale were illustrated with the larger field in the study estimated at $1,599 per acre in the base case scenario, showing the cost per acre reduction when scaling a system. The breakeven analysis suggest larger fields will be more financially suitable for tile drainage system. Nevertheless, the full results provide estimates across soil types that producers can use as guidelines for their specific field and system.

Although this study provides much-needed information such as updated cost estimates, carbon footprint impact estimates, and comparing different soil types for implementing tile drain systems, limitations were found. These include machinery used for excavating. Since the R.S. Means database provided estimates for tractors or tile plows, utilizing the Mississippi State Budget Generator (MSBG) did help to mitigate some of these limitations. This limitation carried over to the carbon footprint by needing a complete estimate for the machinery used and having to use the diesel burned as the best possible option. It should be noted that if a tractor is purchased specifically for implementation, the estimates would increase drastically. Furthermore, we are only considering four different field configurations in this study.

Further work on tile drain systems should focus on better estimates for the excavating and backfilling portions of the model. Additionally, more work needs to be done on accurately predicting the per-acre cost of a system by adding larger fields. The literature estimates have remained relatively unchanged since the early 2010’s (Mahoney et al., 2010; Schnitkey et al., 2022), while the installation process has dramatically changed. This gap has led to an extreme underestimation of cost, which this study addresses. Introducing more fields and better estimations on specific tile drainage pipe costs could help fill the gap even more. Lastly, this accounts for labor costs in the LCC model; however, some of the literature views tile installation as self-installation or "free labor"(Post, 2021). This could further underestimate the cost of these systems. Although labor costs were addressed in this work, a further evaluation of the labor used would be helpful in the literature. Overall, this project fills a gap within the literature and provides recommendations for installing a tile drain system. While there are limitations to the study, the results and recommendations should be used for further research in this area.

2.7 Chapter 2 Tables and Figures

Table 2-1 – Field Descriptions

Field Number	Total Acres	System Design Type	Field Slope
Field 1	36.3	Lateral and Herringbone	0-2%
Field 2	127	Herringbone	0-2%
Field 3	34	Lateral	0-1%
Field 4	32.9	Lateral and Herringbone	0-1%

Table 2-2 – Pipe Spacing and Depth by Soil Type

Soil Type	Target Lateral Depth (inches)	Lateral Spacing (feet)
Sand	63	350
Loamy sand	57	250
Sandy loam	51	190
Silt loam	45	85
Loam	45	85
Sandy clay loam	42.6	80
Clay loam	39	45
Silty clay loam	39	40
Sandy clay	39	45
Silty clay	39	30
Clay	39	35

Table 2-3 – Equations and Assumptions for Pipe Design

Name	Equation	Description	Reference
Drainage Coefficient (in/day)	DC = volume (depth(in) x area (ac)) of water to be removed from field in 24 hours.	The desired water removal rate (Dc)	Panuska,2018
Hooghoudt Equation	$DC = ((8*K_2*d*h)/L^2) + ((4*K_1*h^2)/L^2)$	K is the soil permeability, d is the distance between the drainpipe and the confining layer below, h is the distance between the water table and the drainpipe, and L is the drain spacing.	Panuska,2018
Flow Capacity	Q = [area in acres * DC] / 23.8	Q = Flow Capacity	Wright, 2018

Table 2-4 – Carbon Footprint of Included Materials and Processes Estimates

Item	Unit Process	Impact Estimate	Unit	Database
Single Wall Material	High density, granulate {GLO}| market for | APOS, U	2.0071	(kg CO^2 eq/kg)	Ecoinvent 3
Single Wall Pipe Processing	Extrusion, plastic pipes {GLO}| market for | APOS, U	0.4463	(kg CO^2 eq/kg)	Ecoinvent 3
Dual Wall Material	High density, granulate {GLO}| market for | APOS, U	2.0071	(kg CO^2 eq/kg)	Ecoinvent 3
Dual Wall Pipe Processing	Extrusion, plastic pipes {GLO}| market for | APOS, U	0.4463	(kg CO^2 eq/kg)	Ecoinvent 3
Diesel	Diesel {GLO}| market group for | APOS, U	0.5284	(kg CO^2 eq/kg of Fuel)	Ecoinvent 3
Backfill	Skid-steer loader {GLO}| market for | APOS, U	0.5195	(kg CO^2 eq/m3)	Ecoinvent 3
Transportation	Light commercial vehicle {GLO}| market group for transport, freight, light commercial vehicle | APOS, U	1.891	(kg CO^2 eq/metric ton-km)	Ecoinvent 3

Table 2-5 – Piping Unit Cost by Pipe Size

Item	Cost	Unit	Reference
Single Wall Lateral Pipe Costs	(0.8463*Pipe Diameter) - 0.7354	($/ft)	RS Means
Single Wall Main Pipe Costs	(3.0788*Pipe Diameter) + 2.1737	($/ft)	RS Means
Dual Wall Lateral Pipe Costs	(1.6721*Pipe Diameter) - 7.6171	($/ft)	RS Means
Dual Wall Main Pipe Costs	(7.525*Pipe Diameter) - 34.4	($/ft)	RS Means
Excavation Costs	$0.02	($/Linear ft)	MSGB
Backfill Costs	$2.53	($/yd3)	RS Means
Transportation to Jobsite Costs	$0.67	($/Mile)	RS Means
Tile Plow Costs Breakdown			
Tile Plow	(Purchase Price*R&M%)/(Annual Hr*Useful Life)	($/Acre)	MSGB
Tile Plow	($28,000*.65)/(150*12)	($/Acre)	MSGB

Table 2-6 – Breakeven Cost Estimates for Yield Increase

Item	Cost Increases (Cost per bushel)	Reference
Corn Seed	$0.57	UKY (Halich,2023)
Corn Nitrogen	$0.73	UKY (Halich,2023)
Corn P, K, and Lime	$0.50	UKY (Halich,2023)
Corn Drying, Storage, Transport	$0.23	UKY (Halich,2023)
Machinery and Labor	$0.99	UKY (Halich,2023)
Totals per bushel of corn	$3.02	
Soybean Seed	$1.30	UKY (Halich,2023)
Soybean P, K, and Lime	$1.22	UKY (Halich,2023)
Soybean Drying, Storage, Transport	$0.13	UKY (Halich,2023)
Machinery and Labor	$2.41	UKY (Halich,2023)
Totals per bushel of soybeans	$5.06	

Table 2-7 – Life Cycle Cost for 8-inch Mainline Pipe

LCC Single 3 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$1,778.22	$300.70	$1,671.69	$1,417.88	$1,292.12
Loamy sand	$1,951.12	$363.98	$1,851.05	$1,676.75	$1,460.72
Sandy loam	$2,077.79	$450.56	$1,979.28	$1,887.08	$1,598.67
Silt loam	$2,319.29	$851.79	$2,262.73	$2,215.24	$1,912.26
Loam	$2,319.29	$851.79	$2,262.73	$2,215.24	$1,912.26
Sandy clay loam	$2,333.44	$895.85	$2,225.16	$2,249.46	$1,925.98
Clay loam	$2,429.98	$1,495.07	$2,269.48	$2,394.93	$2,147.36
Silty clay loam	$2,422.69	$1,665.48	$2,298.74	$2,357.53	$2,186.11
Sandy clay	$2,429.98	$1,495.07	$2,269.48	$2,394.93	$2,147.36
Silty clay	$2,404.99	$2,182.98	$2,363.62	$2,314.07	$2,316.41
Clay	$2,415.33	$1,893.78	$2,326.30	$2,325.29	$2,240.17
Average	$2,262.01	$1,131.55	$2,161.84	$2,131.67	$1,921.77
LCC Single 4 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$3,293.47	$464.42	$3,182.98	$2,508.88	$2,362.44
Loamy sand	$3,650.29	$594.54	$3,552.41	$3,041.50	$2,709.69
Sandy loam	$3,912.36	$772.73	$3,817.04	$3,474.78	$2,994.23
Silt loam	$4,411.08	$1,598.75	$4,401.42	$4,151.04	$3,640.57
Loam	$4,411.08	$1,598.75	$4,401.42	$4,151.04	$3,640.57
Sandy clay loam	$4,440.95	$1,689.68	$4,324.58	$4,221.95	$3,669.29
Clay loam	$4,640.89	$2,924.06	$4,416.59	$4,522.24	$4,125.94
Silty clay loam	$4,625.89	$3,274.98	$4,476.83	$4,445.23	$4,205.73
Sandy clay	$4,640.89	$2,924.06	$4,416.59	$4,522.24	$4,125.94
Silty clay	$4,589.44	$4,340.68	$4,610.45	$4,355.72	$4,474.07
Clay	$4,610.72	$3,745.13	$4,533.58	$4,378.84	$4,317.07
Average	$4,293.37	$2,175.25	$4,193.99	$3,979.40	$3,660.50
LCC Single 6 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$5,181.42	$668.41	$5,066.00	$3,868.22	$3,696.01
Loamy sand	$5,766.94	$881.75	$5,671.80	$4,741.56	$4,265.51
Sandy loam	$6,197.19	$1,173.98	$6,105.83	$5,452.15	$4,732.29
Silt loam	$7,015.68	$2,528.84	$7,064.42	$6,561.42	$5,792.59
Loam	$7,015.68	$2,528.84	$7,064.42	$6,561.42	$5,792.59
Sandy clay loam	$7,064.91	$2,678.05	$6,938.46	$6,677.80	$5,839.81
Clay loam	$7,393.23	$4,702.99	$7,089.50	$7,170.50	$6,589.06
Silty clay loam	$7,368.62	$5,278.63	$7,188.31	$7,044.19	$6,719.94
Sandy clay	$7,393.23	$4,702.99	$7,089.50	$7,170.50	$6,589.06
Silty clay	$7,308.84	$7,026.79	$7,407.50	$6,897.35	$7,160.12
Clay	$7,343.75	$6,049.86	$7,281.41	$6,935.28	$6,902.57
Average	$6,822.68	$3,474.65	$6,724.29	$6,280.04	$5,825.41

Table 2-8 – Life Cycle Cost for 10-inch Mainline Pipe

LCC Single 3 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$1,959.19	$377.69	$1,798.24	$1,620.92	$1,439.01
Loamy sand	$2,132.29	$441.09	$1,978.11	$1,880.29	$1,607.95
Sandy loam	$2,259.16	$527.79	$2,106.85	$2,091.12	$1,746.23
Silt loam	$2,500.87	$929.15	$2,390.80	$2,419.78	$2,060.15
Loam	$2,500.87	$929.15	$2,390.80	$2,419.78	$2,060.15
Sandy clay loam	$2,515.10	$973.26	$2,353.44	$2,454.20	$2,074.00
Clay loam	$2,611.76	$1,572.55	$2,398.06	$2,599.97	$2,295.59
Silty clay loam	$2,604.48	$1,742.96	$2,427.32	$2,562.58	$2,334.33
Sandy clay	$2,611.76	$1,572.55	$2,398.06	$2,599.97	$2,295.59
Silty clay	$2,586.78	$2,260.46	$2,492.20	$2,519.11	$2,464.64
Clay	$2,597.11	$1,971.26	$2,454.88	$2,530.34	$2,388.40
Average	$2,443.58	$1,208.90	$2,289.89	$2,336.19	$2,069.64
LCC Single 4 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$3,474.44	$541.41	$3,309.54	$2,711.92	$2,509.33
Loamy sand	$3,831.47	$671.65	$3,679.48	$3,245.04	$2,856.91
Sandy loam	$4,093.74	$849.97	$3,944.61	$3,678.82	$3,141.78
Silt loam	$4,592.66	$1,676.11	$4,529.49	$4,355.58	$3,788.46
Loam	$4,592.66	$1,676.11	$4,529.49	$4,355.58	$3,788.46
Sandy clay loam	$4,622.61	$1,767.09	$4,452.86	$4,426.69	$3,817.31
Clay loam	$4,822.67	$3,001.54	$4,545.17	$4,727.28	$4,274.17
Silty clay loam	$4,807.67	$3,352.46	$4,605.40	$4,650.28	$4,353.95
Sandy clay	$4,822.67	$3,001.54	$4,545.17	$4,727.28	$4,274.17
Silty clay	$4,771.22	$4,418.16	$4,739.03	$4,560.77	$4,622.30
Clay	$4,792.51	$3,822.61	$4,662.16	$4,583.89	$4,465.29
Average	$4,474.94	$2,252.61	$4,322.04	$4,183.92	$3,808.37
LCC Single 6 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$5,362.38	$745.40	$5,192.56	$4,071.26	$3,842.90
Loamy sand	$5,948.11	$958.86	$5,798.86	$4,945.10	$4,412.73
Sandy loam	$6,378.57	$1,251.21	$6,233.40	$5,656.19	$4,879.84
Silt loam	$7,197.26	$2,606.19	$7,192.50	$6,765.96	$5,940.48
Loam	$7,197.26	$2,606.19	$7,192.50	$6,765.96	$5,940.48
Sandy clay loam	$7,246.57	$2,755.46	$7,066.74	$6,882.55	$5,987.83
Clay loam	$7,575.02	$4,780.47	$7,218.07	$7,375.55	$6,737.28
Silty clay loam	$7,550.41	$5,356.12	$7,316.89	$7,249.23	$6,868.16
Sandy clay	$7,575.02	$4,780.47	$7,218.07	$7,375.55	$6,737.28
Silty clay	$7,490.62	$7,104.27	$7,536.08	$7,102.40	$7,308.34
Clay	$7,525.53	$6,127.34	$7,409.99	$7,140.33	$7,050.80
Average	$7,004.25	$3,552.00	$6,852.33	$6,484.55	$5,973.28

Table 2-9 – Life Cycle Cost for Dual Wall 8-inch Mainline Pipe

LCC Dual 3 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$12,454.10	$1,845.06	$11,952.64	$9,599.63	$8,962.86
Loamy sand	$13,777.87	$2,326.32	$13,323.16	$11,570.78	$10,249.53
Sandy loam	$14,753.45	$2,985.57	$14,308.42	$13,177.53	$11,306.24
Silt loam	$16,604.09	$6,038.05	$16,475.69	$15,683.46	$13,700.32
Loam	$16,604.09	$6,038.05	$16,475.69	$15,683.46	$13,700.32
Sandy clay loam	$16,718.42	$6,375.42	$16,196.01	$15,949.36	$13,809.80
Clay loam	$17,463.23	$10,938.99	$16,542.12	$17,065.03	$15,502.34
Silty clay loam	$17,407.79	$12,235.71	$16,764.72	$16,780.48	$15,797.17
Sandy clay	$17,463.23	$10,938.99	$16,542.12	$17,065.03	$15,502.34
Silty clay	$17,273.12	$16,173.67	$17,258.47	$16,449.72	$16,788.74
Clay	$17,351.75	$13,973.00	$16,974.44	$16,535.15	$16,208.59
Average	$16,170.10	$8,169.89	$15,710.32	$15,050.87	$13,775.30
LCC Dual 4 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$16,486.53	$2,280.75	$15,974.54	$12,503.03	$11,811.21
Loamy sand	$18,300.29	$2,939.97	$17,851.42	$15,203.10	$13,573.69
Sandy loam	$19,636.81	$3,843.15	$19,200.27	$17,403.76	$15,021.00
Silt loam	$22,172.75	$8,026.58	$22,169.22	$20,836.87	$18,301.35
Loam	$22,172.75	$8,026.58	$22,169.22	$20,836.87	$18,301.35
Sandy clay loam	$22,329.21	$8,488.84	$21,785.26	$21,200.70	$18,451.00
Clay loam	$23,349.72	$14,743.62	$22,258.72	$22,728.93	$20,770.25
Silty clay loam	$23,273.73	$16,520.96	$22,563.82	$22,338.91	$21,174.36
Sandy clay	$23,349.72	$14,743.62	$22,258.72	$22,728.93	$20,770.25
Silty clay	$23,089.14	$21,918.49	$23,240.58	$21,885.56	$22,533.44
Clay	$23,196.93	$18,902.16	$22,851.28	$22,002.66	$21,738.25
Average	$21,577.96	$10,948.61	$21,120.28	$19,969.94	$18,404.20
LCC Dual 6 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$22,509.73	$2,931.54	$21,982.02	$16,839.81	$16,065.78
Loamy sand	$25,055.40	$3,856.57	$24,615.25	$20,628.69	$18,538.98
Sandy loam	$26,931.10	$5,124.12	$26,507.21	$23,716.47	$20,569.72
Silt loam	$30,490.67	$10,996.85	$30,673.67	$28,534.54	$25,173.93
Loam	$30,490.67	$10,996.85	$30,673.67	$28,534.54	$25,173.93
Sandy clay loam	$30,710.08	$11,645.67	$30,133.95	$29,044.65	$25,383.59
Clay loam	$32,142.41	$20,426.64	$30,797.65	$31,189.14	$28,638.96
Silty clay loam	$32,035.74	$22,921.88	$31,225.98	$30,641.59	$29,206.30
Sandy clay	$32,142.41	$20,426.64	$30,797.65	$31,189.14	$28,638.96
Silty clay	$31,776.59	$30,499.58	$32,176.10	$30,005.12	$31,114.35
Clay	$31,927.90	$26,264.89	$31,629.55	$30,169.51	$29,997.96
Average	$29,655.70	$15,099.20	$29,201.15	$27,317.56	$25,318.41

Table 2-10 – Life Cycle Cost for Dual Wall 10-inch Mainline Pipe

LCC Dual 3 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$13,431.51	$2,260.87	$12,636.18	$10,696.23	$9,756.20
Loamy sand	$14,756.59	$2,742.89	$14,009.58	$12,670.32	$11,044.84
Sandy loam	$15,733.48	$3,402.90	$14,997.72	$14,280.03	$12,103.53
Silt loam	$17,585.43	$6,456.13	$17,167.85	$16,788.90	$14,499.58
Loam	$17,585.43	$6,456.13	$17,167.85	$16,788.90	$14,499.58
Sandy clay loam	$17,700.28	$6,793.81	$16,889.33	$17,055.99	$14,609.85
Clay loam	$18,445.88	$11,357.83	$17,237.17	$18,173.43	$16,303.58
Silty clay loam	$18,390.44	$12,654.55	$17,459.76	$17,888.88	$16,598.41
Sandy clay	$18,445.88	$11,357.83	$17,237.17	$18,173.43	$16,303.58
Silty clay	$18,255.77	$16,592.51	$17,953.52	$17,558.12	$17,589.98
Clay	$18,334.41	$14,391.84	$17,669.49	$17,643.55	$17,009.82
Average	$17,151.37	$8,587.93	$16,402.33	$16,156.16	$14,574.45
LCC Dual 4 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$17,463.94	$2,696.56	$16,658.08	$13,599.63	$12,604.55
Loamy sand	$19,279.01	$3,356.54	$18,537.83	$16,302.65	$14,369.01
Sandy loam	$20,616.84	$4,260.48	$19,889.56	$18,506.25	$15,818.28
Silt loam	$23,154.09	$8,444.66	$22,861.38	$21,942.32	$19,100.61
Loam	$23,154.09	$8,444.66	$22,861.38	$21,942.32	$19,100.61
Sandy clay loam	$23,311.07	$8,907.23	$22,478.58	$22,307.33	$19,251.05
Clay loam	$24,332.37	$15,162.46	$22,953.76	$23,837.33	$21,571.48
Silty clay loam	$24,256.39	$16,939.80	$23,258.86	$23,447.31	$21,975.59
Sandy clay	$24,332.37	$15,162.46	$22,953.76	$23,837.33	$21,571.48
Silty clay	$24,071.80	$22,337.33	$23,935.62	$22,993.96	$23,334.68
Clay	$24,179.58	$19,321.00	$23,546.32	$23,111.06	$22,539.49
Average	$22,559.23	$11,366.65	$21,812.29	$21,075.22	$19,203.35
LCC Dual 6 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$24,179.58	$3,347.36	$22,665.56	$17,936.40	$17,032.23
Loamy sand	$23,487.14	$4,273.14	$25,301.67	$21,728.23	$18,697.55
Sandy loam	$26,034.12	$5,541.44	$27,196.50	$24,818.96	$20,897.76
Silt loam	$27,911.13	$11,414.93	$31,365.83	$29,639.99	$25,082.97
Loam	$31,472.02	$11,414.93	$31,365.83	$29,639.99	$25,973.19
Sandy clay loam	$31,472.02	$12,064.06	$30,827.27	$30,151.28	$26,128.65
Clay loam	$31,691.95	$20,845.48	$31,492.69	$32,297.54	$29,081.91
Silty clay loam	$33,125.06	$23,340.72	$31,921.02	$31,749.99	$30,034.20
Sandy clay	$33,018.39	$20,845.48	$31,492.69	$32,297.54	$29,413.53
Silty clay	$33,125.06	$30,918.42	$32,871.14	$31,113.52	$32,007.04
Clay	$32,759.24	$26,683.73	$32,324.59	$31,277.91	$30,761.37
Average	$29,843.25	$15,517.25	$29,893.16	$28,422.85	$25,919.13

Table 2-11 – Carbon Footprint for Single Wall 8-inch Mainline Pipe

CF Single 3 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	386.3	71	357.8	315.1	282.5
Loamy sand	419	83.6	391.9	366.1	315.2
Sandy loam	441.9	100.7	415.1	406.4	341
Silt loam	487.2	180.4	468.8	469.5	401.5
Loam	487.2	180.4	468.8	469.5	401.5
Sandy clay loam	488.7	188.7	460	475.1	403.1
Clay loam	505.8	306.5	466.8	502.1	445.3
Silty clay loam	504.4	340.3	472.6	494.7	453
Sandy clay	505.8	306.5	466.8	502.1	445.3
Silty clay	500.9	442.7	485.4	486.1	478.8
Clay	502.9	385.5	478	488.3	463.7
Average	475.5	235.1	448.4	452.3	402.8
CF Single 4 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	519.4	85.4	490.6	411	376.6
Loamy sand	567.7	103.8	540.7	485.5	424.4
Sandy loam	601.7	128.8	575.1	544.7	462.6
Silt loam	668.6	245.1	654.3	637.4	551.3
Loam	668.6	245.1	654.3	637.4	551.3
Sandy clay loam	671.2	257.4	641.7	645.9	554
Clay loam	696.7	429.9	652.2	685.7	616.1
Silty clay loam	694.6	479.2	660.6	674.9	627.4
Sandy clay	696.7	429.9	652.2	685.7	616.1
Silty clay	689.5	629	679.4	662.3	665.1
Clay	692.5	545.3	668.6	665.6	643
Average	651.6	325.4	624.5	612.4	553.5
CF Single 6 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	1015.1	138.9	985	767.9	726.7
Loamy sand	1122.1	179	1095.9	930.8	832
Sandy loam	1198.8	233.6	1173.3	1061.5	916.8
Silt loam	1347.7	487.6	1348.6	1265.8	1112.4
Loam	1347.7	487.6	1348.6	1265.8	1112.4
Sandy clay loam	1354.6	514.8	1322.6	1285.5	1119.4
Clay loam	1412.6	892.6	1347.4	1374.6	1256.8
Silty clay loam	1408	1000.4	1365.9	1350.9	1281.3
Sandy clay	1412.6	892.6	1347.4	1374.6	1256.8
Silty clay	1396.8	1327.7	1406.9	1323.4	1363.7
Clay	1403.3	1144.8	1383.3	1330.5	1315.5
Average	1310.9	663.6	1284.1	1211.9	1117.6

Table 2-12 – Carbon Footprint for Single Wall 10-inch Mainline Pipe

CF Single 3 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	431	90	389.1	365.4	318.9
Loamy sand	463.9	102.7	423.3	416.5	351.6
Sandy loam	486.8	119.9	446.7	456.9	377.6
Silt loam	532.2	199.5	500.5	520.2	438.1
Loam	532.2	199.5	500.5	520.2	438.1
Sandy clay loam	533.7	207.8	491.8	525.8	439.8
Clay loam	550.9	325.7	498.7	552.9	482
Silty clay loam	549.4	359.5	504.4	545.5	489.7
Sandy clay	550.9	325.7	498.7	552.9	482
Silty clay	545.9	461.9	517.3	536.9	515.5
Clay	548	404.7	509.9	539.1	500.4
Average	520.5	254.3	480.1	502.9	439.4
CF Single 4 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	564.2	104.4	521.9	461.3	412.9
Loamy sand	612.5	122.9	572.2	535.9	460.9
Sandy loam	646.6	147.9	606.7	595.2	499.1
Silt loam	713.6	264.3	686	688	588
Loam	713.6	264.3	686	688	588
Sandy clay loam	716.2	276.6	673.5	696.6	590.7
Clay loam	741.8	449.1	684	736.6	652.9
Silty clay loam	739.7	498.4	692.5	725.7	664.1
Sandy clay	741.8	449.1	684	736.6	652.9
Silty clay	734.5	648.2	711.3	713.2	701.8
Clay	737.5	564.5	700.5	716.4	679.7
Average	696.5	344.5	656.2	663	590.1
CF Single 6 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	1059.9	158	1016.3	818.2	763.1
Loamy sand	1167	198.1	1127.4	981.2	868.4
Sandy loam	1243.7	252.8	1204.9	1112	953.3
Silt loam	1392.7	506.8	1380.3	1316.5	1149.1
Loam	1392.7	506.8	1380.3	1316.5	1149.1
Sandy clay loam	1399.6	534	1354.4	1336.3	1156.1
Clay loam	1457.7	911.8	1379.3	1425.4	1293.5
Silty clay loam	1453.1	1019.6	1397.8	1401.7	1318
Sandy clay	1457.7	911.8	1379.3	1425.4	1293.5
Silty clay	1441.9	1346.9	1438.8	1374.2	1400.4
Clay	1448.4	1164	1415.2	1381.3	1352.2
Average	1355.8	682.8	1315.8	1262.6	1154.3

Table 2-13 – Carbon Footprint for Dual Wall 8-inch Mainline Pipe

CF Dual 3 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	667.5	106.3	633.7	523.9	482.8
Loamy sand	732.8	130.7	701.4	623.1	547
Sandy loam	779.7	163.9	748.9	702.8	598.8
Silt loam	870.6	318.3	855.8	827.4	718
Loam	870.6	318.3	855.8	827.4	718
Sandy clay loam	874.9	334.9	840.2	839.6	722.4
Clay loam	910.4	564.6	855.6	894	806.2
Silty clay loam	907.6	630.1	866.9	879.6	821.1
Sandy clay	910.4	564.6	855.6	894	806.2
Silty clay	900.8	829.1	891.8	862.9	871.1
Clay	904.8	717.9	877.5	867.2	841.8
Average	848.2	425.3	816.7	794.7	721.2
CF Dual 4 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	713.5	111.2	679.6	557	515.4
Loamy sand	783.5	137.5	752.1	663.8	584.2
Sandy loam	833.4	173.3	802.6	749.2	639.6
Silt loam	930.5	339.7	917.1	882.9	767.6
Loam	930.5	339.7	917.1	882.9	767.6
Sandy clay loam	934.9	357.5	900	895.7	772
Clay loam	972.6	604.8	916	953.8	861.8
Silty clay loam	969.6	675.4	928.1	938.3	877.8
Sandy clay	972.6	604.8	916	953.8	861.8
Silty clay	962.2	889.7	955	920.3	931.8
Clay	966.5	769.9	939.5	924.9	900.2
Average	906.4	454.9	874.8	847.5	770.9
CF Dual 6 inch lateral and 8 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	1289.7	173.5	1254.3	971.9	922.4
Loamy sand	1428.3	225	1397.8	1181.7	1058.2
Sandy loam	1528.2	295.4	1498.7	1350.6	1168.2
Silt loam	1721.3	622.1	1725.6	1614.6	1420.9
Loam	1721.3	622.1	1725.6	1614.6	1420.9
Sandy clay loam	1730.9	657.3	1692.9	1640.7	1430.5
Clay loam	1806.7	1143.9	1726	1756.3	1608.2
Silty clay loam	1800.8	1282.6	1749.8	1725.9	1639.8
Sandy clay	1806.7	1143.9	1726	1756.3	1608.2
Silty clay	1786.4	1703.7	1802.6	1690.5	1745.8
Clay	1794.8	1468.4	1772.2	1699.6	1683.8
Average	1674.1	848.9	1642.9	1545.7	1427.9

