# MODELING ANNUAL AND QUARTERLY U.S. FARM TRACTOR SALES

by

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# ABSTRACT

Farm machinery is a vital input for production agriculture and, as a result, is a significant part of the agricultural economy. Despite its great importance, there has been relatively little academic analysis on the driving forces behind farm machinery sales over the past several decades. The studies that do evaluate farm machinery sales all do so regarding annual sales despite shorter-term sales data being available. These previous studies primarily use traditional macroeconomic variables, tailored to the agricultural industry, to explain farm machinery sales. Recently, with the creation of the *Ag Economy Barometer Survey* in October 2015, farmer sentiment data is being collected. Studies using consumer sentiment data to evaluate consumer demand have found sentiment data useful when including it in demand models, especially for consumer durable goods.

This study evaluates farm machinery sales, specifically two-wheel-drive tractors with 100 horsepower or higher, using both traditional macroeconomic variables and farmer sentiment data. The evaluation begins by looking at annual tractor sales from 1978 to 2019 using machinery prices, prices received for outputs, prices paid for inputs, lagged net farm income, interest rates for loans specifically for farm machinery, farm assets, and the number of acres harvested. The annual models are used to derive elasticities with respect to farm tractor sales, and the quantity demanded is most responsive to changes in machinery prices, the number of acres harvested, prices received for crops and livestock, and the level of farm assets. Out-of-sample estimations aids in evaluating the forecasting power of the models with the best statistical fit. The model with the best out-of-sample performance forecasts 2020 sales of farm tractors with 100 HP and above using various assumptions for agricultural economic conditions in 2020. The model estimates a record low in tractor sales dating back to 1978.

The annual models are then re-estimated using quarterly data spanning from 2009 to 2019. The quarterly models have less statistical fit than their annual counterparts. This reduced model performance is likely due to the seasonal nature of farm tractor sales and that some of the explanatory variables are only updated on an annual basis, limiting their ability to capture the seasonal variations. Finally, the quarterly models are estimated again to include farmer sentiment data. At the time of the study, only 17 quarterly observations of farmer sentiment data had been collected, significantly limiting the evaluation. The limited number of observations results in an inconclusive outcome regarding the explanatory power of farmer sentiment data.

# CHAPTER 1. INTRODUCTION

Economic conditions in the production agriculture industry influence when farmers make investments and how much they invest. Farm machinery is a significant investment for most farms. This analysis investigates the broad agricultural economic conditions that drive farm machinery investment.

## 1.1 Motivation

American farmers invested $11.3 billion in farm machinery in 2018 (USDA National Agricultural Statistics Service, 2020). In the same year, the average American farm had a market value of $582,101 in farm machinery assets, accounting for 18.5% of total farm assets, making machinery the second-largest asset category behind farmland (FINBIN, 2020). Understanding which, and to what extent, macroeconomic factors influence farm machinery demand provides a foundation for building farm machinery demand models. A better understanding of farm machinery demand might assist farm machinery manufacturers in forecasting production and sales.

Previous literature provides insights into the macroeconomic forces driving farm machinery investment. However, there are several gaps in this genre of academic research. The relevant studies date back to the 1920s, but there are a relatively small number of papers published in the decades following and only two published in the past two decades. There is a need for updated farm machinery demand analysis as recent years have seen a significant change in production agriculture. Additionally, all previous studies focus solely on annual machinery sales despite data on quarterly sales being available.

Previous studies use standard macroeconomic measures for the production agriculture industry, such as net farm income, machinery prices, total farm assets, input prices, and output prices, to model farm machinery demand. However, no prior studies use an explicit measure of farmer sentiment data as an explanatory variable. The absence of sentiment data in the literature is because no measure of farmers' sentiment existed until the *Purdue University-CME Group's Ag Economy Barometer Survey* began in 2015. Some studies evaluating demand in the consumer sector find improvement in model performance from including consumer sentiment. This study takes a first step towards learning how farmer sentiment data impacts farm machinery demand.

## 1.2 Objective and Organization

This thesis has the objective of analyzing farm machinery demand on both an annual and quarterly timeframe. Several steps encapsulate this analysis. First, this study reviews previous literature to provide a foundation for analyzing farm machinery demand and developing farm machinery demand models. These model estimations will shine light into which economic conditions influence farm machinery sales. Elasticity estimates from these models help assess how changes in economic conditions impact demand. The next step in evaluating model performance is to provide out-of-sample estimations for the years 2015 to 2019. Finally, farm tractor sales forecast for 2020 using several scenarios are provided.

Currently, incorporation of farm sentiment data is limited in annual models due to only four annual observations of farmer sentiment existing; but, estimating quarterly demand models provides a larger number of sentiment observations. The annual farm machinery demand models are re-estimated with quarterly data in order to incorporate sentiment data. Elasticities are estimated once again and compared to the elasticities calculated from the annual models. The analysis ends with an evaluation of the quarterly models' performance with the inclusion of farmer sentiment data.

Six chapters comprise this thesis. The next section, chapter 2, covers a literature review on farm machinery demand and investment, as well as a review of literature on sentiment data. Chapter 3 provides the methodology used in this study. A discussion of the data used to execute the roadmap discussed in the methodology chapter follows in chapter 4. Chapter 5 comprises of findings from the methodology and data presented in chapters 3 and 4. Lastly, a summary of the study's results comes in chapter 6.

# CHAPTER 2. LITERATURE REVIEW

This chapter contains a review of studies evaluating farm machinery demand and studies using consumer sentiment data in forecasting models. The literature on farm machinery demand is surprisingly sparse, with fewer than a dozen relevant studies dating back to the 1920s found. These studies are summarized first, followed by an overview of the literature assessing consumer sentiment data.

## 2.1 Farm Machinery Demand

Businesses make investments when they deem the money used today will increase their income in the future. Farmers must make this decision in regards to many inputs, and especially for machinery investment. Being a vital input for the production agriculture industry, economists have attempted to build forecasting models for the demand for farm machinery for decades. One of the earliest attempts was “Forecasting Farm Tractor Sales in North Dakota,” published in 1929 by O.S. Powell in the *Journal of the American Statistical Association*. This non-parametric analysis uses a simple linear model. This model includes the variables the price of wheat, deposit-loan ratio, and a straight-line trend based on the previous five year’s tractor sales to explain an anonymous company’s sales of farm tractors in North Dakota (Powell, 1929). The study only uses simple graphs, seemingly drawn by hand, to show the results without reporting any econometric models. Figure 1 provides an example of one of the hand-drawn graphs. Over the years, forecasting models have become more complex, with the application of various econometric methodologies.

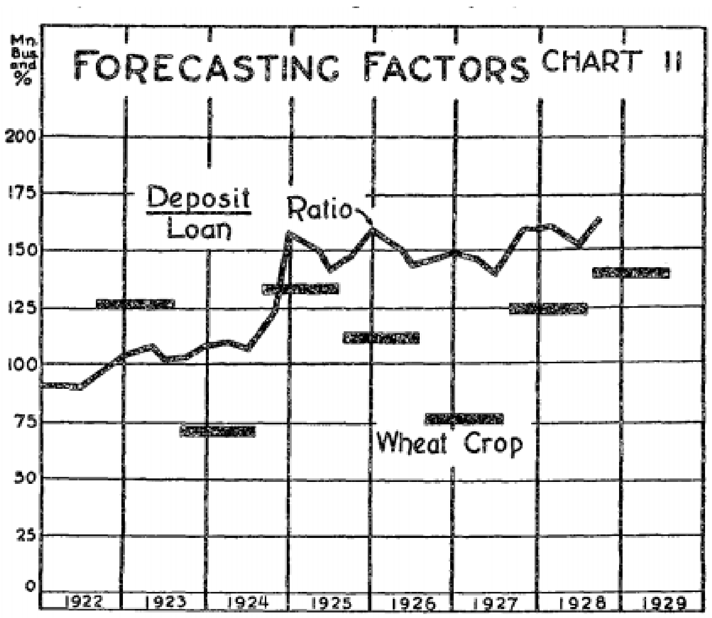

Figure 1: Forecasting Factors for Farm Machinery Demand (Powell, 1929)

Three decades after the 1929 article, forecasting tractor sales still had not been studied extensively. Michigan State University's William A. Cromarty, published "The Farm Demand for Tractors, Machinery and Trucks" in the *Journal of Farm Economics* (1959). He opens his paper by saying, "one of the neglected areas in agricultural demand analysis has been the demand by farmers for inputs produced by non-farmers." In this paper, Cromarty attempts to shine some light on this category by building models to explain annual sales of all farm machinery, tractors, and farm trucks from 1923-1954.

This study uses both an ordinary least squares regression model and a maximum likelihood, limited information estimates model. For all farm machinery, the dependent variable is "the quantity of machinery purchased by farmers" ($Y_1$). Cromarty derives this dependent variable by dividing the value of manufacturers' farm machinery sales by the wholesale farm machinery price index. The former is an estimate from the Agricultural Marketing Service, and the latter is an estimate from the Bureau of Labor Statistics. The derived dependent variable seems to be a limitation of Cromarty's study. Calculating farm machinery sales in this manner creates increased opportunity for error. This method also encompasses all sizes and types of farm machinery, which could have different demand forces driving their sales. Equation 2.1 shows Cromarty's regression model.

$$Y_1 = 2{,}397{,}952 - \underset{(450.0)}{702.5Y_6} + \underset{(255.4)}{235.8Z_2} - \underset{(257.0)}{1206.3Z_3} + \underset{(46.3)}{28.8Z_4} + \underset{(4.1)}{15.6Z_5} + \underset{(22.4)}{38.6Z_6} + \underset{(2549.6)}{1232.9Z_7} - \underset{(126.5)}{433.0Z_9} \quad (2.1)$$

The explanatory variables include the wholesale price index ($Y_6$), an index of crop and livestock prices received by farmers ($Z_2$), an index of prices of production items, excluding labor ($Z_3$), farm machinery value on farms at the beginning of each year divided by the machinery wholesale price level ($Z_4$), farm assets at the beginning of each year ($Z_5$), one-year lagged net farm income ($Z_6$), average acreage per farm ($Z_7$) and an index of farm labor costs ($Z_9$), with all monetary variables deflated by the general price level. Cromarty does not define exactly what he means by the general price level.

This estimation results in an adjusted $R^2$-value of 0.95, and the most insightful variables are machinery prices, farm prices, farm assets, and lagged farm income. When Cromarty evaluates the elasticity estimates, he finds that a 10% fall in machinery purchases followed a 10% increase in machinery prices. A 10% rise in farm prices results in a 7% rise in purchases. Farm asset values rising 10% see a 6% increase in purchases. Similarly, he finds that a 5% rise in purchases is associated with a 10% increase in lagged net farm income. The value of farm machinery already on farms and labor costs seem to have little impact (Cromarty, 1959).

The maximum likelihood, limited information estimates model uses the "value of domestic farm machinery shipments deflated by a retail price index for farm machinery" ($Y_1$) as the dependent variable. The explanatory variables include a farm machinery price index deflated by a wholesale price index for all commodities ($Y_6$), a ratio of prices received to prices paid by farmers ($Z_1$), farmers' assets held at the beginning of each year ($Z_2$), an index of industrial wage rates ($Z_4$), and government price-support programs ($Z_5$). This model finds that the price elasticity of demand is higher at the retail level than at the wholesale level, with elasticities of 2.5 and 1.0, respectively. Farm assets have an elasticity of 0.4, according to this model. Interestingly, the ratio of prices received and prices paid by farmers has a negative coefficient. Equation 2.2 shows this model.

$$Y_1 = 24{,}970 - \underset{(10.0)}{20.76Y_6} - \underset{(10.2)}{8.60Z_1} + \underset{(0.20)}{0.27Z_2} + \underset{(4.4)}{8.96Z_4} + \underset{(391.7)}{512.83Z_5} \quad (2.2)$$

To estimate tractor demand, Cromarty uses manufacturers' shipments of wheel-type tractors for domestic farm use as the dependent variable ($Y_1$). Equation 2.3 provides this regression equation.

$$\underset{}{Y_1 = 2210.69 - \underset{(.864)}{1.689Y_{2/x1}} + \underset{(.058)}{0.092X_2} + \underset{(.389)}{1.434X_3} - \underset{(.195)}{0.990X_9}} \quad (2.3)$$

The explanatory variables are the ratio of the index of retail prices for farm tractors to prices received by farmers ($Y_{2/x1}$), net cash receipts received by farmers lagged one year ($X_2$), the number of tractors on farms as an eight-year weighted average ($X_3$), and the average tractor sales for the previous five and six years ($X_9$). Analysis of the residuals reveals a rough five-year peak-to-trough cycle, leading Cromarty to include this $X_9$ in this model (1959). The paper provides no additional details on this variable. This OLS regression results in an adjusted $R^2$ of 0.78.

