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

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Abstract: *Despite previous research evaluating the cost of grain harvesting operations and combines, there are still major gaps in the literature around the uncertainty of machine prices. Couple this with the recent price increases of new machines that have pushed operations to purchase used equipment. Which has led to the need for evaluating the various precision agriculture technologies and how they impact a combines value. The study proposed will aim to fill the holes in previous studies by predicting combine values across multiple makes and models. Unlike the previous studies, this work will evaluate the impact from various factors such as add-ons centered around precision agriculture in order to better predict the true value of the machine. In order to accomplish this task, the study will combine a hedonic model with an auction dataset from a national machinery sales company.*

Keywords: Harvester, Combine, Precision Agriculture, Production Economics, Farm Management, Farm Machinery

Introduction: Farm machinery is the second largest farm expense behind land, accounting for more than 40 percent of total production expense (Ibendahl,2015). Due to the high cost of combines impacting the overall profitability of grain operations, farm owners must make choices ranging from owning vs. leasing equipment, custom hiring, or a combination of options. If they choose to purchase their own equipment, farmers must consider the equipment's size, age, quantity capabilities, and add-ons needed for the operation. However, given the numerus brands, options, and choices available, is it possible to evaluate a combine during the sale's timeframe accurately. Furthermore, more and more combines are being sold through online outlets, with many of those machines being located hours away from the farmer looking to purchase the equipment. Couple these questions with the rising costs of combines that can range from $350,000 to $500,000 without add-ons (Dodson, 2015), and an inaccurate evaluation could prove to have a massive financial impact on the entire operation.

Previous literature has attempted to evaluate portions of the combine market by using survey data, engineering data, or individual machine resale values to estimate combine values. Still, all have fallen short of evaluating and comparing multiple combines. A recent study from Ellis and Mark (2022) was the first to assess values using a large auction dataset, evaluate the primary factors driving the combine's value, and provide estimates to compare different combines. This study will build upon that work by estimating the value of precision agriculture technologies in the overall value of a combine.

The objectives of this paper is to 1) estimate the change in the various combine values when different technologies are on the combine, 2) compare the change between different manufacturers, and 3) evaluate which technologies are most impactful for the buyers and sellers of the combines. To complete these objectives, an auction dataset from North America's largest farm machinery auction site Machinery Pete was paired with an econometric model to estimate the various factors that affect the combine's value. Initial results suggest that combines sold in the Midwest regions during the spring of 2018 hold the highest values, while John Deere held the highest values for any manufacturer. With the initial results in mind, the full model results will depict the effects of the various parameters on the combine market.

Background: Hedonic models have been used widely in agricultural research dating back to 1974 to estimate land, commodity, and machinery values (Rosen, 1974). The hedonic model estimates the effect of multiple independent variables on the dependent variable. Although these models are often use in estimating land values (Miranowski & Hammes, 1984; Borchers et al., 2014), machinery values can be estimated in a similar fashion (Allison, 2019; Ellis & Mark, 2022). Allison looked at estimating values of row crop planters and aimed to answer the question of "Why do planters cost so much?" Even though the work resulted in significant findings to help answer this question, there are a few issues with the study. The dataset was relatively small for a national study, there was no control for the massive range in sale prices, and other planter specific items will not transfer the work to other farm machines. However, understanding and addressing the issues from previous work will allow for a model of combine harvester values to provide more accurate estimations. As for Ellis and Mark, the study evaluated the value of combines and compared the change in impacts between different manufactures. However, this model did not evaluate the addition of precision agriculture technologies, and therefore left gaps within the results for combines with different add-on components.

The majority 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 (Fettig, 1963). 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 (Leblanc & Hrubovcak, 1985). The two studies found basic factors that will affect a tractor's value are the type of engine and horsepower level (Fettig, 1963), and that input and output prices have a larger effect on tractor values compared to interest rates (Leblanc & Hrubovcak, 1985). As for planters, Cross and Perry (1995) found a significant relationship between value and depreciation factors. This would suggest that the age, hours, and useful life of a machine 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, 2019).

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; Latte & Schnithey, 2019; and Swanson et al, 2020). This approach is similar to Cross and Perry (1995), where the research focuses on valuing 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 the standpoint of a custom harvesting operation and singular farming operation. With respect to a custom hiring operation, a simple enterprise risk analysis was performed comparing different combines and their effect on the operation profitability (Mimra et al., 2017). As for the singular operation, the study aimed to set a minimum annual use in order based on the combines given value (Mimra and Kavka, 2017). In both studies the value of the combine was based on the purchase price of the combine along with operation costs for that combine.

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. While there is an inherent flaw in using the list price of the combines, 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 management efficiency of a combine fleet (Olt et al., 2019).