Table 2-14 – Carbon Footprint for Dual Wall 10-inch Mainline Pipe

CF Dual 3 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	727.9	132	675.9	591.6	531.9
Loamy sand	793.3	156.4	743.8	691	596.1
Sandy loam	840.3	189.7	791.5	770.9	648.1
Silt loam	931.2	344.2	898.6	895.7	767.4
Loam	931.2	344.2	898.6	895.7	767.4
Sandy clay loam	935.6	360.8	883.1	907.9	771.9
Clay loam	971.2	590.5	898.6	962.5	855.7
Silty clay loam	968.4	656	909.8	948.1	870.6
Sandy clay	971.2	590.5	898.6	962.5	855.7
Silty clay	961.6	854.9	934.8	931.4	920.7
Clay	965.6	743.8	920.4	935.7	891.4
Average	908.9	451.2	859.4	863	770.6
CF Dual 4 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	773.9	136.9	721.9	624.8	564.4
Loamy sand	843.9	163.3	794.6	731.7	633.4
Sandy loam	893.9	199.1	845.2	817.4	688.9
Silt loam	991.2	365.6	959.9	951.2	817
Loam	991.2	365.6	959.9	951.2	817
Sandy clay loam	995.6	383.4	942.8	964.1	821.5
Clay loam	1033.3	630.7	958.9	1022.3	911.3
Silty clay loam	1030.3	701.3	971	1006.8	927.3
Sandy clay	1033.3	630.7	958.9	1022.3	911.3
Silty clay	1023	915.6	997.9	988.8	981.3
Clay	1027.3	795.8	982.5	993.4	949.7
Average	967	480.7	917.6	915.8	820.3
CF Dual 6 inch lateral and 10 inch main					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	1350.1	199.2	1296.5	1039.6	890.7
Loamy sand	1488.8	250.8	1440.3	1249.7	1072.7
Sandy loam	1588.8	321.2	1541.3	1418.7	1192.5
Silt loam	1781.9	647.9	1768.4	1683	1422
Loam	1781.9	647.9	1768.4	1683	1470.3
Sandy clay loam	1791.6	683.2	1735.8	1709.1	1477.5
Clay loam	1867.4	1169.8	1769	1824.8	1638.8
Silty clay loam	1861.5	1308.5	1792.8	1794.4	1690.8
Sandy clay	1867.4	1169.8	1769	1824.8	1656.3
Silty clay	1847.1	1729.6	1845.6	1759	1800.4
Clay	1855.5	1494.3	1815.2	1768.1	1731.2
Average	1734.7	874.7	1685.6	1614	1458.5

Table 2-15 – Breakeven Results for Single Wall 8-inch Mainline Pipe

3 inch lateral/8 inch mains					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$ (813.41)	$ 664.11	$ (706.87)	$ (453.07)	$ (327.31)
Loamy sand	$ (986.31)	$ 600.84	$ (886.23)	$ (711.94)	$ (495.91)
Sandy loam	$(1,112.97)	$ 514.26	$(1,014.46)	$ (922.26)	$ (633.86)
Silt loam	$(1,354.48)	$ 113.02	$(1,297.91)	$(1,250.42)	$ (947.45)
Loam	$(1,354.48)	$ 113.02	$(1,297.91)	$(1,250.42)	$ (947.45)
Sandy clay loam	$(1,368.63)	$ 68.97	$(1,260.35)	$(1,284.64)	$ (961.16)
Clay loam	$(1,465.16)	$ (530.26)	$(1,304.67)	$(1,430.11)	$(1,182.55)
Silty clay loam	$(1,457.88)	$ (700.66)	$(1,333.92)	$(1,392.72)	$(1,221.29)
Sandy clay	$(1,465.16)	$ (530.26)	$(1,304.67)	$(1,430.11)	$(1,182.55)
Silty clay	$(1,440.18)	$(1,218.16)	$(1,398.81)	$(1,349.25)	$(1,351.60)
Clay	$(1,450.51)	$ (928.97)	$(1,361.48)	$(1,360.48)	$(1,275.36)
4 inch lateral/8 inch mains					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$(2,328.66)	$ 500.39	$(2,218.17)	$(1,544.07)	$(1,397.62)
Loamy sand	$(2,685.48)	$ 370.28	$(2,587.60)	$(2,076.69)	$(1,744.87)
Sandy loam	$(2,947.55)	$ 192.08	$(2,852.23)	$(2,509.97)	$(2,029.41)
Silt loam	$(3,446.26)	$ (633.94)	$(3,436.60)	$(3,186.22)	$(2,675.76)
Loam	$(3,446.26)	$ (633.94)	$(3,436.60)	$(3,186.22)	$(2,675.76)
Sandy clay loam	$(3,476.14)	$ (724.87)	$(3,359.77)	$(3,257.13)	$(2,704.48)
Clay loam	$(3,676.07)	$(1,959.24)	$(3,451.77)	$(3,557.42)	$(3,161.13)
Silty clay loam	$(3,661.07)	$(2,310.16)	$(3,512.01)	$(3,480.42)	$(3,240.92)
Sandy clay	$(3,676.07)	$(1,959.24)	$(3,451.77)	$(3,557.42)	$(3,161.13)
Silty clay	$(3,624.63)	$(3,375.87)	$(3,645.63)	$(3,390.90)	$(3,509.26)
Clay	$(3,645.91)	$(2,780.31)	$(3,568.77)	$(3,414.02)	$(3,352.25)
6 inch lateral/8 inch mains					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$(4,216.60)	$ 296.41	$(4,101.18)	$(2,903.41)	$(2,731.20)
Loamy sand	$(4,802.13)	$ 83.07	$(4,706.98)	$(3,776.74)	$(3,300.70)
Sandy loam	$(5,232.38)	$ (209.16)	$(5,141.02)	$(4,487.33)	$(3,767.47)
Silt loam	$(6,050.86)	$(1,564.02)	$(6,099.61)	$(5,596.60)	$(4,827.77)
Loam	$(6,050.86)	$(1,564.02)	$(6,099.61)	$(5,596.60)	$(4,827.77)
Sandy clay loam	$(6,100.10)	$(1,713.24)	$(5,973.65)	$(5,712.99)	$(4,874.99)
Clay loam	$(6,428.42)	$(3,738.18)	$(6,124.68)	$(6,205.69)	$(5,624.24)
Silty clay loam	$(6,403.81)	$(4,313.82)	$(6,223.50)	$(6,079.37)	$(5,755.12)
Sandy clay	$(6,428.42)	$(3,738.18)	$(6,124.68)	$(6,205.69)	$(5,624.24)
Silty clay	$(6,344.02)	$(6,061.97)	$(6,442.69)	$(5,932.54)	$(6,195.31)
Clay	$(6,378.93)	$(5,085.04)	$(6,316.60)	$(5,970.47)	$(5,937.76)

Table 2-16 – Breakeven Results for Single Wall 10-inch Mainline Pipe

3 inch lateral/10 inch mains					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$ (994.37)	$ 587.12	$ (833.43)	$ (656.10)	$ (474.20)
Loamy sand	$(1,167.48)	$ 523.73	$(1,013.30)	$ (915.48)	$ (643.13)
Sandy loam	$(1,294.35)	$ 437.02	$(1,142.03)	$(1,126.31)	$ (781.42)
Silt loam	$(1,536.06)	$ 35.66	$(1,425.99)	$(1,454.97)	$(1,095.34)
Loam	$(1,536.06)	$ 35.66	$(1,425.99)	$(1,454.97)	$(1,095.34)
Sandy clay loam	$(1,550.29)	$ (8.44)	$(1,388.62)	$(1,489.39)	$(1,109.19)
Clay loam	$(1,646.95)	$ (607.74)	$(1,433.25)	$(1,635.16)	$(1,330.77)
Silty clay loam	$(1,639.66)	$ (778.15)	$(1,462.50)	$(1,597.77)	$(1,369.52)
Sandy clay	$(1,646.95)	$ (607.74)	$(1,433.25)	$(1,635.16)	$(1,330.77)
Silty clay	$(1,621.96)	$(1,295.65)	$(1,527.39)	$(1,554.30)	$(1,499.82)
Clay	$(1,632.30)	$(1,006.45)	$(1,490.06)	$(1,565.53)	$(1,423.58)
4 inch lateral/10 inch mains					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$(2,509.63)	$ 423.41	$(2,344.73)	$(1,747.10)	$(1,544.51)
Loamy sand	$(2,866.65)	$ 293.16	$(2,714.66)	$(2,280.23)	$(1,892.09)
Sandy loam	$(3,128.92)	$ 114.85	$(2,979.79)	$(2,714.01)	$(2,176.97)
Silt loam	$(3,627.84)	$ (711.30)	$(3,564.68)	$(3,390.77)	$(2,823.65)
Loam	$(3,627.84)	$ (711.30)	$(3,564.68)	$(3,390.77)	$(2,823.65)
Sandy clay loam	$(3,657.80)	$ (802.28)	$(3,488.04)	$(3,461.88)	$(2,852.50)
Clay loam	$(3,857.86)	$(2,036.73)	$(3,580.35)	$(3,762.47)	$(3,309.35)
Silty clay loam	$(3,842.86)	$(2,387.65)	$(3,640.59)	$(3,685.46)	$(3,389.14)
Sandy clay	$(3,857.86)	$(2,036.73)	$(3,580.35)	$(3,762.47)	$(3,309.35)
Silty clay	$(3,806.41)	$(3,453.35)	$(3,774.21)	$(3,595.95)	$(3,657.48)
Clay	$(3,827.69)	$(2,857.80)	$(3,697.35)	$(3,619.07)	$(3,500.48)
6 inch lateral/10 inch mains					
Soil Type	Field 1	Field 2	Field 3	Field 4	Average
Sand	$(4,397.57)	$ 219.42	$(4,227.74)	$(3,106.44)	$(2,878.08)
Loamy sand	$(4,983.30)	$ 5.95	$(4,834.05)	$(3,980.28)	$(3,447.92)
Sandy loam	$(5,413.75)	$ (286.40)	$(5,268.59)	$(4,691.38)	$(3,915.03)
Silt loam	$(6,232.44)	$(1,641.38)	$(6,227.68)	$(5,801.15)	$(4,975.66)
Loam	$(6,232.44)	$(1,641.38)	$(6,227.68)	$(5,801.15)	$(4,975.66)
Sandy clay loam	$(6,281.76)	$(1,790.65)	$(6,101.93)	$(5,917.74)	$(5,023.02)
Clay loam	$(6,610.20)	$(3,815.66)	$(6,253.26)	$(6,410.74)	$(5,772.46)
Silty clay loam	$(6,585.59)	$(4,391.30)	$(6,352.07)	$(6,284.42)	$(5,903.35)
Sandy clay	$(6,610.20)	$(3,815.66)	$(6,253.26)	$(6,410.74)	$(5,772.46)
Silty clay	$(6,525.81)	$(6,139.46)	$(6,571.26)	$(6,137.59)	$(6,343.53)
Clay	$(6,560.72)	$(5,162.53)	$(6,445.18)	$(6,175.51)	$(6,085.98)

Figure 2-1 – Overhead Picture of Field 1

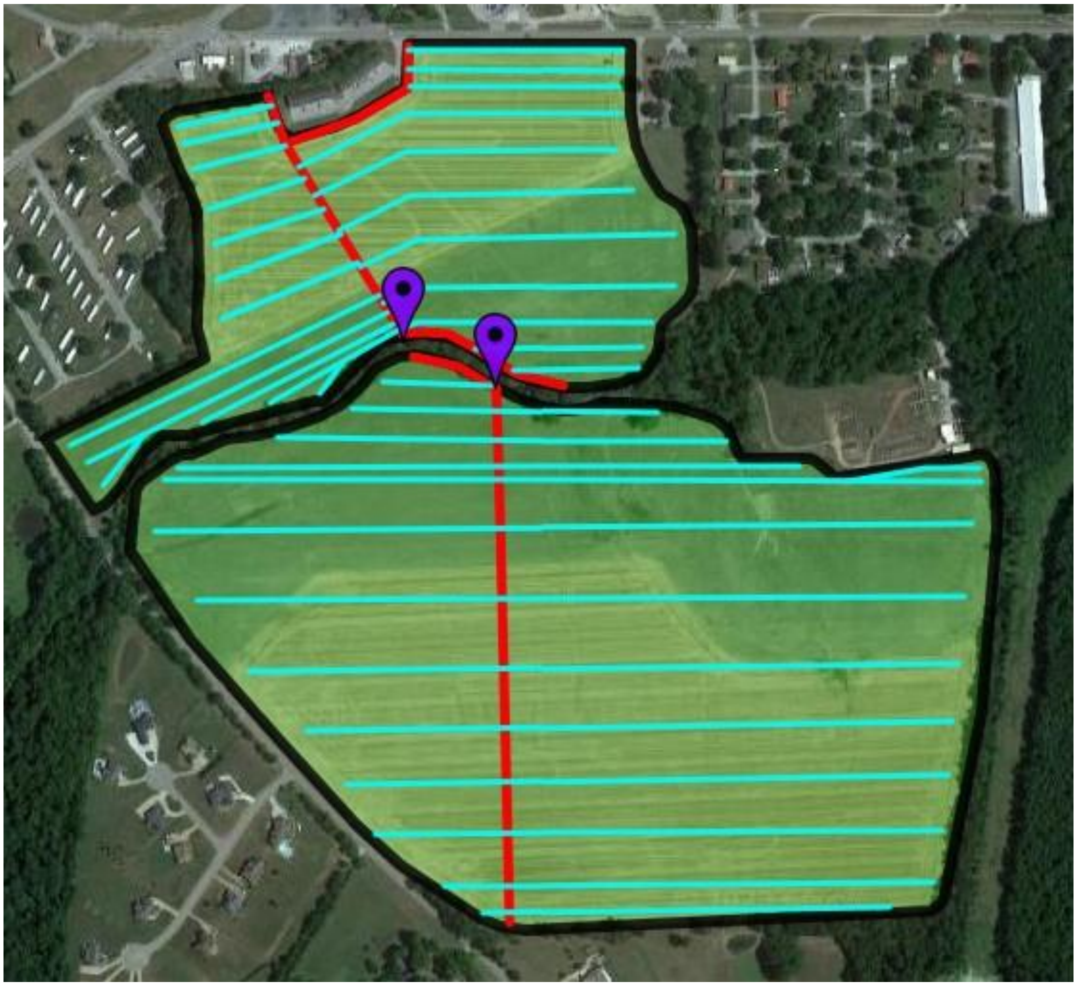


Figure 2-2 – Overhead Picture of Field 2

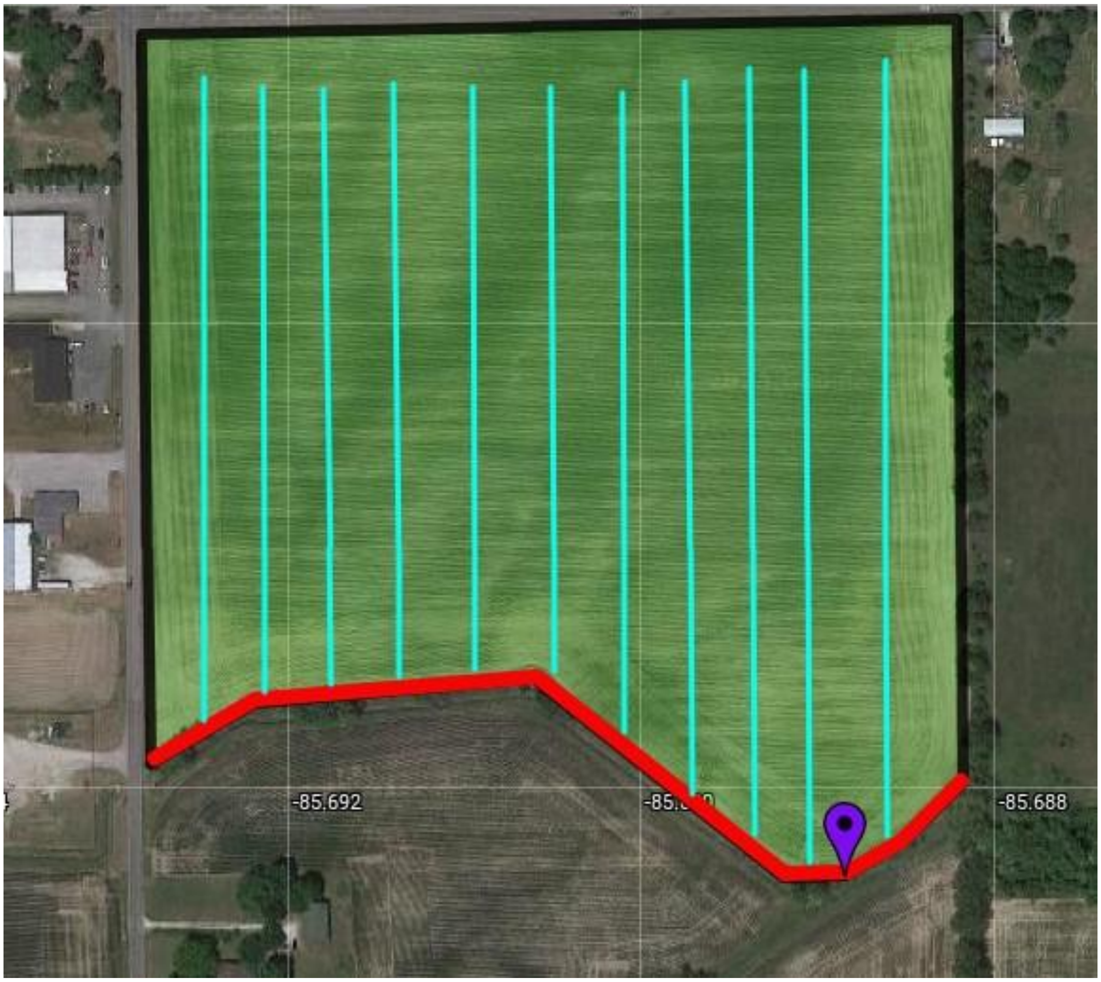


Figure 2-3 – Overhead Picture of Field 3

Figure 2-4 – Overhead Picture of Field 4

CHAPTER 3. EVALUATING THE EFFECT OF PRECISION AGRICULTURE TECHNOLOGIES ON HARVESTING COMBINE VALUES IN NORTH AMERICA.

3.1 Introduction

The relationship between a growing population and the decrease in the portion of the population in agriculture has continued to remain a topic of interest over recent decades. Additionally, public perception centered around environmental and natural resources concerns has further increased production stress on the agriculture industry. At the same time, producers have faced higher costs of production with labor, equipment, and inputs. Precision agricultural technology (PAT) has become a vital component of farming to combat the rising concerns and costs, with many row crop farmers utilizing some form of PAT (Mcfadden et al., 2023). Although adoption has increased for PAT, so has machinery cost, leading to its label as the second largest farm expense, accounting for more than 40 percent of total production expense (Ibendahl, 2015).

For grain operations, a large portion of production expense is contributed to the combine harvester. For harvesting practices, farm owners must make choices ranging from owning vs. leasing equipment, custom hiring, or a combination. Farmers must consider new or used equipment, size, age, and condition if they choose to purchase equipment. Additionally, the market for combine sales has seen the number of combines sold through online outlets increase, leading to rising costs of combines ranging from $350,000 to $500,000 without add-ons (Dodson, 2019). The increase in online sales has further increased the number of used combines on the market. Unlike the new combine market, many of the used combines include add-ins and technologies that aren’t easily valued, leaving producers questioning how to properly evaluate these machines and how to compare value differences between a variety of PAT elements.

Precision Agriculture started as a concept that farming practices are not consistent across operations and fields; instead, it includes a high rate of variability in crop production (*Precision Agriculture Technology*, n.d.). When the concept is put into practice, operations aim to increase accuracy and control for growing crops (Schmaltz, 2017). From the initial concept, the term Precision Agricultural Technologies is used further to indicate the type of component used. For combines, PAT includes harvest-related items such as yield monitors, moisture trackers, and grain loss, operator-related items such as guidance systems and displays, and data-related components such as data sharing and receivers.

This study builds upon the previous work from Ellis et al. (2022) that investigated what factors drove combine prices and aimed to provide estimates for combine various combines. Although the work was one of the first to evaluate the used combine market, this work utilizes a much larger dataset and further incorporates precision agricultural technologies into the analysis. The goal of this study was to provide additional information for producers questioning how to evaluate combines, and PAT add-ons by providing a comprehensive evaluation of the factors that affect used combine values in the United States. To complete this goal, the objectives of this paper were 1) estimate the factors that impact used combine values, 2) compare the change between different manufacturers, and 3) evaluate which precision agriculture technologies are most impactful for the buyers and sellers of the combines.

The objectives were accomplished using an auction dataset from North America's largest farm machinery auction site, Machinery Pete. The data included used combine sales for the United States between 2010 and 2022 and included characteristics related to the sale information and machinery specifics. Additionally, variables were generated to represent the various PAT components represented within the data. The dataset was paired with econometric models to estimate the various factors that affect the combine's value. Results suggest that combines sold in the Midwest regions during the winter season held the highest values, while John Deere held the highest values for any manufacturer. Furthermore, precision technologies related to data sharing were estimated to have the highest impact on the combine's value for the PAT variables.

3.2 Background

3.2.1 Hedonic Models

To evaluate the secondary combine market, a hedonic model was chosen due to its use in previous agricultural research to estimate cattle, commodity, land, and machinery values (Allison et al., 2022; Borchers et al., 2014; Davis & Ethridge, 1982; Martinez et al., 2021; Miranowski & Hammes, 1984). Hedonic pricing models were initially developed by Griliches (1961) to analyze the quality of cars. The approach was further developed by Rosen (1974) to investigate product differentiation. The hedonic model estimates the effect of multiple independent variables on the dependent variable. For agriculture, models are often used in estimating land values (Borchers et al., 2014; Miranowski & Hammes, 1984); recent work has illustrated that machinery values can be estimated in a similar fashion (Allison et al., 2022; R. Ellis et al., 2022). Allison et al. (2022) looked at estimating values of row crop planters and aimed at examining the key factors that drive the price of planters. Even though the work resulted in significant findings to help answer this question, there are a few issues with the study. Furthermore, the dataset was limited to observations between 2015 and 2018. Ellis et al. (2022) evaluated combine values and compared the impact change between different manufacturers. However, the dataset only included observations from 2015 to 2018 and excluded variables to differentiate between potential value-added technologies.

3.2.2 Farm Machinery

Most of the previous literature on agricultural machinery has focused on assessing the value of tractors. One of the first studies to assess tractor values did so by focusing on comparing different qualities of tractors and developing a price index to explain the changes in tractor prices. Further work in the 1980s examined the effects of the change in the interest rate on the investment in agricultural machinery using duality to compare tractor values (Diekmann et al., 2008; Fettig, 1963; Leblanc & Hrubovcak, 1985). Fettig's (1963) study found fundamental factors will affect a tractor's value are the type of engine and horsepower level. While Leblanc & Hrubovcak (1985) determined that input and output prices have a larger effect on tractor values than interest rates. More recently, the type of sale for tractors was investigated (Diekmann et al., 2008). This study evaluated the price differences for tractors sold online or in-person. Cross and Perry (1995) found a significant relationship between value and depreciation factors for planters. This would suggest that a machine's age, hours, and useful life are important factors in determining the value of a planter. More recently, a hedonic model was developed to evaluate planter values which found that make, condition, row spacing, and sale specifics were all significant in planter values (Allison et al., 2022).

3.2.3 Combine Harvesters

Previous research relating to combines has focused primarily on the operation or machinery costs of using the combines. Many studies have compared the costs of owning a combine with the cost of custom hiring for harvesting (Edwards & Hanna, 2009; Ibendahl, 2015; Lattz & Schnitkey, 2021; Swanson et al., 2020). This approach is similar to Cross and Perry (1995), who valued the machinery based on the useful life or level of work needed to justify the combine's cost. Although this is a valuable question related to an operation’s profitability, this approach does not evaluate the value of the combine because of issues around over or under-capitalization of the operation. Other studies have taken a risk analysis approach to combine values from both standpoints of a custom harvesting operation or a farming operation. Concerning a custom hiring operation, a simple enterprise risk analysis was performed comparing different combines and their effect on the operation’s profitability (Mimra et al., 2017). From the farming operation side, a minimum annual value use was found based on the combine’s value (Mimra & Kavka, 2017). In both studies, the value of the combine was based on a listed purchase price of the combine, which can differ from the actual price paid for the machine.

Another relevant study applied both multilinear and linear regressions to a combine dataset to evaluate the factors that determine combine costs (Yezekyan et al., 2020). The research used key characteristics for the various combines such as model, functional mechanism, threshing type, leveling system, and other equipment, to explain the combine's listing price. Similar to both Mimra (2017) and Mimra & Kavka (2017), there is an inherent flaw in using the list price of the combines since the list price can be drastically different from the actual price paid to purchase the combine due to sellers often offering different types of discounts. Nevertheless, this work does illustrate the importance of other combine parameters on price. Other notable studies focused on fuel efficiency (Rogovskii et al., 2021), comparing domestic and foreign combines (Vinevsky et al., 2020), and the management efficiency of a combine fleet (Olt et al., 2019). Although all these studies help to provide insight into evaluating combines, all are limited by either the number of manufacturers or the number of combines evaluated. To provide estimates for combine value, an evaluation of multiple models and various combines needs to be used. The use of a comprehensive data set would allow for an estimate of the changes and impacts on the entire combine market instead of only a few combines.

Recently, a study looked at a combine sales dataset that included multiple manufacturers and multiple years of data (R. Ellis et al., 2022). This study used a dataset of auction sales of used combines from 2015 through 2018 and investigated the impact of precision agriculture technologies on combine values. The major finding for non-precision agriculture technologies variables was that 100 combine separator hours would decrease the value by 2.14% (R. Ellis et al., 2022). At the same time, a one-year increase in age would result in a 10.9% decrease in value. Another important finding of the study lead to value change estimations for location, time of sale, and combine condition, where the highest values were found in the Great Lakes and Upper Midwest production regions (R. Ellis et al., 2022). Additionally, combines sold during the winter season held higher expected values, followed by the spring, summer, and fall seasons. As for combine condition, results illustrate the expected order in value from excellent down to poor (R. Ellis et al., 2022).

For the precision agriculture technology (PAT) variables, the study classified technologies by function and then ran three models, one with all manufacturers, one for John Deere only combines, and one for Case IH only combines. Separating the technologies this way allowed for a clearer understanding and evaluation since the model would see one variable for each function and not a different variable for each brand and function of the technology. Furthermore, since most of the technologies are manufacturer-specific, running a John Deere and Case IH only model would allow manufacturer-specific estimates to be calculated. The major PAT results were the value added from technologies such as Auto Steer, Receiver, Yield Monitor, Moisture Tracker, and Displays (R. Ellis et al., 2022). While the findings are interesting, the issues of the study start with the dataset. Again, only having a relatively limited sample of three years of combine sales is not enough to estimate major market impacts. The data cleaning process was not sound for eliminating vintage combines and outliers that might influence the results. Moreover, some of the PAT variables were not properly separated to ensure the correct functional unit was represented, nor avoiding variables being correlated from the data cleaning process. Even though the recent work from Ellis et al. (2022) falls short, it provides a starting point and insight for this study.

3.2.4 Current Combine Market

An investigation of the recent combine market is needed to build on the previous research. Starting back in 2012, North American grain operations saw an industry-wide drought resulting in the increase of commodity prices for procedures. These increases in price led to increases in planted acres of grain crops in the following years, resulting in price drops that drove net farm income downward from 2013 through 2016 (Farm Income and Wealth Statistics, 2023). Net farm income remained relatively flat between 2016 and 2020 (Figure 3.1)(Farm Income and Wealth Statistics, 2023). Along with these lower years of net farm income, two major changes in the combine market happened with an order policy change, as well as the introduction of precision agriculture technologies. In 2013, combine manufacturers shifted to an order-only policy for producing new combines. This means that manufacturers were no longer producing a set number of machines. Instead, they would only produce combines that had been ordered by a specific operator, leading to further customization of specific combines. The market also saw a major influx of precision agriculture technologies. PAT technologies saw major increases in adoption. For the first time, Guidance was over 45% in both corn and soybeans, soil mapping saw an increase of over 20% in corn and soybeans, and variable rate input application was pushing closer to 25% in corn and soybean planted acres (Mcfadden et al., 2023). Suggesting that PAT adoption was steadily on the rise. Couple this with the order policy change, and combines have become extremely farm-specific. Joining all three of these factors together left operators with less income to upgrade machinery, plus a lack of available income to place orders for new machinery, resulting in operators having to move into the secondary market to upgrade machinery or simply continue to use the machinery they have as it ages and becomes more expensive to maintain.