This study finds that during times of contraction, lagged net farm income explains machinery purchases better than during times of expansion. The author argues that this indicates that farmers will reduce spending faster during times of trouble than the speed at which they increase spending during economic prosperity. The model does overestimate tractor sales for 1957 and 1958, and the author reasons that this is due to the increased demand for horsepower during this time instead of farms demanding an increased number of smaller tractors (Cromarty, 1959).

Rayner and Cowling, both economists at English universities, reiterates the stance that the demand for tractors in the United States is driven more by the need for additional horsepower than replacement tractors in their paper "Demand for Farm Tractors in the United States and the United Kingdom" (1968). This study evaluates driving forces behind the number of tractors shipped from the manufacturers and the amount of horsepower purchased in the United States and the United Kingdom from the years 1947-1962.

According to Rayner and Cowling, the best explanation for the shipment of tractors in the United States ($Y_{1t}$) comes via the weighted lagged average net income of farmers ($w_{t-1}$), one-year lagged average farm acreage ($A_{t-1}$), one-year lagged stock of tractors ($N_{t-1}$), the total number of farms ($F_t$), and the average age of the tractor stock ($Age_t$). This model results in an OLS adjusted $R^2$ of 0.93. Equation 2.4 shows this regression equation.

$$Y_{1t} = -398.4 + \underset{(30.46)}{39.62w_{t-1}} - \underset{(54.20)}{159.13A_{t-1}} + \underset{(48.91)}{124.02N_{t-1}} + \underset{(101.33)}{156.38F_t} + \underset{(60.36)}{124.69Age_t} \quad (2.4)$$

The study also determines that the horsepower investment in the United States ($Y_{2t}$) is best explained by the one-year lag of stock of tractor horsepower ($H_{t-1}$), the current index of crop production ($C_t$), the number of farms ($F_t$), and the average age of the current tractor stock ($Age_t$). The study defines horsepower investment as the current horsepower purchases in millions. However, this model shows a much weaker statistical fit than the number of tractors shipped model with an OLS adjusted $R^2$ of only 0.64. The authors conclude that U.S. investment in tractors is driven mostly by the need to increase horsepower instead of the need to substitute labor. This conclusion aligns with Cromarty (1959). Rayner and Cowling retrieved the U.S. data from the December 1963 edition of the *Federal Reserve Bulletin* and the U.S. Department of Agriculture's *Agricultural Statistics*. Equation 2.5 provides the regression equation.

$$\begin{array}{l} Y_{2t} = -261.0 + \underset{(6.44)}{20.79H_{t-1}} + \underset{(5.20)}{11.54C_t} + \underset{(14.90)}{11.54C_t} + \underset{(14.90)}{52.29F_t} + \underset{(8.30)}{17.22Age_{t-1}} \end{array} \quad (2.5)$$

Gary W. Krutz and D. H. Doster, both from Purdue University, and Jeff Moyer from Harris Bank build forecasting models for farm and industrial tractor demand in "Techniques for Forecasting Farm and Industrial Tractor Sales" (1978). Equation 2.6 provides the regression equation for industrial tractor sales. The study does not provide the $R^2$-value and standard errors. Explanatory variables are all lagged one year and consist of the deflated dollar amount of the GNP that went toward construction with the base year as 1967 (D), an index of construction machinery and equipment prices (C), and total new housing starts (J).

$$IT = 24{,}500 + 562D - 137C + .36J \quad (2.6)$$

The authors state that "no leading indicators for farm tractors were found" and that "because of this, only a causal model was formulated" (Krutz et al., 1978). This model uses farm tractor sales (S) as the dependent variable. The explanatory variables are oat acreage (O), wheat (W) and hog prices (H), the change in durable goods inventory (I), and the number of tractors on farms (T). However, the latter two variables result in a negative correlation with tractor sales despite being statistically significant. Once again, the study provides no standard errors or $R^2$ values. Equation 2.7 lists the regression equation.

$$S = -465{,}000 - 3.3(O) + 1200I + 10{,}350W + 132T + 1830H \quad (2.7)$$

The study also briefly explores how farmers' buying intentions correlate with sales (Krutz et al., 1978). Using Ag-Pulse's Farmers Buying Intention Index, the authors conclude that farmers' buying intentions serve as a two-month leading indicator for sales of tractors with 100 horsepower and above. The authors provide no statistical equations for this result and only spend a brief paragraph in total on this topic.

Nine years later, Krutz and Doster, along with Cho and Jones, publish their forecasting model for combine sales in their paper, "An Expert System for Forecasting Combine Sales in U.S.A." (1987). This paper, published by the Society for Automotive Engineers *Technical Paper Series*, couple an econometric model with a "rule-based expert system." The authors define an expert system as "the collection of programs or computer software that solves problems in a domain of interest," which aims to support human expertise in predictive modeling. The human experts design the rules and assumptions that the computer system, a Texas Instruments' *Personal Consultant Plus*, uses to come to conclusions.

The econometric model is a linear regression equation, using the annual number of combine sales for the years 1975-1986 as the dependent variable. The study uses a stepwise regression procedure to select explanatory variables that show high enough significance to be used for the right-hand side of the equation. After beginning the procedure with twenty-four variables, ten make the final cut. These variables are farm real estate debt ($p_1$), an index of farm real estate values with the base year of 1977 ($p_2$), interest on farm mortgage debt ($p_3$), level of rice export ($p_5$), the prime rate charged by banks ($p_6$), and the prices of corn ($p_4$), wheat ($p_7$), hogs ($p_8$), calves ($p_9$), and soybeans ($p_{10}$). Their system includes the econometric model shown in equation 2.8, as one of its rules. The authors do not provide standard errors.

$$\begin{aligned} Sales \ = \ & -22{,}112.56 + 69.37p_1 + 595.26p_2 - 7260.30p_3 - 4347.58p_4 \\ & + 1{,}650.47p_5 - 2577.43p_6 + 7821.68p_7 + 304.44p_8 - 78.86p_9 \\ & + 1126.13p_{10} \end{aligned} \tag{2.8}$$

The authors' expert system has the goal of modeling sales, mainly whether sales will increase or decrease based on the previous year. This simulation is based on 29 parameters and 52 rules. Parameters for the system consisted of, but are not limited to, acres planted, combine inventory, the price of used combines, cost of living, and various crop and livestock prices. Krutz, Doster, and Kohls act as the domain experts and create approximately half the rules in the system.

Jones, the expert system programmer, creates the remaining rules. An example of a rule is that if wheat prices did not increase, combine sales would not increase in the following year. A certainty value is then assigned to the respective rule. The subframe consisted of 11 data variables and three rules to predict the number of units sold.

The system provides certainty factors for each prediction. These values range from 81% to 100% certainty. The authors state that the expert system can forecast four to six months ahead. The authors argue that combining the econometric model and the expert system provides a more accurate prediction for combine sales than either model individually (1987).

In the December 1988 edition of the *Western Journal of Agricultural Economics*, Cole R. Gustafson, an assistant professor of agricultural economics at North Dakota State University, and two professors at the University of Illinois, Peter J. Barry and Steven T. Sonka, publish "Machinery Investment Decisions: A Simulated Analysis for Cash Grain Farms." This paper analyzes what drives farms to make investments. The study uses information from 78 farms that were included in the Illinois Farm Business Farm Management Association database from 1976 to 1983 that met various requirements such as location, farm type, size, allocation of farm receipts between cash crops and livestock, and had been members.

Eight groups are created by separating the 78 farms based on combinations of high and low levels of tenure positions, leverage ratios, and the age of machinery complements owned by the farm. One farmer from each of these eight groups is selected to take part in the study. However, one farmer had recently retired, reducing the number of farmers to seven. The farmers next "completed a data input form, questionnaire, and attitudinal survey." This information gathering provides insight on past financial performance, attributes specific to the farm and farmer, predictions for upcoming commodity prices, commodity yields, and interest rates, and a ranking of the level of importance farmers assigned to factors that go into their final decisions (Gustafson et al., 1988).

The study then asks farmers to make investment decisions based on their farm situations and under three policy scenarios. These scenarios consist of lower commodity prices, tax code changes, and lower interest rates due to a state-sponsored buydown program. All policy changes, especially tax reform, are found to be relatively unimportant. Farmers rate cash on hand, price of machinery, future farm income potential, and the current age of their machinery as being most relevant to their machinery investment decision. The farmers all voice a desire to limit the variation in their machinery investments over time. However, the variation in investment levels shows that the farmers do not abide by this desire (Gustafson et al., 1988).

The authors determine that the data is to be considered pooled observations due to it having both a cross-sectional and a time-series nature. Dummy variables estimate the fixed effects of the variation in farm characteristics, policy scenarios, and the product of the slope coefficients for the explanatory variables and the explanatory variable itself. The farmer's investment in dollars per acre acts as the dependent variable for this model. The study finds a strong link between high machinery investment and high farmland ownership and that machinery investment has a negative relationship with high leverage.

The authors point out that, overall, the farmers report a pessimistic outlook for the short-term economic future, and having high leverage during rocky times is problematic. Farms with older machinery show higher machinery investment per acre. Financial ratios, the current ratio being the exception, showed statistical significance. The three policy scenarios, lower commodity prices, tax code changes, and a state-sponsored buydown program, which would reduce interest rates, all show little to no impact on investment decisions. The authors argue that this is indicative of machinery investment being need-based (Gustafson et al., 1988).

Biondi, Monarca, and Panaro, all associated with the Instituto di Genio Rurale in Viterbo, Italy, attempt to build forecasting models for tractor demand for the countries of Italy, France, and the United States. The authors publish their results in The *Journal of Agricultural Engineering Research*, under the title "Simple Forecasting Models for Farm Tractor Demand in Italy, France and the United States" (1998). The study uses univariate autoregressive integrated moving average models and multivariate OLS models. For both models, the annual number of tractors sold is the dependent variable due to a lack of data on monetary expenditures available in Italy and France.

The multivariate model uses the logarithmic value of the one-year lagged real farm income, real tractor prices (indexed), the tractor stock lagged one year, and the dependent variable lagged one year to limit autocorrelation. The monetary variables are deflated by a cost of living index for each country. The authors retrieve the data related to farm income and the cost of living for the United States from the USDA's *Agricultural Statistics*, and data related to tractor purchases from the Equipment Manufacturers Institute. The Equipment Manufacturers Institute merged with the Construction Industry Manufacturers Association in 2002 to become the Association of Equipment

Manufacturers (Association of Equipment Manufacturers, n.d.). The Association of Equipment Manufacturers is the source of the farm machinery sales data used in this thesis.

The dependent variable undergoes a logarithmic transformation in the univariate model. This univariate model is an autoregressive integrated moving average (ARIMA) model. Based on the standard error, an ARIMA(1,1,1)$(1,0,0)_6$ model is the best model for Italy. This model results in an $R^2$ of 0.944, a standard error of 0.0710, and a Durbin-Watson test of 2.24. France's best model is an ARIMA(1,1,4) and has results of an $R^2$ of 0.901, a standard error of 0.1204, and a Durbin-Watson test of 1.86. The United States model has an $R^2$ of 0.886, a standard error of 0.0970, and a Durbin-Watson test of 1.57 from an ARIMA(1,1,1)$(1,0,0)_5$ model. The ARIMA models show greater statistical validity for the United States and Italy than the multivariate model (Biondi et al., 1998).

While the multivariate models, which are dynamic regressions, perform similarly to the univariate models for the United States and Italy, they still show intriguing results. Italy's multivariate model has an $R^2$ of 0.979, a standard error of 0.0708, and a Durbin-Watson test of 1.6. The models for France and the United States have $R^2$-values of 0.955 and 0.801, standard errors of 0.0818 and 0.1298, and Durbin-Watson tests of 1.6 and 1.8, respectively. The real tractor price variable is not statistically significant at the 5% level for the Italy and France models and thus, omitted. For the United States, the lagged net farm income variable is statistically insignificant and omitted. The authors hypothesize that the lack of statistical significance is due to the United States having already met a saturation point for tractor demand. In contrast, tractor use for France and Italy is a more recent development. Thus, at the time of the study, the two European countries seem to be still catching up to the United States (Biondi et al., 1998).