Although the previous studies help to assess combine values, no work has produced a full comprehensive model for evaluating combine values. Another factor that goes into creating a full model is the makeup and conditions of the combine market. Currently most operations in North America do not have the option of custom hiring their harvesting operations, resulting in the need to own the combine machine. This decision results in less flexibility with changing market conditions, causing major problems when combine prices skyrocket. Recently between 2008 and 2015, combine prices have increased up to 30% (Mimra et al., 2017), leaving operations struggling with profitability from the increased operation costs. Furthermore, new combine prices are at an all-time high ranging between from $330,000 to $500,000 without headers or add-ons (Dodson, 2015), 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 both prices and add-on options (Dodson, 2015), leading operations to struggle with estimating some of the equipment's value. Some industry experts have gone as far as to suggest that buying used equipment is the best option for most operations (Ellis, 2021). Understanding the current market along with the gaps in previous literature has left the industry with a long overdue need for an evaluation of the value of used combines.

The only full model for combines, found that 1000 hours of use would decrease the value by 2.14% (Ellis and Mark, 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 (Ellis & Mark, 2022).

Data: In order to build upon the previous literature, an auction dataset with sales from 2015 to 2018 was used for the study. The dataset consists of sales from North America's largest online farm machinery auction company, Machinery Pete. The original dataset contained 6,719 observations with variables for price, make, model, year, hours used, sale date, sale type, sale location, and specs. In order to appropriately use this dataset, a data cleaning process was performed to remove missing observations resulting in a final dataset with 4,820 observations. Additionally, the data was processed to add dummy variables for the various different types of sales.

The full summary statistics can be found in Table 1. The final dataset can be broken into groups that will then be used in the hedonic model as vectors. These groups are machine condition, machine specification, and sale characteristics. For the machine condition group, the variables include the age of the combine which was calculated using the difference between the year the combine was made and the year in which it was sold. Dummy variables were used to represent the different conditions for excellent, fair, good, and poor. For this dataset the mean age was between 13 and 14 years old with around 82% of the combines being classified as in "good" condition.

The machine specification grouping variables included various dummy variables to represent the appropriate manufacturer for each combine. In order to appropriately group manufacturers, parent company and subsidiary relationships were consolidated into the same dummy variable. For example, AGCO owns Challenger, Gleaner, Massey Ferguson, and White. Therefore, all combines representing these manufacturers were placed under the AGCO variable.

Variables pertaining to sale type, sale date, and sale location were all used in the dataset. In order to accurately represent this data dummy variables were created for each sale year in the dataset and a seasonal dummy variable for spring, summer, fall, and winter was used to address the time of the year when the sale took place. The sale type was broken down into consignment, dealer, farm, online, and other. Sale location variables were grouped into 12 US regions and 1 Canadian region based off a USDA breakdown (USDA) (Figure 1). 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.

In order to generate variables for technologies, dummy variables were created for yield monitor, moisture tracker, GPS, Ag Leader software, auto steer, and Brown Box software. The observations were pulled from a specs category, in which the auctioneer would type in the details about the combine. Similar to the manufacturer variables, observations were combined to represent the type of technology. For example, a John Deere auto steer package and a Case IH auto steer would both hold a one for the auto steer variable.

Material and Methods: The existing literature on other hedonic models was used to construct one model that contained all manufacturers within the dataset, and two separate models containing only the manufacturers John Deere and Case IH since those companies hold the strongest market share (More, 2021). Furthermore, when a variance Inflation factor test (VIF) was performed to evaluate what variables might show multicollinearity, John Deere and Case IH were the only two variables with results over 5 (Table 2). This would suggest that the two variables might be highly correlated, which could be due to both manufacturers making up a large portion of the entire dataset.

In all three models the price of the combine was transformed into a natural log in order to limit the impact of potentially skewed results from higher prices. The equation used in this study can be expressed as:

$$\ln P = f(\alpha, \theta, \delta, \lambda)$$

where the dependent variable lnP is the natural log of the price at which the combine was sold. The independent variables include vectors that represent the three groups mentioned previously in the data section. The vector for the group of machine condition is represented by α, the machine specification group is represented by θ, the sale characteristics group is represented by δ, and the precision agriculture technology group is represented by λ.

Expectations of the model are based on economic principles and market trends. For the model including all manufactures, the expectation would be for John Deere, Case IH, Agco, and Ford New Holland to all have positive coefficients with respect to the other makes category since these manufacturers hold the highest market share and yearly sales for the combine market (More, 2021). The variables hours and age are both expected to hold a negative coefficient, 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 down to poor.