The effects can be seen in combine prices. Between 2008 and 2015, combine prices increased by up to 30% (Mimra et al., 2017), leaving operations struggling with profitability from the increased ownership costs. Furthermore, new combine price in 2015 ranged between $330,000 to $500,000 without headers or add-ons (Dodson, 2019) leading to corn and soybean operations spending well over half of a million dollars to purchase a new machine. These high costs have resulted in many operations upgrading their equipment by buying used machinery. However, the used equipment market has a much broader range in price and add-on options (Dodson, 2019). Leading operations to need help with estimating equipment values. Some industry experts have gone as far as to suggest that buying used equipment is the best option for most operations (S. Ellis, 2021). Understanding the current market and the gaps in previous literature has left the industry with a long-overdue need to evaluate the value of used combines.

3.3 Data

Unique to this study, an auction dataset containing multiple auction companies and machinery dealers throughout North America was compiled and accessed through Machinery Pete's "Auction Price Data" database (*Used Farm Equipment for Sale*, n.d.). The raw dataset contains 27,020 secondary combine sales between January 2000 and December 2022 and includes variables for the price, make, model, year, hours used, sale date, sale type, sale location, and specs. To appropriately use this dataset, a data cleaning process was performed to remove missing observations resulting in a final dataset with 8,487 combine sales.

One of the major accomplishments of the study was the data-cleaning process that allowed the model to estimate the impacts of the PAT variables. A data tree illustrating the data learning process is shown in Figure 3.2. The cleaning process started by removing any combines manufactured before 2000. This allowed for combines within the analysis to have the option of adding a PAT to a combine. In addition, this would remove any combine sales that might be inflated due to being a vintage or collectible combine model, resulting in a more accurate estimate of the combine market. Next, combines sold before January 2010 were removed to account for PAT investment and to focus on the time period of increased PAT usage as stated in the previous work (Mcfadden et al., 2023). The remaining data was then processed to remove observations with missing values for price, sale date or location, and hours resulting in a final dataset that contained 8,487 combine sales.

The dataset was further developed to add the appropriate variables to analyze the various characteristics of each combine. These variables can be categorized into three categories: sale variables, standard combine variables, and spec variables. The variable descriptions can be found in Tables 3.1 and 3.2. The sale variables include region of the sale, type of the sale, season of the sale, and year of the sale. Sale location was grouped into 12 US regions based on a USDA breakdown (Figure 3.3) (*USDA - National Agricultural Statistics Service - Regional Field Offices*, n.d.). The sale type was organized as Consignment, Dealer, Farm, Online, and Other. Seasonally was accounted for with Spring (March 21st-June 20th), Summer (June 20th-September 20th), Fall (September 21st-December 20th), and Winter (December 21st-March 20th) variables to address the time of the year when the sale occurred, and variables for the year of sale.

The standard combine variable category included a continuous variable for the separator hours of use on each combine, a discrete variable representing a combine's age, and a series of variables for manufacturer and condition. Combine manufacturers were grouped to represent market consolidation that occurred during the time in the dataset. For example, AGCO includes Challenger, Gleaner, Massey Ferguson, and White. Therefore, all combines representing these manufacturers were placed under the AGCO variable.

These consolidations resulted in five variables for manufacturers John Deere, Case IH, AGCO, Ford-New Holland, and CLAAS. Machine condition was given in the original dataset from Machinery Pete and represented as Excellent, Good, Fair, or Poor condition. The individual auctioneer gives condition groups before the combine goes up for auction; mechanical correlation was illustrated during the study of the condition variables' structure. To decrease the magnitude of the mechanical correlation, condition types Excellent and Good were grouped together, and Fair and Poor combines were grouped together. Further explanation of this process is found below in Section 3.4.

The data presented challenges in illustrating precision agriculture technologies (PAT). Within the data set, a column labeled as "specs" where the auctioneer would type in the details about the combine at the time of sale. This description contained information on the various brands, models, and functions of the technologies. To provide consistency among the PAT variables, the "specs" column was processed to account for the functional use of the PAT. Additionally, a series of variables for the PAT brand were generated to allow for individual brand impacts to be estimated. The PAT variables represented functions for auto steer, data sync, display, GPS, grain loss monitor, moisture tracker, receiver, row sensor, yield monitor, and yield monitor with moisture tracker. For example, a John Deere auto steer package and a Case IH auto steer package would hold one for the auto steer variable and one under John Deere PAT and Case IH PAT, respectively. To avoid correlation between some of the PAT variables, variables represent a sale that states the combine only has that specific PAT variable. For example, the auto steer function, by default requires GPS to operate. Therefore, the dataset would illustrate a one under auto steer and a zero under GPS so as not to overestimate the impact of GPS. On the other hand, if an observation shows a one under GPS, then no other PAT variables requiring GPS were in the “specs” description.

The full summary of statistics can be found in Tables 3.1 and 3.2. The average auction price for combines was just over $102,259, the average separator hours were 2,189, and the average age was 8.7 years. The majority of the sales were conditioned as "Excellent or Good" machines. Figure 3.4 illustrates the percentage of the dataset held by each manufacturer. As expected, John Deere holds the majority of the market share, followed by Case IH, Ford-New Holland, AGCO, and Claas. The major areas for sales in this dataset came from the Northern Plains, Upper Midwest, Heartland, and Great Plains, which is the area traditionally known as the "corn belt" of the US. As for precision agriculture technologies, Figure 3.5 shows the breakdown of each technology and the percentage of each manufacturer within that technology.

3.4 Methods

A hedonic model was employed using the previously mentioned variables to evaluate the factors effecting used combine values. The study uses two different models, the base model and the precision agricultural technology (PAT) model. The base model was developed to evaluate the combine market without PAT variables. This base model was developed from the work of Ellis et al. (2022). The model from previous work provided insight and allowed for an omitted variable bias and robustness check for the new dataset before adding the PAT variables to the model. The base model differed from Ellis et al. (2022) by including the Claas manufacture group, better manufacture consolidation, and changes in reference groups for better interpretation. The second model is the PAT model, this model built upon the base model and the Ellis et al. (2022) study. The PAT model incorporates the PAT variables into the base model for evaluation. Initially, the model was run with all of the manufacturers and incorporated variables related to PAT brand. Further investigation led to the PAT model being run individually for John Deere, Case IH, and AGCO only combines to investigate if the impacts were different for the three largest combine manufacturers in North America.

For both models, multicollinearity was expected due to the data structure and variables included. A variance inflation factor test (VIF) was performed to evaluate what variables might show multicollinearity. The mean VIF score for the base model was 3.88 (Table 3.3), while the PAT model was 3.35 (Table 3.4). As mentioned in the previous Section 3.3, due to mechanical correlation, the condition scores were grouped into two variables Excellent or Good and Fair or Poor. The initial model contained all four conditions which resulted in VIF score over 20, which would be considered high. Further investigation suggested that only a few variables illustrate and correlation concerns. A correlation matrix was estimated on the condition variables resulting in Excellent and Good having a high correlation along with Fair and Poor having a high correlation. The condition variables were expected to be correlated since other variables such as hours, age, manufacture, sale year, and location would likely influence the condition score of the combine. However, the matrix results suggested that the majority of the correlation was between the condition variables, which is explained as mechanical correction since the data requires one of the four variables must have a 1 and all others must be 0. A potential way to address this issue would be to remove the condition variables from the model and rerun the VIF test. This approach was tested and lowered the mean VIF score to under 5, which would indicate multicollinearity was not an issue for the model. However, based on the previous models (Allison et al., 2022; R. Ellis et al., 2022), the condition score needs to be part of evaluating the combine's value. Further investigation of the initial VIF scores resulted in the joining of combines labeled as Excellent or Good into one variable and combines labeled as Fair or Poor into one variable.

3.4.1 Equations

The base model of this study can be expressed as equation one:

$$\ln(P_{it}) = \beta_0 + \beta_1 H_{it} + \beta_2 A_{it} + \beta_3 M_i + \beta_4 C_i + \beta_5 S_i + \beta_6 T_i + \rho_r + \tau_t + \varepsilon_{it}$$

where the dependent variable $\ln P_{it}$ is the natural log of the price of combine *i* sold in sale year *t*. The independent variables represent the three categories mentioned previously in the data section 3.3. Where *H* is the number of separator hours used, *A* represents the age of the combine, *M* is the manufacturer of the combine, *C* is the condition of the machine, and *S* is the season and *T* is the type of sale. As for the fixed effect portion of the equation, ρ_r illustrated the regional fixed effects of region *r*, while τ_t is the fixed effects of sale year *t*.

Equation two modified equation one by including PAT variables. The precision agriculture technology model can be represented by equation two expressed as:

$$\ln(P_{it}) = \beta_0 + \beta_1 H_{it} + \beta_2 A_{it} + \beta_3 M_i + \beta_4 C_i + \beta_5 S_i + \beta_6 T_i + \beta_7 PAT_{it} + \rho_r + \tau_t + \varepsilon_{it}$$

where the only change from equation one can be seen with the addition of PAT, which represents the variables of precision agriculture technologies mentioned in the data section, present on combine *i* in sale year *t*.

3.4.2 Expectations

Expectations for the standard and sale variables were the same for both models and based on economic principles, market trends, and previous literature discussed in Section 3.2. Standard variables expectations would be for John Deere, Case IH, Ford New Holland, and AGCO to all have positive coefficients with respect to Claas since these manufacturers hold the highest market share and yearly sales for the combine market (*Combine Harvester Cost: Today's Used Combine Prices*, n.d.). The variables of separator hours and age are expected to hold negative coefficients since older and more frequently used machines should have lower values. Similarly, the condition of the machine should decrease the value of the combine as it goes from Excellent or Good to Fair or Poor.

As for the sale variables, the sale type of "farm" was expected to hold the highest value of sale types based on previous work (Allison et al., 2022). It was also expected that "online" sales would be the lowest type based on the findings from Diekmann et al. (2008). Combines sold during the Winter season were anticipated to have the highest coefficient since the timing of on-farm operations would cause issues with the time available to purchase machinery. Furthermore, all sale years within the dataset are expected to increase gradually due to inflation over the period of the data. For the sales years of 2020 and 2021, a potential increase in values from the COVID-19 pandemic could be seen but would be beyond the scope of this study. As for the location of the sale, the heartland region would be expected to hold the highest coefficient since it represents the prominent grain-producing area of the US.

The PAT model expectations were for all technologies to increase the value of the combine. Due to the process of incorporating the PAT variables mentioned in the data

Section 3.3, the expectation for each PAT variable would be for that specific function. Variables related to operator use were expected to be higher due to the ability to increase operating hours and harvesting efficiency. These variables included Auto Steer, Displays, GPS, and Row Sense. Following operator variables, harvest-related variables, such as Yield Monitors and Moisture Trackers, were expected to reflect the potential for increases in harvesting efficiency and potential long-term increase in crop returns. This expectation was built on the fact that yield monitors would provide locational information within the field for areas of lower or higher yields, which the farmer could potentially address the following year. While the moisture tracker assists the operator in either not harvesting crops with higher moisture content or a better understanding of the drying costs that will be incurred if the crop is harvested, resulting in lower moisture deductions when crops were sold. Lastly, the expected results for data-related variables were to be lower compared to the other PAT variables. The expectation was based on a farmer purchasing the combine would be willing to pay more for technologies directly related to operator efficiency or revenue increase. Furthermore, the data-related variables, Data Sync, and Receiver were technologies centered around data sharing, which the operator could do manually.

3.5 Results

The previously mentioned hedonic model and dataset were joined using STATA software (*StataCorp LLC*, 2015) to analyze combine machine values and estimate the factors affecting auction price. The base model used to evaluate the market without precision agriculture technologies and compare the newer dataset and updated model with the previous work of Ellis et al. (2022). Results can be found in Table 3.5. This model held an R-squared value of 0.88, which illustrated that the model accounts for 88% of the total variance within the dataset. Estimated coefficients are shown as both the coefficients as well as the percent change in combine value for that coefficient; for the results section, all impacts are discussed as the percent impact on a combine's value.

3.5.1 Base Model Results

The most notable finding among the standard variables was the impact of separator hours and age on the combine’s value. Although both were found to be negative, as expected, the magnitude of the two variables was noticeable. Each hour increase in separator hours was found to have a -0.02% impact on the combine’s value. In comparison, an additional year of age was estimated at -8.6%, both at the 1% level. When separator hours were scaled to represent the average number of separator hours per year of 285, an estimated impact of –5.7% was found, suggesting that buyers' willingness to pay is impacted more by age than by the number of separator hours.

As for the manufacturer of the combine, the brand order followed expectations, with John Deere holding the highest value at 25.3% at the 1% significance level, compared to the reference group of CLAAS. Case IH held the second highest value at 15.8%, also at the 1% significance level. Conversely, AGCO and Ford New Holland held negative estimates of -6.7% at the 5% significance level for AGCO and -11% at the 1% significance level for Ford New Holland. To sum up the standard variable group, the condition of the combine impacted the value as expected, with Excellent or Good condition combines holding a 37% increase over Fair or Poor conditioned combines.

As expected, the location of the sale had a significant impact on a combine's value. Each impact was statistically significant, with the Southern region being significant at the

10% level and all others significant at the 1% level. Only four regions held positive impact estimates when compared to the reference group of the Heartland region. The highest impact estimate was found in the Great Lakes region, which held an increase of 3.9%, followed by the Southern, Upper Midwest, and Northern Plains regions, with estimates of 3.2%, 2.3%, and 1.3%, respectively. The Great Lakes, Heartland, Upper Midwest, and Northern Plains were expected to hold higher values due to higher potential returns from more productive land. The Southern region also has highly productive lands; however, they are more spread out. Thus, the southern region could experience increased prices due to lower combine supply.

Along with expectations, the remaining regions all held negative impact estimates at the 1% significance level. The regions of Northeastern, Mountain, Southern Plains, and Eastern Mountains estimated values of -3.8%, -5%, -6.5%, and -6.6%, respectively. Similar to the Great Plains, Upper Midwest, and Heartland, the impacts' magnitude could be caused by the lower production potentials in these regions. Interestingly, the Northeastern region which was expected to have a large price decrease from the heartland was quantitatively, the closest estimate to the Heartland. This result could be caused by the close proximity of the region to the higher-value region of the Great Lakes. As our data only includes auction locations, we cannot capture where the combine is resold. This potential explanation suggests that retailers are willing to pay up to the cost of a combine in the Great Lakes region minus the transportation cost to move the machine out of the Northeastern region. Other regions held estimates lower than -10%, including the Northwest, Delta, and Pacific regions, with impacts of -12.8%, -20.1%, and -65.2%, respectively.

As for the type of sale, Farm sales held the highest value when compared to the reference group of Dealer sales, with a 6.9% increase at the 1% significance level. Consignment sales were estimated at -4.5% at the 1% significance level, and Online sales were estimated at a decrease of 5.3% at the 1% significance level. The type of sale followed expectations and previous work from Allison et al. (2022). Similarly, the season of sale followed expectations, sales in the winter season held the highest impact of 3.4% at the 1% significance level compared to the fall season. At the same time, the Spring and Summer season of sale was not found to be significant. The year of sales variables presented an unexpected finding. When compared to the year 2010, the years 2015 through 2018 were not found to be significant. Sales occurring from 2011 through 2014 all held negative estimates at the 1% significance level, with the lowest estimate found in 2012 of -20.4%. As for the years with a positive estimate compared to 2010, 2019 was found to be significant at the 10% level with a coefficient of 6%, while the years 2020 and 2021 held an estimate of 12.6% and 10%, respectively.

3.5.2 Precision Agriculture Technology Model Results

Precision Agriculture Technology variables were added to the base model, individual PAT variables were discussed in Section 3.3. The results of the second model, referred to as the PAT model, can be found in Table 3.6. The PAT model held an R-squared value of 0.882, which illustrated that the model accounts for 88% of the total variance within the dataset. Estimated coefficients are again shown as the percent change in combine value in Table 3.6. The results section discusses all impacts as the percent impact on combine values.

When the standard variables are compared between the base model and the PAT model, we find all significant variables hold the same significance level and maintain estimates within the base model confidence interval. As for the sale variables, type of sale and season of sale hold the same significance level and remain within the confidence interval from the base model. Conversely, minor changes are found in the location of the sale and year of sale results. Significance levels among the location variables were consistent with all locations except for the Northeastern, Southern, and Northern Plains regions, where Northeastern results fall to the 5% level, the Southern region significantly increases to the 1% level from the 10% level, and the Northern Plains is not significant in the PAT model. Estimated coefficients for the location of the sale are consistent with all regions except the Eastern Mountain and Pacific. The Eastern Mountain region was estimated at -5.7%, compared to the Heartland region. At the same time, the Pacific region estimated at –73.2% in the PAT model. Variables for the year of sale held consistent in terms of the estimated impacts, with only the year 2017 changing significance at the 10% level in the PAT model. Sales in 2017 were estimated to be 4.2% higher than sales in 2010, at the 10% significance level. In the base model, 2017 was not significant at any level.

Only one of the manufacturer-specific precision agriculture technology variables was found to hold significance, Ag Leader branded technologies held a 10% significance level and was estimated to have a –4.8% impact. The results from the manufacturer-specific technologies were unexpected with the negative estimates and are further examined in the discussion section. (Section 3.6) Five of the precision agricultural technology variables presented in the study were found to be significant. For the operator-related technologies, Row Sense held the highest value of 9.1% at the 10% significance level, followed by Displays with an estimated 2.8% increase at the 1% significance level. GPS and Autosteer were not found to be significant. The harvest-related technologies found Yield Monitors to have the highest impact on values, with an estimated increase of 4.1% at the 1% significance level. No other harvest-related technologies were found to be significant. The data-related technologies were expected to hold the lowest impact estimates among the three categories. Although, results suggested that data-related technologies had the highest impact on a combine's value. Data Sync was the highest at 13%, followed by Receivers at an impact of 6.7%, both at the 1% significance level.

3.5.3 Manufacture-Specific Results

Building upon the PAT model, the model was run individually for each of the three major manufacturers in North America John Deere, Case IH, and AGCO. Full results for the three manufacturer-specific models can be found in Tables 3.7, 3.8, and 3.9. John Deere combines held consistent estimates for the standard variables compared to the PAT model. Separator hours were estimated to have a negative impact on value at -0.02% per hour, while age was estimated at -8.2% per year increase at the 1% significance level. Condition score was significantly lower than the results in the PAT Model with a positive estimate of 21.8% for combines in the Excellent or Good groups compared to combines in either Fair or Poor condition groups. Additionally, combine condition category did drop significance to the 5% level with John Deere combines. The sale variables illustrated a loss of significance for season of sale variables with the Winter season falling to the 10% level, and a lower significance level of 5% for the sale types of consignment and farm sales. Even with the change in significance level, the estimated impacts remain within the confidence interval of the PAT model.

As for the year of sale, no considerable changes were found with the impact estimates, although minor differences were found with significance level. The year 2018 became significant at the 10% level, while the year 2017 increased from a 10% level to a 5% significance level. A similar story is shown with the location of the sale with most regions holding the same significance level as the PAT model. Two regions saw a change in significance level, with the Northern Plains holding a 1% level, and the Mountain region no longer holding significance at any level. On the other hand, coefficient estimates expressed changes in six regions, with all six estimates being positive compared to the PAT model. The largest change was seen in the Pacific and Delta regions, where the estimated impact for John Deere combines was -37% and -12.8% respectively. The increases seen in the Southern and Northeastern regions followed, where the impact estimates were 10.6% and 3.8%. The smallest change was seen in the Northwest and Eastern Mountain regions at –10.6% and –3.4% respectively. More notable was the change for the Northern Plains region of 1.9% for John Deere combines at the 1% level compared to the PAT model that was not significant at any level.

All except for one of the significant precision agriculture technology variables from the PAT model returned significant for John Deere combines. Receivers were not found to be significant at any level for John Deere combines. Other small changes with significance levels were seen with row senses moving to the 5% level, and Data-Sync moving to the 1% level. As for the coefficient changes, all precision agricultural technology variables remained consistent except for yield monitors which increased to an estimate of 6.5%.

The majority of standard variables for Case IH combines remained consistent with the results from the PAT model. Unlike John Deere combines, the Case IH only results held significance for the spring and winter seasons at the 1% level. Compared to the fall season, combines sold in the spring season were estimated to have an increase of 5%, while the winter season was estimated at a 4.7% increase. For the type of sale, online sales were no longer significant for Case IH combines. Consignment and Farm sales dropped in significance level to 5% and were estimated at -3% and 8.3%, respectively. Sale years 2011 through 2014 held the same significance level as the PAT model with consistent estimates. The sales years of 2017, 2019, and 2020 were not found to be significant with Case IH combines, and combines sold in 2021 were estimated within the PAT model confidence interval but fell to the 5% significance level.

The location of the sale illustrates few differences from the PAT and John Deere model in terms of variable significance changes, with only the Upper Midwest and Northern Plains regions changing. On the other hand, the estimated coefficient changes in eight of the regions. The Southern region estimated the first decrease in value for the region at –15.6%. Case IH combines sold in the Northern Plains are estimated to be –5.0% lower than those sold in the Heartland region. The regions of Eastern Mountains, Northeastern, Northwest, Delta, Southern Plains and Mountain all resulted in estimates lower than the PAT model at –21.1%, -16.0%, -31.0%, -26.2%, -8.7%, and –16.5% respectively. The only region estimated to have a greater impact than the PAT model was the Pacific region at –47.4% As for the precision agriculture technology variables, only two held significance with Case IH combines. Receivers and Displays held consistent estimated impacts with the PAT model. Receivers remained at the 1% significance level, while Displays did increase to the 5% significance level. Yield Monitors were not significant in the Case IH model and Row Sensors and Data Sync were omitted.

The last of the three manufacturer-specific models was AGCO combines. Substantial differences were found for the standard variables. Although age remained significant at the 1% level, separator hours fell to the 5% level and condition no longer held significance. As for the impacts, separator hours decreased in magnitude from the PAT model to -0.016% per hour, while an increase in age increased the estimate to -10.1% per year. Furthermore, sale variables held vastly different estimates from the PAT model, combines sold as farm sales help an increased value of 11.6% at the 5% significance level. Online sales estimated a decrease of -12.9% at the 1% significance level, and consignment sales followed at - 13.7% both at the 10% significance level. Spring sales were estimated at 14.8% higher than fall sales at the 1% significance level, and winter sales increased to 14% at the 5% significance level compared to fall sales. For AGCO combines, the only years 2015, 2020, and 2021 held significance at the 5% level with all three holding positive coefficients. 2015 was estimated to have the smallest impact on price at 15.7%, followed by 2020 at 28.6%, and 2021 at 23.6%. The location of the sale illustrated major differences from the PAT model, with only five regions holding significance. The only positive estimate compared to the Heartland regions was the Northern Plains with an impact of 4.1% at the 1% significance level. The Eastern Mountain region fell to the 10% significance level and was estimated at –8.4%. The Northwest regions showed similar changes with a drop in significance to the 5% level and a lower estimated impact of –24% for AGCO combines. Combines sold in the Northeastern and Delta regions maintained a significance level of 1%, but held estimates lower than the PAT model at –49.1% and –34.4%, respectively.

3.6 Discussion

The results from the base and PAT models illustrated similarities with variance accounted for and numerous coefficients included in each model. For the standard variables, separator hours and age held the most notable finding of the study. Both models estimated hours as a -0.02% decrease in value for each additional separator hour of use, while age was estimated at -8.6% and -8.4%, respectively. The relationship between the two use variables is a notable finding because of the impact on traditional depreciation methods of farm machinery. Traditionally depreciation, as shown by Edwards (2015), has been calculated based on age, projected annual use in hours, and type of machine. Given these variables, index tables are used to find the salvage value of a machine based on the purchase price. The findings from this study allow for a more accurate estimation of a machine's depreciation value. They could be used to investigate the depreciated value individually from either hours or age instead of the general combination of the two. Although the finding is notable, it should serve as the starting point for further work into investigating depreciation values on farm machinery. In addition to the depreciation method, the relationship between separator hours and age was further investigated in this study. To compare the two variables accurately, the estimated separator hours was multiplied by the average separator hours per year in the dataset of 285 hours. A decrease of -5.7% was estimated for a year's worth of use in separator hours, suggesting that a year increase in age has a larger impact on the value of a combine compared to a year of separator hours. Although the result was similar to Ellis et al. (2022), the larger dataset allows a better estimate of the findings. For producers looking to buy or sell combines, the relationship between separator hours and age could be important when trying to accurately evaluate a combine’s value. From a seller’s perspective, selling a combine with more hours and lower age would be expected to hold a higher value. While a buyer would look for combines of high age and lower hours to reduce the purchase price. Although a seller might not be able to directly control the number of separator hours on the combine, the findings would allow for future planning of combine use and when to sell a combine.

Condition variables were consistent between the two models and estimated that Excellent or Good condition combines would hold higher values. Given the previously mentioned consolidation of the condition groups, other than Excellent or Good condition holding higher values, it is difficult to provide an in-depth analysis of the result. On the other hand, the combine manufacturer provided the expected value order with John Deere holding the highest value of the combines. Even though the results were similar to Allison et al. (2022) and Ellis et al. (2022), the magnitude of the estimates and comparison of the coefficients allows for a better understanding of values in the combine market. Based on the study, producers can expect to pay around 10% more for John Deere combines than Case IH combines. Additionally, the estimated coefficients for AGCO and Ford New Holland suggest that Claas is the third highest manufacturer value in the dataset. Manufacturers’ order for combine values should be used by producers during the buying or selling process and provides a better comparison when determining the difference between combine options. Additionally, the estimated values should be part of estimating future salvage or resale values for combines.

Sale variable results outline how, when, and where to buy or sell a combine. Combines sold as Farm sales were estimated to have higher values than all other sale types. In theory, Online sales should provide the largest pool of buyers and therefore, might be expected to project a higher price compared to the other sale types. However, Diekmann et al. (2008) illustrated buyers' willingness to pay differences between in-person or online auctions. Similar to their findings, the combine market suggests that buyers may have reservations about paying more for online sales due to asymmetric information. Buyers are willing to pay more for combines they can see in person and physically inspect rather than relying on the information provided online by an individual they do not know.

Combines sold in the Winter season were expected to hold the highest values, followed by the Spring and then Fall season. Similar to Allision et al. (2022) findings, machines sold during the season where the major operation occurs will hold the lowest values. For planters, that was the spring season, while for combines that would be the fall season. Additional investigation found that more combines were on the market during the fall season which would suggest greater supply resulting in lower prices. The findings of the study did not fully support this hypothesis. Only the Winter season was found to be significant when compared to the Fall. Combines sold in the Winter are expected to have higher values, but the remaining order of the seasons cannot be determined based on these results. Overall year of sale suggested a decrease in values from years 2011 through 2014 and an increase in the years 2019 through 2021. Given these are historical variables, they provide insight into the current trends of the market, but market shifts should be considered when using the estimated coefficients. Results for the year of sale suggest that the used combine market has recovered from the decrease in the early 2010s and has potentially stabilized around 6% to 9% higher than sales in 2010.

Combines in the Great Lakes region hold the highest value in the base model and second highest in the PAT model differing from expectations. Based on the crop production potential in the Heartland, it was expected that combine values in the Heartland would be higher than in any other region. Since the results do not support this expectation, further examination is needed on the demand side of the combine market. One potential conclusion is the Great Lakes region might present more buyers than the Heartland and, therefore, cause higher prices due to higher demand and basis. USDA QuickStats (*USDA/NASS QuickStats*, n.d.) data is consolidated from each state within the two regions to compare number of operations, acres harvested, and price and yield for corn, soybeans, and wheat. However, USDA data does not support this theory since the Heartland region held higher values for the number of operations, acres per operation, acres harvested, and average yield for corn and soybeans. Additionally, wheat yields are only lower in one Heartland state compared to the Great Lakes region, but little difference in wheat acres harvested are found.