At the 2004 Agricultural Economics Association's annual meeting, Micheels, Katchova, and Barry, all from the Department of Agricultural Economics at the University of Illinois, presented their paper, "Machinery Investment in Illinois: A Study Examining Existing Investment Motivations." This paper explores how technological developments and the emotional desire to "keep up with the Joneses" impacted machinery investment (Micheels et al., 2004). The study uses data from the Illinois Farm Business Farm Management database for all variables. The authors restrict their sample to grain farms in the database from 1995-2002 for at least two consecutive years. Eligible farms have revenues that exceeded $40,000. Two models are estimated, a technology model and an emotional model. The technology model aims to capture the impact of past investment decisions on future purchases. The emotional model attempts to capture how factors that are not measured by a financial statement, such as wanting to maintain one's social appearance, impact machinery investment. The emotional model seems to be an early attempt to measure a form of farmer sentiment before data on farmer sentiment was available.

Each model consists of two equations. For the emotional model, equation 2.9 uses cash purchases of machinery (CP) as the dependent variable, and equation 2.10 uses machinery purchased per acre (MPA). Each equation for this model uses cash flow (CF) to garner a flow measure, return-on-equity (ROE) to capture profitability, debt-to-asset (dta) to measure leverage, operator age (age), and farm acreage (ac) as explanatory variables. The CP equation also uses the mean county machinery purchases (CO), its lag ($CO_{t-1}$), and the one-year lagged the cash flow ($CF_{t-1}$). The MPA equation uses a per acre version of mean county machinery purchases (MMPA). Equations 2.9 and 2.10 provide the emotional models.

$$\begin{aligned} CP \;=\; & \underset{(4.25)}{7746.82} - \underset{(31.61)}{0.967CO} + \underset{(0.17)}{0.005CO_{t-1}} - \underset{(1.74)}{0.009CF_{t-1}} + \underset{(0.05)}{0.04ROE} + \underset{(4.23)}{57.843dta} \\ & - \underset{(-9.23)}{260.710age} + \underset{(20.97)}{6.805ac} \end{aligned} \tag{2.9}$$

$$\begin{aligned} MPA \;=\; & \underset{(-2.82)}{31.624} + \underset{(12.67)}{1.327MMPA} - \underset{(-0.92)}{0.00002958CF} - \underset{(-0.09)}{0.0004843ROE} + \underset{(2.40)}{0.192dta} \\ & - \underset{(-4.03)}{4.02age} - \underset{(-2.89)}{0.007ac} \end{aligned} \tag{2.10}$$

The technology model also uses cash purchases of machinery as a dependent variable in equation 2.11. It contains the same variables as the emotional model, but substitutes the county level purchases for a one-year lag of cash purchases ($CP_{t-1}$) and adds the age of machinery (mage). The age of machinery is estimated by dividing the dollar amount of repairs by the total value of the machinery. The second equation for the technological model, equation 2.12, uses net cash purchases of machinery (NCP) as the dependent variable. The explanatory variables are the same as the first technological equation, but the one-year lag of net cash purchases ($NCP_{t-1}$) replaces lagged cash purchases. Equations 2.11 and 2.12 lists the technology models.

$$\begin{aligned} CP \;=\; & 20{,}473 \;+\; 0.331CP_{t-1} + 0.011CF_{t-1} - 0.341ROE - 198.386age \\ & (11.68) \qquad (33.57) \qquad\quad (2.02) \qquad\quad (-0.45) \qquad (-6.89) \\ & + 53.749dta - 1.243mage + \; 5.733ac \\ & \quad (3.66) \qquad\quad (-0.98) \qquad (17.14) \end{aligned} \tag{2.11}$$

$$\begin{aligned} NCP \;=\; & 21{,}166 \;+\; 0.303NCP_{t-1} + 0.013CF_{t-1} - 0.250ROE - 218.375age \\ & (12.18) \qquad (30.20) \qquad\quad (2.35) \qquad\quad (-0.33) \qquad (-7.65) \\ & + 43.168dta - 1.201mage + \; 5.602ac \\ & \quad (2.97) \qquad\quad (-0.95) \qquad (16.92) \end{aligned} \tag{2.12}$$

The first emotional model, equation 2.9, implies a large difference between the impact of current year purchases and the lagged purchases variables. The former has a coefficient of 0.967, whereas the latter has a coefficient of nearly zero. The authors argue that this gives credence to the "keeping up with the Joneses" theory as a one-year delay in the purchase removes impulse purchasing (Micheels et al., 2004). Lagged cash flow is also statistically significant for this regression. The second emotional model, equation 2.10, indicates that mean county purchases per acre is statistically significant.

Interestingly, the acreage variable has a negative coefficient for the per acre regression. The authors state that this indicates smaller farms are spending more on machinery than needed to "keep up" with the larger farms nearby (Micheels et al., 2004). Equation 2.9 has an $R^2$-value of 0.1707, and equation 2.10 has an $R^2$-value of 0.0128. For the technological models, the age of machinery shows no statistical significance. Equation 2.11 has an $R^2$ of 0.1610, and equation 2.12 has an $R^2$ of 0.1413. Debt-to-assets, age of the operator, and acreage are significant for all four regressions.

*Biosystems Engineering* published Unakitana and Akdemirb's paper "Tractor Demand Projection in Turkey" (2007). This study forecasts Turkish tractor demand using a Box-Jenkins ARIMA(2,2,2) univariate model. The authors use the Food and Agricultural Organization's estimation of the Turkish tractor stock from 1961-2003 and find both the first and second differences of tractor stock are stationary, tested by a Dickey-Fuller unit-root test. The model uses the tractor stock lagged by both one-year and two-years, the moving average lagged by two years, and a time trend as the explanatory variables. This model results in an $R^2$ term of 0.91 and an F-statistic of 84.99. Their model suggests that tractor demand will continue to rise, but at a slower pace than in the past (Unakıtan & Akdemir, 2007).

As covered above, farm machinery demand models tend to rely heavily on traditional macroeconomic and financial statement variables. Each study uses a different combination of variables and various modeling techniques. What is universal across these studies, however, is that none of them provides an analysis of how an actual measure of farmer sentiment impacts economic models focused on the production agriculture industry. This omission is in contrast to other industries that have used the University of Michigan's Survey of Consumers (MCS) to utilize sentiment in forecasting models.

## 2.2 Consumer Sentiment

Mueller's 1963 paper, "Ten Years of Consumer Attitude Surveys: Their Forecasting Record," explores the explanatory power of consumer sentiment concerning new car sales. This study uses variables such as the University of Michigan's *Index of Consumer Attitudes* (which later became the *Index of Consumer Sentiment*), new car prices, current income relative to the highest level of past income, and unemployment rate. Consumer sentiment routinely adds forecasting value to equations using various combinations of explanatory variables over the ten-year life of the index (Mueller, 1963).

Seven years later, the paper "Consumer Durable Spending: Explanation and Prediction" also found that consumer sentiment can add accuracy to automobile spending forecasting models (Hymans et al., 1970). This study uses several lagged economic variables to forecast automobile spending. These variables include one quarter lagged real disposable personal income, net of transfers ($DYKTR_{-1}$), the one-quarter lagged unemployment rate for males twenty years old or older ($UM_{-1}$), the one-quarter lagged actual auto stock ($KA_{-1}$), the implicit auto price deflator divided by the implicit price deflator for personal consumer expenditures (AUTOD/PCED), the one-quarter lagged change in consumer sentiment ($EICS_{-1}$). The model contains a variable accounting for strikes against significant players of the auto industry in the 1960s (STRIKE). AUTOD and PCED both have the base year of 1958. The dependent variable is the portion of the national income accounts spent by consumers on autos and parts, deflated to 1958 dollars, and seasonally adjusted at annual rates (CARK). Equation 2.13 shows the model's coefficients and standard errors.

$$\begin{aligned} CARK \;=\; & \underset{(2.08)}{22.841} + \underset{(8.01)}{0.195 DYKTR_{-1}} - \underset{(-3.44)}{0.758 UM_{-1}} - \underset{(-5.45)}{0.147 KA_{-1}} - \underset{(-6.82)}{28.366\left(\frac{AUTOD}{PED}\right)} \\ & + \underset{(1.35)}{0.065 EICS} + \underset{(13.87)}{1.674 STRIKE} \end{aligned} \tag{2.13}$$

Consumer sentiment did improve forecasting accuracy to the model, but it is the weakest of the variables included in the model. Overall, this model results in an $R^2$ of 0.958, a standard error of 1.175, and a Durbin-Watson test of 1.82. However, when the study applies a filtration system to capture meaningful changes in consumer sentiment, it proves to be much more reliable (Hymans et al., 1970).

This filtration system creates a new variable, called *J*, which takes on specific values depending on how the *Survey of Consumers Index of Consumer Sentiment* (ICS) changes over two or three quarters. *J* takes the value of the average of $\Delta ICS_{-1}$ and $\Delta ICS_{-2}$ if $\Delta ICS_{-1}$, $\Delta ICS_{-2}$, and $\Delta ICS_{-3}$ all moved in the same direction or if the absolute value sum of $\Delta ICS_{-1}$ and $\Delta ICS_{-2}$ is greater than or equal to seven. When *J* satisfies neither condition, it is assigned a value of zero. Equation 2.14 provides the regression equation.

$$\begin{aligned} CARK \;=\; & \underset{(3.71)}{23.071} + \underset{(7.69)}{0.171 DYKTR_{-1}} - \underset{(-4.02)}{0.767 UM_{-1}} - \underset{(-4.78)}{0.117 KA_{-1}} - \underset{(-4.98)}{27.867\left(\frac{AUTOD}{PED}\right)} \\ & + \underset{(3.85)}{0.297 J} + \underset{(4.44)}{1.732 STRIKE} \end{aligned} \tag{2.14}$$

When *J* replaces the change in consumer sentiment variable, the model has an $R^2$ of 0.965, a standard error of 1.062, and a Durbin-Watson test of 1.88. The coefficient for *J* is 0.297, much higher than the 0.065 parameter estimate for the non-filtered consumer sentiment variable. The income and price elasticities for both equations are very similar in both the long and short-run (Hymans et al., 1970).

C. Alan Garner, a senior economist at the Federal Reserve Bank of Kansas City, evaluates whether economists should consider sentiment surveys when forecasting consumer spending in his paper, "Forecasting Consumer Spending: Should Economists Pay Attention to Consumer

Confidence Surveys" (1991). The ICS and the *Conference Board's Indexes of Consumer Confidence* (ICC) are the sentiment surveys used. He determines that sentiment indexes did not act as sufficient forecasting tools for determining future consumer consumption by themselves. The author reaches this conclusion by graphing the percent change of durable goods sold from twelve months before against both indexes from 1978 to 1991. Garner calculates the correlation coefficients for the sentiment indexes and durable goods purchases. The ICS has a correlation coefficient of 0.12 when no lag is in place. This coefficient drops to 0.03 when lagged for six months. The ICC scores a negative coefficient when lagged four, five, and six months. None of the scores are statistically significant at the 5% level (Garner, 1991).

The study next examines whether consumer sentiment adds forecasting value when used alongside other macroeconomic variables. Garner regresses the changes in durable goods purchases against past changes in durable goods purchases and past sentiment index values. Both indexes show statistical significance at the 5% level with F-statistics of 2.55 for the ICC and 2.86 for the ICS. Next, economic measures such as past values of real disposable income, unemployment rate, and the consumer price index are included instead of past durable goods purchases. These equations are not statistically significant at the 5% level. This result suggests that consumer sentiment adds little forecasting power when paired with other macroeconomic variables (Garner, 1991).

Garner then evaluates how well the ICS and the ICC anticipate consumption during abnormal times. The study finds that the indexes do not add much value during economic shocks, such as the stock market collapse of 1987. However, during non-economic shocks, such as the Persian Gulf Crisis in the early 1990s, the models that include consumer sentiment more accurately forecast consumer spending than models that omitted it. The author uses three Bayesian vector autoregressive models (BVAR) to determine their forecasting power during the Persian Gulf Crisis, one for the ICS, one for the ICC, and one that did not include either. All BVARs has explanatory variables of real purchases of durable goods, real non-durable goods and services purchases, the S&P 500, the unemployment rate, real disposable income, the imported crude oil price, the Consumer Price Index (CPI), and six-month commercial paper rate. During ordinary times, the equations which included the ICS and ICC reduced the forecasts' accuracy (Garner, 1991).