As for the sale characteristics vector, the sale type of "dealer" should have the lowest value due to the bidding or competition between buyers in other sale types. Combines sold during the winter season should hold the highest coefficient since the timing of on-farm operations would cause issues of time available to purchase machinery. Furthermore, all sale years within the dataset are expected to have a gradual increase due to inflation overtime as well as the lack of major price changes in either the corn or soybean markets (USDA, 2021). As for the location of the sale, the heartland region would be expected to hold the highest coefficient since it represents the major grain producing area of the US.

The vector of precision agriculture technologies, contains the dummy variables for yield monitor, moisture tracker, GPS, Ag Leader software, Auto Steer, and Brown Box software. The expectation is for all technologies to increase the value of the combine in order of auto steer, GPS, yield monitor, moisture tracker, Ag Leader software, and Brown Box software from highest impact to lowest. This order is based on the incorporation of one technology into the other. For example, GPS is needed for the auto steer. Therefore, auto steer would be a higher valued technology.

To develop the two models for John Deere and Case IH machines, all variables other than manufacturer were included. Similarly, the reference variables were also kept the same in the two models.

Results: The previously mentioned model and dataset were combined using STATA software to properly analyze combine machine prices and estimate the factors that affect those prices. Multicollinearity was evaluated through the use of a VIF test resulting in a mean VIF of 2.6 and only two variables, John Deere and Case IH, having a VIF over 5. As previously mentioned, this correlation is likely due to the large share of observations that each manufacturer holds in the dataset.

The full model results can be found in Tables 3, 4, & 5. All three models were able to account for over 92% of the total variance in combine values. The base model suggested that John Deere would have the highest value at 42% greater than other models, followed by Case IH at 24% higher, both at a 1% significance level. Ford-New Holland estimated a 9% decrease at a 5% significance level compared to the other make variable.

For the machine condition vector, all three models found hours, age, good condition, fair condition, and poor condition significant at the 1% level. Per 1000 hours, the base model suggested a drop of 2.31%, while Case IH and John Deere estimated a decline of 2.02% and 1.43%, respectively. All three models estimated a decrease of around 10% for each year of age on the combine, and all condition variables followed exceptions with good condition drop between 23.67% and 20.61%, fair condition dropping between 44.25% and 41.81%, and poor condition falling between 70.98% and 79.63%. These results are similar to the work of Ellis and Mark (2022). These results suggest that a John Deere combine's value will decrease at a higher percentage range initial, but at the lower condition scores, John Deere will not decrease as much as other manufacturers.

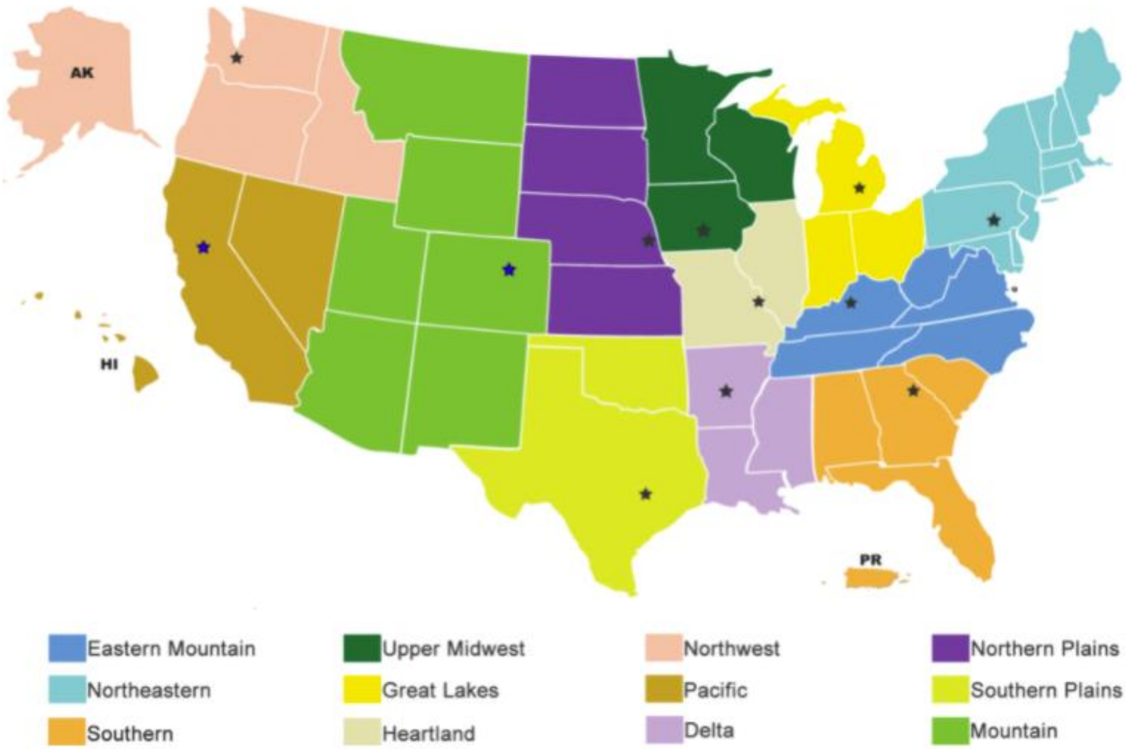
For the sale characteristics, results indicated that all three models found the sale types of farm sale and consignment significant along with the sale years of 2017 and 2018. Only the Case IH and John Deere models found online sales to be statistically significant. These estimates suggest in order to maximize the value of a combine; only Case IH should be sold online, while all other manufacturers should focus on selling through consignment, holding all other variables constant. Similarly, Case IH combines help higher values during the 2018 sale year, while others help higher values during the 2017 sale year. In addition, all manufacturers other than Case IH found that selling a combine during the fall season would negatively impact the value. As for the sale location, both the base and Case IH model found that sales in the Great Lakes region were estimated to have a 3% and 7% increase in value compared to the Heartland region. All other regions were estimated to have a decrease in value compared to the Heartland.