Further investigation is needed to explain why the Great Lakes region holds higher combine values. A few possible explanations include the shorter harvesting window in the Great Lakes, resulting in the need for larger combines to cover fewer acres. Another reason could be limitations in our Machinery Pete dataset. Although Machinery Pete is one of the largest auction houses in the country, it could have less of a presence in the Great Lakes, leading to a higher estimation of values as less of a presence could include higher auction costs in the region, increasing combine prices from our Machinery Pete. Additionally, the higher values could be related to transportation costs to move a combine. Given the market, it is plausible that the Great Lakes prices reflect the cost of buying a combine in the Heartland and transporting it to an operation in the Great Lakes; however, this theory is not supported by the coefficients in the other regions. The remaining significant regions hold negative values compared to the Heartland, as expected. In order of decreasing value as Northeastern, Mountains, Southern Plains, Eastern Mountains, Northwest, Delta, and Pacific region. The Northeastern region was the closest significant region group to the Heartland with an estimated –3.8% decrease in the base model and -3% decrease in PAT model. Although the region contained a small number of sales, the estimated value could likely be due to the region's proximity to the higher-value regions, which could cause buyers to purchase a combine in the region and transport it back to the higher-value regions.

3.6.1 PAT Variables Discussion

Precision agricultural technologies were found to have an impact on the overall value of the combine. For the PAT model, operator-related technologies did not hold as high of an impact as expected, with only Displays and Row Sense having statistical significance. At the 1% level, Displays were estimated to increase a combine's value by 2.8%, which was much lower than the harvest or data-related technologies. A potential reason for the lower impact could be due to displays not impacting the returns or overall efficiency as much as the other technologies. Another option could be the use of older and cheaper displays since this technology has not seen major updates or changes in recent years. As for Row Sense, the variable was significant only at the 10% level and held a low number of observations. Given that Row Sense is a similar technology compared to Auto Steer, yet Auto Steer was not significant, it is difficult to provide an in-depth reason for the estimate and could be related to the lower number of observations in the dataset.

Harvest-related technologies were the next highest impact group and offered three technologies with significance. Yield Monitors without Moisture Trackers were estimated at 4.1% at the 1% level. Harvest-related variables were expected to have positive impacts on a combine’s value since each technology should increase the returns for the combine. The Yield Monitor technologies allow the operator to increase or decrease the speed of harvest based on the crop yields within the area of the field. Overall, the technology allows the combine to harvest the crop more efficiently across an entire field rather than having one speed for the entire field or relying on operator judgment. Given the benefit of having Yield Monitors on the combine, the increase estimate was the value added from the increase in harvesting operation.

Data-related technologies held the highest impact values of the precision agricultural technologies investigated in the study. Receivers were found to have an impact of 6.7%, while the presence of Data Sync was estimated at an increase of 13% of a combine’s value. Receiver’s impact was expected since that the technology allows for communication between machines, operators, and data storage to occur. Additionally, Receivers were expected to have a higher impact compared to other technologies since a receiver is required for a majority of the new technologies related to geographical locations within the field. An unexpected result was the magnitude of the estimated increase from Data Sync. By far the largest estimated coefficient, Data Sync allows producers to automate the transfer of data between machines within the operation. Since this transfer can be and has historically been done by the operator, the study did not expect buyers to be willing to pay a premium for the technology. The high estimate indicated that buyers are willing to pay more to avoid the manual transfer of data and indicated that manual transfer is either very time consuming or not reliable. In either case, including the Data Sync technology when reselling a combine could drastically increase the price received for the machine.

3.6.2 Manufacturers Specific Models Discussion

Investigating the difference in estimates from different manufacturers could lead to a better understanding of how factors impact combine values based on the make and potentially illustrate willingness to pay differences in production regions. The John Deere specific model held the largest number of operations followed by Case IH and then AGCO. Standard variables across the three models illustrated different decreases for the usage variables. It was estimated that AGCO combines had the lowest separator hours decrease. When scaled to represent one year's worth of use at 285 hours, AGCO combines estimated a negative 4.5%, John Deere followed at negative 5.7%, then Case IH at negative 6.6%. On the other hand, age estimations illustrated a different order with AGCO holding the highest impact value at negative 10.1%, followed by John Deere at negative 8.2%, then Case IH at negative 8.1% per year increase in age. The results illustrated that AGCO combines are more likely to hold their value with respect to separator hours, while John Deere and Case IH combines are more likely to hold their value when age is increased. Contrary to the previous studies on evaluating combine values based on economic depreciation or using index tables (Edwards, 2015; Lattz & Schnitkey, 2021), these finding suggest decreases in combine values from usage differ based on the manufacturer of the machine. Additionally, this could lead to the need for different evaluation structures for combines given the manufacturer. Condition of the combine was only significant in the John Deere and Case IH models, with John Deere estimating an increase of 21.8% at the 5% significance level and Case IH estimating an increase of 36.1% at the 1% significance level for combines holding an Excellent or Good condition values. Although interesting and similar to the findings from Allision et al. (2022) with planters, the joining of Excellent and Good condition groups leads to further work needing to be done to fully understand the relationship between condition groups, manufacturer and combine values.

Sale variables produced different results for each manufacture. The Farm sale type was found to have the highest value across all manufacturers, followed by Dealer sales having the second highest value. John Deere combines estimated that Consignment sales would have a negative impact on value at -4.6%, followed by Online sales at –5.8%. On the other hand, AGCO combines estimated that Online sales would have less of a decrease in value than Consignment at –12.9% and -13.7%, respectively. Case IH combines only found significance with Consignment sales at a -3% compared to Dealer sales, but no significance was found for Online sales. The Year of sale was found to have varying significance levels across manufacturers. For John Deere and Case IH combines, 2011 through 2014 found significance, and all illustrated negative impact estimates similar to the PAT model. More recent years, 2017 and 2020, estimated significant positive impacts for John Deere with a similar magnitude to the PAT model. For 2021, both John Deere and Case IH held significant estimates within the confidence interval of the PAT model. Although both manufacturers estimated results within the confidence interval of the PAT model, all of the John Deere coefficients were, except for 2021, larger in magnitude while the Case IH coefficients were all smaller in magnitude. However, given the factors outside of this study, such as the pandemic or supply chain issues, further work is needed on the year of sale results. The AGCO model only found significance for the years 2015, 2020, and 2021 with all three having a positive estimate. Sales for the 2015 year with AGCO combines could be explained by the release of a new line of Massey Ferguson and Gleaner combines, both under the parent company of AGCO (Potter, 2014). As for the 2020 and 2021 sale years, the pandemic is a possible reason for increased values.

For the season of sale, only the Winter season was significant with John Deere combines similar to the base and PAT models, while both Case IH and AGCO found significance in the Spring and Winter seasons compared to the reference group of Fall sales. Case IH combines were estimated to have an increase of 5% in the Spring, while AGCO combines estimated an increase of 14.8% compared to the Fall season. Winter sales also estimated increases in value for both manufacturers, with Case IH estimating an increase of 4.7% and AGCO at 14%. The order of season of sale did not follow expectations with the finding of Ellis et al. (2022). However, further investigation illustrates there is no statistical difference between the Spring and Winter season, suggesting that the increase in values could be due to a continuation of the after-harvest price increase discussed in the expectations.

Displays held significance in both the John Deere and Case IH models with estimated impacts similar to the PAT model results. Row Sense held a higher significance level with John Deere combines compared to the PAT model; however, the estimate was not statistically different. Harvest-related technologies were only significant in the John Deere model, with Yield Monitors without Moisture Trackers having a higher impact than the PAT model at 6.5%. Similarly, Data Sync was found to be significant in the John Deere and AGCO models, with the estimate for the AGCO model slightly above the coefficient in the PAT model results. Receivers were not found to be significant with John Deere combines and was estimated significantly higher for AGCO combines compared to the PAT model. The similarities of John Deere combines with the PAT model were expected due to the market share represented by John Deere in the dataset. Alternatively, the differences shown with Case IH and AGCO could illustrate the value differences for adding PAT elements to those combines since no manufacture specific brand technology was significant. This potential result would suggest that Case IH and AGCO combine owners would increase their combines value by adding these technologies, while John Deere owners would not experience the same value increase.

3.7 Conclusion

The dramatic increase in combine values has had a direct impact on profitability, causing farmers to reevaluate machinery purchasing options. For many grain operations, buying a used combine could be the best option, but the lack of evaluation methods does not provide a clear understanding of pricing used combines. Additionally, the continual market changes from the introduction of precision agriculture technologies (PAT) have further complicated estimating the true value of a combine. This study expands on the previous work of Ellis et al. (2022) and provides two models that estimate a used combines value. Utilizing a Machinery Pete dataset of auction sales between 2010 and 2022, the base model estimates values before incorporating PAT variables and helps to compare this study to the previous work. The second model builds upon the base model by incorporating PAT variables for the combines in the dataset. This study provides three additional models to evaluate the impact of precision agricultural technologies on the top three manufacturers of combines in North America to estimate different evaluation structures for each manufacturer.

Usage variables for combines indicated that an increase in the age of the machine would decrease the value more than an increase in separator hours. When separator hours were scaled to reflect the average years' worth of use, combined values decreased by around 5.7%, while an additional year in age was estimated to have an 8.6% decrease. Although seemingly a simple finding, the relationship between age and separator hours could change how the industry calculates economic depreciation. Additionally, the study estimated combines will hold higher values when sold during the winter season through farm auctions. PAT variables were estimated to have the highest value if their function related to data communication, followed by harvest-related functions, and lastly, operator-related functions. This result suggests that operators are willing to pay more for technologies that enhance in-field communication and data sharing between machines. The major finding of the study provides a starting point for understanding how to evaluate used combines in North America, and the full results should be used to assist operators with comparing various combine options.

3.8 Chapter 3 Tables and Figures

Table 3-1 – Combine Data Description and Summary Statistics

Variable	**Definition**	**Number of Observations**	**Mean**	**Std. Dev**	**Range**
Independent					
Price	Final Sale Price ($)	8,487	$102,259.90	$61,929.61	$1,750-$480,000
Dependent					
Usage Factors					
Hours	Total separator hours of use on the machine	8,487	2,188.83	1,135.25	0-9123
Age	Total years since manufacturing	8,487	8.65	4.80	0-22
Excellent_Good	= 1 if condition score is either Excellent or Good	8,407	0.99	0.10	0 - 1
Fair_Poor	= 1 if condition score is either Fair or Poor	80	0.01	0.10	0 - 1
Make					
John Deere	= 1 if John Deere was the make	5,698	0.671	0.470	0 - 1
Case IH	= 1 if Case IH was the make	1,994	0.235	0.424	0 - 1
AGCO	= 1 if AGCO was the make	357	0.042	0.201	0 - 1
Ford New Holland	= 1 if Ford-New Holland was the make	277	0.033	0.178	0 - 1
Claas	= 1 if Claas was the make	161	0.019	0.136	0 - 1
Sale Variables					
Spring Sale	= 1 if sale occurred in the Spring season	1,257	0.148	0.355	0 - 1
Summer Sale	= 1 if sale occurred in the Summer season	3,269	0.385	0.487	0 - 1
Fall Sale	= 1 if sale occurred in the Fall season	2,149	0.253	0.435	0 - 1
Winter Sale	= 1 if sale occurred in the Winter season	1812	0.214	0.410	0 - 1
Dealer	= 1 if sale occurred at a dealership	834	0.098	0.298	0 - 1
Consignment	= 1 if sale was for consignment	3098	0.365	0.481	0 - 1
Farm	= 1 if sale occurred on farm	1,635	0.193	0.394	0 - 1

Online	= 1 if sale occurred online	2,868	0.338	0.473	0 - 1
Other	= 1 if sale was not through Dealer, Consignment, Farm, or Online	52	0.006	0.078	0 - 1
Year of Sale					
Year 2010	= 1 if the sale occurred in the 2010 sale year	191	0.023	0.148	0 - 1
Year 2011	= 1 if the sale occurred in the 2011 sale year	314	0.037	0.189	0 - 1
Year 2012	= 1 if the sale occurred in the 2012 sale year	478	0.056	0.231	0 - 1
Year 2013	= 1 if the sale occurred in the 2013 sale year	498	0.059	0.235	0 - 1
Year 2014	= 1 if the sale occurred in the 2014 sale year	440	0.052	0.222	0 - 1

Table 3.1 Continued – Combine Data Description and Summary Statistics

Year 2015	= 1 if the sale occurred in the 2015 sale year	657	0.077	0.267	0 - 1
Year 2016	= 1 if the sale occurred in the 2016 sale year	688	0.081	0.273	0 - 1
Year 2017	= 1 if the sale occurred in the 2017 sale year	774	0.091	0.288	0 - 1
Year 2018	= 1 if the sale occurred in the 2018 sale year	630	0.074	0.262	0 - 1
Year 2019	= 1 if the sale occurred in the 2019 sale year	1089	0.128	0.334	0 - 1
Year 2020	= 1 if the sale occurred in the 2020 sale year	1116	0.131	0.338	0 - 1
Year 2021	= 1 if the sale occurred in the 2021 sale year	962	0.113	0.317	0 - 1
Year 2022	= 1 if the sale occurred in the 2022 sale year	650	0.077	0.266	0 - 1
Region of Sale					
Eastern Mountain	= 1 if the sale was in Eastern Mountain Region	136	0.016	0.126	0 - 1
Northeastern	= 1 if the sale was in Northeastern Region	27	0.003	0.056	0 - 1
Southern	= 1 if the sale was in Southern Region	14	0.002	0.041	0 - 1
Upper Midwest	= 1 if the sale was in Upper Midwest Region	2087	0.246	0.431	0 - 1
Great Lakes	= 1 if the sale was in Great Lakes Region	872	0.103	0.304	0 - 1
Heartland	= 1 if the sale was in Heartland Region	2137	0.252	0.434	0 - 1

Northwest	= 1 if the sale was in Northwest Region	32	0.004	0.061	0 - 1
Pacific	= 1 if the sale was in Pacific Region	11	0.001	0.036	0 - 1
Delta	= 1 if the sale was in Delta Region	213	0.025	0.156	0 - 1
Northern Plains	= 1 if the sale was in Northern Plains Region	2,702	0.318	0.466	0 - 1
Southern Plains	= 1 if the sale was in Southern Plains Region	141	0.017	0.128	0 - 1
Mountain	= 1 if the sale was in Mountain Region	115	0.014	0.116	0 - 1
Controls					
US Cash Receipts	US Cash Receipts at time of Sale	8,487	$211,000,000	$27,300,000	$180,000,000-$286,000,000
PPI	Producer Price index at time of sale	8,487	183.32	56.18	119.9-322.7
Region Diesel Price	Region Diesel price at time of sale	8,487	3.14	0.76	1.9-5.8

Table 3-2 – Combine Precision Agriculture Technology Data Description and Summary Statistics

Variable	Definition	Number of Observations	Mean	Std. Dev	Range
PAT Variables					
Yield Monitor	= 1 if Yield Monitor was included	276	0.03	0.18	0 - 1
Moisture Tracker	= 1 if Moisture Tracker was included	83	0.01	0.10	0 - 1
Yield Monitor with Moisture Tracker	= 1 if Yield Monitor with Moisture Tracker was included	872	0.10	0.30	0 - 1
Grain Loss Monitor	= 1 if Grain Loss Monitor was included	91	0.01	0.10	0 - 1
GPS	= 1 if GPS was included	66	0.01	0.09	0 - 1
Auto Steer	= 1 if Auto Steer was included	1637	0.19	0.39	0 - 1
Row Sense	= 1 if Row Sense was included	54	0.01	0.08	0 - 1
Data Sync	= 1 if Data Sync was included	38	0.00	0.07	0 - 1
Receiver	= 1 if Receiver was included	292	0.03	0.18	0 - 1
Display	= 1 if Display was included	2089	0.25	0.43	0 - 1
PAT Manufacturer					
John Deere PAT	= 1 if the PAT manufacturer was John Deere	1320	0.16	0.36	0 - 1
Case IH PAT	= 1 if the PAT manufacturer was Case IH	78	0.01	0.10	0 - 1
Ag Leader PAT	= 1 if the PAT manufacturer was Ag Leader	158	0.02	0.14	0 - 1
Ford New Holland PAT	= 1 if the PAT manufacturer was Ford-New Holland	46	0.01	0.07	0 - 1

Table 3-3 – Combine Base Model VIF Results

Variable		**VIF**	**1/VIF**
Usage Factors			
	Hours	2.73	0.366
	Age	2.95	0.339
	Excellent_Good	1.04	0.958
Make			
	John Deere	12.36	0.081
	Case IH	10.56	0.095
	AGCO	3.17	0.316
	Ford New Holland	2.7	0.371
Sale Variables			
	Spring Sale	1.52	0.657
	Summer Sale	1.72	0.583
	Winter Sale	1.52	0.657
	Consignment	3.46	0.289
	Farm	2.76	0.362
	Online	4.46	0.224
	Other	1.11	0.902
Year of Sale			
	Year 2011	2.51	0.398
	Year 2012	2.43	0.411
	Year 2013	2.11	0.473
	Year 2014	2.53	0.395
	Year 2015	4.34	0.231
	Year 2016	5.29	0.189
	Year 2017	4.85	0.206
	Year 2018	3.69	0.271
	Year 2019	5.65	0.177
	Year 2020	7.18	0.139
	Year 2021	4.46	0.224
Region of Sale			
	Eastern Mountain	1.08	0.926
	Northeastern	1.03	0.974
	Southern	1.02	0.980
	Upper Midwest	1.8	0.554
	Great Lakes	1.35	0.742
	Northwest	1.03	0.968
	Pacific	1.05	0.949
	Delta	1.14	0.879
	Northern Plains	1.82	0.549
	Southern Plains	1.1	0.912

	Mountain	1.1	0.913
Controls			
	US Cash Receipts	11.89	0.084
	PPI	12.82	0.078
	Region Diesel Price	16.01	0.062
	Mean VIF	3.88	

Table 3-4 – Combine PAT Model VIF Results

	Variable	**VIF**	**1/VIF**
Usage Factors			
	Hours	2.75	0.364
	Age	3.2	0.313
	Excellent_Good	1.05	0.954
Make			
	John Deere	12.76	0.078
	Case IH	10.98	0.091
	AGCO	3.2	0.313
	Ford New Holland	2.93	0.342
Sale Variables			
	Spring Sale	1.53	0.654
	Summer Sale	1.72	0.580
	Winter Sale	1.63	0.613
	Consignment	3.48	0.287
	Farm	2.79	0.359
	Online	4.5	0.222
	Other	1.11	0.898
Year of Sale			
	Year 2011	2.52	0.397
	Year 2012	2.46	0.407
	Year 2013	2.12	0.471
	Year 2014	2.54	0.394
	Year 2015	4.37	0.229
	Year 2016	5.31	0.188
	Year 2017	4.88	0.205
	Year 2018	3.71	0.269
	Year 2019	5.72	0.175
	Year 2020	7.31	0.137
	Year 2021	4.49	0.223
Region of Sale			
	Eastern Mountain	1.09	0.922
	Northeastern	1.03	0.972
	Southern	1.02	0.978
	Upper Midwest	1.85	0.541
	Great Lakes	1.35	0.738
	Northwest	1.04	0.965
	Pacific	1.15	0.872
	Delta	1.15	0.871
	Northern Plains	1.91	0.523
	Southern Plains	1.1	0.910

	Mountain	1.1	0.907
Controls			
	US Cash Receipts	12.15	0.082
	PPI	12.86	0.078
	Region Diesel Price	16.08	0.062

Table 3.4 Continued – Combine PAT Model VIF Results

PAT Variables			
	Yield Monitor	1.29	0.777
	Moisture Tracker	1.18	0.845
	Yield Monitor with Moisture Tracker	1.49	0.672
	Grain Loss Monitor	1.05	0.954
	GPS	4	0.250
	Auto Steer	4.17	0.240
	Row Sense	1.55	0.644
	Data Sync	1.63	0.613
	Receiver	1.13	0.883
	Display	1.5	0.669
PAT Manufacturer			
	John Deere PAT	1.34	0.744
	Case IH PAT	1.08	0.927
	Ag Leader PAT	1.1	0.910
	Ford New Holland PAT	1.23	0.810
	Mean VIF	3.35	

Table 3-5 – Combine Base Model Regression Results

R-Squared 0.8794

Variable		**Co Ef.**		**Robust Std Error**	**95% Confidence Interval**	
Usage Factors						
	Hours	-0.0002	***	0.00001	-0.00022	-0.00018
	Age	-0.0868	***	0.002	-0.091	-0.081
	Excellent_Good	0.3705	***	0.041	0.280	0.460
Make						
	John Deere	0.2534	***	0.030	0.187	0.320
	Case IH	0.1582	***	0.037	0.077	0.239
	AGCO	-0.0677	**	0.027	-0.128	-0.007
	Ford New Holland	-0.1102	***	0.027	-0.169	-0.051
Sale Variables						
	Spring Sale	0.0213		0.012	-0.005	0.048
	Summer Sale	-0.0089		0.006	-0.023	0.005
	Winter Sale	0.0339	***	0.008	0.016	0.052
	Consignment	-0.0455	***	0.011	-0.071	-0.020
	Farm	0.0687	***	0.012	0.041	0.096
	Online	-0.0533	***	0.014	-0.085	-0.021
	Other	-0.0155		0.038	-0.099	0.068
Year of Sale						
	Year 2011	-0.0940	***	0.017	-0.132	-0.056
	Year 2012	-0.2039	***	0.016	-0.239	-0.169
	Year 2013	-0.1165	***	0.019	-0.158	-0.075
	Year 2014	-0.0906	***	0.015	-0.123	-0.058
	Year 2015	-0.0048		0.028	-0.066	0.056
	Year 2016	0.0081		0.039	-0.077	0.093
	Year 2017	0.0413		0.026	-0.016	0.099
	Year 2018	0.0466		0.033	-0.027	0.120
	Year 2019	0.0597	*	0.030	-0.006	0.126
	Year 2020	0.1260	***	0.026	0.069	0.183
	Year 2021	0.0996	***	0.021	0.053	0.146
Region of Sale						
	Eastern Mountain	-0.0657	***	0.002	-0.070	-0.062
	Northeastern	-0.0382	***	0.008	-0.057	-0.020

	Southern	0.0316	*	0.015	-0.001	0.064
	Upper Midwest	0.0234	***	0.004	0.015	0.032
	Great Lakes	0.0394	***	0.004	0.031	0.048
	Northwest	-0.1282	***	0.010	-0.150	-0.107
	Pacific	-0.6523	***	0.018	-0.691	-0.613
	Delta	-0.2018	***	0.005	-0.212	-0.192
	Northern Plains	0.0131	***	0.003	0.007	0.020
	Southern Plains	-0.0649	***	0.004	-0.074	-0.056
	Mountain	-0.0504	***	0.012	-0.077	-0.024
Controls						
	US Cash Receipts	0.0000	***	0.000	0.000	0.000
	PPI	0.0005	***	0.000	0.000	0.001
	Region Diesel Price	0.0134		0.012	-0.012	0.039
Constant		10.93146	***	0.106	10.698	11.164

**p-value* <0.10, ***p-value*<0.05, ****p-value <0.01*

Table 3-6 – Combine PAT Model Regression Results

R-Squared 0.8815

Variable		**Co Ef.**		**Robust Std Error**	**95% Confidence Interval**	
Usage Factors						
	Hours	-0.0002	***	0.00001	-0.00022	-0.00018
	Age	-0.0838	***	0.002	-0.089	-0.078
	Excellent_Good	0.3683	***	0.043	0.273	0.463
Make						
	John Deere	0.2462	***	0.032	0.176	0.317
	Case IH	0.1371	***	0.039	0.052	0.223
	AGCO	-0.0760	**	0.029	-0.139	-0.013
	Ford New Holland	-0.1145	***	0.026	-0.172	-0.057
Sale Variables						
	Spring Sale	0.0227		0.013	-0.007	0.052
	Summer Sale	-0.0075		0.006	-0.021	0.006
	Winter Sale	0.0373	***	0.008	0.020	0.055
	Consignment	-0.0458	***	0.013	-0.074	-0.018
	Farm	0.0660	***	0.014	0.035	0.097
	Online	-0.0615	***	0.017	-0.100	-0.023
	Other	-0.0302		0.040	-0.119	0.058
Year of Sale						
	Year 2011	-0.0902	***	0.019	-0.132	-0.049
	Year 2012	-0.1948	***	0.020	-0.239	-0.151
	Year 2013	-0.1085	***	0.021	-0.155	-0.062
	Year 2014	-0.0857	***	0.013	-0.114	-0.058
	Year 2015	-0.0078		0.023	-0.058	0.042
	Year 2016	0.0070		0.033	-0.066	0.080
	Year 2017	0.0424	*	0.021	-0.004	0.089
	Year 2018	0.0424		0.031	-0.025	0.110
	Year 2019	0.0530	*	0.029	-0.010	0.117
	Year 2020	0.1109	***	0.025	0.057	0.165
	Year 2021	0.0905	***	0.020	0.046	0.135
Region of Sale						
	Eastern Mountain	-0.0568	***	0.002	-0.061	-0.053
	Northeastern	-0.0302	**	0.010	-0.052	-0.008
	Southern	0.0486	***	0.015	0.015	0.083

	Upper Midwest	0.0185	***	0.003	0.011	0.026
	Great Lakes	0.0381	***	0.005	0.027	0.049
	Northwest	-0.1288	***	0.007	-0.145	-0.113
	Pacific	-0.7322	***	0.039	-0.818	-0.646
	Delta	-0.1930	***	0.004	-0.201	-0.185
	Northern Plains	0.0069		0.006	-0.005	0.019
	Southern Plains	-0.0628	***	0.006	-0.076	-0.049
	Mountain	-0.0465	***	0.012	-0.072	-0.021
Controls						
	US Cash Receipts	0.0000	***	0.000	0.000	0.000
	PPI	0.0005	***	0.000	0.000	0.001
	Region Diesel Price	0.0145		0.010	-0.008	0.037

Table 3.6 Continued – Combine PAT Model Regression Results

PAT Variables						
	Yield Monitor	0.0414	***	0.009	0.021	0.061
	Moisture Tracker	-0.0132		0.025	-0.069	0.043
	Yield Monitor with Moisture Tracker	0.0395		0.024	-0.012	0.091
	Grain Loss Monitor	-0.0174		0.011	-0.041	0.006
	GPS	-0.0011		0.020	-0.045	0.043
	Auto Steer	0.0150		0.023	-0.036	0.066
	Row Sense	0.0911	*	0.046	-0.010	0.192
	Data Sync	0.1300	**	0.056	0.006	0.254
	Receiver	0.0667	***	0.019	0.026	0.108
	Display	0.0283	***	0.008	0.012	0.045
PAT Manufacturer						
	John Deere PAT	-0.0133		0.008	-0.030	0.003
	Case IH PAT	0.0126		0.040	-0.076	0.101
	Ag Leader PAT	-0.0483	*	0.024	-0.101	0.005
	Ford New Holland PAT	-0.0514		0.036	-0.130	0.028
Constant		10.9784	***	0.100	10.758	11.199

**p-value* <0.10, ***p-value*<0.05, ****p-value <0.01*

Table 3-7 – PAT John Deere Combines Model Regression Results

R-Squared 0.9002

Variable	**Co Ef.**		**Robust Std Error**	**95% Confidence Interval**	
Usage Factors					
Hours	-0.0002	***	0.000004	-0.000209	-0.000189
Age	-0.0817	***	0.001	-0.084	-0.080
Excellent_Good	0.2179	**	0.073	0.057	0.379
Sale Variables					
Spring Sale	0.0040		0.016	-0.032	0.039
Summer Sale	-0.0120		0.012	-0.040	0.016
Winter Sale	0.0251	*	0.012	-0.001	0.051
Consignment	-0.0455	**	0.019	-0.088	-0.003
Farm	0.0508	**	0.022	0.003	0.099
Online	-0.0580	***	0.017	-0.095	-0.021
Other	-0.0503		0.046	-0.151	0.051
Year of Sale					
Year 2011	-0.1150	***	0.020	-0.159	-0.071
Year 2012	-0.2049	***	0.013	-0.234	-0.176
Year 2013	-0.1122	***	0.025	-0.167	-0.057
Year 2014	-0.0773	***	0.011	-0.102	-0.053
Year 2015	0.0123		0.021	-0.033	0.058
Year 2016	0.0439		0.027	-0.016	0.104
Year 2017	0.0696	**	0.030	0.004	0.135
Year 2018	0.0623	*	0.029	-0.002	0.127
Year 2019	0.0699	*	0.037	-0.012	0.152
Year 2020	0.1141	***	0.030	0.048	0.181
Year 2021	0.0924	***	0.017	0.055	0.130
Region of Sale					
Eastern Mountain	-0.0339	***	0.006	-0.048	-0.020
Northeastern	0.0383	***	0.006	0.025	0.052
Southern	0.1057	***	0.020	0.061	0.150
Upper Midwest	0.0255	***	0.006	0.013	0.038
Great Lakes	0.0425	***	0.006	0.029	0.056
Northwest	-0.1055	***	0.013	-0.135	-0.076
Pacific	-0.3703	***	0.013	-0.399	-0.342
Delta	-0.1280	***	0.010	-0.149	-0.107
Northern Plains	0.0187	***	0.005	0.008	0.030
Southern Plains	-0.0644	***	0.006	-0.077	-0.052
Mountain	-0.0231		0.013	-0.052	0.006