Conversely, incorporating the indexes make the forecasts more accurate when durable goods purchases fell dramatically during the Persian Gulf crisis. None of the models foresee the decrease in purchasing. The models that include the consumer confidence indexes are only slightly better than those that omitted it. The author proposes that a potential reason for this is that economic events have at least some predictability, and that unforeseeable, non-economic shocks result in a quick change in consumer confidence (Garner, 1991).

"Using Attitude Data to Forecast Housing Activity" evaluates the predictive power of sentiment surveys in regards to housing sales (Goodman, 1994). This study is published in *The Journal of Real Estate Research* and uses data from surveys that interview consumers, builders, and lenders on their outlook for home sales. The studies use these attitude variables, lagged housing market activity, and the average interest rate on fixed-rate mortgages to forecast future housing sales. The study finds that only the builders' survey showed explanatory power, while the other surveys add little to no value (Goodman, 1994).

Huth, et al. examine whether the consumer sentiment indexes act as reliable leading indicators for future consumer consumption in their paper "The Indexes of Consumer Sentiment and Confidence: Leading or Misleading Guides to Future Buyer Behavior" (1994). To test their hypothesis, the authors compare how well the indexes reflect the sales of vehicles, other durable goods, non-durable goods, single-family housing starts, and sales and stock market performance. The authors' results show a connection between consumer expectations and durable goods sales (Huth et al., 1994). The ICS provides a useful insight for the future changes in the demand for durable goods. However, the ICC outperforms the ICS as a leading indicator of economic activity such as housing starts, housing sales, and stock market performance. Huth et al. reach this conclusion by using vector autoregressions (VAR) and Granger causality tests ascertained from the VARs. The VARs included variables related to consumer spending, business activity, and business conditions.

Kwan, from The Chinese University of Hong Kong, and Cotsomitis, from Concordia University, investigate how well the MCS, specifically the ICS and the *Index of Consumer Expectations* (ICE), predicts household spending for the United States. Published in the *Southern Economic Journal,* this paper is titled "Can Consumer Attitudes Forecast Household Spending in the United States? Further Evidence from the Michigan Survey of Consumers" (2004). The model consists of a reduced-form equation. The dependent variables consist of four versions of the change in the logarithmic value of consumer spending as the dependent variable: total personal consumption expenditures, durable goods, non-durable goods, and services. Explanatory variables include consumer confidence and a vector of control variables. Consumer confidence variables include the ICS, ICE, and specific questions that comprise the ICS. The control variables consist of "four lags of the dependent variable and four lags of the growth in real labor income." All data is quarterly and begins in the first quarter of 1960 and ends in the second quarter of 2002.

First, the Kwan and Cotsomitis omit the control vector to determine if the confidence variable can provide quality forecasting on its own (2004). All showed forecasting value, but ICE has the most consistency throughout the dependent variables. Next, the study includes the control vector. The forecasting value drops considerably across all combinations of dependent and explanatory variables. ICE still provides more forecasting power than ICS. However, the question regarding business conditions over the next twelve months outperforms ICE in three of the four versions when the control vector is incorporated. The authors reason that ICE provides a more reliable forecast because it consists of only forward-looking questions. In contrast, ICS consists of both forward-looking questions and questions regarding current economic conditions (Kwan & Cotsomitis, 2004).

James Wilcox, a professor at the Haas School of Business at the U.C. Berkeley, published "Forecasting Components of Consumption with Components of Consumer Sentiment" in the October 2007 edition of *Business Economics*. As a result of this paper, the author received the 2007 E.A. Mennis Contributed Paper Award. This study looks at the specific questions comprising the ICS and how well they predict consumer consumption in comparison to the ICS alone.

First, Wilcox determines that the specific questions have a high correlation with the ICS. Four of the five questions have a correlation coefficient of 0.88 or higher. The lowest correlation comes from the question related to durable goods. Conversely, the questions themselves have a correlation coefficient of around 0.70 (Wilcox, 2007).

Next, Wilcox creates "baseline models." The dependent variables include six growth rates of consumption categories: total consumption, durable goods, vehicles, non-vehicle durable goods, non-durable goods, and services. Explanatory variables consist of the dependent variable lagged, disposable personal income, non-home-equity, home-equity, the one-year nominal interest Treasury bill yield, and the one-year percentage change in seasonally-adjusted, quarterly-averaged total CPI. All variables consist of quarterly data from the first quarter of 1960 to the third quarter of 2006. Each regression is estimated twice, once with a one-quarter lag and once with a four-quarter lag. The F-tests reveal much about the variables' explanatory power. Income has little explanatory power for both lags. Net worth attributable to non-home assets has explanatory power for the short term, but not for the long term, while home-equity improves forecasts better for the long term than the short term. The interest rate has explanatory power for both periods for almost all dependent variables. Inflation improves forecasting durables but has little forecast power elsewhere (Wilcox, 2007).

Wilcox next takes the baseline models and adds the ICS and its questions. He finds only minor improvement in the short-term model. Most of this improvement comes in the non-durables. The long-term model shows much more promise. The ICS and its questions, except the second question, all improve long term forecasts of durable goods and vehicle consumption. On the whole, the F-statistics are higher for the specific questions than for the ICS (Wilcox, 2007).

The MCS regularly asks consumers about their expectations of gasoline prices for one and five years ahead. In the 2011 paper, "Forecasting Gasoline Prices Using Consumer Surveys," published in *The American Economic Review,* Anderson, et al. use this data to evaluate consumers' predictions forecast actual gasoline prices. The authors find that consumers' predictions are no better than the no-change predictions, or a forecast that the future price is the same as the current price. The only time the MSC sees a significant departure from the realized retail price came in the 2008 financial crisis. However, the study finds that consumers predicted the retail price would bounce back with much higher accuracy than the no-change forecast. Anderson et al. argue that while during ordinary times a no-change forecast suffices, the MSC shows the value in monitoring consumer predictions when markets behave abnormally (2011).

*The Journal of Real Estate Research* published "Information Content and Forecasting Ability of Sentiment Indicators: Case of Real Estate Market," written by Marcato and Nanda, both from the University of Reading, in 2016. This study analyzes the impact of adding a sentiment variable to real estate forecasting models. A vector autoregression (VAR) model is used to avoid endogeneity issues. The authors evaluate both the residential real estate market and the non-residential market. The study uses sentiment variables such as the *Housing Market Index* (HMI), the *Architecture Bilings Index* (ABI), the *Chicago Fed National Activity Index*, the MSC, the *Institute for Supply Management's Purchasing Managers Index*, and the *Tech Pulse Index*. The HMI acts as a proxy for sentiment for residential real estate, and the ABI provides a proxy for non-residential real estate sentiment (Marcato & Nanda, 2016). The study uses one, two, and three-month lags of all sentiment variables.

The explanatory variables include lags of the dependent variable and traditional macroeconomic variables, include the real GDP growth rate, changes in the CPI, the real interest rate, the term spread, and the credit spread. The researchers estimate a Granger causality test before the selection of all explanatory variables. The dependent variables for non-residential real estate used are the *NCREIF's Transaction-Based Index* (price and total return) and changes in the *Valuation Based Total Return Index*. The dependent variables for residential real estate are the *S&P/Case-Shiller Home Price Index and FHFA House Price Index* for residential real estate, both of which garner changes in house prices.

The residential sector shows that sentiment adds explanatory power to the model, notably when lagged by one or two months. The adjusted $R^2$ ranges from 0.71 to 0.75 for the S&P/Case-Shiller regressions and 0.85 to 0.88 for the FHFA regressions. The real estate sentiment variables have statistical significance at the 5% level for all equations. General sentiment only has statistical significance for the S&P/Case-Shiller regression when the Chicago variable acts as the sentiment variable, and when the MSC acts the sentiment variable for the FHFA regression. Sentiment variables add very little to the transaction-based non-residential models. The adjusted $R^2$ ranges from 0.04 to 0.26 for both dependent variables. The Chicago general sentiment variable is the sole statistically significant sentiment variable for each model. However, for the valuation-based regression, the adjusted $R^2$ ranged from 0.73 to 0.88, and the sentiment variable has statistical significance when the models include no general sentiment. The MCS also shows statistical significance.

The authors hypothesize that this stark difference between the transaction-based and valuation-based non-residential models stems from prices being appraisal-based. They also argue that sentiment acts as a more potent explanatory variable for residential than non-residential real estate because of the information gap between buyers and sellers being less for non-residential real estate transactions. Also, long-term contracts for the non-residential sector could limit the role of sentiment in short-run forecasts (Marcato & Nanda, 2016).

Previous research finds that changes in economic conditions drive impacts farm machinery demand in the production agricultural industry. However, two only of the previous studies tangentially evaluate the impact farmer sentiment has on farm machinery demand (Gustafson et al., 1988; Krutz et al., 1978). The lack of sentiment data usage is despite researchers finding sentiment useful regarding the consumer sector. This success is seen especially in times of abnormality. The gap in research regarding farmer sentiment data is primarily due to sentiment data not being available until the launch of the *Purdue University-CME Group's Ag Economy Barometer Survey* (AEB) in October 2015.

## 2.3 Farmer Sentiment

The *Ag Economy Barometer Survey* is modeled after the *University of Michigan's Survey of Consumers* and is issued monthly (Purdue University's Center for Commercial Agriculture, 2020). Like the MSC, the AEB's purpose is to capture the sentiment agricultural producers have in the agricultural production industry every month. Each month a stratified survey of 400 producers of the major agricultural commodities is conducted. The survey is stratified such that it's representative of producers with an estimated gross farm income of $500,000 and up who have corn, soybean, wheat, cotton, hog, beef cattle and dairy enterprises. Stratification is based upon the USDA's 2012 Agricultural Census. Survey respondents answer a series of questions regarding their opinions on the status of their own farms as well as the U.S. agricultural economy (Mintert et al., 2017).

The first five questions of the AEB remain the same from month-to-month. Each question is assigned a score based on the percentage of respondents who answer positively minus the percentage of negative responses, plus 100, creating a range of 100 (the most pessimistic score possible) to 200 (the most optimistic score possible). Indices comprising different combinations of the first five questions are also released each month.

These indices include the *Ag Economy Barometer*, calculated from all five base questions, the *Index of Current Conditions*, comprising of questions regarding the present economic conditions, and the *Index of Future Expectations*, which combines the forward-looking questions. The indices are calculated by adding the scores from the relevant questions and then dividing by the average score for the base period of October 2015 to March 2016 (Mintert et al., 2017). Table 1 lists all five AEB base questions, its indices, and which questions encompass the respective index.

Table 1: Ag Economy Barometer Survey Questions.

| Question # or Index Title | Question |
|---|---|
| Q1 | We are interested in how farmers are getting along financially. Would you say that your operation today is financially better off, worse off, or about the same compared to a year ago? |
| Q2 | Now, looking ahead, do you think that a year from now your operation will be better off financially, worse off, or just about the same as now? |
| Q3 | Turning to the general agricultural economy as a whole, do you think that during the next twelve months there will be good times financially, or bad times? |
| Q4 | Looking ahead, which would you say is more likely, U.S. agriculture during the next five years will have widespread good times or widespread bad times? |
| Q5 | Thinking about large farm investments – like buildings and machinery — generally speaking, do you think now is a good time or bad time to buy such items? |
| Ag Economy Barometer Index | All five base questions |
| Index of Current Conditions Index | Q1 and Q5 |
| Index of Future Expectations Index | Q2, Q3, Q4 |

The *Ag Economy Barometer Index* is the AEB's equivalent to *MSC's Index of Consumer Sentiment* (ICS). Figure 2 compares the two indices throughout the *Ag Economy Barometer Index's* lifetime, beginning in October 2015 to December 2019. As Figure 2 shows, the *Ag Economy Barometer Index* has higher volatility than the Index of Consumers. Does this higher volatility indicate there is more information in the *Ag Economy Barometer Index*, or is it only noise? The success of the MSC lends credence to the hypothesis of the sentiment data collected by the *Ag Economy Barometer* having some explanatory power.