Expanding upon the previous work, the precision agriculture technology variables were the major contribution of this paper. Only three variables were statistically significant, yield monitor, moisture tracker, and auto steer. In the base model, all three were significant at the 1% level, with the yield monitor holding the highest increase in value at 7%, followed by an auto steer at 6% and moisture tracker at 5%. Although this result was not expected, it provides a new insight that farmers might value a yield monitor over having auto steer. As for the Case IH model, results suggest that moisture tracker was a 5% increase at the 10% significance level, while auto steer was almost an 8% increase at the 1% significance level. In comparison, the John Deere model estimated an 8% increase from having a yield monitor at a 1% significance level and auto steer having a 3% increase at a 5% significance level.

Compiling these results, the model suggests that John Deere combines while holding higher values than any other manufacturer. Furthermore, the age of the combine will affect the value more than the hours the combine has been used. While the decrease in value as condition score drops is relatively close between all combines. The results should help both buyers and sellers of a combine. For a buyer, the results suggest buying manufacture other than John Deere and focusing on buying during the fall season in regions outside of the Heartland, Great Lakes, or Upper Midwest. As well as comparing the difference in the value from different add-ons. From a sellers' point, the manufacture and other variables would be given for the specific combine being sold. However, the results can be used to estimate the value of that combine. As well as suggesting transporting a combine into one of the higher valued sale locations, if possible. Concerning the precision agriculture technologies, the model would suggest that adding a yield monitor would increase the value of the machine more than auto steer or a moisture tracker.

Conclusion: The dramatic increases in combine costs along with the numerus options for add-ons, evaluating the value of a combine is more complex than ever. This study provides three models for assessing the value of used combines using a Machinery Pete dataset of auction sales between 2015 and 2018. The base model found statistical significance in all condition variables, sale characteristics, location, and make of the combine. Specifically, the precision agriculture technology variables, yield monitors, moisture trackers, and auto steer all illustrated a positive relationship with the value. When the model was restricted to Case IH, only moisture tracker and auto steer were significant. Similarly, only yield monitor and auto steer showed significance in the John Deere model. The results presented in this study can compare various combines and assist both buyers and sellers in properly evaluating a combines value.