Controls						
	US Cash Receipts	0.0000	***	0.000	0.000	0.000
	PPI	0.0006	***	0.000	0.000	0.001
	Region Diesel Price	0.0229	**	0.008	0.006	0.040

Table 3.7 Continued – PAT John Deere Combines Model Regression Results

PAT Variables						
	Yield Monitor	0.0651	***	0.015	0.031	0.099
	Moisture Tracker	-0.0341		0.026	-0.092	0.024
	Yield Monitor with Moisture Tracker	0.0364		0.026	-0.021	0.094
	Grain Loss Monitor	0.0219		0.016	-0.013	0.057
	GPS	-0.0065		0.015	-0.039	0.026
	Auto Steer	0.0113		0.019	-0.031	0.054
	Row Sense	0.1048	**	0.036	0.026	0.183
	Data Sync	0.1216	***	0.029	0.057	0.186
	Receiver	-0.0120		0.013	-0.041	0.017
	Display	0.0301	***	0.007	0.015	0.046
Constant		11.2829	11.2829	0.072	11.124	11.442

*_p-value_ <0.10, **_p-value_<0.05, ***_p-value <0.01_

Table 3-8 – PAT CASE IH Combines Model Regression Results

R-Squared 0.8807

Variable	Co Ef.		Robust Std Error	95% Confidence Interval	
Usage Factors					
Hours	-0.0002	***	0.00001	-0.00026	-0.00021
Age	-0.0806	***	0.004	-0.090	-0.071
Excellent_Good	0.3614	***	0.065	0.219	0.503
Sale Variables					
Spring Sale	0.0500	***	0.011	0.025	0.075
Summer Sale	-0.0106		0.009	-0.030	0.009
Winter Sale	0.0472	***	0.012	0.021	0.073
Consignment	-0.0300	**	0.012	-0.057	-0.003
Farm	0.0828	**	0.029	0.019	0.147
Online	-0.0351		0.034	-0.109	0.039
Other	0.0121		0.033	-0.060	0.085
Year of Sale					
Year 2011	-0.0765	***	0.023	-0.127	-0.026
Year 2012	-0.1783	***	0.042	-0.272	-0.085
Year 2013	-0.0846	***	0.025	-0.140	-0.029
Year 2014	-0.0798	***	0.020	-0.124	-0.036
Year 2015	-0.0452		0.034	-0.120	0.029
Year 2016	-0.0650		0.054	-0.184	0.054
Year 2017	0.0019		0.037	-0.080	0.083
Year 2018	-0.0127		0.051	-0.124	0.099
Year 2019	0.0006		0.031	-0.069	0.070
Year 2020	0.0949		0.059	-0.035	0.225
Year 2021	0.1040	**	0.046	0.002	0.206
Region of Sale					
Eastern Mountain	-0.2105	***	0.012	-0.237	-0.184

	Northeastern	-0.1604	***	0.024	-0.214	-0.107
	Southern	-0.1555	***	0.032	-0.225	-0.086
	Upper Midwest	-0.0151		0.010	-0.036	0.006
	Great Lakes	0.0374	***	0.006	0.025	0.050
	Northwest	-0.3102	***	0.024	-0.363	-0.257
	Pacific	-0.4738	***	0.069	-0.626	-0.321
	Delta	-0.2619	***	0.010	-0.284	-0.239
	Northern Plains	-0.0501	***	0.009	-0.070	-0.030
	Southern Plains	-0.0870	***	0.019	-0.128	-0.046
	Mountain	-0.1652	***	0.008	-0.183	-0.147
Controls						
	US Cash Receipts	0.0000	***	0.000	0.000	0.000
	PPI	0.0005	**	0.000	0.000	0.001
	Region Diesel Price	-0.0056		0.044	-0.101	0.090

Table 3.8 Continued – PAT CASE IH Combines Model Regression Results

PAT Variables					
Yield Monitor	0.0258		0.027	-0.034	0.085
Moisture Tracker	0.0583		0.071	-0.097	0.214
Yield Monitor with Moisture Tracker	0.0393		0.024	-0.014	0.092
Grain Loss Monitor	0.0227		0.030	-0.044	0.089
GPS	0.0132		0.023	-0.037	0.064
Auto Steer	0.0337		0.024	-0.020	0.087
Receiver	0.0670	***	0.018	0.027	0.107
Display	0.0160	**	0.006	0.002	0.030
Row Sense	Omitted				
Data Sync	Omitted				
Constant	11.35319	11.3532	0.162	10.998	11.709

**p-value* <0.10, ***p-value*<0.05, ****p-value <0.01*

Table 3-9 – PAT AGCO Combines Model Regression Results
R-Squared 0.7698

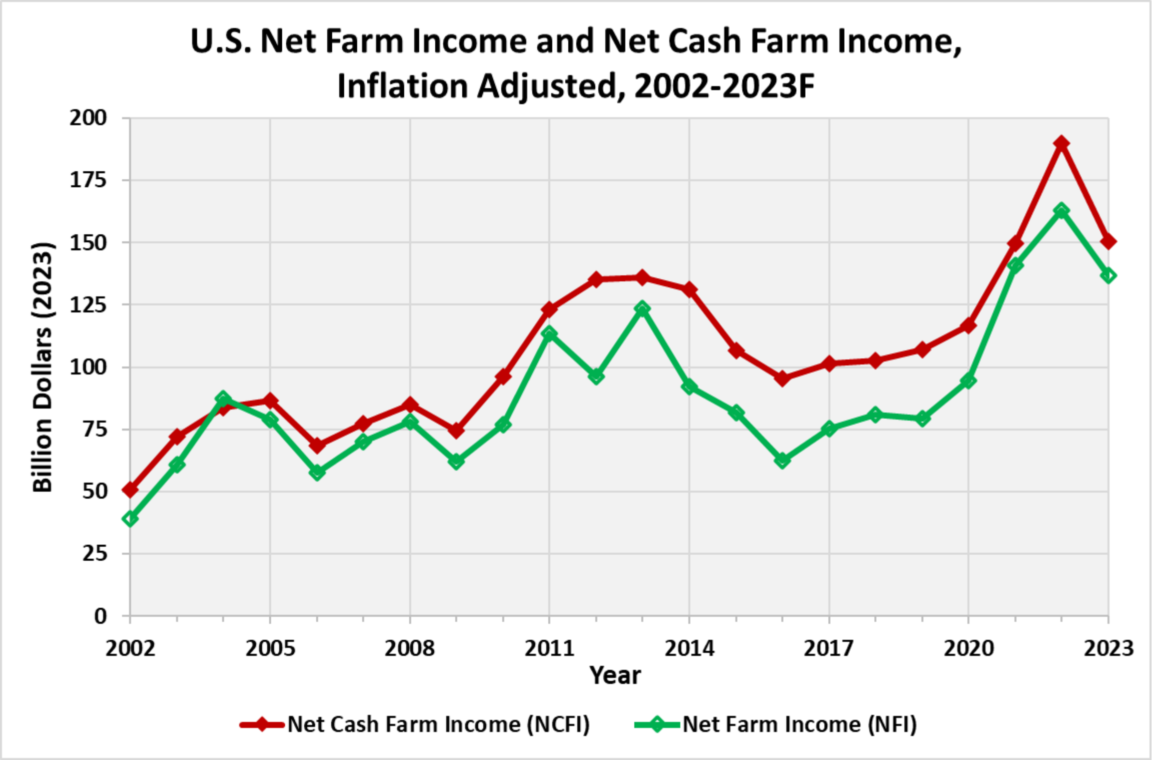
Variable		Co Ef.		Robust Std Error	95% Confidence Interval	
Usage Factors						
	Hours	-0.0002	**	0.00005	-0.00027	-0.00005
	Age	-0.1009	***	0.009	-0.122	-0.080
	Excellent_Good	0.8320		0.612	-0.551	2.215
Sale Variables						
	Spring Sale	0.1476	***	0.019	0.105	0.190
	Summer Sale	0.0472		0.041	-0.045	0.139
	Winter Sale	0.1396	**	0.057	0.010	0.269
	Consignment	-0.1374	*	0.064	-0.282	0.007
	Farm	0.1162	**	0.045	0.014	0.218
	Online	-0.1292	***	0.033	-0.204	-0.054
	Other	Omittted				
Year of Sale						
	Year 2011	0.0387		0.132	-0.259	0.336
	Year 2012	0.0914		0.115	-0.168	0.350
	Year 2013	0.0011		0.032	-0.072	0.075
	Year 2014	-0.0598		0.047	-0.165	0.046
	Year 2015	0.1569	**	0.061	0.019	0.295
	Year 2016	0.0659		0.098	-0.156	0.288
	Year 2017	0.0517		0.083	-0.137	0.241
	Year 2018	0.1515		0.083	-0.037	0.340
	Year 2019	0.1676		0.091	-0.039	0.374
	Year 2020	0.2856	**	0.098	0.065	0.507
	Year 2021	0.2364	**	0.101	0.007	0.466
Region of Sale						
	Eastern Mountain	-0.0840	*	0.045	-0.185	0.017
	Northeastern	-0.4912	***	0.065	-0.637	-0.345
	Southern	Omitted				
	Upper Midwest	0.0037		0.039	-0.084	0.091
	Great Lakes	-0.0082		0.026	-0.067	0.051
	Northwest	-0.2394	**	0.091	-0.446	-0.033
	Pacific	Omitted				
	Delta	-0.3437	***	0.058	-0.475	-0.213
	Northern Plains	0.0413	***	0.010	0.019	0.064
	Southern Plains	0.0213		0.073	-0.145	0.187
	Mountain	-0.0960		0.054	-0.218	0.026

Controls						
	US Cash Receipts	0.0000	*	0.000	0.000	0.000
	PPI	-0.0011		0.001	-0.004	0.002
	Region Diesel Price	0.1589	*	0.073	-0.006	0.324

Table 3.9 Continued – PAT AGCO Combines Model Regression Results

PAT Variables						
	Yield Monitor	0.0752		0.163	-0.294	0.444
	Moisture Tracker	-0.2139		0.273	-0.831	0.403
	Yield Monitor with Moisture Tracker	-0.0856		0.070	-0.244	0.072
	Grain Loss Monitor	-0.0402		0.087	-0.238	0.157
	GPS	-0.1905	*	0.088	-0.389	0.008
	Auto Steer	0.1932	*	0.095	-0.023	0.409
	Row Sense	Omitted				
	Data Sync	0.2593	*	0.129	-0.032	0.551
	Receiver	0.2609	**	0.110	0.012	0.510
	Display	0.0635		0.036	-0.018	0.145
Constant		10.2896	10.2896	0.666	8.783	11.796

**p-value* <0.10, ***p-value*<0.05, ****p-value <0.01*



Source: (U.S. and State-Level Farm Income and Wealth Statistics, 2023)

Figure 3-1 – Historic Net Farm Income Graph by Year

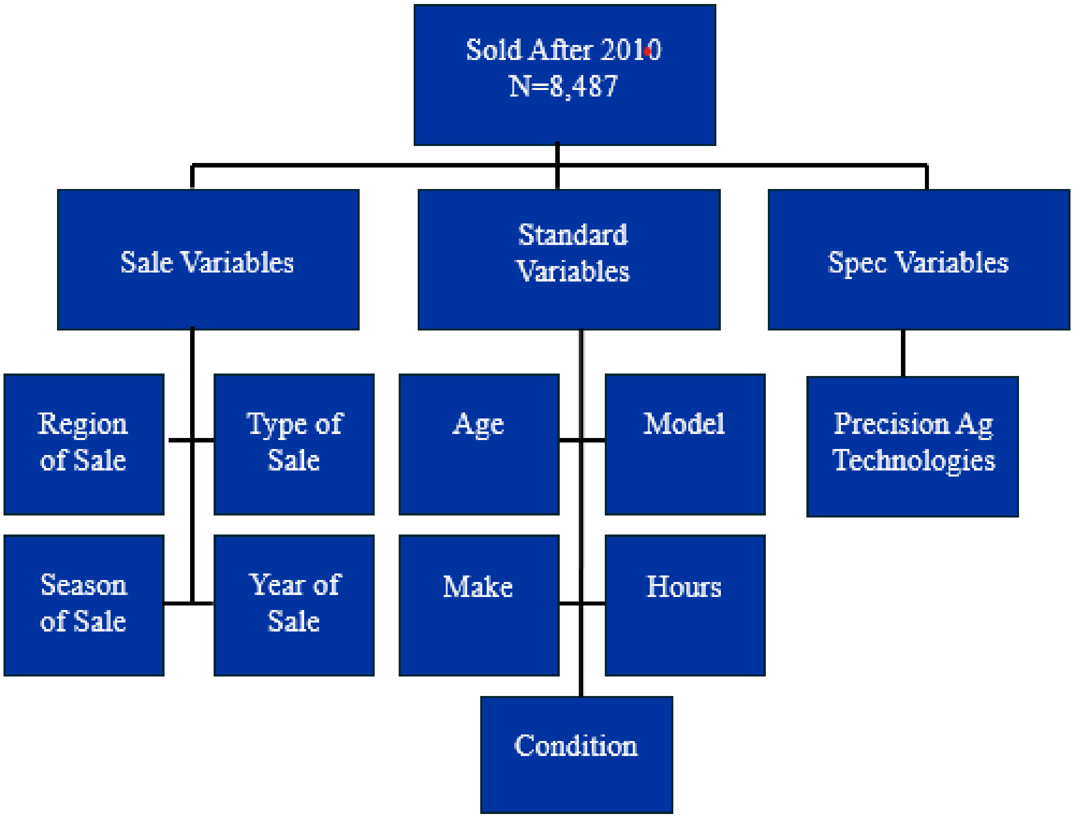
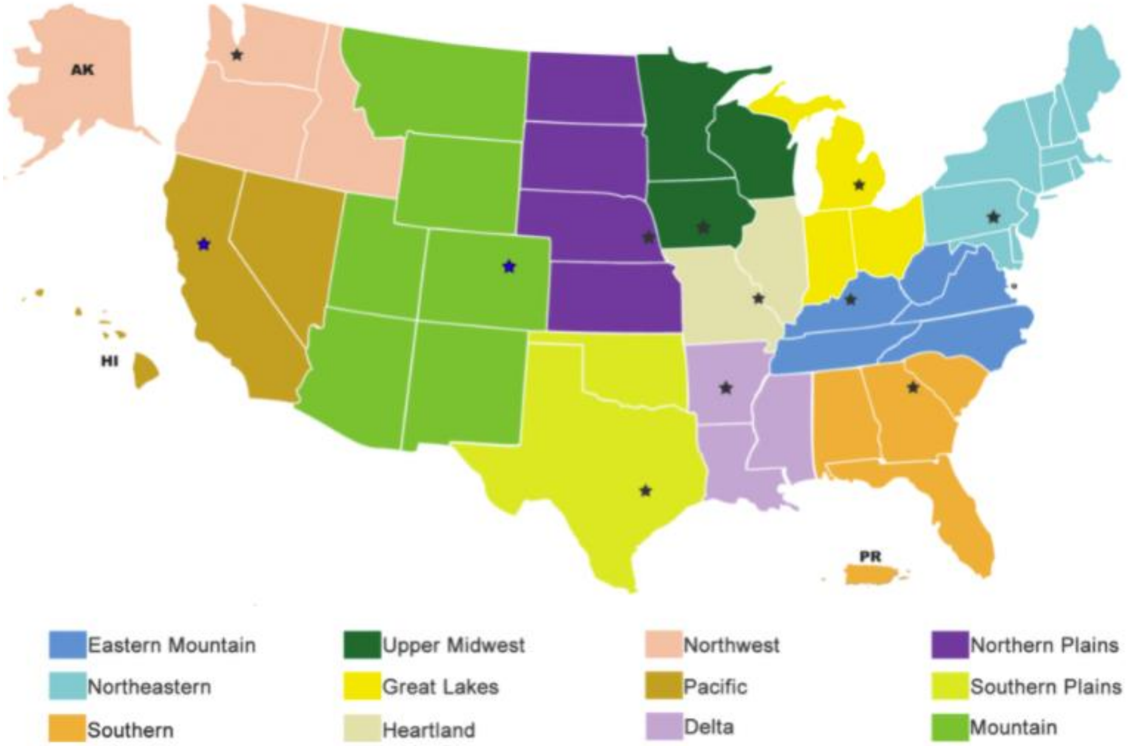


Figure 3-2 – Combine Data Cleaning Tree



Source: (*USDA - National Agricultural Statistics Service - Regional Field Offices*, n.d.)
Figure 3-3 – Regional USDA Map

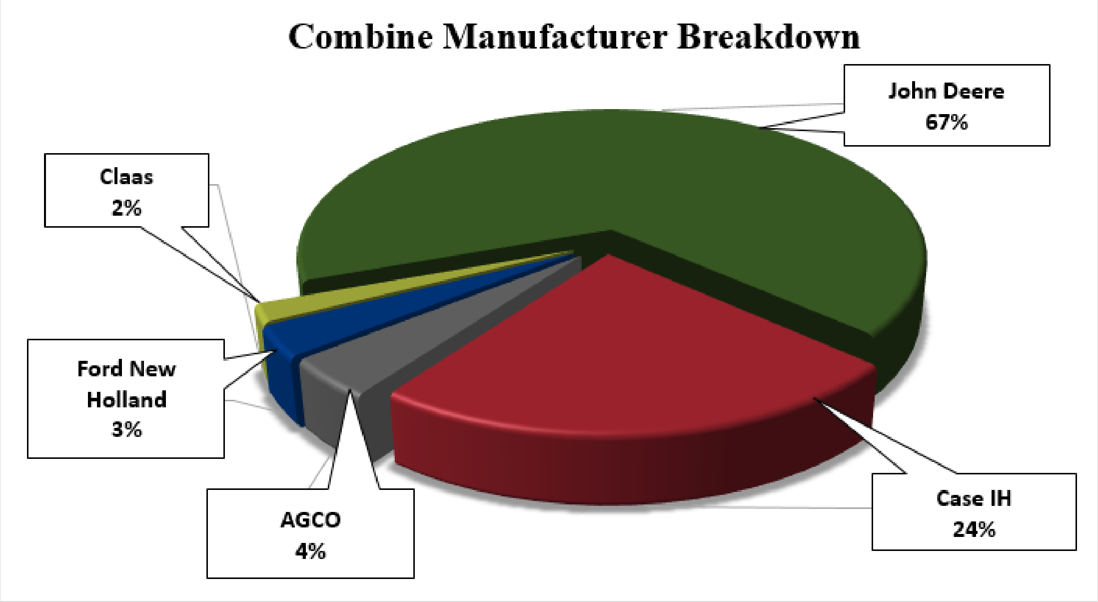


Figure 3-4 – Combine Data Percent of Manufacturer

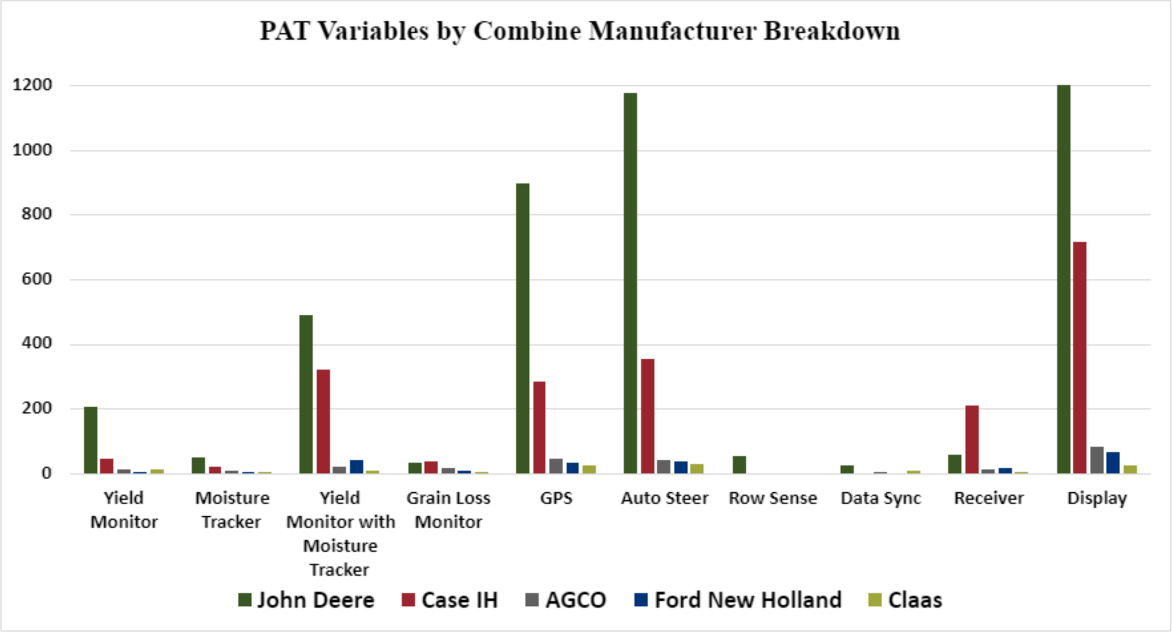


Figure 3-5 – Combine Data Percent of Manufacturer for Each PAT Variable

CHAPTER 4. EVALUATING THE IMPACT OF COVID-19 ON THE SECONDARY TRACTOR MARKET IN NORTH AMERICA

4.1 Introduction

Farm machinery has been a topic in agriculture economics for years. Still, despite previous research evaluating the cost of farm machinery, much of the research is outdated or lacks a comprehensive view of the market (Daninger, 2017; Edwards, 2015; Lattz & Schnitkey, 2021). Furthermore, gaps in pricing evaluation due to a lack of observations, exclusion of major brands, or focus on single market locations limit the work's impact. Additionally, recent market shifts from the pandemic have further complicated machinery decision-making. For today's farm machinery market, producers must juggle supply chain challenges, increases in online auctions, and a drive towards "smart agricultural" practices doming agriculture news and USDA headlines. Before the pandemic, operators buying or selling machinery had to consider the equipment's size, age, quality, capabilities, and compatibility with other implements. However, post-pandemic operators have added decisions around machinery availability, changes in precision technology options (due to limited availability), and higher repair costs to the equation (Anderson, 2022). Unfortunately, such complicated decisions can lead to suboptimal decision-making when purchasing equipment. In an effort to provide information for producers and answer the previously stated question of what impact the COVID-19 pandemic had on tractor values, three objectives were used: 1) identify the key variables that impact a used tractor's value, 2) estimate the impact of the COVID-19 pandemic on the tractor market, and 3) evaluate how the timing of the pandemic shutdown impacted the used tractor market.

To accomplish the objectives, the study evaluated the impact of COVID-19 on used tractor values for the United States market. A unique dataset was used from one of North America's largest online farm machinery auction companies. The dataset contains auction sales from 2010 through 2022 for tractors, including characteristics related to the sale information and machinery specifics for each tractor. Additionally, effective state-of-emergency dates were used as indicators for the start of the pandemic in each state. The dataset was paired with two different econometric models, where the base model addressed objectives 1 and 2, while the second model addressed objective 3. Initial results estimate that John Deere tractors sold in the winter will hold higher values when compared to other brands and seasons. Specifically for pandemic impacts, it was estimated that the overall impact since the effective dates was 16.3%, with short-term monthly impacts ranging between 6% and 16.8%.

The COVID-19 pandemic sent shockwaves through the world economy and impacted every industry with issues around world trade, available workforce, and the shutdown of retail locations. Although the order of industry importance is arguable, the agriculture industry often holds priority due to its essential label as a vital role in human existence. Additionally, the structure of the agricultural industry differs from the other with its reliance on seasonal production, global trade, and immigrant workforce. For agricultural producers, the pandemic not only resulted in unfavorable prices for commodities and inputs but also destroyed the supply of resources vital for production, with tractors being one of those vital resources used in nearly all agricultural enterprises. Agriculture operations are capital-intensive; behind land, farm machinery is the largest asset for most operations (Ibendahl, 2015). Since the pandemic, used machinery prices have continued to increase even in the headwinds of rising interest rates, diesel prices, and fertilizer. Farm machinery saw an estimated cost-per-hour increase between 2.1% and 19.4% from 2019 to 2021 (Lattz & Schnitkey, 2021). Although these estimates are shocking, the rise of used tractor prices has continued upward. The year-over-year change in used tractor prices from June 2021 to June 2022 was between 10% and 13% (Schmidt, 2022). Anderson predicts an increase of 8.7% to 13.9% for tractors in 2023 (Anderson, 2022). These drastic increases in machinery costs, specifically in the used tractor market, have led to the question of what impact the COVID-19 pandemic had on tractor values.

4.2 Background

A hedonic model was employed to estimate the secondary tractor market. The initial development of hedonic models dates back to the early 1960s when the model was used to analyze vehicle quality in car markets (Griliches, 1961), and then further developed in the 1970s to investigate differentiation between products under pure competition (Rosen, 1974). Since then, hedonic models have been commonly used in agriculture to estimate various topics such as cattle, commodities, land, and machinery values (Allison et al., 2022; Borchers et al., 2014; Davis & Ethridge, 1982; Ellis et al., 2022; Martinez et al., 2021; Miranowski & Hammes, 1984; Rosen, 1974). Utilizing monthly auction data Martinez et al. (2021), examined the factors that impact feeder cattle prices and premiums. For commodities, previous literature investigated the impact of crop quality attributes on producer prices (Davis & Ethridge, 1982). Although the previous work on cattle and commodity pricing is notable, the majority of hedonic models in agricultural research have focused on land values (Borchers et al., 2014; Miranowski & Hammes, 1984). In the 1980s, (Miranowski & Hammes, 1984) investigated the price of soil characteristics on farmland in Iowa. This work provided evidence that soil characteristics such as topsoil depth and erosion potential both had a significant impact on farmland prices. Furthermore, the study was able to provide marginal value estimates and suggestions for buyers and sellers based on erosion potential reduction (Miranowski & Hammes, 1984). More recently, (Borchers et al., 2014) found that farmland prices were only partially explained by agricultural returns. The study determined that a portion of farmland values are determined by nonagricultural attributes, such as the development potential of the land (Borchers et al., 2014).

4.2.1 Farm Machinery

Although the majority of the previous work on farm machinery values has focused on tractors over other farm machinery types, most have not used hedonic models. Previous combine and planter work has focused on evaluating machinery based on the cost of ownership, custom hire alternatives, risk analysis, and operation profitability (Edwards & Hanna, 2009; Ibendahl, 2015; Kavka et al., 2016; Lattz & Schnitkey, 2021; Mimra & Kavka, 2017; Swanson et al., 2020). Cost of ownership of a combine has been estimated utilizing the alternative option to owning a combine; custom hiring for harvest (Edwards & Hanna, 2009). In this work, the custom hiring rates were used to determine what level of use was needed to justify the cost of owning the combine. Using a different approach Lattz & Schnithey (2021), provided per-acre cost estimates for harvest cost based on the purchase price of the machine, overhead, fuel, and labor. Each study provides a valuable estimate for machinery costs; nevertheless, both studies fail to utilize the actual price of the combine and only use the purchase price of the machine. Additionally, the studies assume consistent use of the machine over time and do not allow for the cost estimates to change in relation to operation size or efficiency.

Mimra et al. (2017) preformed a risk analysis for business profitability of custom hire harvesting companies. Given that a key variable in the analysis was the value of the combine, a combine's value could be assessed by the profitability the machines output attributes to the company. Similarly, Mimra and Kavka (2017) further investigated the risk associated with a combine's annual use. Although both studies focus on custom hiring operations, a combine's value could be assessed based on a company's profit from the machine or through the useful life of the machine. However, the two studies only compare a few new John Deere combine models. The lack of combine models, brands, and secondary market options leaves the study falling short on providing any evidence for the values of combines within the market.