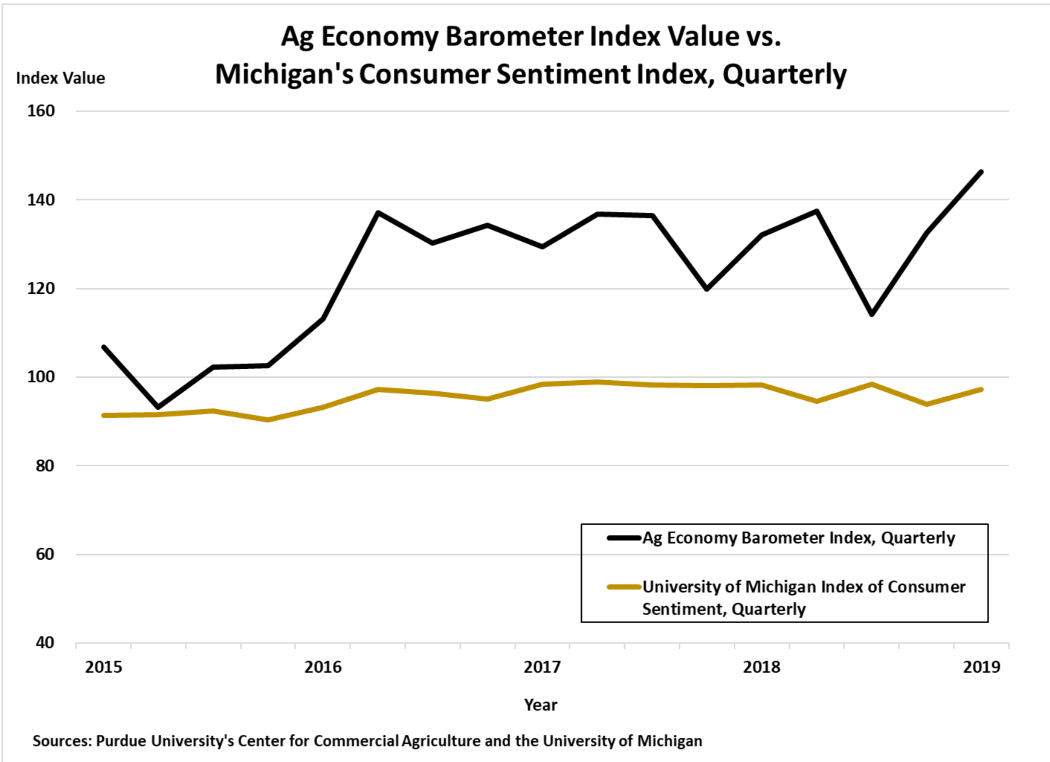


Figure 2: Index of Consumer Sentiment and Ag Economy Barometer Index, 2015Q4-2019Q4

# CHAPTER 3. METHODOLOGY

## 3.1 Explanatory Models for Farm Machinery Sales

The studies highlighted in the literature review show how many factors impact investment decisions for farm machinery. Variables employed by researchers fall into several categories. The first group focused on economic conditions in the broader U.S. economy, such as interest rates and wage rates, and the second group focuses on measuring economic conditions within the U.S. agricultural sector. Key variables in this group included crop and livestock prices, input prices, net farm income, debt levels, land values, and total U.S. acreage devoted to crop production. The final group of variables focused more specifically on farm machinery. It included the machinery price level, horsepower, age of farm machinery, and the size of the existing stock of farm machinery. Table 2 summarizes these categories and variables. All models in this study will be estimated using ordinary least squares (OLS).

Table 2: Factors Identified to Impact Farm Machinery Investment.

| Economic sector | Economic characteristic |
|---|---|
| General Economy | |
| Financial markets | Interest rates |
| | Wage rates |
| Agricultural Economy | |
| Farm income | Prices received for crops and livestock sold |
| | Prices paid for inputs |
| | Net farm income |
| | Level of debt |
| | Farmland values |
| Farm machinery characteristics | Prices paid for machinery |
| | Horsepower levels |
| | Age of machinery |
| | Existing stock of machinery |

### 3.1.1 Re-estimate Cromarty's Model

An econometric model can be used to gain a deeper understanding of the economic factors that drive farm machinery sales, and Cromarty's study from 1959 provides a good starting point. The era Cromarty evaluated, 1923-1958, saw American agriculture undergo a massive structural change as farmers were transitioning from horses to horsepower. Today's production agriculture industry provides a similar argument. Farmers are now purchasing machinery, no longer solely for an increase in horsepower, but also for the improvements in computer technology often included new machinery. The first step is to re-evaluate and re-estimate models based on Cromarty's (equation 3.1). Table 3 lists the definitions Cromarty provided for both his dependent and explanatory variables and the equivalent modern data sources used for the modernized model in this study.

$$\begin{aligned} Sales_t = \; & \beta_0 + \beta_1 MachPr_t + \beta_2 CrLivePr_t + \beta_3 InputPr_t + \beta_4 MachVal_t \\ & + \beta_5 Assets_t + \beta_6 NFI_{t-1} + \beta_7 Acre_t + \beta_8 Labor_t \end{aligned} \tag{3.1}$$

Table 3: Variable Names, Definitions, and Sources for Modern Comparison Model.

| Variable | Cromarty Variable Definitions | Equivalent Modern Variable and Source |
|---|---|---|
| Sales (Dependent) | Value of manufacturers' farm machinery sales, deflated by the wholesale farm machinery price index | Sales of Farm Machinery with 100 horsepower or above, 1978-2019 (Association of Equipment Manufacturers Data), quarterly and annually |
| $MachPr_t$ | The wholesale price index for farm machinery, deflated by the general price level | Machinery Totals – Index for Price Paid, retail prices, 1975-2019 (NASS), quarterly and annually |
| $CrLivePr_t$ | Prices received from crops and livestock by farmers, indexed, by the general price level | Index for Price Received, 1910-1914 base, 1909-2019 (NASS), quarterly and annually |
| $InputPr_t$ | Prices paid by farmers for inputs, excluding labor, deflated by the general price level | Production Items – Index for Price Paid, 1910-1914 base, 1923-2019 (NASS), quarterly and annually |
| $MachVal_t$ | Farm machinery value on farms at the beginning of each year, deflated by the wholesale farm machinery price index | Farm Machinery and Vehicles, nominal, 1960-2019F (ERS's Farm Sector Balance Sheet), annually |
| $Assets_t$ | Farmers' asset positions at the beginning of each year, deflated by the general price level | Farm Sector Assets, nominal, 1960-2019F (ERS's Farm Sector Balance Sheet), annually |
| $NFI_{t-1}$ | One-year lagged realized net income, deflated by the general price level | Net Farm Income, nominal, 1910-2019F (ERS's Net Income Statement), annually |
| $Acre_t$ | Average acreage per farm | Aggregation of corn, cotton, hay, rice, sorghum, soybeans, and wheat acres harvested (NASS), annually |
| $Labor_t$ | Farm labor costs, indexed, deflated by the general price level | Labor, Wage Rates – Index for Price Paid, 1910-1914 base, 1923-2019 (NASS), quarterly and annually |
| $MachInt_t$ | N/A | Average Effective Interest Rate on Farm Machinery and Equipment Loans Made to Farmers (Federal Reserve Bank of Kansas City), quarterly and annually |

### 3.1.2 Additional Annual Models

There is a significant difference between Cromarty's dependent variable and the dependent variable in this study. Cromarty did not have access to actual data on farm machinery sales, such as the data collected and published by the Association of Equipment Manufacturers, and instead had to contrive it by taking the ratio of the value of manufacturers' farm machinery sales by an index of wholesale farm machinery prices. This study has access to the actual number of machines sold to the end-user.

Additionally, Cromarty's model, listed in equation 3.1, potentially suffered from over-identification. The model uses independent variables, including prices received for crops and livestock, input prices, and lagged net farm income. Net farm income is primarily a function of the prices received for crops and livestock and input prices. Two additional models will be estimated to correct this potential over-identification. One model omitting lagged net farm income equation 3.2, and another omitting the crop and livestock prices received, and input prices paid variables, equation 3.3. Also, as farm machinery value on farms is included in the Farm Sector Assets in the U.S. Department of Agriculture's Balance Sheet the farm machinery value on farms, making it accounted for twice in Cromarty's analysis (USDA Economic Research Service, 2020). Taking total farm assets into account seems advantageous as assets drive a farm's borrowing capacity when applying for a loan, typically needed to purchase large machinery. For this reason, only equation 3.1 includes farm machinery value, and total farm assets remain in the following regression models.

Cromarty's model also includes a measure of labor costs for farms. During the time period he studies, farms were mechanizing, substituting machinery for physical labor, and thus, labor costs were likely a higher driver for machinery investment than it is today. His models also do not include an interest rate variable. Models omitting labor costs and including interest rates, as seen in equation 3.4 and equation 3.5, follow. Both equation 3.4 and equation 3.5 attempt to correct potential over-identification by separating lagged net farm income from prices paid for inputs and prices received for crops and livestock. However, by lagging net farm income, Cromarty may have prevented over-identification. As a result, equation 3.6 includes lagged net farm income, crop and livestock prices received, and prices paid for inputs to evaluate this possibility.

$$Sales_t = \beta_0 + \beta_1 MachPr_t + \beta_2 CrLivePr_t + \beta_3 InputPr_t + \beta_4 Assets_t + \beta_5 Acre + \beta_6 Labor_t \quad (3.2)$$

$$Sales_t = \beta_0 + \beta_1 MachPr_t + \beta_2 Assets_t + \beta_3 NFI_{t-1} + \beta_4 Acre_t + \beta_5 Labor_t \quad (3.3)$$

$$Sales_t = \beta_0 + \beta_1 MachPr_t + \beta_2 CrLivePr_t + \beta_3 InputPr_t + \beta_4 Assets_t + \beta_5 Acre_t + \beta_6 MachInt_t \quad (3.4)$$

$$Sales_t = \beta_0 + \beta_1 MachPr_t + \beta_2 Assets_t + \beta_3 NFI_{t-1} + \beta_4 Acre_t + \beta_5 MachInt_t \quad (3.5)$$

$$Sales_t = \beta_0 + \beta_1 MachPr_t + \beta_2 CrLivePr_t + \beta_3 InputPr_t + \beta_4 NFI_{t-1} + \beta_5 Assets_t + \beta_6 Acre_t + \beta_7 MachInt_t \quad (3.6)$$

Annual models will be estimated according to the availability of the dependent variable, beginning in 1978 and ending in 2019, providing 42 annual observations. The evaluation of the models' explanatory power is made by comparison of the various models' statistical fit, the statistical significance of the independent variables, and a comparison of the independent variables' signs with the signs expected. The best performing annual models will then be estimated again with quarterly data.

Quarterly models are estimated according to the availability of the quarterly dependent variable, which is 2009 Q1 to 2019 Q4. These models will consist of 44 quarterly observations. As highlighted in the data chapter, farm machinery sales are highly seasonal, with peaks coming in Q4 and lows coming in Q1. The inclusion of dummy quarterly variables should control for the seasonality in the data.

$MachVal_t$, $NFI_{t-1}$, and $Acre_t$ consist of data that are updated on an annual basis and will thus only change in value once every twelve months and once every four quarters. All other explanatory variables are updated monthly and aggregated into quarterly observations. Evaluating the explanatory power of the models and their variables is done by comparing the statistical fit of the various models and the expected signs for the independent variables with the estimated signs. Table 4 lists the variable name, definition, the expected sign, and the reasoning behind each expectation.