Figure 1: Map of the Regions used for Location Variables



Source: USDA - https://www.nass.usda.gov/Statistics_by_State/RFO/index.php

Table 1: Summary Price Statistics for used Combines

Variable		Description of Variables	Number of Obs	Mean	Std. Dev.	Min	Max
Independent							
	Price	Final Sale Price ($)	4,820	73556.12	62733.89	250	372238
Dependent							
Usage Factors							
	Hours	Total hours of use on the machine	4,820	1348.945	1925.911	1	40900
	Age	Total years since manufacturing	4,820	13.71909	9.566378	0	48
Machine Condition							
	Excellent	= 1 if condition is Excellent	321	0.066598	0.24935	0	1
	Good	= 1 if condition is Good	3977	0.824896	0.380095	0	1
	Fair	= 1 if condition is Fair	512	0.106224	0.308156	0	1
	Poor	= 1 if condition is Poor	11	0.002282	0.047722	0	1
Season of Sale							
	Sale Spring	= 1 if the sale occurred in the Spring season	817	0.169502	0.375234	0	1
	Sale Summer	= 1 if the sale occurred in the Summer season	1922	0.398548	0.48965	0	1
	Sale Fall	= 1 if the sale occurred in the Fall season	1202	0.249378	0.432698	0	1
	Sale Winter	= 1 if the sale occurred in the Winter season	880	0.182573	0.386356	0	1
Year of Sale							
	Sale 2015	= 1 if the sale occurred in the 2015 sale year	1097	0.227593	0.419322	0	1
	Sale 2016	= 1 if the sale occurred in the 2016 sale year	1299	0.269295	0.443639	0	1
	Sale 2017	= 1 if the sale occurred in the 2017 sale year	1472	0.305394	0.460622	0	1
	Sale 2018	= 1 if the sale occurred in the 2018 sale year	953	0.197718	0.39832	0	1
Make							
	AGCO	= 1 if AGCO was the make	315	0.065353	0.247173	0	1
	Case IH	= 1 if Case IH was the make	1281	0.265768	0.441787	0	1
	Ford New Holland	= 1 if Ford or New Holland was the make	288	0.059751	0.23705	0	1
	John Deere	= 1 if John Deere was the make	2859	0.592946	0.491336	0	1
	Other	= 1 if any other make	78	0.016183	0.12619	0	1
Sale Type							
	Consignment	= 1 if the sale was for consignment	2313	0.479668	0.499638	0	1
	Dealer	= 1 if the sale occurred at a dealership	1230	0.085685	0.279927	0	1
	Farm	= 1 if the sale occurred on farm	413	0.255187	0.436011	0	1
	Online	= 1 if the sale occurred online	865	0.179461	0.383777	0	1
Sale Location							
	Canada	= 1 if the sale was in Canada	624	0.130	0.336	0	1
	EasternMont	= 1 if the sale was in Eastern Mointain Region	66	0.013693	0.116225	0	1
	Northeaster	= 1 if the sale was in Northeaster Region	22	0.004564	0.067412	0	1
	Southern	= 1 if the sale was in Southern Region	3	0.000622	0.024943	0	1
	UpperMidwest	= 1 if the sale was in Upper Midwest Region	806	0.16722	0.373211	0	1
	GreatLakes	= 1 if the sale was in Great Lakes Region	510	0.105809	0.307625	0	1
	Heartland	= 1 if the sale was in Heartland Region	863	0.178838	0.383257	0	1
	Northwest	= 1 if the sale was in Northwest Region	25	0.005187	0.071839	0	1
	Pacific	= 1 if the sale was in Pacific Region	7	0.001452	0.038085	0	1
	Delta	= 1 if the sale was in Delta Region	72	0.014938	0.121316	0	1
	NorthernPlains	= 1 if the sale was in Northern Plains Region	1676	0.347718	0.476295	0	1
	SouthernPlains	= 1 if the sale was in Southern Plains Region	92	0.019087	0.136846	0	1
	Mountain	= 1 if the sale was in Mointain Region	54	0.011203	0.105262	0	1
Precision							
	Yield Monitor	= 1 if the combine has a yield monitor	1265	0.262448	0.440011	0	1
	Moisture Tracker	= 1 if the combine has a moisture tracker	634	0.131535	0.33802	0	1
	GPS	= 1 if the combine has a GPS	112	0.023237	0.15067	0	1
	Ag Leader	= 1 if the combine has Ag Leader software	130	0.026971	0.162015	0	1
	Auto Steer	= 1 if the combine has a auto steer	729	0.092946	0.290387	0	1
	Brown Box	= 1 if the combine has Brown Box software	50	0.010373	0.101331	0	1

Table 2: VIF Results

Variable	VIF	1/VIF
John Deere	15.68	0.06376
Case IH	13.21	0.075688
AGCO	4.87	0.205262
Ford New Holland	4.49	0.222879
Consignment	3.95	0.252906
Fair	3.31	0.302059
Farm	3.31	0.302476
Online	3.14	0.318526
Good	2.58	0.388341
Summer	2.28	0.43917
Northern Plains	2.21	0.45281
Canada	2.08	0.479661
Fall	2.07	0.483644
Yield Monitor	2	0.50115
Age	1.99	0.502631
Moisture Tracker	1.96	0.510908
Upper Midwest	1.91	0.522917
Sale2017	1.9	0.52673
Sale2018	1.89	0.528582
Winter	1.88	0.533317
Sale2016	1.68	0.596952
Great Lakes	1.51	0.661401
Hours	1.33	0.752924
Auto Steer	1.17	0.854207
Southern Plains	1.14	0.873365
Mountain	1.12	0.895795
Delta	1.1	0.905427
Eastern Mont	1.1	0.912687
Ag Leader	1.08	0.924313
GPS	1.07	0.931624
Northwest	1.06	0.940677
Poor	1.06	0.942235
Brown Box	1.04	0.96203
Northeaster	1.03	0.967174
Pacific	1.02	0.979915
Southern	1.01	0.993229