Similarly, a large portion of previous work related to tractor evaluation has not employed econometric models (Edwards, 2015; Fettig, 1963; Laughlin & Spurlock, n.d.; Leblanc & Hrubovcak, 1985). Price index and per-acre cost estimations are commonly used for evaluating operation machine cost (Edwards, 2015; Lattz & Schnitkey, 2021; Laughlin & Spurlock, n.d.). Although these estimates are useful when estimating an operation's profitability, the use of new purchase prices for machinery and theoretical salvage value for these calculations does not provide adequate evaluations for machinery values.

Hedonic models for pricing research have seen an uptick recently with machinery evaluations. Initially, in the planter market, a national auction dataset of secondary planter sales was used to evaluate the key factors impacting planter values (Allison et al., 2022).

The work found significance in machinery specifics such as manufacture, age, configuration, row number, and row spacing (Allison et al., 2022). Developed further from Allison et al. (2022), the combine market was evaluated by Ellis et al. (2022). Similar to the planter market findings, the study determined that key factors such as manufacturer, age, type of sale, and time of sale all impacted a machine’s value. Additionally, the study found factors such as separator hours, condition, and location of the sale to hold significance for a combine’s value (Ellis et al., 2022). Although both studies provided a further investigation of farm machinery markets, the largest market of tractors still lacks a comprehensive evaluation.

Although both studies provided a much-needed explanation of values, some issues should be noted. Most notably, the datasets used for the planter and combine studies are limited with respect to the time frame of sales. The Allison et al. (2022) paper only includes sales between 2016 and 2018, while the Ellis et al. (2022) is limited to 2015 through 2018. Moreover, both studies lack a full evaluation of sale location by only evaluating the location of a sale as a region. To provide a full evaluation of the national market for used tractors, a larger dataset is needed, as well as a more specific evaluation of the location of a sale.

Fettig (1963) was one of the first to employ an econometric model on tractor values. The study used a cross-sectional dataset to estimate the change in tactor prices from quality. Quality was found to be significant, leading to potential issues in the accuracy of the price indexes used at the time of the study. Limitations of the study included the lack of data available and changes in the tractor industry over time would result in the model failing to accurately estimate tractor values in the future. Additionally, the data used lacks observations and details needed for estimating tractor values today. Other early studies viewed tractors as an investment and evaluated the effect of a changing interest rate on tractor prices (Leblanc & Hrubovcak, 1985). With the massive rise in interest rates during the 1980s, this study could not have been more time relevant. Expectations were that recent changes in interest rates would have influenced farm machinery by lowering the investment in machinery and ultimately resulting in shifts in optimal machinery levels. However, results indicated that interest rates had little effect on the optimal level of machinery. Adjustment rates have a higher sensitivity to input/output price ratio compared to interest rate ended up being the major finding of the study. Although the findings are insightful, the major limitation of the model is the limited number of manufacturers and models in the dataset. s in the dataset.

Different depreciation values for different manufacturers were investigated by Cross and Perry (1995) on combines, tractors, and implements. On tractors specifically, the study breaks the data into categories based on horsepower group and performs individual analysis on each group separately. Variables for hours and age held different coefficients for all groups, illustrating that tractors depreciated at different rates given the size of the machine. John Deere was found to hold a price premium, and variables from condition and sale type were found to be significant. The sale location was not found to be significant. Overall, the study provides insights into the tractor market, given the findings for manufacture and model differences. On the other hand, the work lacks a full explanation of the manufacturing results and does not provide a full description of the data used.

Diekman et al. (2008) used an auction dataset to compare willingness to pay for tractors to compare the difference between in-person and online auctions. The study found that buyers would actually pay less for online tractor sales than in-person auctions and provided evidence that coefficients for horsepower and age would differ with sale type. With online sales increasing in use, the study was needed to understand the impact on tractor values. Although important, the study only provides insight into the impact of sale venue and lacks the needed evaluation of tractor mechanical variables and sale variables that have drastically changed in recent years.

Tractor values have been on the rise in recent years (L. Anderson, 2022; Lattz & Schnitkey, 2021; Schmidt, 2022), with the exact impact still up for debate. Nevertheless, the cause of the increase has been determined as the effects of the recent COVID-19 pandemic. There are numerous different reasons, such as supply chain issues, limited raw materials, and lack of an available workforce, to name a few (Miller, 2023). Tractor prices have increased between 7% and 27% between 2020 and 2021, followed by another increase for tractors in 2022 of 10% to 13% (Mowitz, 2021; Schmidt, 2022). Additionally, used equipment inventory has declined in recent years, which has furthered the issue of rising prices (Garvey, 2022). Although all farm machinery have experienced price increases, the tractor market could be the most impactful. Tractors are the most commonly used piece of farm equipment due to the number of different enterprises that rely on a tractor for operation. Given the recent price increases and inventory issues in the tractor market and interruptions from COVID-19, an evaluation of the market and the factors impacting tractor values in warranted.

4.3 Data

Building upon the previous work, an auction dataset from one of North America's largest online farm machinery auction companies, Machinery Pete, was used for this study (Used Farm Equipment for Sale, n.d.). The original dataset contained 40,579 secondary tractor sales occurring between 2000 and 2022, which included information on price, manufacturer, model, year, engine hours, sale date, sale type, sale location, and specs. To appropriately use the dataset, missing observations, sales prior to 2010, tractors built before 2000, and tractors with less than 100 horsepower were removed, resulting in a final dataset consisting of 14,101 sale observations.

Cleaning the dataset was a major undertaking to allow the model to estimate COVID-19 related impacts. A data tree illustrating the data-cleaning process is shown in Figure 4.1. The cleaning process started by removing any tractors manufactured before 2000, to avoid escalated values from vintage or collectible models. Tractors sold prior to January 2010 were removed to focus on the period leading up to the pandemic and to avoid estimating impacts from previous market shifts. The remaining data was then processed to remove observations with missing values for price, sale data or location, and hours resulting in a final dataset that contained 14.101 tractor sales.

4.3.1 Sale Variables

Further development of the dataset was done by adding appropriate variables to analyze the three categories of variables: sale variables, standard variables, and COVID variables. Variable descriptions and summary statistics can be found in Tables 4.1 and 4.2. Sale variables included state of sale, type of sale, season of sale, and year of sale. The state of sale was addressed through adding the appropriate FIPS code for each state ("Appendix

D - USPS State Abbreviations and FIPS Codes : U.S. Bureau of Labor Statistics," 2005). Type of sale included variables for Consignment, Dealer, Farm, Online, and Other. The season of sale was broken down by calendar seasons for Spring (March 21st-June 20th), Summer (June 20th-September 20th), Fall (September 21st-December 20th), and Winter (December 21st-March 20th). Additionally, the year of sale was accounted for through variables for each year of sales in the dataset. However, during the reviewing process of the study, year of sale was removed from the model due to correlation with the COVID-19 variables. Since the COVID- 19 variables by definition are derived from the time of sale this correlation is not surprising.

4.3.2 Standard Variables

The standard variables within the dataset included a continuous variable for engine hours and a discrete variable for the age of the tractor. Manufacturers of the tractors were consolidated to represent market consolidations seen over the period of the dataset resulting in the seven manufacturers of John Deere, Case IH, AGCO, Ford-New Holland, Kubota, Mahindra, and Other. Additionally, the condition of the tractor at the time of the sale was represented as Excellent, Good, Fair, and Poor condition. For the reason discussed below in Section 4.4.1 the final dataset combined the condition groups of Excellent and Good, as well as, Fair and Poor. During the period of this dataset, the EPA required the use of tier-4 engines in tractors (Nelson, 2018). Tier-4 motors allow for the use of ultra-low sulfur diesel fuel to be used and were an effort for the EPA to lower the environmental impact of diesel motors. Given that these tractors were resold in the dataset, a variable for tractors with tier-4 engines was added to the standard variable category.

4.3.3 Covid Section

The COVID variable group uses each state's declaration for state of emergency date to indicate when pandemic shutdowns occurred. For the first model, one variable was generated for tractor sales within a state occurring after that state's date for declaring a state of emergency. Additionally, ten lead and ten lag variables were generated for the second model. The lead and lag variables indicate one-month intervals before or after each state's declaration for it's state of emergency date, which allowed the model to estimate immediate changes for the months before and after the state of emergency occurred.

4.3.4 Summary Statistics

Summary statistics can be found in Table 4.1. Tractors sold in the dataset averaged a price of $97,154 with average engine hours of 3,327, and an average age of 8.5 years. Tractors with the "Good" condition score represented the majority of the sales. The manufacturer's percentage of total sales is shown in Figure 4.2, as expected, John Deere (62.4%) held the largest percentage, followed by Case IH (21.7%), AGCO (7.5%), Ford-New Holland (6.5%), Kubota (1.4%), Mahindra (0.2%), and Other (0.2%). As for tractor engines, most of the sales were with tractors over 175 horsepower, and most of the tractors did not have tier 4 engines. Winter sales presented the highest number of sales between the four seasons. Sale type saw Online and Consignment sales to have the most observations in the dataset. The location of sales was concentrated in the Upper Midwest, and Corn Belt areas starting up in North Dakota down to Kansas and Missouri, then ranging over to Ohio and back up to Wisconsin and Minnesota. The concentration is not surprising since this is the predominant area of crop production in the US and should represent higher returns per acre.

Although the year of sale was not included in the model, summary statistics were included to provide more insight on the dataset. The year of sale illustrated an increasing number of sales up until the COVID-19 state of emergency date and then a decreasing number of sales after the state of emergency. However, the average price for tractors was highest between 2012 and 2014, with a recent uptick in 2021 and 2022. 19% of the sales occurred after the COVID shutdown date, with average prices, hours, and age all increasing after the shutdown. Although average and maximum price, hours, and age are not surprising based on inflation and the year 2000 for manufacture cutoff of the date. Sales occurring after the shutdown date held a lower minimum for hours, while minimums for price and age did not change.

4.4 Methods

Utilizing the previously mentioned dataset, a hedonic model was used to evaluate the factors affecting used tractor sales and the impact of the COVID shutdown on the used tractor market. Two different models were employed on the dataset. The first model uses one variable to indicate if a sale occurred after a state's COVID state of emergency date. Representing all sales after the date, allows the model to evaluate the total impact on the used tractor market, and provides insight as to whether or not the second model is needed. Model two separates sales into ten lead and ten lag variables based on the months before or after a state's state of emergency date in which the sale occurred. Additionally, sales occurring more than ten months before or after a state's shutdown date will not hold a value in any of the lead or lag variables. The second model investigates more precise changes in the market related to the immediate aftermath of the shutdown and will provide insight as to if the market has corrected since the shutdown.

4.4.1 Sale and Standard Variables

Developed from Ellis et al. (2022) and Allision et al. (2022), the previous combine and planter works were used to structure the sale and standard variables for the two tractor models presented in this study. For the sale variables, Diekman (2008) found that the type of sale would impact the value of a tractor and concluded that in-person sales would hold higher values compared to online sales. To test the previous work, the two models include the type of sale and provide additional options from just in-person or online sales. Similarly, Allision et al. (2022) found significance in the timing of a sale both with the season when the sale occurred and the year in which the sale occurred. Although this dataset is much larger, the same principle applies, the model was able to estimate impact from the season of the sale and the year in which the sale to place. Ellis et al. (2022) estimated combine value impacts based on the region of sale since combines are directly related to only harvesting operation. As for tractors, both models estimate impacts based on the state of sale. Unlike combines, tractors are not tied to one specific farming operation.

Standard variables included usage variables for engine hours and tractor age based on previous literature (Edwards, 2015; Ellis et al., 2022). Tractor manufacturers were investigated to compare to the previous findings of Daninger (2017) and based on the manufacturer’s impact of value in the combine (Ellis et al., 2022) and planter (Allison et al., 2022) markets. Additionally, manufacturers’ inclusion allowed the model to estimate potential value differences due to the size of market share. Quality of the tractor was included in the model based previous literature (Allison et al., 2022; Ellis et al., 2022).

Allison et al. (2022) and Ellis et al. (2022) both include condition variables as Excellent, Good, Fair, and Poor. Originally, models included all four condition variables, although multicollinearity was an issue. Further investigation, through a pairwise correlation test, showed that the Excellent and Good condition variables were highly correlated. It was determined that combining the two condition groups together would be a better solution than not including condition variables in the models.

4.4.2 Covid Variables – Difference Between the Two Models

The importance of this work lies in the estimation of COVID-related impacts. As previously mentioned, this study employed two models to evaluate the impact on the used tractor market from the COVID pandemic. Start dates for the pandemic were established by each date each state declared a state of emergency (Table 4.2) (2020-2021 State Executive Orders – COVID-19 Resources for State Leaders, n.d.). Model one used one variable to indicate if the sale occurred after the state of emergency was declared and estimated the pandemic's overall impact. The significance of model one's results illustrated the need for further investigation with model two.

Model two included all the same variables as model one, with the exception of the COVID variable. For the second model, ten lag and ten lead variables were generated to correspond to tractors sold during a given month before or after a state of emergency was declared. Adding the lag and lead variables allowed the model to estimate specific monthly changes in the used tractor market and illustrated short-term changes from the pandemic. Additionally, model two provides in-depth analysis of the tractor market's reaction, whereas model one illustrates the long-term overview of the pandemic's effects. Due to the structure of the data and the reliance of the interest variables directly developed from the sale dates, the year of sale variables were not used in this study. Although previous work (Allison et al., 2022; Ellis et al., 2022) includes the year of sale, preliminary work found the correlation to be too high to include these variables with the pandemic related variables. The structure of the dataset and multiple time-related variables included in the models led to expected multicollinearity which was addressed through a variance inflation factor test (VIF). As mentioned above, condition variables initially resulted in higher VIF scores which led to the consolidation of condition variables into Excellent or Good and Fair or Poor. With only the two condition variables, the mean VIF score in the first model was 1.63, and 1.44 in the second model, with no scores over 10 (Tables 4.3 and 4.4).

4.4.3 Equations

Model one of this study is expressed as equation one:

$$\ln(P_{it}) = \beta_0 + \beta_1 H_{it} + \beta_2 A_{it} + \beta_3 M_i + \beta_4 C_i + \beta_5 S_i + \beta_6 T_i + \beta_7 COVID_{sm} + \rho_s + \tau_t + \varepsilon_{it}$$

where the dependent variable $\ln P_i$ is the natural log of the price of tractor *i*. The independent variables represent the three categories mentioned previously in the data section. Where *H* is the number of engine hours used, *A* represents the age of the tractor, *M* is the manufacturer of the tractor, *C* is the condition of the machine, *S* is the season of sale, *T* is the type of sale, and *COVID* indicated if the sale occurred before or after the given state's effective state of emergency date. As for the fixed effect portion of the equation, ρ_s illustrated the state fixed effects of state *s*, while τ_t is the fixed effects of sale year *t*.

Equation two was modified from equation one by including lead and lag COVID variables and is represented as:

$$\ln(P_{it}) = \beta_0 + \beta_1 H_{it} + \beta_2 A_{it} + \beta_3 M_i + \beta_4 C_i + \beta_5 S_i + \beta_6 T_i + \beta_7 LeadLag^{10} COVID_{sm} + \rho_s + \tau_t + \varepsilon_{it}$$

where the change can be seen by the COVID variable from equation one, now illustrated as LeadLag^{10}Covid. Equation two expanded the one COVID variable to represent the time a sale occurred before or after the given state's effective state of emergency date. For this model, variables representing up to ten months before or after the state's date were used. An example for the state of Alabama, which had an effective state of emergency date of March 13, 2020. Sales in Alabama occurring between February 13th, 2020, and March 13th, 2020, would hold a 1 for the LagCovid^{1} variable and a 0 in all other lead and lag variables.

4.4.4 Expectations

Based on the previous work of Diekmann et al. (2008), sale type was expected to illustrate higher values for in-person auction compared to online auction. Allison et al. (2022) and Ellis et al. (2022) work further illustrated that "farm" sales are expected to hold the highest tractor values, while "online" sales would hold the lowest value among the types of sale variables. Season of sale expectations were tractors sold in the Winter season would have the highest value, followed by the Spring, Summer, and then Fall seasons based on the findings in the planter and combine markets (Allison et al., 2022; Ellis et al., 2022). The location of the sale was more complicated for tractors due to their use across more agriculture production types. Ellis et al. (2022) divided combine data into production regions and estimated values based on the whole region which could lead to misestimating for this study given the different COVID dates represented within a region. Therefore, this study used FIPS codes to represent each state individually for COVID dates, and to estimate impacts for each state. Although states are represented individually, it was still expected that states with higher crop production would hold higher tractor values. This expectation was due to the higher revenue per acre present in major grain crop states compared to other agricultural enterprises present in non-row crop areas The lowest values were expected in the West Coast and Northeast states since tractor usage for crop production isn’t as widespread.

Allison et al. (2022) and Ellis et al. (2022) both suggested the impact of manufacture market share on farm machinery values. Therefore, it was expected that John Deere would hold the highest values, followed by Case IH, AGCO, Ford-New Holland, Kubota, Mahindra, then Other. Use variables for engine hours and tractor’s age should hold negative coefficients to reflect the Likewise, the condition variables are expected to have the highest value with the Excellent or Good condition group, then decrease for the Fair or Poor condition group.

The singular COVID variable for sales occurring after the effective state of emergency date used in the first model was expected to be positive based on the market shocks that limited tractor supply, such as factory shutdowns and limitations in acquiring raw materials (Mowitz, 2021). Additionally, popular press articles from Garvey and Anderson, illustrated rising prices due to limited supply and increases in sales projections due to unfilled orders (Anderson, 2022; Garvey, 2022). When the singular COVID variable was expanded into the Lead and Lag COVID variables, it was expected that an initial decrease would be seen, followed by an increase in tractor values. The initial decrease was expected due to the implementation of the COVID-related shutdowns limiting buying and selling opportunities, and an immediate market shock would limit buyers' willingness to buy machinery due to the uncertainty of the market. Given time, it was expected the market would readjust to open more sales avenues and adapt to COVID restrictions, which would lead to a market correction for the previous limit of supply, causing increases in tractor values.

4.5 Results

The hedonic model and dataset laid out in the previous sections were combined using STATA software (StataCorp LLC, 2015) to evaluate tractor values and estimate the impact of various factors on auction prices. Two models were used in this study, the first model analyzed the tractor market with one variable for the COVID-19 pandemic occurring. This first model was shown previously in Equation 1 and is referred to as the COVID model, with full results found in Table 4.5. The COVID model held an R-squared value of 0.75, which indicated 75% of the variance within the data is accounted for by the model. Estimated coefficients are shown as the percent change in tractor value for that coefficient; for the results section, all impacts are discussed as the percent impact on a tractor's value.

4.5.1 COVID Model Results

The standard variables for use of the tractor illustrated a negative relationship with tractor values for both engine hours and age as expected. Each additional year in age resulted in a decrease of 4.4% in value while every hour in use suggested a decrease of 0.08% in the tractor’s value, both significant at the 1% level. When hours were scaled to represent the average number of hours per year of 358, an estimated impact of -3% was found, suggesting that buyers' willingness to pay is impacted more by age than by the number of engine hours. Tractor manufacturers followed expectations with John Deere holding the highest value at 32% higher that the reference manufacture of AGCO at the 1% significance level. Case IH followed as the second highest impact with an increase of 12.5% at the 1% level. Ford New Holland was not found to be statistically significant when compared to AGCO. Kubota, Mahindra, and Other were all estimated to have a negative impact on value with Kubota and Mahindra significant at the 1% level and Other significant at the 5% level. Kubota was the closest value to AGCO at -13.7%, followed by Other at -17.9%, then Mahindra at –63.6%. Condition of the tractor variables were consolidated due to the large VIF factor discussed in Section 4.4.2. Tractors in Excellent or Good condition were estimated to hold an increase of 28.6% in value compared to a Poor or Fair condition. To sum up the standard variable category, the lack of a tier four engine was not statistically significant in the COVID model.

Although variables within the sale variables category followed expectations, the results provide an updated estimate and further elaborate on the work from Diekmann et al. (2008), Allison et al. (2022), and Ellis et al. (2022). Tractors sold at a Farm sale type held the highest values of any sale type with an increase of 3.4% at the 1% level compared to Online sales. Tractors sold under the Other sale type were not significant, and all other sale types were found to have a negative estimate at the 1% level. Dealer sales were the closest estimated coefficient to Online sales at -5.3%, followed by Consignment sales at -9%. Tractors sold during the Winter season held the highest estimated value when compared to the Fall season with an impact of 4.5% at the 1% level. Sales occurring in the Spring season were found to hold a negative impact of -2.1% at the 5% level compared to the Fall season, while summer season sales were not found to be significant.

The State of Emergency going into effect represented by the COVID-19 variable was estimated to increase tractor sales by 16.3% at the 1% level, for all tractors sold after a states given effective date (Table 4.2). Since the variable indicates a sale occurred after the effective date, the estimate would apply for all sales between the effective date and the end of the 2022 year. Therefore, the increase includes the entire time after the pandemic and does not break estimates into groups based on the time after the effective date. Since the variable was positive and significantly different from zero, it provides a baseline for the second model and suggested further investigation is needed.

4.5.2 Lead-Lag Model Results

Model one was further developed as discussed in Section 4.4, to create the second model referred to as the Lead-Lag Model. The Lead-Lag Model aimed to further investigate the impact from the pandemic and provide results for sales occurring ten months before or after a given state's effective state of emergency date. The full results for the Lead-Lag Model can be found in Table 4.6. An R-squared of 0.75 was calculated for the Lead-Lag Model, which illustrated that 75% of the total variance in the data is accounted for by the model. For the results section, all impacts are discussed as the percent impact on a tractor's value.

When the standard variables from the Lead-Lag model were compared to the COVID model, no changes in estimated coefficients outside of the 95% confidence interval were found. The sale variables illustrated small changes in estimation, with Spring sales no longer holding significance. Additionally, sales occurring during the Winter season dropped significance levels to the 5% instead of the 1% level. Sale type estimates remained at the same significance level and within the confidence intervals with only slight changes to the estimate with the addition of the Lead and Lag variables. All state estimates maintained the same significance level in both models, with only a few estimate changes outside of the COVID model confidence interval. California, Colorado, Iowa, Nevada, New York, Tennessee and Wyoming all estimated lower negative coefficients in the Lead-Lag model that were just outside of the 95% confidence intervals from the COVID model. Additionally, Montana was estimated to have a higher positive value in the Lead and Lag model. The states of Louisiana and Nebraska were estimated to have larger negative values, while New Mexico resulted in a lower positive coefficient. The control variable for diesel price was significant in the Lead-Lag model at the 1% level. Since the only change between the COVID and Lead-Lag models was related to the pandemic variables, the lack of change in estimates was expected and was a robustness check for the Lead-Lag model. Although a few changes in estimated coefficients were noted, all were minor changes and did not raise any concern around the interpretation of the Lead-Lag results.

The importance of the Lead-Lag model centers around the monthly variables for tractors sold ten months before or after a state’s effective state of emergency date that estimate the short-term impacts from the pandemic. The lag variables indicating tractors sold before the state of emergency effective date estimated a price increase in months seven and six (Variables: Covid Lag 7 and Covid Lag 6) of 9.1% and 7.9% at the 5% and 1% levels, respectively. Additionally, three and two months prior to the effective date estimated tractor value increase at the 5% significance level for month three (Covid Lag 3) and 1% significance level for month two (Covid Lag 2) with results illustrating an increase of 7.2% and 11%. The month prior to the effective date (Covid Lag 1) estimated an increase of 6.7% at the 10% significance level.

Tractors sold within the ten months after the effective date denoted through the Lead variables. Similar to the Lag variables, not all Lead variables were significant, seven of the ten variables held significance at the 1%, 5%, or 10% levels. In chronological order, Lead 1 was significant at the 5% level and estimated that tractor values increased by 6.9% holding all other variables constant. Tractors sold within one month of the effective dates held similar values to tractors sold in the month prior. However, the model did not find a statistical difference from zero for Lead variables 2 and 3, with both variables having confidence intervals reaching as low as negative 5%. Lead variables 4 and 5 moved confidence intervals back above zero and held statistical significance at the 5% and 10% levels with both variables estimating an increase of over 6%. Six months after the state of emergency dates saw a larger increase in tractor values, thus far, with an estimate of 11.1% at the 1% significance level. However, the following month indicated as Lead 7 was not significant and estimated a confidence interval below zero similar to months two and three. Months eight, nine, and ten after the state of emergency date all held an estimated increase of over 10%. Tractors sold eight months after the pandemic dates were estimated to have a value increase of 16.2% at the 5% level, followed by an increase of 11.5% at the 1% level for tractors sold in the ninth month after the effective date. Finally, month ten estimated an increase of 16.8% in tractor values at the 1% significance level.

4.6 Discussion

The results for the COVID and Lead-Lag models illustrated similarities with variance accounted for and the majority of the standard and sale variables estimated. For the standard variables in both models, hours and age held a notable difference in estimated value decrease. The estimated impact for hours was multiplied by the average hours per year for dataset of 358 hours per year, resulting in a decrease of 2.9% in a tractor’s value. Additionally, the model estimated that the increase of one year in age would decrease the tractor’s value by just over 4%, which suggests that buyer’s willingness to pay is impacted more by the tractor’s age than the tractor’s hours. Compared to a similar study on combine harvesters, the relationship between age and hours impact of tractor values seems closer than that relationship with combine values (Ellis et al., 2022), but further investigation shows the magnitude of the decrease in age is around 33% higher than a year‘s worth of hours. Tractor depreciation has traditionally been calculated on index tables and used the tractor’s purchase price, age, annual hours, and useful life (Edwards, 2015). Although a widely used method, all variables are projections and only consider new tractor purchase prices. The finding of this work allows for a more accurate estimate of a tractor’s depreciation value and can be used for future work on evaluating tractor machinery cost. For producers that are selling or buying tractors, the change in the relationship between hours and age could serve as an important variable in determining the price of a used tractor. When selling a tractor, it is suggested that a machine with higher hours and lower age would be expected to hold a higher value compared to a machine with higher age and lower hours. With this in mind, sellers can better plan when to sell tractors and how additional use would impact the machine’s value. Buyers on the other hand, would have the opposite reaction when looking to buy a tractor. Based on the results provided, buyers would look to buy machines with higher age and lower hours to pay a lower price. Although a buyer will not have control over either variable, the relationship should allow buyers to compare tractors and buying options between machines.

Tractors listed with the condition of Excellent or Good held higher values as expected. Due to the consolidation of the condition types outlined in Section 4.4, further in-depth explanation is not realistic. Tractor manufacturer order followed expectations with John Deere holding the highest value, followed by Case IH, Ford New Holland, and AGCO. Although manufacturers groups of Kubota, Mahindra, and Other did not follow the expected in terms of the order of value. Compared to previous studies by Allison et al. (2022) and Ellis et al. (2022), the order for John Deere and Case IH were in line with results for other machinery types (Allison et al., 2022; Ellis et al., 2022). Although this study found a switch in the order between AGCO and Ford New Holland in the tractor market compared to combines (Chapter 3), both markets suggest no significant difference between the two manufacturers. Although the estimated coefficients cannot be directly compared between combines and tractors, the magnitude within each model can provide a better understanding of willingness to pay changes among the manufacturers. The magnitude of the increase for John Deere tractors suggests that buyers are willing to pay a lot more for a John Deere than the others and are estimated to pay a higher percentage compared to Case IH in the tractor market than in the combine market (Chapter 3) (Ellis et al., 2022). Additionally, if the magnitude differences were compared for between Case IH in the tractor and combine market, the largest difference would be seen with Ford New Holland. Case IH tractors would hold an 11% increase in value over Ford New Holland, while combines suggested a 16.8% difference. The remaining manufacturers all held smaller shares of the tractor market and were estimated to hold lower values than those with larger market shares. Additionally, the smaller groups of Kubota, Mahindra, and Other all accounted for less than 1.5% of the total observations within the dataset, and therefore, more observations are needed to increase the accuracy of the results. Although it was expected that the other manufacturers would have lower values, the results could be explained by either industry and producer perceptions of better technology, nevertheless these estimated values and manufacturers relationships should serve as a foundation for future research examining farm machinery resale values.