Table 4: Variable Definitions, Expected Signs, and Reasoning for Each Expectation.

| Variable | Definition | Expected Sign | Reasoning |
|---|---|---|---|
| $MachPr_t$ | Prices paid by farmers for farm machinery | Negative | As machinery prices increase, the quantity of machinery demanded decreases |
| $CrLivePr_t$ | Crop and livestock prices received by farmers | Positive | Increases in crop and livestock prices increase farmers' income available to purchase machinery |
| $InputPr_t$ | Prices paid by farmers for inputs | Negative | Increases in inputs prices are expected to decreases farmers' income available to purchase machinery |
| $MachVal_t$ | The value of farm machinery already on farms | Negative | As the value already on farms increases, producers are expected to be less likely to make additional purchases |
| $Assets_t$ | The value of farm assets | Positive | Increases in assets indicate increases borrowing capability |
| $NFI_{t-1}$ | Net Farm Income, lagged one year | Positive | Increases in income the previous year the buying power for the next year |
| $Acre_t$ | The sum of corn, cotton, hay, rice, sorghum, soybeans, and wheat acreage | Positive | Increases in acreage increase the demand for machinery |
| $Labor_t$ | Prices paid by farmers for farm labor | Positive | As labor costs increase, the substitution of machinery for labor is expected to increase |
| $MachInt_t$ | Average Effective Interest Rate of Farm Machinery and Equipment Loans Made to Farmers | Negative | Increases in interest rates raise the cost of machinery ownership |

### 3.2 Add Farmer Sentiment Data

As highlighted in the literature review, studies using consumer sentiment survey data, usually measured by the University of Michigan's *Survey of Consumers* (MSC), have found sentiment data useful. This benefit is typically seen when building explanatory models for consumer consumption, especially in regards to durable goods. As consumer durable goods are large, long-lasting purchases, such as vehicles, it seems reasonable to assume that farm machinery, large and long-lasting purchases for agricultural producers, is the agricultural producer's equivalent. For this reason, it also seems reasonable that farmer sentiment data might improve farm machinery investment models.

Evaluating sentiment data's performance is limited at the time of this study due to the *Ag Economy Barometer Survey*'s relatively short lifespan. There are only four annual observations as the survey's first observation takes place in October 2015. This lack of data eliminates any possibility of incorporating farmer sentiment data into annual models. Estimating quarterly models allows for more observations. Only having 17 quarterly observations available is still limiting but is the best option at hand.

To evaluate whether farmer sentiment data can improve quarterly farm machinery demand models, quarterly models, which include sentiment data, need to be compared to quarterly models estimated over the same period, beginning in the 4th quarter of 2015 and ending in the 4th quarter of 2019. The best performing models from section 3.1 will be estimated again over this period.

Following that, the same models will be estimated again over the same timeframe but including sentiment, measured by the *Ag Economy Barometer Survey*, as an additional explanatory variable. Again, the lack of sentiment observations is a hindrance. When re-estimating the best performing models from section 3.1 over the shorter timeframe, the number of available observations drop from 44 to 17. Calculating the quarterly sentiment data is done by taking the average of the respective three months' sentiment data values. The models will be compared based on their statistical fit, along with a comparison of the expected signs for the independent variables with the estimated signs.

As discussed in section 2.3, this study focuses on the AgBar, CurrCon, FutExp, and Question 5, or the Farm Capital Investment Index, specifically. Due to the limited observations, all sentiment variables will be contemporaneous. Again, the models will be compared based on their statistical fit, along with a comparison of the expected signs for the independent variables with the estimated signs.

# CHAPTER 4. DATA

## 4.1 Dependent Variables

### 4.1.1 Association of Equipment Manufacturers

The dependent variables used in model estimation consist of data purchased from the Association of Equipment Manufacturers (AEM). AEM provides the units sold, both annually and monthly, within the United States for various categories of farm machinery in their "Ag Tractor & Combine Retail Statistics" data package. These categories include total farm wheel tractors sold, two-wheel-drive (2WD) tractors under 40 horsepower sold (HP); 2WD tractors between 40 and 100 HP sold; 2WD tractors above 100 HP sold; four-wheel drive (4WD) tractors sold; and self-propelled combines sold. Taking the sum of tractors between 40 and 100HP and tractors above 100 HP creates an additional category of 2WD tractors above 40 HP. All data are reported at the national level. Table 5 lists all available annual and quarterly dependent variables and their definitions.

Table 5: Dependent Variable Names and Definitions.

| Variable | Definition |
|---|---|
| aunder40 | Annual sales of two-wheel drive tractors with under 40 horsepower |
| a40to100 | Annual sales of two-wheel drive tractors between 40 horsepower and 100 horsepower |
| a40up | Annual sales of two-wheel drive tractors with above 40 horsepower |
| a100up | Annual sales of two-wheel drive tractors with 100 horsepower and above |
| a4wd | Annual sales of four-wheel drive tractors |
| atottrac | Annual sales of total tractors sold |
| qunder40 | Quarterly sales of two-wheel drive tractors with under 40 horsepower |
| q40to100 | Quarterly sales of two-wheel drive tractors between 40 horsepower and 100 horsepower |
| q40up | Quarterly sales of two-wheel drive tractors with above 40 horsepower |
| q100up | Quarterly sales of two-wheel drive tractors with 100 horsepower and above |
| q4wd | Quarterly sales of four-wheel drive tractors |
| qtottrac | Quarterly sales of total tractors |

AEM defines a unit as sold when delivery of a unit to the end-user takes place and the settlement/title transfer of the unit by the retailer to the end-user is complete. AEM collects data for the previous month from participating manufacturers between the first and ninth day of every month for publication on the tenth of each month. For example, data for February is routinely published on the tenth day of March. Annual data spans the years from 1978 to 2019 for all categories except two-wheel drive tractors under 100 horsepower, which is only available from 1982 forward. Monthly data begins in January 2009 and continues through December 2019 for all categories of tractors sold. Monthly sales data combine to create quarterly observations where the first quarter, or Q1, is the sum of sales during January, February, and March. April, May, and June comprise the sales for the second quarter, or Q2. Aggregation for the third and fourth quarters follows the same pattern.

As can be seen in Figure 3, total sales of farm wheel tractors exhibit strong seasonality and a powerful upward trend over the past decade. Tractor sales hit annual lows in Q1 and annual highs in Q2 for every year in the data series. The strong, continuous uptrend in total tractor sales suggests that year-to-year variation in agricultural sector economic conditions has relatively little impact on total tractor sales. The lack of influence might be attributable to the fact that 2WD tractors under 100 HP accounted for 85% of total tractors sold over the past decade. Demand for smaller tractors comes from a wide variety of sources, not just the agricultural sector, suggesting that total tractor sales might not be very responsive to changes in economic conditions within the farm sector alone. As a result, the categories of total sales for farm-wheel tractors sold, 2WD tractors under 40 HP sold, and 2WD tractors between 40 and 100 HP sold were not the primary focus of this study.

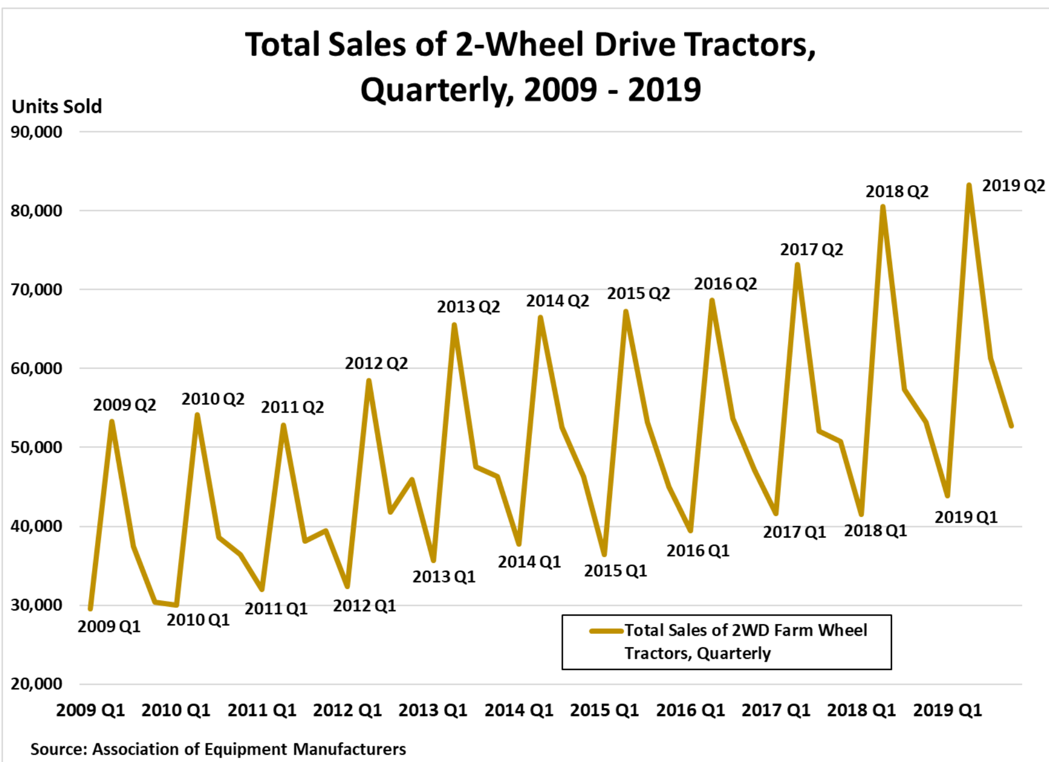


Figure 3: Total Sales of Farm Wheel Tractors from 2009-2019, Quarterly

An examination of the quarterly sales of 4WD tractors (Figure 4) and self-propelled combines (Figure 5) beginning in 2009 suggests these categories are impacted more by shifting farm sector economic conditions than lower horsepower farm tractor categories mentioned previously. Sales of both 4WD tractors and combines were much higher in the early 2010s when the farm economy peaked and have fallen dramatically during the recent recession in the agricultural economy. However, due to the demand for these two categories likely being more specialized and likely responsive to shifting acreage of individual crops than for 2WD tractors above 100 HP, they were not selected as the primary focus for this study.