Mean VIF	2.65

Table 3: Base Model Results

Base Model	R-Squared		0.9225
Variable	Coefficient		Percent Change
Hours	-0.0000231	***	-0.00231
Age	-0.1048329	***	-9.95250
Good	-0.252292	***	-22.29822
Fair	-0.5842182	***	-44.24584
Poor	-1.476699	***	-77.16096
Farm	0.1244472	***	13.25222
Consignment	-0.051997	***	-5.06683
Online	-0.0277952		-2.74125
Sale2016	0.0024694		0.24725
Sale2017	0.0808947	***	8.42567
Sale2018	0.0698295	***	7.23253
Summer	-0.0125464		-1.24680
Fall	-0.0653019	***	-6.32154
Winter	0.0012884		0.12892
AGCO	-0.0345115		-3.39228
Case IH	0.2131391	***	23.75568
Ford New Holland	-0.0989224	*	-9.41870
John Deere	0.3497005	***	41.86426
Canada	-0.0163571		-1.62240
Eastern Mont	-0.0672936		-6.50793
Northeaster	0.0884967		9.25306
Southern	-0.2777131	**	-24.24859
Upper Midwest	0.0237911		2.40764
Great Lakes	0.0296191	*	3.00621
Northwest	-0.6089509	***	-45.60788
Pacific	-0.9831329	***	-62.58629
Delta	-0.1908869	***	-17.37740
Northern Plains	-0.0559499	***	-5.44135
Southern Plains	-0.1547873	***	-14.34026
Mountain	-0.0532083		-5.18175
Yield Monitor	0.0695407	***	7.20157
Moisture Tracker	0.0494403	***	5.06829
GPS	0.0159937		1.61223
Ag Leader	0.0177328		1.78910
Auto Steer	0.0591031	***	6.08846
Brown Box	-0.0423244		-4.14412
Cons	12.15269		

* $p< 0.10$ ** $p< 0.05$ *** $p< 0.01$

Table 4: Case IH Model Results

CASE IH Model	R-Squared		0.9249
Variable	Coefficient		Percent Change
Hours	-0.0000202	***	-0.00202
Age	-0.1064018	***	-10.09367
Good	-0.2309234	***	-20.61997
Fair	-0.5548995	***	-42.58700
Poor	-1.591344	***	-79.63483
Farm	0.2771943	***	31.94227
Consignment	0.0696252	*	7.21063
Online	0.1021775	**	10.75800
Sale2016	0.0056591		0.56751
Sale2017	0.0793974	***	8.26345
Sale2018	0.0879928	***	9.19803
Summer	0.0508638		5.21796
Fall	-0.0183218		-1.81550
Winter	-0.012325		-1.22494
Canada	-0.0688864		-6.65673
EasternMont	-0.0495687		-4.83602
Northeaster	0.0852155		8.89517
Southern	-0.5037699	***	-39.57516
UpperMidwest	0.0233645		2.36396
GreatLakes	0.0683872	**	7.07798
Northwest	-0.3622356	***	-30.38817
Pacific	-0.6780362	***	-49.23871
Delta	-0.428502	***	-34.85157
NorthernPlains	-0.0626673	**	-6.07441
SouthernPlains	-0.2155388	***	-19.38930
Mountain	-0.1941793		-17.64898
Yield Monitor	0.0256749		2.60073
Moisture Tracker	0.0489957	*	5.02158
GPS	-0.0370089		-3.63324
Ag Leader	0.0624683		6.44607
Auto Steer	0.0756354	***	7.85693
Cons	12.22883		

* $p< 0.10$ ** $p< 0.05$ *** $p< 0.01$

Table 5: John Deere Model Results

John Deere Model	R-Squared		0.9325
Variable	**Coefficient**		**Percent Change**
Hours	-0.0000143	***	-0.00143
Age	-0.1029693	***	-9.78453
Good	-0.2701238	***	-23.67150
Fair	-0.5415081	***	-41.81299
Poor	-1.237214	***	-70.98084
Farm	0.0651848	***	6.73563
Consignment	-0.0974905	***	-9.28890
Online	-0.0701959	***	-6.77888
Sale2016	-0.0094786		-0.94338
Sale2017	0.0592791	***	6.10713
Sale2018	0.030557	*	3.10287
Summer	-0.0153339		-1.52169
Fall	-0.0722429	***	-6.96951
Winter	0.0068024		0.68256
Canada	0.0782762	***	8.14213
EasternMont	-0.0769487		-7.40626
Northeaster	0.0447157		4.57305
Southern	-0.1848611		-16.87803
UpperMidwest	0.0220985		2.23445
GreatLakes	0.0288342		2.92539
Northwest	-0.4407807	***	-35.64662
Pacific	-1.160217	***	-68.65818
Delta	-0.1258236	***	-11.82296
NorthernPlains	-0.0498146	***	-4.85942
SouthernPlains	-0.1414357	***	-13.18890
Mountain	-0.0562939		-5.47387
Yield Monitor	0.0782483	***	8.13911
Moisture Tracker	0.0073917		0.74191
GPS	-0.0111062		-1.10448
Ag Leader	-0.0168428		-1.67018
Auto Steer	0.03471	**	3.53194
Cons	12.53662		