Variables within the Sale variable category assist in understanding how, when, and where to sell or buy a tractor to obtain a better evaluation for a given producer's situation. The presence of a larger buyer pool presented with Online sales in theory should result in higher sale values. Diekmann et al. (2008) found this theory to not be true for online tractors sales and estimated that buyers were willing to pay more for tractors sold as in-person sales. Further exploration of the study's results suggest online sales also introduce issues of asymmetric information which could be the reason for the decrease in value compared to in-person sale types. For this study, more sale type options were included than just in-person or online. Sale type of Farm sales, which would be considered an in-person sale, were found to hold the highest value among the sale types which aliens with the findings in the planter and combine markets (Allison et al., 2022; Ellis et al., 2022). The higher values are likely due to buyer's ability to physically inspect a tractor in person rather than relying on the provided online information. Although the sale type does not provide complete perfect information, it is likely that buyers trust their own inspection rather than a third party's which would result in the transaction falling closer to perfect information rather than asymmetric.

Previous work estimated that machinery sold during the season when the major operation occurs would hold the lowest value (Allison et al., 2022; Ellis et al., 2022).

Contrary to planters and combines, the versatility and variety of operations that use tractors, no one season can truly be singled out as having the majority of operations occurring. Results indicated that sales occurring during the Winter season held the highest value in both the COVID and Lead-Lag models. While no other season was found to be significant with the Lead-Lag model, the COVID model found that sales occurring during the Spring season held lower values compared to the Fall. Ellis et al. (2022) suggested that the value order for sales was related to the number of sales and the availability of machinery for the combine market, which would result in the difference in values being explained by the changes in supply (Ellis et al., 2022). Although further investigation showed that the Winter season held the most sales for tractors, followed by Fall, Summer, than Spring, which contradicts the combine market findings. Since no season is considered to hold the major operation for tractors, and the supply of tractors does not explain the results presented in the model, further work is needed to understand how season of sale impacts the value of a tractor.

4.6.1 Covid Discussion

The pandemic having a positive impact on tractor values was expected, given recent press articles (Anderson, 2022; Garvey, 2022). Nevertheless, this is the first study aimed at estimating the magnitude of those increases. Since the state of emergency order went into effect, the tractor market has experienced an increase of 16.3% in secondary tractor values. The estimated increase covers tractor values over multiple years, which is not seen in other studies (Schmidt, 2022). Therefore, results are compared to similar articles, a similar market in Canada estimated farm implement sales increased by 10% in 2021, and 22.3% in 2022 for manufacturer sales (Anderson, 2022). For tractors specifically, Schmidt found that the average used tractor prices increase by around 12.5% between 2021 and 2022 (Schmidt, 2022). These studies cannot be directly compared with this study due to data timelines and machinery type differences, rather serve as a guideline of magnitude seen within the market. The estimated increase found in the COVID model allows producers to better estimate tractor values and compare pre-pandemic values with the current market. In order to better estimate the impact from the pandemic and fill the time gaps between the start of the pandemic and previous work (Schmidt, 2022), the Lead-Lag model calculated monthly impacts from the pandemic.

Prior to the state of emergency effective dates, increases in tractor values were estimated for Lag variables sever, six, three, two, and one which correspond with sales occurring seven, six, three, two, and one month before the effective date. Of the five months, only months seven and two held a statistical significance level of 1%. The increase estimated in month seven was not expected and does not correspond to a critical pandemic related date. On the other hand, Lag variable two contains sales in January and February with the exact date depending on the state in which the sale occurred. This variable includes the date in which the first COVID-19 case was reported in the United States on January 20th (Sencer, 2023). Since the variable includes this date and observes sales occurring after this report, it is likely that the increase is the reaction of the market from the report of COVID-19 in the US. Although values did not show similar estimated with the Lag one variable. Following the first US reported case, sales occurring in Lag One were estimated to have lower value than Lag Two and were only significant at the 10% level. The model estimated similar results for sales occurring in the month after the effective date at the 5% level but did not find significant results for months two or three after the effective date.

Joining the three months before and after the pandemic dates better illustrates the rise in values seen around the first reported US case, and further suggests that impacts returned to zero within the following few months.

For the remaining Lead variables two separate changes in tractor values were illustrated. The first increase was estimated with Lead variables four, five, and six with increases of 6%, 6.9%, and 11% respectfully. Lead four and five held statistical significance at the 10% and 5% levels, while Lead variable six was significant at the 1% level. The variables correspond to June, July, and August tractor sales. During this time period, the United States Department of Agriculture (USDA) issued payments for the Coronavirus Food Assistance Program (CFAP) (USDA Issues First Coronavirus Food Assistance Program Payments, 2020). The program aimed to provide financial assistance for agriculture commodity producers who experienced a price decrease of 5% or more due to the pandemic (USDA Issues First Coronavirus Food Assistance Program Payments, 2020). Although the tractor value increases estimated are likely due to a complex combination of issues, part of the increase is likely attributed to the inflow of financial assistance from this program. Since newer machinery would provide lower per unit cost and better efficiency, producers facing lower prices would likely find an investment in machinery could lead to lower production costs therefore resulting better positioning if prices remained lower after the pandemic. For this reason, producers could have seen the CFAP payment as the opportunity to update machinery and forecast operations profitability for the near future.

The last increase seen in the estimated results was with Lead variables eight, nine, and ten, which correspond to sales occurring in October, November, and December. Lead variable eight was estimated to have an increase of 16.2% at the 5% significance level, followed by Lead variable nine having an increase of 11.5% and the 1% level, and Lead variable ten estimating an increase of 16.8% also at the 1% level. Although the exact reason for the increase is not certain, this period followed the application date for the first CFAP of September 11th (Coronavirus Food Assistance Program 1, n.d.), with some states having an extended deadline into October (Coronavirus Food Assistance Program 1, n.d.). Similar to the estimated value increase for Lead variables four, five, and six, the increase is likely a response to producer payments from CFAP.

Secondary tractor values estimated increase of 16.3% in value since the COVID state of emergency went into effect and the monthly estimates around that date need further research to provide a better understanding of exactly why the increase happened. Although the exact reason is not certain, the results presented in this study provide evidence that the increases are related to the occurrence of the state of emergency for the pandemic and provides evidence that CFAP had an impact on the increases in tractor values. Additionally, future work is needed to understand the market landscape and should investigate the role of auction availability and supply chain issues in the tractor market on the increase in tractor values.

4.7 Conclusion

For farming operations, increases in tractor prices are leading to tighter margins and an increase in the efforts of machinery expense management. The recent changes mentioned in chapter one, with lower net farm income and government payments, have even furthered the issue. Unfortunately, farmers must combat these issues to survive a changing agricultural industry, and one of the first steps to doing so is by evaluating the second largest operational asset. This chapter provides two models to evaluate the factors that impact the used tractor market, estimate the changes in values due to the pandemic, and further assess the cause. These results suggest a 16.3% increase in tractor values due to the COVID-19 effects, with a range of -5.5% to 16.8% for the ten months before and after state shutdowns started. Overall, the results provide a starting point for stakeholders to evaluate their current machinery as well as estimate potential buying opportunities.

Auction data for used tractors sold between 2010 and 2022 from Machinery Pete was used to estimate the differences in used tractor sales prices and the impact of COVID-19. Although full results from this study can be used to aid buyers and sellers in valuing used tractors, some specific results were found to be critical in estimating tractor values. Estimates for the differences among manufacturers were found, along with suggestions on the loss in value from use hours, age, and condition group. Additionally, the impacts of location, time, and type on tractor values were explored. The changes related to COVID-19 were likely due to the supply of tractors at auction. This study addresses a research gap in the used tractor market and the magnitude of the market shifts from the pandemic.

4.8 Chapter 4 Tables and Figures

Table 4-1 – Tractor Data Description and Summary Statistics

Variable	**Definition**	**Number of Observations**	**Mean**	**Std. Dev**	**Range**
Independent					
Price	Final Sale Price ($)	14,101	$97,154.35	57513.84	14,750-470,100
Dependent					
Usage Factors					
Hours	Total separator hours of use on the machine	14,101	3327.22	2590.004	2-22,605
Age	Total years since manufacturing	14,101	8.539323	4.956802	0-22
Excellent_Good	= 1 if condition score is either Excellent or Good	13,968	0.990568	0.096663	0 - 1
Fair_Poor	= 1 if condition score is either Fair or Poor	133	0.009432	0.096663	0 - 1
Make					
John Deere	= 1 if John Deere was the make	8,798	0.623927	0.484416	0 - 1
Case IH	= 1 if Case IH was the make	3,066	0.217431	0.412513	0 - 1
AGCO	= 1 if AGCO was the make	1,063	0.075385	0.264021	0 - 1
Ford New Holland	= 1 if Ford-NewHolland was the make	918	0.065102	0.246714	0 - 1
Kubota	= 1 if Kubota was the make	200	0.014183	0.118251	0 - 1
Mahindra	= 1 if Mahindra was the make	33	0.00234	0.048321	0 - 1
Make_Other	= 1 if make was not in other groups	23	0.001631	0.040355	0 - 1
Sale Variables					
Spring Sale	= 1 if sale occurred in the Spring season	2,792	0.198	0.398506	0 - 1
Summer Sale	= 1 if sale occurred in the Summer season	3,225	0.228707	0.420015	0 - 1
Fall Sale	= 1 if sale occurred in the Fall season	3,844	0.272605	0.445315	0 - 1

Winter Sale	= 1 if sale occurred in the Winter season	4,240	0.300688	0.458573	0 - 1
Dealer	= 1 if sale occurred at a dealership	943	0.066875	0.249814	0 - 1
Consignment	= 1 if sale was for consignment	4,508	0.319694	0.466374	0 - 1
Farm	= 1 if sale occurred on farm	3,811	0.270265	0.444112	0 - 1
Online	= 1 if sale occurred online	4,769	0.338203	0.473115	0 - 1
Other	= 1 if sale was not through other type	70	0.004964	0.070284	0 – 1
Controls					
US Cash Receipts	US Cash Receipts at time of Sale	14,101	210,000,000	28,600,000	180,000,000-286,000,000
PPI	Producer Price index at time of sale	14,101	177.4732	53.78394	119.9-322.7
Diesel Price	Region Diesel price at time of sale	14,101	3.109513	0.778305	1.873-6.489
HP 175 and up	= 1 if the tractor has 175 horsepower or higher	10,644	0.75484	0.430197	0 - 1
Pre-2014	= 1 if the tractor was manufactured prior to 2014	11,462	0.81285	0.390046	0 - 1

Table 4.1 Continued – Tractor Data Description and Summary Statistics

Covid Gov S.E.	= 1 if the sale occurred after the state in which it was sold issued a state of emergency for COVID-19	4,258	0.301964	0.459126	0 - 1
Covid Gov S.E. Lag 10	= 1 if the sale occurred between 9 and 10 months prior to the state in which it was sold issued a state of emergency for COVID-19	138	0.009503	0.097022	0 - 1
Covid Gov S.E. Lag 9	= 1 if the sale occurred between 8 and 9 months prior to the state in which it was sold issued a state of emergency for COVID-19	119	0.008439	0.09148	0 - 1
Covid Gov S.E. Lag 8	= 1 if the sale occurred between 7 and 8 months prior to the state in which it was sold issued a state of emergency for COVID-19	107	0.007588	0.086782	0 - 1
Covid Gov S.E. Lag 7	= 1 if the sale occurred between 6 and 7 months prior to the state in which it was sold issued a state of emergency for COVID-19	111	0.007872	0.088376	0 - 1
Covid Gov S.E. Lag 6	= 1 if the sale occurred between 5 and 6 months prior to the state in which it was sold issued a state of emergency for COVID-19	168	0.011914	0.108503	0 - 1
Covid Gov S.E. Lag 5	= 1 if the sale occurred between 4 and 5 months prior to the state in which it was sold issued a state of emergency for COVID-19	62	0.004397	0.066165	0 - 1
Covid Gov S.E. Lag 4	= 1 if the sale occurred between 3 and 4 months prior to the state in which it was sold issued a state of emergency for COVID-19	140	0.009928	0.099149	0 - 1
Covid Gov S.E. Lag 3	= 1 if the sale occurred between 2 and 3 months prior to the state in which it was sold issued a state of emergency for COVID-19	314	0.022268	0.147559	0 - 1

Covid Gov S.E. Lag 2	= 1 if the sale occurred between 1 and 2 months prior to the state in which it was sold issued a state of emergency for COVID-19	162	0.011489	0.106571	0 - 1
Covid Gov S.E. Lag 1	= 1 if the sale occurred within 1 month prior to the state in which it was sold issued a state of emergency for COVID-19	201	0.014254	0.118542	0 - 1
Covid Gov S.E. Lead 1	= 1 if the sale occurred within 1 month after to the state in which it was sold issued a state of emergency for COVID-19	205	0.014538	0.119698	0 - 1
Covid Gov S.E. Lead 2	= 1 if the sale occurred between 1 and 2 months after to the state in which it was sold issued a state of emergency for COVID-19	88	0.006241	0.078754	0 - 1
Covid Gov S.E. Lead 3	= 1 if the sale occurred between 2 and 3 months after to the state in which it was sold issued a state of emergency for COVID-19	79	0.005602	0.074642	0 - 1
Covid Gov S.E. Lead 4	= 1 if the sale occurred between 3 and 4 months after to the state in which it was sold issued a state of emergency for COVID-19	107	0.007588	0.086782	0 - 1
Covid Gov S.E. Lead 5	= 1 if the sale occurred between 4 and 5 months after to the state in which it was sold issued a state of emergency for COVID-19	153	0.01085	0.103602	0 - 1
Covid Gov S.E. Lead 6	= 1 if the sale occurred between 5 and 6 months after to the state in which it was sold issued a state of emergency for COVID-19	216	0.015318	0.122819	0 - 1
Covid Gov S.E. Lead 7	= 1 if the sale occurred between 6 and 7 months after to the state in which it was sold issued a state of emergency for COVID-19	38	0.002695	0.051844	0 - 1
Covid Gov	= 1 if the sale occurred between 7 and 8 months after to the state	48	0.003404	0.058247	0 - 1

S.E. Lead 8	in which it was sold issued a state of emergency for COVID-19				
Covid Gov S.E. Lead 9	= 1 if the sale occurred between 8 and 9 months after to the state in which it was sold issued a state of emergency for COVID-19	188	0.013332	0.114698	0 - 1
Covid Gov S.E. Lead 10	= 1 if the sale occurred between 9 and 10 months after to the state in which it was sold issued a state of emergency for COVID-19	218	0.01546	0.123377	0 - 1

Table 4.1 Continued – Tractor Data Description and Summary Statistics

State	Fips Code					
Alabama	1	= 1 if the sale occurred in Alabama	115	0.008155	0.089942	0 - 1
Arizona	4	= 1 if the sale occurred in Arizona	22	0.00156	0.03947	0 - 1
Arkansas	5	= 1 if the sale occurred in Arkansas	191	0.013545	0.115597	0 - 1
California	6	= 1 if the sale occurred in California	191	0.013545	0.115597	0 - 1
Colorado	8	= 1 if the sale occurred in Colorado	139	0.009858	0.098798	0 - 1
Connecticut	9	= 1 if the sale occurred in Connecticut	0			0 - 1
Delaware	10	= 1 if the sale occurred in Delaware	3	0.000213	0.014585	0 - 1
Florida	12	= 1 if the sale occurred in Florida	147	0.010425	0.101572	0 - 1
Georgia	13	= 1 if the sale occurred in Georgia	228	0.016169	0.12613	0 - 1
Idaho	16	= 1 if the sale occurred in Idaho	79	0.005602	0.074642	0 - 1
Illinois	17	= 1 if the sale occurred in Illinois	1537	0.108999	0.31165	0 - 1
Indiana	18	= 1 if the sale occurred in Indiana	631	0.044749	0.206759	0 - 1
Iowa	19	= 1 if the sale occurred in Iowa	1595	0.113113	0.316742	0 - 1
Kansas	20	= 1 if the sale occurred in Kansas	531	0.037657	0.190372	0 - 1
Kentucky	21	= 1 if the sale occurred in Kentucky	95	0.006737	0.081806	0 - 1

Louisiana	22	= 1 if the sale occurred in Louisiana	85	0.006028	0.077408	0 - 1
Maryland	24	= 1 if the sale occurred in Maryland	23	0.001631	0.040355	0 - 1
Michigan	26	= 1 if the sale occurred in Michigan	281	0.019928	0.139757	0 - 1
Minnesota	27	= 1 if the sale occurred in Minnesota	1608	0.114035	0.317864	0 - 1
Mississippi	28	= 1 if the sale occurred in Mississippi	270	0.019148	0.137049	0 - 1
Missouri	29	= 1 if the sale occurred in Missouri	1004	0.071201	0.257169	0 - 1
Montana	30	= 1 if the sale occurred in Montana	56	0.003971	0.062896	0 - 1
Nebraska	31	= 1 if the sale occurred in Nebraska	1360	0.096447	0.295214	0 - 1
Nevada	32	= 1 if the sale occurred in Nevada	1	7.09E-05	0.008421	0 - 1
New Jersey	34	= 1 if the sale occurred in New Jersey	8	0.000567	0.023813	0 - 1
New Mexico	35	= 1 if the sale occurred in New Mexico	7	0.000496	0.022276	0 - 1
New York	36	= 1 if the sale occurred in New York	64	0.004539	0.067219	0 - 1
North Carolina	37	= 1 if the sale occurred in North Carolina	41	0.002908	0.053846	0 - 1
North Dakota	38	= 1 if the sale occurred in North Dakota	1175	0.083327	0.276386	0 - 1
Ohio	39	= 1 if the sale occurred in Ohio	481	0.034111	0.181521	0 - 1

Oklahoma	40	= 1 if the sale occurred in Oklahoma	201	0.014254	0.118542	0 - 1
Oregon	41	= 1 if the sale occurred in Oregon	19	0.001347	0.036684	0 - 1
Pennsylvania	42	= 1 if the sale occurred in Pennsylvania	215	0.015247	0.122539	0 - 1
South Carolina	45	= 1 if the sale occurred in South Carolina	34	0.002411	0.049046	0 - 1
South Dakota	46	= 1 if the sale occurred in South Dakota	532	0.037728	0.190544	0 - 1
Tennessee	47	= 1 if the sale occurred in Tennessee	167	0.011843	0.108184	0 - 1
Texas	48	= 1 if the sale occurred in Texas	572	0.040565	0.197286	0 - 1
Utah	49	= 1 if the sale occurred in Utah	15	0.001064	0.032599	0 - 1
Vermont	50	= 1 if the sale occurred in Vermont	6	0.000426	0.020624	0 - 1
Virginia	51	= 1 if the sale occurred in Virginia	10	0.000709	0.026622	0 - 1
Washington	53	= 1 if the sale occurred in Washington	63	0.004468	0.066694	0 - 1
Wisconsin	55	= 1 if the sale occurred in Wisconsin	255	0.018084	0.133259	0 - 1
Wyoming	56	= 1 if the sale occurred in Wyoming	44	0.00312	0.055775	0 - 1

Table 4-2– Tractor Data State of Emergency Date by State

State	Date Declared
Alabama	3/13/2020
Arizona	3/11/2020
Arkansas	3/11/2020
California	3/4/2020
Colorado	3/10/2020
Connecticut	3/10/2020
Delaware	3/12/2020
Florida	3/1/2020
Georgia	3/14/2020
Idaho	3/13/2020
Illinois	3/9/2020
Indiana	3/6/2020
Iowa	3/9/2020
Kansas	3/9/2020
Kentucky	3/6/2020
Louisiana	3/11/2020
Maryland	3/5/2020
Michigan	3/11/2020
Minnesota	3/13/2020
Mississippi	3/4/2020
Missouri	3/13/2020
Montana	3/12/2020
Nebraska	3/13/2020
Nevada	3/12/2020
New Jersey	3/9/2020
New Mexico	3/11/2020
New York	3/7/2020
North Carolina	3/10/2020
North Dakota	3/13/2020
Ohio	3/9/2020
Oklahoma	3/15/2020
Oregon	3/8/2020
Pennsylvania	3/6/2020
South Carolina	3/13/2020
South Dakota	3/13/2020
Tennessee	3/12/2020
Texas	3/13/2020
Utah	3/6/2020
Vermont	3/16/2020

Virginia	3/12/2020
Washington	2/29/2020
Wisconsin	3/12/2020
Wyoming	3/12/2020

Table 4-3 – Tractor COVID Model VIF Results

Variable		VIF	1/VIF
Usage Factors			
	Hours	1.69	0.591696
	Age	2.35	0.426038
	Excellent_Good	1.02	0.975806
Make			
	John Deere	3.63	0.27539
	Case IH	3.13	0.319166
	Ford New Holland	1.78	0.563318
	Kubota	1.25	0.799105
	Mahindra	1.07	0.933522
	Make_Other	1.03	0.971369
Sale Variables			
	Spring Sale	1.5	0.664804
	Summer Sale	1.5	0.664701
	Winter Sale	1.68	0.593847
	Dealer	1.39	0.721252
	Consignment	1.88	0.530781
	Farm	1.62	0.615645
	Other	1.03	0.971554
Covid Variables			
	Covid Gov S.E.	3.73	0.268114
Controls			
	US Cash Receipts	8.69	0.115086
	PPI	5.88	0.170102
	Region Diesel Price	5.75	0.17384
	HP 175 and up	1.17	0.8556
	Pre-2014	1.62	0.61697

Table 4.3 Continued – Tractor COVID Model VIF Results

State			
1	Alabama	1.1	0.911885
4	Arizona	1.03	0.970045
5	Arkansas	1.12	0.890282
6	California	1.18	0.846123
8	Colorado	1.09	0.915149
10	Delaware	1	0.995267
12	Florida	1.14	0.876893
13	Georgia	1.2	0.836741
16	Idaho	1.06	0.942635
17	Illinois	1.82	0.548853
18	Indiana	1.38	0.725024
19	Iowa	1.78	0.562573
20	Kansas	1.31	0.765626
21	Kentucky	1.06	0.942501
22	Louisiana	1.06	0.945887
24	Maryland	1.02	0.981125
26	Michigan	1.17	0.857076
28	Mississippi	1.19	0.840234
29	Missouri	1.59	0.628965
30	Montana	1.04	0.965658
31	Nebraska	1.75	0.569934
32	Nevada	1	0.997537
34	New Jersey	1.01	0.992038
35	New Mexico	1.01	0.994041
36	New York	1.05	0.953728
37	North Carolina	1.03	0.969713
38	North Dakota	1.62	0.61778
39	Ohio	1.28	0.778685
40	Oklahoma	1.12	0.891423
41	Oregon	1.03	0.972887
42	Pennsylvania	1.23	0.816273
45	South Carolina	1.03	0.973622
46	South Dakota	1.3	0.770636
47	Tennessee	1.12	0.894787
48	Texas	1.41	0.706843
49	Utah	1.01	0.988583
50	Vermont	1.01	0.985743
51	Virginia	1.01	0.991224
53	Washington	1.06	0.94591
55	Wisconsin	1.15	0.870113

56	Wyoming	1.03	0.967713
	Mean VIF	1.63	

Table 4-4 – Tractor Lead and Lag Model VIF Results

Variable		VIF	1/VIF
Usage Factors			
	Hours	1.69	0.590953
	Age	2.34	0.427141
	Excellent_Good	1.03	0.973768
Make			
	John Deere	3.65	0.274266
	Case IH	3.14	0.31822
	Ford New Holland	1.78	0.561978
	Kubota	1.25	0.798169
	Mahindra	1.08	0.928458
	Make_Other	1.03	0.969688
Sale Variables			
	Spring Sale	1.82	0.55069
	Summer Sale	1.84	0.542989
	Winter Sale	1.87	0.53535
	Dealer	1.39	0.718539
	Consignment	1.86	0.536458
	Farm	1.65	0.605051
	Other	1.04	0.96398
Covid Variables			
	Covid Gov S.E. Lag 10	1.09	0.916108
	Covid Gov S.E. Lag 9	1.05	0.949329
	Covid Gov S.E. Lag 8	1.07	0.932619
	Covid Gov S.E. Lag 7	1.06	0.945458
	Covid Gov S.E. Lag 6	1.09	0.915475
	Covid Gov S.E. Lag 5	1.04	0.958976
	Covid Gov S.E. Lag 4	1.06	0.944451
	Covid Gov S.E. Lag 3	1.1	0.906783
	Covid Gov S.E. Lag 2	1.06	0.940584
	Covid Gov S.E. Lag 1	1.08	0.927435
	Covid Gov S.E. Lead 1	1.08	0.927965
	Covid Gov S.E. Lead 2	1.07	0.935259
	Covid Gov S.E. Lead 3	1.07	0.936634
	Covid Gov S.E. Lead 4	1.07	0.93377
	Covid Gov S.E. Lead 5	1.09	0.919274
	Covid Gov S.E. Lead 6	1.14	0.880842
	Covid Gov S.E. Lead 7	1.02	0.976635

	Covid Gov S.E. Lead 8	1.06	0.939152
	Covid Gov S.E. Lead 9	1.14	0.878235
	Covid Gov S.E. Lead 10	1.1	0.909544
Controls			
	US Cash Receipts	6.06	0.165092
	PPI	5.89	0.169825
	Region Diesel Price	4.25	0.235132
	HP 175 and up	1.17	0.852821
	Pre-2014	1.64	0.611153

Table 4.4 Continued – Tractor Lead and Lag Model VIF Results

State			
1	Alabama	1.1	0.90769
4	Arizona	1.05	0.95603
5	Arkansas	1.13	0.881744
6	California	1.18	0.846068
8	Colorado	1.1	0.911942
10	Delaware	1	0.99527
12	Florida	1.16	0.865611
13	Georgia	1.2	0.830075
16	Idaho	1.07	0.936653
17	Illinois	1.84	0.542745
18	Indiana	1.39	0.720201
19	Iowa	1.78	0.560775
20	Kansas	1.31	0.762282
21	Kentucky	1.06	0.939167
22	Louisiana	1.06	0.940962
24	Maryland	1.02	0.980781
26	Michigan	1.17	0.854324
28	Mississippi	1.2	0.832402
29	Missouri	1.6	0.62474
30	Montana	1.06	0.939328
31	Nebraska	1.76	0.567437
32	Nevada	1	0.997501
34	New Jersey	1.01	0.991664
35	New Mexico	1.01	0.98944
36	New York	1.05	0.951838
37	North Carolina	1.03	0.967788
38	North Dakota	1.63	0.612734
39	Ohio	1.29	0.776485
40	Oklahoma	1.13	0.882183
41	Oregon	1.03	0.969122
42	Pennsylvania	1.22	0.819349
45	South Carolina	1.03	0.966348
46	South Dakota	1.31	0.765873
47	Tennessee	1.12	0.892772
48	Texas	1.42	0.703893
49	Utah	1.02	0.984048
50	Vermont	1.01	0.985502
51	Virginia	1.01	0.990813
53	Washington	1.06	0.942192
55	Wisconsin	1.15	0.867306

56	Wyoming	1.04	0.964504
	Mean VIF	1.44	

Table 4-5 – Tractor COVID Model Results

		R-Squared 0.7482				
Variable		**Co Ef.**		**Robust Std Error**	**95% Confidence Interval**	
Dependent						
Usage Factors						
	Hours	-0.00008	***	0.000003	-0.000088	-0.000077
	Age	-0.0440	***	0.002	-0.048	-0.040
	Excellent_Good	0.2861	***	0.035	0.216	0.356
Make						
	John Deere	0.3209	***	0.022	0.276	0.365
	Case IH	0.1252	***	0.016	0.092	0.158
	Ford New Holland	0.0149		0.021	-0.027	0.057
	Kubota	-0.1369	***	0.032	-0.202	-0.071
	Mahindra	-0.6359	***	0.050	-0.738	-0.534
	Make_Other	-0.1790	**	0.081	-0.342	-0.016
Sale Variables						
	Spring Sale	-0.0213	**	0.009	-0.040	-0.002
	Summer Sale	-0.0129		0.013	-0.040	0.014
	Winter Sale	0.0447	***	0.010	0.025	0.064
	Dealer	-0.0903	***	0.018	-0.127	-0.054
	Consignment	-0.0527	***	0.018	-0.088	-0.017
	Farm	0.0343	***	0.008	0.019	0.050
	Other	0.0278		0.026	-0.026	0.081
Covid Variables						
	Covid Gov S.E.	0.1628	***	0.015	0.133	0.192
Controls						
	US Cash Receipts	0.0000		0.000	0.000	0.000
	PPI	0.0000	***	0.000	0.000	0.000
	Region Diesel Price	0.0158		0.013	-0.011	0.043
	HP 175 and up	0.7517	***	0.018	0.716	0.787
	Pre-2014	-0.0015		0.012	-0.026	0.023