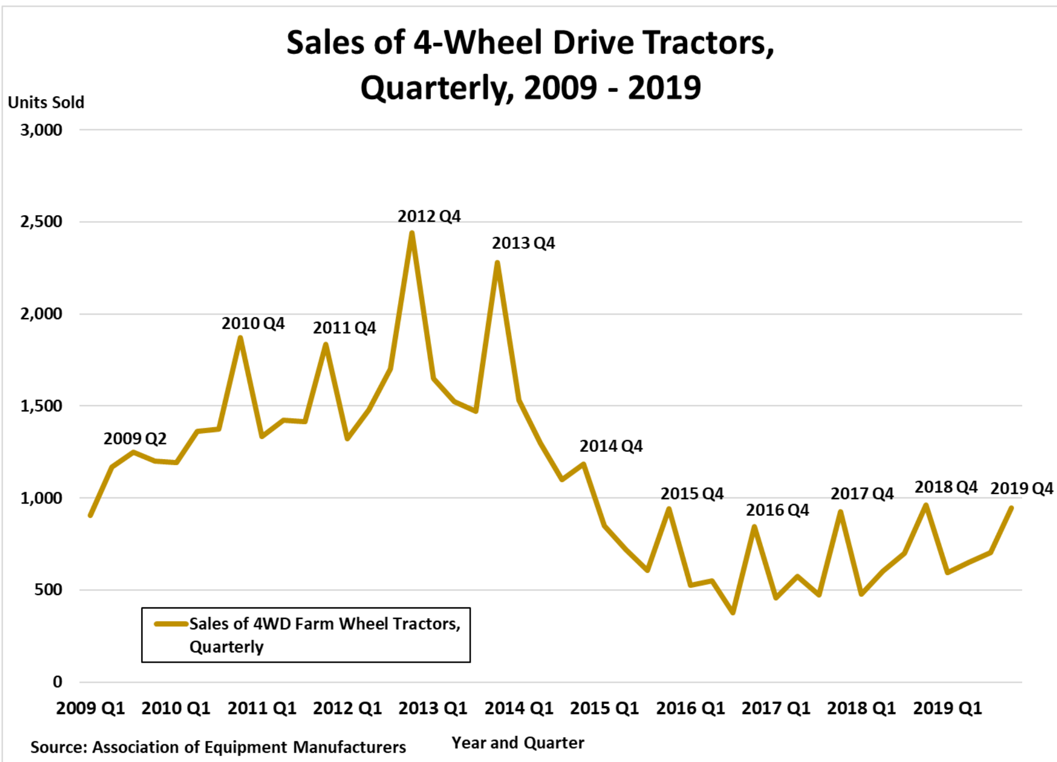


Figure 4: Sales of Four-Wheel Drive Tractors from 2009-2019, Quarterly

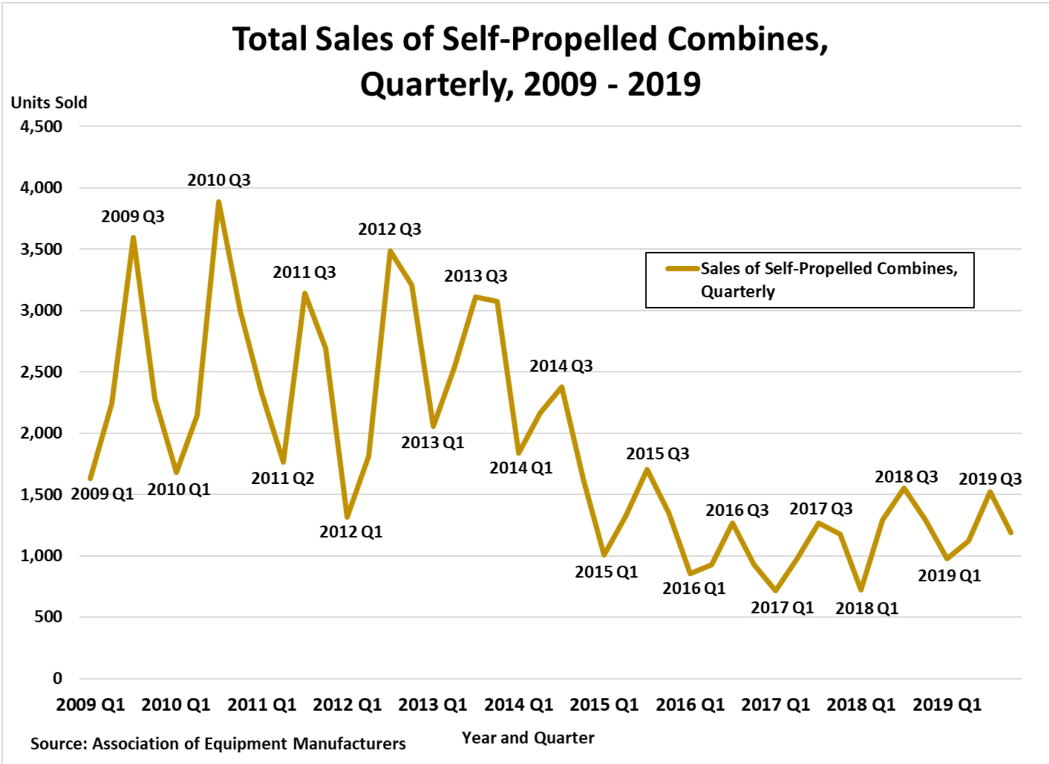


Figure 5: Sales of Self-Propelled Combines from 2009-2019, Quarterly

As Figure 6 shows, sales of 2WD tractors above 100 HP seem to respond to shifting economic conditions in the agricultural sector. Note that sales of 2WD tractors above 100 HP plummeted during the Farm Crisis of 1981-1984 and then stayed within a relatively broad range until the late 1990s. When farm income weakened in the early 2000s, sales declined before recovering strongly from 2006 until peaking in 2013, when USDA's net farm income estimate also peaked. During the most recent agricultural recession, sales fell back to levels observed in the 1990s and early 2000s. Figure 7 shows quarterly sales of 2WD tractors above 100 HP, and once again, the impact of agricultural economic conditions is observable. A comparison of quarterly sales of 2WD tractors above 100 HP to that of 4WD tractors and self-propelled combines from 2009-2019 reveals that sales of 2WD tractors above 100 HP were, on average, more than double the combined sales of 4WD tractors and self-propelled combines. Given the larger sales volume of 2WD tractors above 100 HP, and the resulting greater economic impact associated with this 2WD tractor sales category, this study employs sales of 2WD farm-wheel tractors over 100 HP as the dependent variable employed in model estimation.

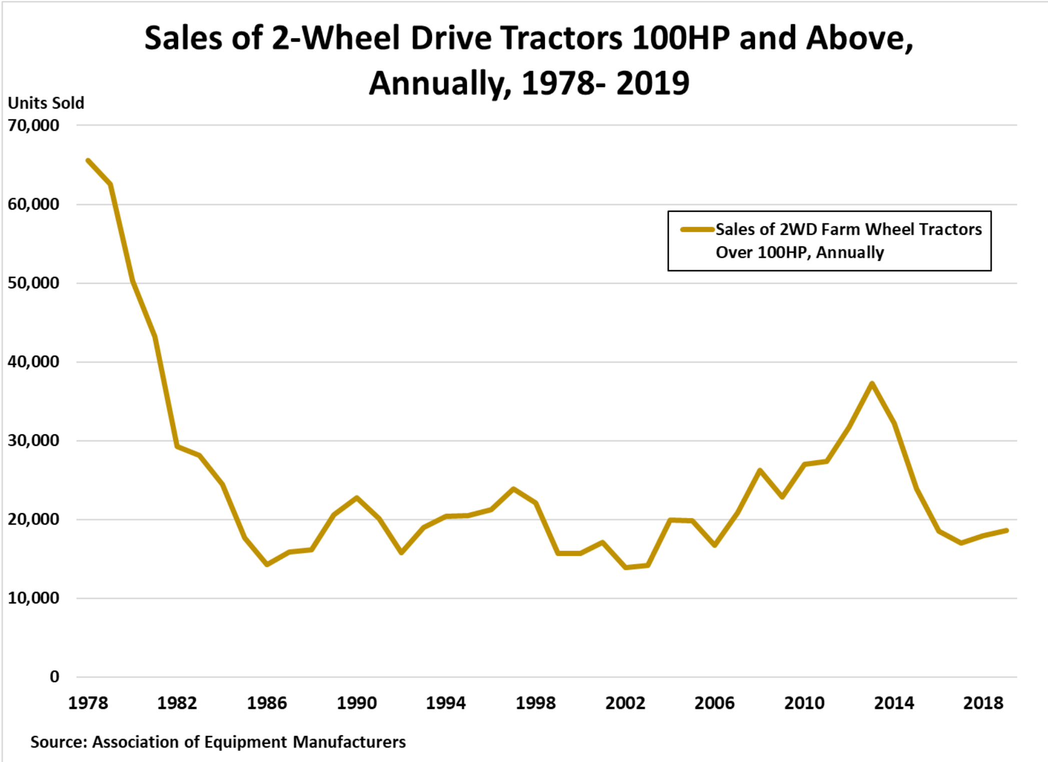


Figure 6: Sales of Two-Wheel-Drive Tractors ≥100 Horsepower from 1978-2019, Annually

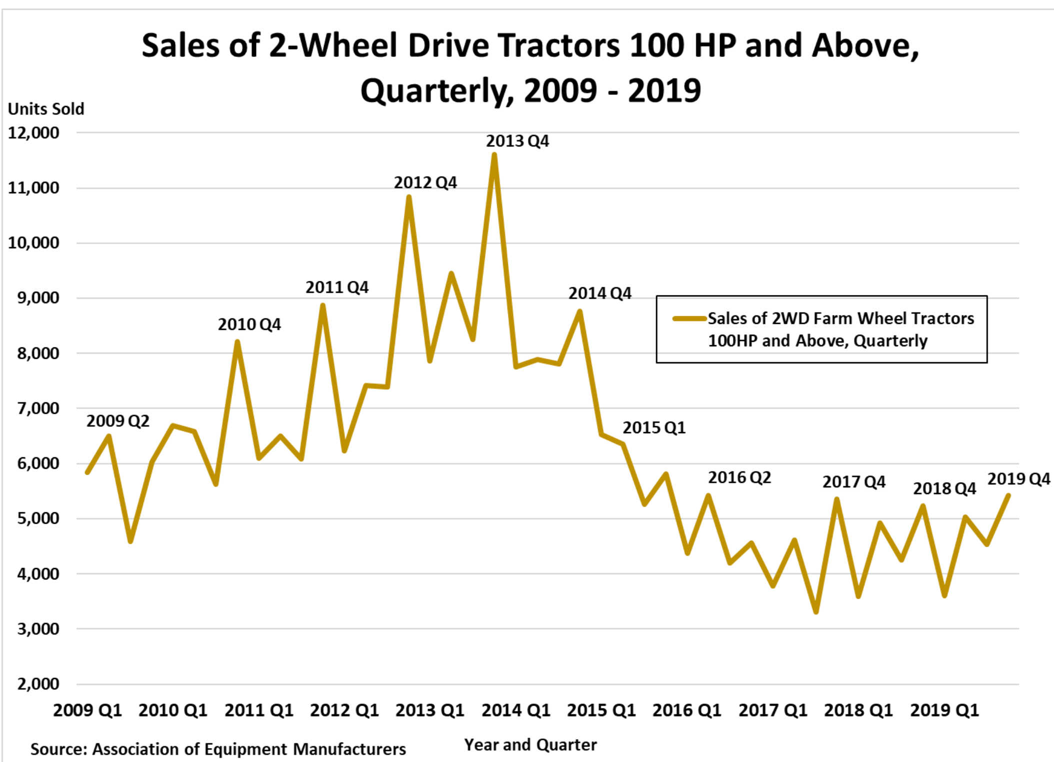


Figure 7: Sales of Two-Wheel Drive Tractors ≥100 Horsepower from 2009 Q1-2019 Q4

### 4.2 Independent Economic Variables

Several sources provide the data for independent variables used in model estimation including the USDA's National Agricultural Statistics Service's (NASS) QuickStats online database, the US Bureau of Labor Statistics (BLS), the Federal Reserve (FED), and the USDA's Economic Research Service's (ERS) *Farm Income and Wealth Statics* database. All data are available in both annually and monthly timeframes. If quarterly data are not available from the source, averaging the quarter's corresponding monthly data generates an observation for the quarter. Thus, Q1 is calculated by computing within each year the average of January, February, and March, Q2 is the average of April, May, and June, Q3 is the average of July, August, and September and Q4 is the average of October, November, and December. All annual data used in this study span the period from 1978 to 2018 and all monthly and quarterly data span the period from January 2009 to November 2019, unless otherwise noted. Table 6 lists all independent variables, their definitions, frequencies, and sources. The remainder of section 4.2 provides more detailed information on each variable along with directions on how to access the data from its respective source.

Table 6: Variable Descriptions, Frequencies, and Sources.

| Variable | Definition | Frequency | Source |
|---|---|---|---|
| $CrLivePr_t$ | Crop and livestock prices received by farmers | Annual, Quarter, Month | NASS |
| $InputPr_t$ | Prices paid by farmers for inputs | Annual, Quarter, Month | NASS |
| $Labor_t$ | Prices paid by farmers for farm labor | Annual, Quarter, Month | NASS |
| $Acre_t$ | Sum of corn, cotton, hay, rice, sorghum, soybeans, and wheat acres harvested | Annual | NASS |
| $MachPr_t$ | Prices paid by farmers for farm machinery | Annual, Quarter, Month | BLS |
| $MachInt_t$ | Average effective interest rate of farm machinery and equipment loans made to farmers | Annual, Quarter | FED |
| $MachVal_t$ | Dollar value of farm machinery | Annual | ERS |
| $NFI_{t-1}$ | Net farm income | Annual | ERS |
| $Assets_t$ | Dollar amount of farm assets | Annual | ERS |

### 4.2.1 Crop and Livestock Prices Received by Farmers

This study uses NASS's *Index for Prices Received* with a base period of 1910-1914 to measure the prices farmers receive for crops and livestock. Base years of 1990-1992 and 2011 were also available but did are not available for the entire 1978-2019 time period. NASS surveys major buyers in "top producing states" each month inquiring about the "total quantity purchased and total dollars received" to collect data for the major crops. Livestock price data is collected by USDA's Agricultural Marketing Service on daily, weekly, and monthly timeframes from packing plants and livestock auctions. NASS then calculates monthly averages for the commodities (USDA National Agricultural Statistics Service, n.d.). The specific route taken within QuickStats to locate the data is as follows: Program: Survey, Sector: Economics, Group: Income, Commodity: Commodity Totals, Category: Index for Price Received, 1910-1914, Data Item: Commodity Totals - Index for Price Received, 1910-1914, Domain: Total, Geographic Level: National, State: US Total, Year: 1978-2019, Period: Annual and Monthly.

### 4.2.2 Input Prices Paid by Farmers

NASS's *Production Items – Index for Price Paid* with a base period 1910-1914 measures prices farmers paid for inputs. NASS collects this data by surveying agribusinesses "on the prices producers paid for recent sales of approximately 450 key agricultural inputs" annually, with publication in the following April. The monthly indexes update the annual numbers by using data from several sources, including the Bureau of Labor Statistics, the USDA's Agricultural Marketing Service, and the USDA's Economic Research Service (USDA National Agricultural Statistics Service, n.d.). Like the index for prices received, different base years are also available but do not cover the entire time needed for this study. The specific route taken within QuickStats to locate the data is as follows: Program: Survey, Sector: Economics, Group: Prices Paid, Commodity: Production Items, Category: Index for Price Paid, 1910-1914, Data Item: Production Items - Index for Price Paid, 1910-1914, Domain: Total, Geographic Level: National, State: US Total, Year: 1978-2019, Period: Annual and Monthly.