* p< 0.10 ** p< 0.05 *** p< 0.01

WORK CITED

AGCO brands. AGCO Brands | Challenger | Fendt | Massey Ferguson | Valtra. (n.d.). Retrieved January 2, 2022, from https://www.agcocorp.com/brands.html

Ag Service Finder. Posted March 17, 2020 by A. S. F. 2020, November 25. "Combine Harvester Cost: Today's Used Combine Prices." https://www.agservicefinder.com/combine-cost/

Agrotechnomarket.com. 2019, January 2. "List of The Latest Combine Harvester Price from Various Manufacturers." World Agriculture. https://www.agrotechnomarket.com/2019/01/combine-harvester-price.html.

Allison, John T. Jr. 2019."TWO ESSAYS ON INPUT SUBSTITUTION AND OPTIMAL DECISION MAKING IN CROP AND LIVESTOCK PRODUCTION SYSTEMS". *Theses and Dissertations--Agricultural Economics*. 80

Borchers, A., Ifft, J., & Kuethe, T. 2014. "Linking the price of agricultural land to use values and amenities." *American journal of agricultural economics*, *96*(5), 1307-1320.

Boyce, D. S., & Rutherford, I. 1972. "A deterministic combine harvester cost model." *Journal of agricultural engineering research*, *17*(3), 261-270.

Cross, T.L., and G.M. Perry. 1995. "Depreciation Patterns for Agricultural Machinery." *American Journal of Agricultural Economics* 77(1): 194-204.

De Toro, A., Gunnarsson, C., Lundin, G., & Jonsson, N. 2012. "Cereal harvesting–strategies and costs under variable weather conditions." *Biosystems engineering*, *111*(4), 429-439.

Diekmann, F., Roe, B. E., & Batte, M. T. 2008. "Tractors on eBay: Differences between internet and in-person auctions." *American Journal of Agricultural Economics*, *90*(2), 306–320. https://doi.org/10.1111/j.1467-8276.2007.01113.x

Dodson, Don. 2019, June 25. "How much is that combine in the window? Gazette." https://www.news-gazette.com/news/how-much-is-that-combine-in-the-window/article_01a8f117-72b2-54d1-9dae-b3152063f8c0.html

Edwards, William M. and Hanna, H. Mark. 2009. "Ag Decision Maker: Combine Ownership or Custom Hire". *Agriculture and Environment Extension Publications*. 111

Edwards, W. M. 2011. "Grain harvesting equipment and labor in Iowa." Iowa State University, Department of Economics.

Ellis, Robert and Tyler Mark. 2022. "Utilizing Auction Sale Data to Estimate the Value of Used Combine Harvesters in the US and Canada". *Southern Association of Agricultural Scientists*

Ellis, S. 2021, January 14. "Different Types of Combine Harvester: How Much They Cost. Farm & Animals." https://farmandanimals.com/different-types-of-combine-harvester/.

Fettig, L. 1963. "Adjusting Farm Tractor Prices for Quality Changes, 1950-1962." Journal of Farm Economics 45(3): 599-611.

Golovkov, A., Moskovskiy, M., & Khamuev, V. 2019. "Justification of the type of combine harvester for farms." In *E3S Web of Conferences* (Vol. 126, p. 00029). EDP Sciences.

Ibendahl, Gregg. 2015. “The Effects of Machinery Costs on Net Farm Income.” Journal of ASFMRA, pp. 113–123. JSTOR, www.jstor.org/stable/jasfmra.2015.113. Accessed 17 June 2021.

Kavka, M., Mimra, M., & Kumhála, F. 2016. “Sensitivity analysis of key operating parameters of combine harvesters.” *Research in Agricultural Engineering,* 62(No. 3), 113–121. https://doi.org/10.17221/48/2015-rae

Lattz, D. and G. Schnitkey. 2019. "Machinery Cost Estimates for 2019." farmdoc daily (9):144, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, August 6, 2019.

LeBlanc, M., and J. Hrubovcak. 1985. “The Effects of Interest Rates on Agricultural Machinery Investment.” Agricultural Economics Research 37(3): 11. Machinery Pete. 2018. “Auction Price Data”. Retrieved from https://www.machinerypete.com/users/sign_in?path=auction

Masek, J., Novak, P., & Pavlicek, T. 2015. Evaluation of combine harvester fuel consumption and operation costs. In *14th International Scientific Conference Engineering for Rural Development Proceedings* (Vol. 14, pp. 78-83).