Table 4.5 Continued – Tractor COVID Model Results

State of Sale						
State	Fips Code					
Alabama	1	-0.4595	***	0.008	-0.476	-0.443
Arizona	4	-0.2177	***	0.017	-0.251	-0.184
Arkansas	5	-0.2237	***	0.005	-0.234	-0.213
California	6	-0.3600	***	0.011	-0.382	-0.338
Colorado	8	-0.0636	***	0.004	-0.072	-0.056
Delaware	10	-0.2208	***	0.019	-0.259	-0.183
Flordia	12	-0.4705	***	0.013	-0.496	-0.445
Georgia	13	-0.2769	***	0.010	-0.298	-0.256
Idaho	16	-0.1918	***	0.008	-0.208	-0.176
Illinois	17	-0.0030		0.006	-0.014	0.008
Indiana	18	-0.0347	***	0.004	-0.043	-0.026
Iowa	19	-0.0218	***	0.002	-0.025	-0.019
Kansas	20	-0.0621	***	0.004	-0.069	-0.055
Kentucky	21	-0.1123	***	0.006	-0.125	-0.099
Louisiana	22	-0.3005	***	0.005	-0.312	-0.289
Maryland	24	-0.0608	***	0.012	-0.084	-0.037
Michigan	26	-0.1091	***	0.004	-0.117	-0.101
Mississippi	28	-0.2448	***	0.008	-0.260	-0.229
Missouri	29	-0.0378	***	0.006	-0.050	-0.026
Montana	30	0.0318	***	0.004	0.023	0.040
Nebraska	31	-0.0495	***	0.004	-0.057	-0.042
Nevada	32	-0.1998	***	0.022	-0.244	-0.156
New Jersey	34	-0.3276	***	0.012	-0.352	-0.303
New Mexico	35	0.0629	***	0.009	0.045	0.080
New York	36	-0.1964	***	0.009	-0.214	-0.179
North Carolina	37	-0.3061	***	0.007	-0.321	-0.291
North Dakota	38	0.0732	***	0.004	0.066	0.081
Ohio	39	-0.0819	***	0.004	-0.090	-0.073
Oklahoma	40	-0.1591	***	0.004	-0.168	-0.150
Oregon	41	-0.1856	***	0.016	-0.219	-0.153
Pennsylvania	42	-0.2988	***	0.014	-0.328	-0.270
South Carolina	45	-0.2804	***	0.010	-0.300	-0.261
South Dakota	46	0.0245	***	0.003	0.018	0.031
Tennessee	47	-0.2218	***	0.007	-0.236	-0.207
Texas	48	-0.1785	***	0.007	-0.192	-0.165

Utah	49	-0.5426	***	0.008	-0.559	-0.526
Vermont	50	-0.3505	***	0.024	-0.398	-0.303
Virginia	51	-0.3594	***	0.015	-0.390	-0.329
Washington	53	-0.1355	***	0.012	-0.160	-0.111
Wisconsin	55	-0.0874	***	0.004	-0.096	-0.079
Wyoming	56	-0.2393	***	0.008	-0.256	-0.223
Constraint		10.17006	***	0.065	10.038	10.302

Table 4-6 – Tractor Lead and Lag Model Results

R-Squared 0.7472

Variable		Co Ef.		Robust Std Err	95% Confidence Interval	
Dependent						
Usage Factors						
	Hours	-0.00008	***	0.000003	-0.000089	-0.000077
	Age	-0.0432	***	0.002	-0.047	-0.040
	Excellent_Good	0.2870	***	0.034	0.217	0.356
Make						
	John Deere	0.3204	***	0.022	0.276	0.365
	Case IH	0.1234	***	0.016	0.091	0.155
	Ford New Holland	0.0142		0.020	-0.027	0.055
	Kubota	-0.1375	***	0.032	-0.202	-0.073
	Mahindra	-0.6483	***	0.051	-0.752	-0.544
	Make_Other	-0.1863	**	0.081	-0.350	-0.023
Sale Variables						
	Spring Sale	-0.0076		0.010	-0.027	0.012
	Summer Sale	-0.0136		0.015	-0.044	0.016
	Winter Sale	0.0277	**	0.011	0.005	0.050
	Dealer	-0.1050	***	0.017	-0.140	-0.070
	Consignment	-0.0698	***	0.017	-0.105	-0.035
	Farm	0.0256	***	0.008	0.009	0.043
	Other	0.0331		0.028	-0.024	0.090
Covid Variables						
	Covid Gov S.E. Lag 10	-0.0549	*	0.029	-0.114	0.004
	Covid Gov S.E. Lag 9	0.0388		0.044	-0.051	0.128
	Covid Gov S.E. Lag 8	0.0779		0.062	-0.046	0.202
	Covid Gov S.E. Lag 7	0.0912	**	0.039	0.013	0.169
	Covid Gov S.E. Lag 6	0.0792	***	0.028	0.022	0.136
	Covid Gov S.E. Lag 5	-0.0174		0.038	-0.094	0.059

	Covid Gov S.E. Lag 4	0.0424		0.026	-0.011	0.096
	Covid Gov S.E. Lag 3	0.0718	**	0.034	0.003	0.141
	Covid Gov S.E. Lag 2	0.1097	***	0.025	0.060	0.160
	Covid Gov S.E. Lag 1	0.0668	*	0.037	-0.008	0.141
	Covid Gov S.E. Lead 1	0.0691	**	0.031	0.007	0.131
	Covid Gov S.E. Lead 2	0.0068		0.029	-0.051	0.065
	Covid Gov S.E. Lead 3	0.0269		0.038	-0.049	0.103
	Covid Gov S.E. Lead 4	0.0605	**	0.025	0.010	0.111
	Covid Gov S.E. Lead 5	0.0690	*	0.034	0.000	0.138
	Covid Gov S.E. Lead 6	0.1107	***	0.017	0.076	0.146
	Covid Gov S.E. Lead 7	0.0289		0.035	-0.043	0.100
	Covid Gov S.E. Lead 8	0.1619	**	0.070	0.021	0.303
	Covid Gov S.E. Lead 9	0.1153	***	0.033	0.049	0.181
	Covid Gov S.E. Lead 10	0.1683	***	0.011	0.145	0.191
Controls						
	US Cash Receipts	0.0003		0.000	0.000	0.001
	PPI	0.0000	***	0.000	0.000	0.000
	Region Diesel Price	-0.0413	***	0.013	-0.067	-0.015
	HP 175 and up	0.7519	***	0.017	0.717	0.787
	Pre-2014	-0.0072		0.012	-0.032	0.018

Table 4.6 Continued – Tractor Lead and Lag Model Results

State of Sale

State	Fips Code					
Alabama	1	-0.4746	***	0.008	-0.491	-0.458
Arizona	4	-0.2072	***	0.017	-0.241	-0.174
Arkansas	5	-0.2292	***	0.005	-0.239	-0.220
California	6	-0.3330	***	0.011	-0.356	-0.310
Colorado	8	-0.0492	***	0.004	-0.058	-0.040
Delaware	10	-0.1758	***	0.020	-0.216	-0.136
Flordia	12	-0.4460	***	0.014	-0.475	-0.418
Georgia	13	-0.2721	***	0.010	-0.291	-0.253
Idaho	16	-0.1920	***	0.010	-0.211	-0.173
Illinois	17	-0.0035		0.006	-0.015	0.009
Indiana	18	-0.0355	***	0.005	-0.045	-0.026
Iowa	19	-0.0175	***	0.002	-0.021	-0.014
Kansas	20	-0.0578	***	0.004	-0.065	-0.050
Kentucky	21	-0.1200	***	0.007	-0.134	-0.106
Louisiana	22	-0.3128	***	0.006	-0.324	-0.301
Maryland	24	-0.0544	***	0.012	-0.078	-0.031
Michigan	26	-0.1068	***	0.004	-0.116	-0.098
Mississippi	28	-0.2476	***	0.008	-0.263	-0.232
Missouri	29	-0.0336	***	0.007	-0.047	-0.020
Montana	30	0.0404	***	0.011	0.019	0.062
Nebraska	31	-0.0571	***	0.004	-0.065	-0.049
Nevada	32	-0.1413	***	0.021	-0.185	-0.098
New Jersery	34	-0.3154	***	0.014	-0.344	-0.287
New Mexico	35	0.0328	**	0.016	0.001	0.064
New York	36	-0.1726	***	0.008	-0.189	-0.156
North Carolina	37	-0.3122	***	0.007	-0.326	-0.298
North Dakota	38	0.0787	***	0.004	0.070	0.087
Ohio	39	-0.0833	***	0.004	-0.092	-0.075
Oklahoma	40	-0.1665	***	0.004	-0.176	-0.157
Oregon	41	-0.1557	***	0.019	-0.195	-0.116
Pennsylvania	42	-0.2768	***	0.013	-0.303	-0.251
South Carolina	45	-0.2950	***	0.009	-0.314	-0.276
South Dakota	46	0.0283	***	0.003	0.021	0.035
Tennessee	47	-0.2061	***	0.007	-0.220	-0.192

Texas	48	-0.1867	***	0.007	-0.201	-0.172
Utah	49	-0.5300	***	0.010	-0.551	-0.509
Vermont	50	-0.3192	***	0.024	-0.369	-0.270
Virginia	51	-0.3597	***	0.014	-0.388	-0.331
Washington	53	-0.1492	***	0.014	-0.177	-0.121
Wisconsin	55	-0.0871	***	0.004	-0.096	-0.078
Wyoming	56	-0.2193	***	0.009	-0.237	-0.201
Constraint		9.770863	***	0.058	9.654	9.888

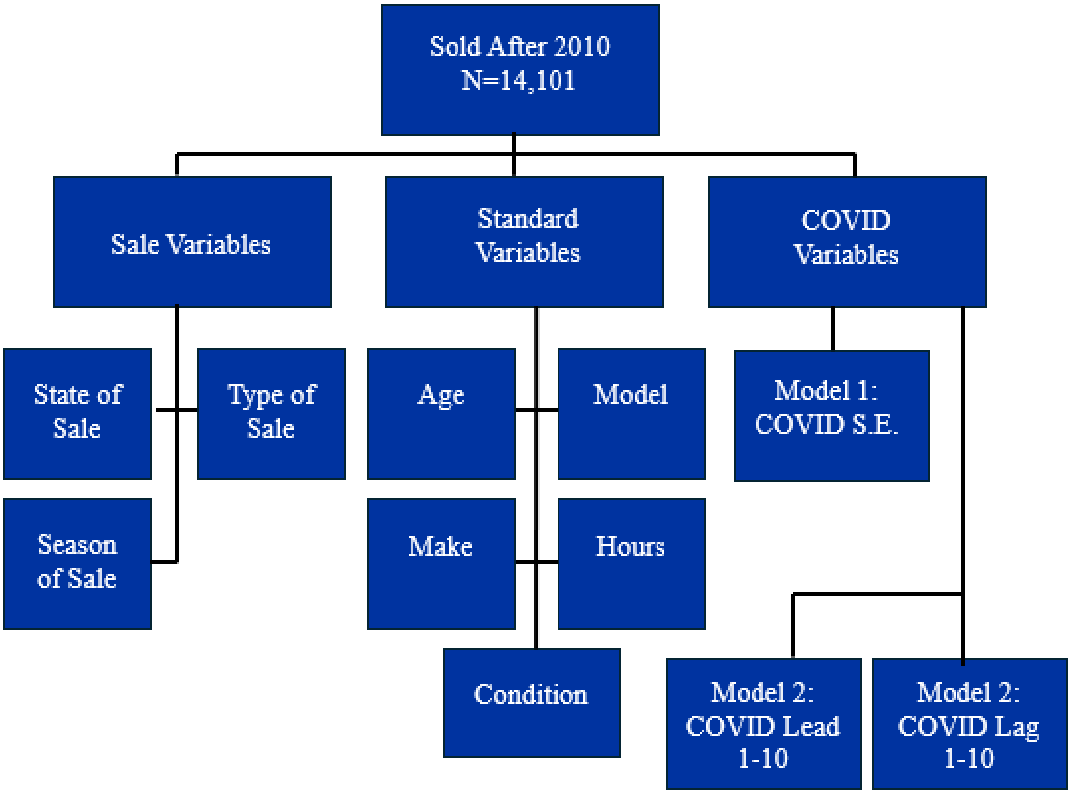


Figure 4-1 – Tractor Data Cleaning Tree

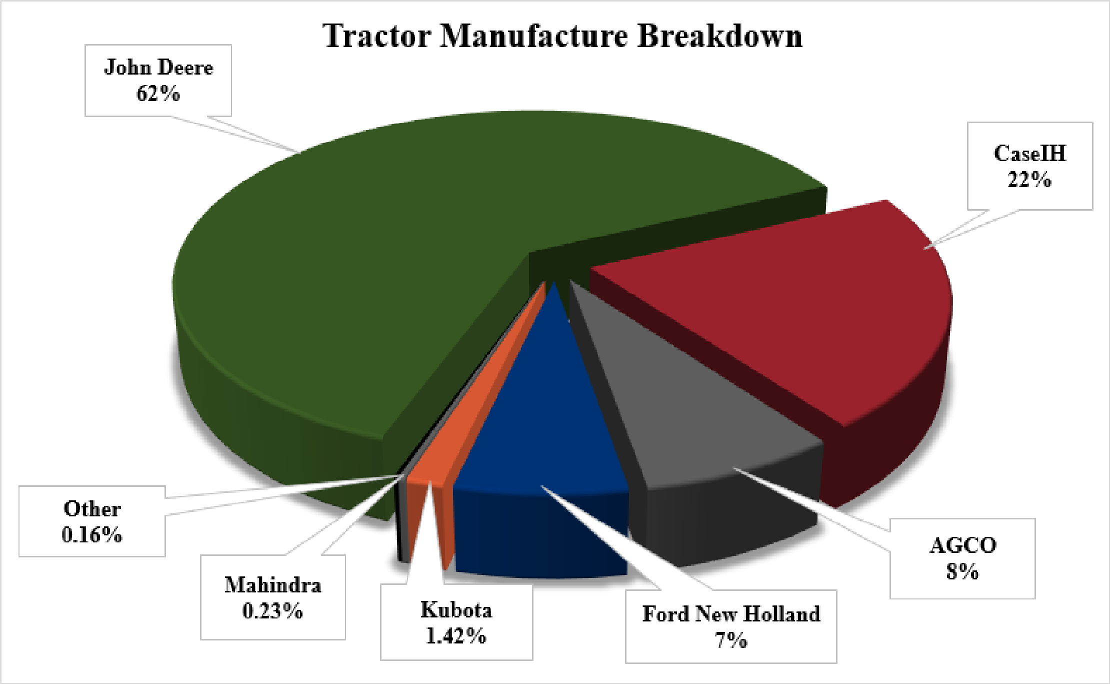


Figure 4-2 – Tractor Data Percent of Manufacturer

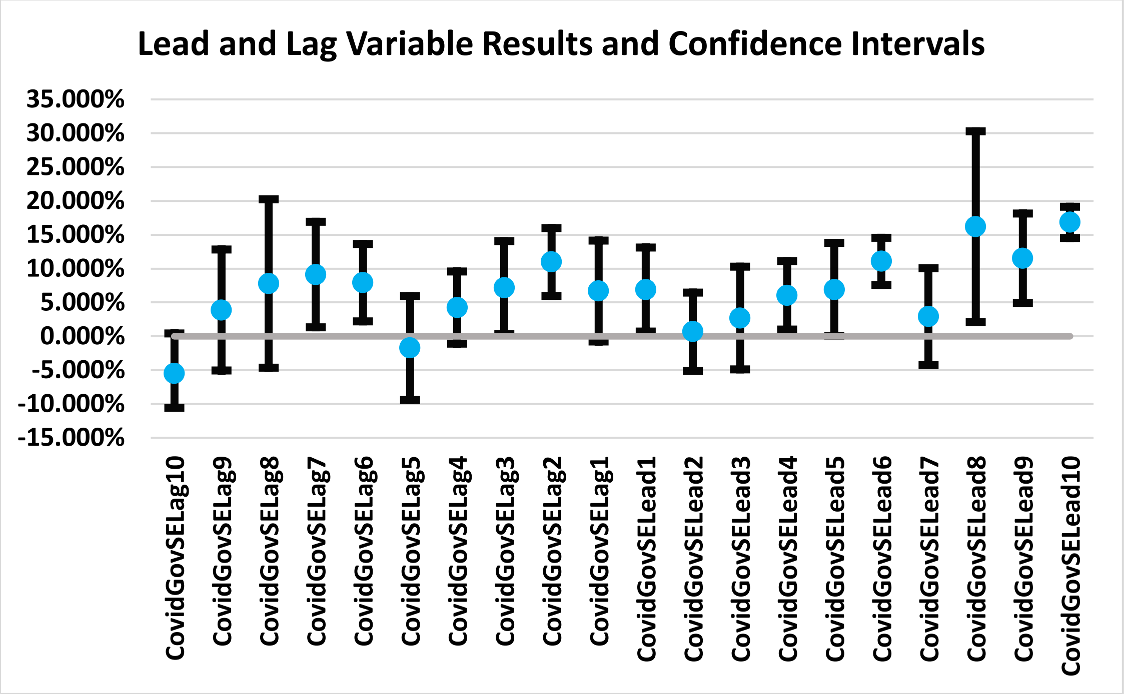


Figure 4-3 – Lead and Lag Variable Results and Confidence Intervals

CHAPTER 5. SUMMARY CHAPTER

The recent COVID-19 pandemic radically changed the landscape of major industries, and agriculture was no different. For the farming industry, government payments have assisted in maintaining operations through the shutdowns but moving forward; producers will have to manage the new landscape without government assistance. With projected future decreases in government assistance, operators will likely need to optimize their decision-making to maximize net income by increasing revenue or decreasing expenses. Given the decrease in planted acres, one option for increasing net income would be to farm on higher saturated or historically non-farmed acres. Chapter 2 of this dissertation performs a life cycle cost and carbon footprint analysis for implementing a tile drainage system, while chapters 3 and 4 focus on the production expense side of net income by evaluating secondary combine and tractor values.

The second chapter tackles the issue of the continual decrease in farmland and investigates the economics of furthering row crop operations into areas of high saturation. A life cycle cost and carbon footprint analysis were developed to analyze the economic feasibility and estimate the carbon impacts of installing a tile drainage system. With the study's goal in mind, the objectives were to establish four representative fields for installing a tile drain system, design a system for each field with the ability to change the soil type, perform a life cycle cost and carbon footprint on the various systems, and evaluate and provide results for producer use of the various combinations.

During the initial study, an additional breakeven analysis was developed to provide a deeper understanding of the results. Carbon footprint estimates suggested the average across all fields in the base case scenario would result in the carbon impact of 551.3 kg

CO_2 eq per acre, with an average cost of that system at $3,641 per acre. The largest field in the study held the lowest cost at $1,599 per acre, illustrating the significant decrease in cost due to economies of scale with the larger area. When soil types were evaluated, estimates followed the expected order due to lateral pipe spacing, but the results will allow producers to estimate their own fields for installation accurately. The break-even analysis is likely the most industry-impactful finding for the study. For corn, a 28-bushel per acre was needed to offset the cost of the system, while soybeans needed an 11-bushel increase. The results presented in this chapter provide a deeper analysis of tile drainage systems and allow producers to have adequate information for implementation.

Chapters three and four are associated with the second largest farm asset of farm machinery. Chapter three addresses the adoption of precision agricultural technologies on combine harvesters. Over the past decade, combines have drastically changed with the further development of precision agricultural technologies. A unique dataset for auction sales in North America was paired with a logarithmic-hedonic model to evaluate the factors that impact combine values. Given the base model results, a secondary model was constructed to evaluate the impact on values, specifically from the type of technology. Results were then used to suggest the value added by various technologies. Although full results are needed to assess a combine's value accurately, the model found estimates for manufacturer differences in value, estimated that usage hours have less of an impact on price than the age of the combine and that data-sharing technologies have the largest increase in value among the technologies. The chapter provides a more in-depth evaluation of the market and the changing technologies that will assist operators in properly evaluating combine machinery.

The fourth chapter evaluates the farm machinery market changes by investigating the impacts of the COVID-19 pandemic on the used tractor market. Similar to the third chapter, an auction dataset was used to estimate value changes. Additional variables were generated in order to represent the differences between tractors, as well as illustrate each state's pandemic shutdown date. The final dataset was then paired with a hedonic pricing model to estimate the impacts of the various factors. Overall, the model estimated an increase of 16.3% in tractor values due to the pandemic. However, further investigation suggested that the impacts range from –5.5% to 16.8%, depending on the timing of the sale. Furthermore, the model was able to estimate impacts from general variables such as manufacture, usage rates, and sale characteristics. Utilizing these key findings with the full model results will allow producers to accurately evaluate their on-farm machinery and future buying and selling opportunities.

In conclusion, the farming industry has seen major changes in the past decade from limited land availability, new technologies, and a pandemic. The chapters presented in this dissertation provide much needed information on evaluating potential opportunities for farmers to combat recent changes. Although a farming operation has many different parts, this dissertation addresses the two largest asset areas for most operations. The suggestions and results illustrated here will allow operators to accurately assess their current operations as well as future opportunities with land and machinery management.

CHAPTER 6. APPENDIX

6.1 Appendix 1. Tile Drainage Systems Breakeven Model Inputs

Financial Variables for Model
Term of Payback: 50 Years
Discount Rate: 8%
Percent Increase of Crop Yields from Tile Drainage System: 20%
Corn Estimated Prices and Yields (Note years 2003-2021 were used for estimates after year 2033)

Year	Corn Yield	Soybean Yields	Corn Price	Soybean Price
2003	129.3	38.0	$ 2.32	$ 5.53
2004	142.2	33.9	$ 2.42	$ 7.34
2005	160.3	42.2	$ 2.06	$ 5.74
2006	147.9	43.1	$ 2.00	$ 5.66
2007	149.1	42.9	$ 3.04	$ 6.43
2008	150.7	41.7	$ 4.20	$ 10.10
2009	153.3	39.7	$ 4.06	$ 9.97
2010	164.4	44.0	$ 3.55	$ 9.59
2011	152.6	43.5	$ 5.18	$ 11.30
2012	146.8	42.0	$ 6.22	$ 12.50
2013	123.1	40.0	$ 6.89	$ 14.40
2014	158.1	44.0	$ 4.46	$ 13.00
2015	171.0	47.5	$ 3.70	$ 10.10
2016	168.4	48.0	$ 3.61	$ 8.95
2017	174.6	51.9	$ 3.36	$ 9.47
2018	176.6	49.3	$ 3.36	$ 9.33
2019	176.4	50.6	$ 3.61	$ 8.48
2020	167.5	47.4	$ 3.56	$ 8.57
2021	171.4	51.0	$ 4.53	$ 10.80
2022	176.7	51.7	$ 6.00	$ 13.30
2023	173.3	49.5	$ 6.69	$ 14.23
2024	181.0	51.6	$ 5.32	$ 12.17
2025	183.0	52.1	$ 4.84	$ 11.82
2026	185.1	52.6	$ 4.66	$ 11.37
2027	187.4	53.2	$ 4.50	$ 11.18
2028	189.5	53.8	$ 4.42	$ 10.99
2029	191.7	54.3	$ 4.33	$ 10.89
2030	193.7	54.9	$ 4.23	$ 10.73
2031	195.8	55.6	$ 4.17	$ 10.61
2032	197.6	56.1	$ 4.09	$ 10.48
2033	199.2	56.6	$ 3.99	$ 10.33
2034	198.6	57.2	$ 4.79	$ 12.22

2035	200.6	57.8	$ 4.80	$ 12.28
2036	202.6	58.4	$ 4.82	$ 12.34
2037	204.6	59.1	$ 4.84	$ 12.41
2038	206.6	59.7	$ 4.85	$ 12.47
2039	208.5	60.3	$ 4.87	$ 12.53
2040	210.5	60.9	$ 4.88	$ 12.59
2041	212.5	61.6	$ 4.90	$ 12.65
2042	214.5	62.2	$ 4.91	$ 12.71
2043	216.5	62.8	$ 4.93	$ 12.77
2044	218.4	63.4	$ 4.94	$ 12.84
2045	220.4	64.1	$ 4.96	$ 12.90
2046	222.4	64.7	$ 4.97	$ 12.96
2047	224.4	65.3	$ 4.99	$ 13.02
2048	226.3	65.9	$ 5.00	$ 13.08
2049	228.3	66.6	$ 5.02	$ 13.14
2050	230.3	67.2	$ 5.04	$ 13.20
2051	232.3	67.8	$ 5.05	$ 13.27
2052	234.3	68.4	$ 5.07	$ 13.33
2053	236.2	69.0	$ 5.08	$ 13.39
2054	238.2	69.7	$ 5.10	$ 13.45
2055	240.2	70.3	$ 5.11	$ 13.51
2056	242.2	70.9	$ 5.13	$ 13.57
2057	244.2	71.5	$ 5.14	$ 13.64
2058	246.1	72.2	$ 5.16	$ 13.70
2059	248.1	72.8	$ 5.17	$ 13.76
2060	250.1	73.4	$ 5.19	$ 13.82
2061	252.1	74.0	$ 5.20	$ 13.88
2062	254.1	74.7	$ 5.22	$ 13.94
2063	256.0	75.3	$ 5.24	$ 14.00
2064	258.0	75.9	$ 5.25	$ 14.07
2065	260.0	76.5	$ 5.27	$ 14.13
2066	262.0	77.2	$ 5.28	$ 14.19
2067	264.0	77.8	$ 5.30	$ 14.25
2068	265.9	78.4	$ 5.31	$ 14.31
2069	267.9	79.0	$ 5.33	$ 14.37
2070	269.9	79.7	$ 5.34	$ 14.43
2071	271.9	80.3	$ 5.36	$ 14.50
2072	273.8	80.9	$ 5.37	$ 14.56
2073	275.8	81.5	$ 5.39	$ 14.62

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Publications

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The 23rd International Farm Management Congress. Evaluating the Effect of Precision Agriculture Technologies on Harvesting Combine Values in North America. 2022

Presentations

Scoular Cultivating Sustainability: Regenerative Ag, Data Insights and Farm Engagement. Economics of Soil Health. Online. April 2024.

Southern Agriculture Economics Association. Evaluating the Impact of Precision Agriculture on the US Secondary Combine Market. Atlanta, GA. February 2024.

Western Agricultural Economics Association. Evaluating the impact of the Pandemic on Used Forage Machinery Values. Whistler, BC. July 2023

Southern Agricultural Economics Association. Evaluating the impact of Covid-19 supply chain issues on the secondary tractor market in North America. Oklahoma City, OK. February 2023

Southern Agricultural Economics Association. Strategies for Farm Machinery Rising Cost. Oklahoma City, OK. February 2023

The 23rd International Farm Management Congress. Life Cycle Cost and Analysis of Implementing Drain Tile System in Row Crop Operations. Copenhagen, Denmark. June 2022.

The 23rd International Farm Management Congress. Evaluating the Effect of Precision Agriculture Technologies on Harvesting Combine Values in North America. Copenhagen, Denmark. June 2022.

The 23rd International Farm Management Congress. The Economic Costs and Optimal Machinery for Cover Crops in Kentucky. Copenhagen, Denmark. June 2022.

Southern Extension Committee Meetings. Evaluating the Impact of Precision Technologies on Combine Values. Clearwater, FL. June 2022.

Southern Agricultural Economics Association. Utilizing Auction Sale Data to Estimate the Value of Used Combine Harvesters in the US and Canada. New Orleans, LA. February 2022

UKY Food Energy Water Symposium. Evaluating the Economic Costs and Optimal Machinery for Cover Crops in Kentucky. Lexington, KY. December 2021.

Mississippi State University Row Crop Field Day. Economics Cost of Cover Crop. Delta, MS. July 2018.

Mississippi State University Row Crop Field Day. Machinery Cost of Cover Crop. Clarksdale, MS. March 2019

Southern Agriculture Economics Association. Cover Crops Effect on Cropland Values. Birmingham, AL. February 2019.