Mimra, M., & Kavka, M. 2017. “Risk analysis regarding a minimum annual utilization of combine harvesters in agricultural companies.”

Mimra, M., Miroslav, K., & Frantisek, K. 2017. “Risk analysis of the business profitability in agricultural companies using combine harvesters.” *Research in Agricultural Engineering*, *63*(3), 99-105.

Miranowski, J. A., & Hammes, B. D. 1984. “Implicit prices of soil characteristics for farmland in Iowa.” *American journal of agricultural economics*, *66*(5), 745-749.

Modern Combine Harvester Market: 2021 Business Size, Increasing Demand Status, Covid-19 Impact on Global Business Efficiencies, Top Companies Outlook with Growth Share till 2026. rfdtv.com. (n.d.). https://www.rfdtv.com/story/43103378/modern-combine-harvester-market-2021-business-size-increasing-demand-status-covid-19-impact-on-global-business-efficiencies-top-companies-outlook.

More, Ajay. 2021. “Combine Harvester Market Insight 2021, latest trend, technology, target audience, key challenges, competition and forecast to 2027.” CENTRAL. Retrieved January 14, 2022, from https://central.newschannelnebraska.com/story/44477569/combine-harvester-market-insight-2021-latest-trend-technology-target-audience-key-challenges-competition-and-forecast-to-2027

Morning Ag Clips. 2020, September 2. “Cost management: Harvest operations.” https://www.morningagclips.com/cost-management-harvest-operations/.

Muratova, E., Muratov, D., Makarenko, E., Shepelev, S., Korobeynikova, O., Chegge, V., & Kabanova, Y. 2020. “Methodology of grain heap quantity and structure determination and economic evaluation of Harvester-Thresher Cleaning Enhancement.” *E3S Web of Conferences, 175,* 01009. https://doi.org/10.1051/e3sconf/202017501009

Olt, J., Küüt, K., Ilves, R., & Küüt, A. 2019. “Assessment of the harvesting costs of different combine harvester fleets.” *Research in Agricultural Engineering*, *65*(1), 25-32.

Perrigne, I., & Vuong, Q. 2019. “Econometrics of auctions and nonlinear pricing.” *Annual Review of Economics*, *11*(1), 27–54. https://doi.org/10.1146/annurev-economics-080218-025702

Prístavka, M., Krištof, K., & Findura, P. 2017. “Reliability monitoring of grain harvester.” *Agronomy Research*, *15*(3), 817-829.

Rogovskii, I. L., Voinash, S. A., Sokolova, V. A., & Krivonogova, A. S. 2021, March. “Research on Fuel Consumption for Different Values of Capacity Factor of Engine of Combine Harvester.” In *IOP Conference Series: Earth and Environmental Science* (Vol. 666, No. 3, p. 032093). IOP Publishing.

Rosen, S. 1974. “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition.” Journal of Political Economy 82(1): 34-55.

Seymour, C. 2019, December 13. *What's the lifespan of a typical combine?* Farm Equipment. Retrieved January 14, 2022, from https://www.farm-equipment.com/blogs/6-opinions-columns/post/17735-whats-the-lifespan-of-a-typical-combine

Swanson, K., Schnitkey, G., Paulson, N., Coppess, J., & Zulauf, C. 2020, September 4. “Cost Management: Harvest Operations.” *farmdoc daily*. https://farmdocdaily.illinois.edu/2020/09/cost-management-harvest-operations.html

U.S. Department of Agriculture. 2021. *Prices Received: Corn Prices Received by Month, US*. USDA. Retrieved January 10, 2022, from https://www.nass.usda.gov/Charts_and_Maps/Agricultural_Prices/pricecn.php

U.S. Department of Agriculture. 2021. *Statistics by State*. USDA. Retrieved January 2, 2022, from https://www.nass.usda.gov/Statistics_by_State/RFO/index.php

Vasylieva, N., & Pugach, A. 2017. Economic assessment of technical maintenance in grain production of Ukrainian agriculture.

Vinevsky, E. I., Papusha, V. K., & Nikitenko, N. A. 2020. Assessment of the competitiveness of domestic and foreign combine harvesters. In *E3S Web of Conferences* (Vol. 193, p. 01027). EDP Sciences.

Wehrspann, J. 1999, July 1. “Combine buying: can you justify?” Farm Progress. Retrieved January 14, 2022, from https://www.farmprogress.com/print/163820

Yezekyan, T., Marinello, F., Armentano, G., Trestini, S., & Sartori, L. 2020. Modelling of harvesting machines’ technical parameters and prices. *Agriculture*, *10*(6), 194.

Ziel, F., & Steinert, R. 2016. Electricity price forecasting using sale and purchase curves: The X-Model. *Energy Economics*, *59*, 435–454. https://doi.org/10.1016/j.eneco.2016.08.008