### 4.2.3 Labor Prices

Economic theory indicates that farmers will substitute human labor for machinery as labor costs rise relative to the cost of machinery. NASS's *Labor, Wage Rates – Index for Price Paid* with a base period of 1910-1914 provides a measure of the prices paid by farmers for labor. Like the index for prices received, several other base years for this data series are available but do not cover the entire time frame of this study. Data for this index and the data for input prices paid are collected contemporaneously (USDA National Agricultural Statistics Service, n.d.). The specific route taken within QuickStats to locate the data is as follows: Program: Survey, Sector: Economics, Group: Prices Paid, Commodity: Labor, Category: Index for Price Paid, 1910-1914, Data Item: Labor Wage Rates - Index for Price Paid, 1910-1914, Domain: Total, Geographic Level: National, State: US Total, Year: 1978-2019, Period: Annual and Monthly.

### 4.2.4 Acreage

A total acreage variable was aggregated by summing the acres harvested data for crops that are prominent nationally and are machinery intensive. Changes in national acreage levels are expected to impact machinery usage and, therefore, impact tractor sales. Data is collected by NASS through a probability-based survey "based on a probability area frame survey with a sample of approximately 9,000 segments or parcels of land (average approximately 1 square mile) and a probability list frame survey with a sample of approximately 68,100 farm operators" during the first two weeks of June (USDA National Agricultural Statistics Service, n.d.). Shifts in major crop acreage likely to influence tractor sales include corn, cotton, hay, rice, sorghum, soybeans, and wheat. These crops are referred to as "commodity name" in the following sentence specifying how to download data from USDA. The specific route taken within QuickStats to locate the data is as follows: Program: Survey, Sector: Crops, Group: Field Crops, Commodity: (commodity name), Category: Area Harvested, Data Item: (commodity name), Grain – Acres Harvested, Domain: Total, Geographic Level: National, State: US Total, Year: 1978-2019, Period: Annual. For scaling and presentation purposes, the total acreage data is in terms of millions of acres.

### 4.2.5 Machinery Prices

The data provided by AEM does not include machinery prices. To measure the impact machinery prices have on tractor sales, the *Producer Price Index by Commodity for Machinery and Equipment: Agricultural Machinery and Equipment* provided by the U.S. Bureau of Labor Statistics was selected (U.S. Bureau of Labor Statistics, n.d.). This index has the base year of 1982 and is not seasonally adjusted. The data is retrievable through the Federal Reserve Economic Data (FRED) database made available by the St. Louis Federal Reserve Bank. To locate this data within the FRED database, either its full title listed above or its FRED code, WPU111, can be used. The selected aggregation method within the FRED database is “average” for the quarterly and annual data.

### 4.2.6 Interest Rates on Farm Machinery and Equipment Loans

Interest rates act as a measure of how expensive it is for farmers to take on debt. The interest rate used in this study is the Average Effective Interest Rate on Farm Machinery and Equipment Loans Made to Farmers. This data is provided by the Federal Reserve Bank of Kansas City in the *Ag Finance Databook* published on a quarterly and annual basis. The data are estimates calculated from the stated rate and other terms of the loans and then weighted by loan size (Federal Reserve Bank of Kansas City, n.d.). The annual data encompasses the required 1978-2019 time period. The *Ag Finance Databook* lists this data in Table A.5. The path to this data is the Federal Reserve Bank of Kansas City’s Research and Data webpage, under the Indicators & Data tab, and then by selecting National Data.

### 4.2.7 Value of Farm Machinery

The U.S. Department of Agriculture’s *Farm Sector Balance Sheet*, published by USDA’s Economic Research Service, is used to measure the value of farm machinery already on farms. The ERS’s *Farm Income and Wealth Statistics* category houses this data. The data is titled “machinery and vehicles” within the balance sheet (USDA Economic Research Service, 2020). This series is reported in nominal dollars annually. The dollar value for the United States was selected and not the dollar values for individual states. For scaling and presentation purposes, the value of farm machinery data is in terms of millions of dollars.

### 4.2.8 Net Farm Income

The ERS's *Net Farm Income Statement*, found in their *Farm Income and Wealth Statistics* category, naturally provides the data on net farm income. It is titled "net farm income" in the income statement. These are nominal dollars reported annually. The dollar value for the United States was selected and not the dollar values for individual states (USDA Economic Research Service, 2020b). For scaling and presentation purposes, the value of net farm income data is in terms of millions of dollars.

### 4.2.9 Farm Assets

The U.S. Department of Agriculture's *Farm Sector Balance Sheet*, published by the Economic Research Service, measures the value of farm assets. The data is titled "farm sector assets" in the balance sheet. The total farm sector assets data includes the value of farm machinery for the United States (USDA Economic Research Service, 2020). These are nominal dollars reported annually. For scaling and presentation purposes, the farm assets data is in terms of millions of dollars.

## 4.3 Independent Sentiment Variables

As discussed in section 2.3, the *Purdue University-CME Group's Ag Economy Barometer Survey* is the source for farmer sentiment data. This survey began in October 2015 and poses five base questions to agricultural producers' every month. Each question is assigned a score based on the percentage of respondents who answer positively minus the percentage of negative responses, plus 100, creating a range of 0 (the most pessimistic score possible) to 200 (the most optimistic score possible).

Indices comprised of different combinations of the first five questions are also released each month. These indices include the *Ag Economy Barometer* (AgBar), calculated using results from all five base questions, the *Index of Current Conditions* (CurrCon), comprised of questions regarding the present economic conditions, and the *Index of Future Expectations* (FutExp), which aggregates responses to the forward-looking questions in the survey. The indices are calculated by adding the scores from the relevant questions and then dividing by the average score for the base period of October 2015 to March 2016. The *Farm Capitalization Index* (FarmInv), encompassing a single question in the monthly survey, is also included. FarmInv is the only question that explicitly asks producers whether now is a good time or a bad time to make large investments, in things like farm machinery and buildings, in their farming operation (Purdue University's Center for Commercial Agriculture, 2020). Table 7 lists all sentiment variables, the survey questions used to derive them, and their question number or index title.

Table 7: Ag Economy Barometer Survey Questions.

| Question # or Index Title | Question | Variable Name |
|---|---|---|
| Q1 | We are interested in how farmers are getting along financially. Would you say that your operation today is financially better off, worse off, or about the same compared to a year ago? | |
| Q2 | Now, looking ahead, do you think that a year from now your operation will be better off financially, worse off, or just about the same as now? | |
| Q3 | Turning to the general agricultural economy as a whole, do you think that during the next twelve months there will be good times financially, or bad times? | |
| Q4 | Looking ahead, which would you say is more likely, U.S. agriculture during the next five years will have widespread good times or widespread bad times? | |
| Q5 | Thinking about large farm investments – like buildings and machinery — generally speaking, do you think now is a good time or bad time to buy such items? | FarmInv |
| Ag Economy Barometer | All five base questions | AgBar |
| Index of Current Conditions | Q1 and Q5 | CurrCon |
| Index of Future Expectations | Q2, Q3, Q4 | FutExp |

Table 8 displays the correlation coefficients between each of the questions and indices listed in Table 9. Unsurprisingly, the indices have high correlation coefficients with the questions that comprise the indices, typically being near 0.90. The exception being FarmInv, or Q5, which has correlations coefficients of 0.38 or below for all except the *Index of Current Conditions*, of which it is a component.

Table 8: Correlation Coefficients for Ag Economy Barometer Questions and Indices.

| | Q1 | Q2 | Q3 | Q4 | Q5: FarmInv | AgBar | CurrCon | FutExp |
|---|---|---|---|---|---|---|---|---|
| Q1 | 1.00 | | | | | | | |
| Q2 | 0.60 | 1.00 | | | | | | |
| Q3 | 0.65 | 0.90 | 1.00 | | | | | |
| Q4 | 0.50 | 0.77 | 0.84 | 1.00 | | | | |
| Q5: FarmInv | 0.37 | 0.38 | 0.36 | 0.11 | 1.00 | | | |
| AgBar | 0.79 | 0.91 | 0.95 | 0.83 | 0.49 | 1.00 | | |
| CurrCon | 0.91 | 0.62 | 0.64 | 0.42 | 0.73 | 0.81 | 1.00 | |
| FutExp | 0.62 | 0.94 | 0.97 | 0.93 | 0.30 | 0.95 | 0.59 | 1.00 |

The low correlations between FarmInv and the other sentiment variables suggest that there is information in FarmInv that is not collected elsewhere. FarmInv is the only question that directly asks about investing in farm machinery. FarmInv's low correlation aligns with the University of Michigan's Survey of Consumers durable goods question having a lower correlation with the other questions and indices. Wilcox states that the MSC's consumer durable goods question was a "stellar performer" in improving forecasting models for consumer consumption (2007). Much like how the *Ag Economy Barometer Index* has more volatility than its consumer sentiment equivalent, the FarmInv is more volatile than the MSC's question regarding consumer durable goods purchasing. FarmInv has an average quarter-to-quarter change of 13%, while MSC's durable goods question has an average quarter-to-quarter change of only 2%

# CHAPTER 5. RESULTS AND DISCUSSION

This chapter presents and discusses the OLS regressions outlined in the methodology chapter. The discussion begins with a review of the results and implications from the annual models listed in section 4.1 and elasticities estimated from them. Next, the estimations of the quarterly model are presented and discussed, along with their elasticities. The chapter concludes with results from the estimation of the quarterly models, which include farmer sentiment data. All models are explanatory models estimated using OLS regressions in Stata 15 (StataCorp., 2017).

## 5.1 Annual Farm Machinery Demand Models

This section evaluates and discusses the OLS regression models examining the economic factors driving annual demand for farm tractors with 100 HP and above. First, Cromarty's model from 1959 is compared to a model containing similar explanatory variables but estimated using more recent data. Additional models are estimated to address potential problems in Cromarty's model. The three best performing models, selected by overall model fit and the statistical significance of the independent variables, are used to estimate elasticities. Out-of-sample forecasts are estimated to select the best performing model to forecast 2020 sales of tractors with 100 HP and above.

### 5.1.1 Comparison of Cromarty (1959) and Modernized Model

Cromarty's 1959 model provides the foundation for the models estimated in this study. Table 9 lists the results from Cromarty's model and the results from model estimation with modern data. Several differences are noticeable. First, the signs for the value of machinery on farms and labor cost flip between the two models. The positive sign on the modernized model's labor cost variable conforms to economic theory since the quantity demanded of tractors over 100 horsepower is expected to rise as farmers substitute larger farm machinery for labor. Likewise, the negative sign on the modernized model's value of machinery on farms aligns with the expectation discussed in Table 4. Second, the variable accounting for the dollar value of the machinery inventory on farms is not statistically significant in either model.

There are several other differences between Cromarty's model and the modernized model. The input prices and lagged net farm income variables are no longer statistically significant in the modernized model, whereas they are significant in Cromarty's model. The statistical significance of labor costs and farm assets fall from the 1% level in Cromarty's model to the 5% and 10% level, respectively, in the modernized model. However, the level of statistical significance for machinery prices increases from the 10% level in Cromarty's model to the 1% level in the modernized model. The $R^2$-value falls from .95 in Cromarty's model to .75 in the modernized model indicating Cromarty's model had better explanatory power during the estimation period of 1923 through 1954 than the modernized model had over the 1978 through 2019 period. Cromarty did not list an F-statistic for his model, but the modernized model resulted in an F-statistic of 12.58. The F-statistic is jointly testing the null hypothesis that all the independent variable parameters are equal to zero, and 12.58 is high enough to reject the null hypothesis with confidence.

Table 9: Regression Results from Cromarty (1959) and the Modernized Model, 1978-2019.

| Variables | Cromarty (1959) | Modernized Model |
|---|---|---|
| Machinery Prices$_t$ | -702.5* | -921.5*** |
| | (450.0) | (271.6) |
| Crop and Livestock Prices$_t$ | 235.8 | 64.07* |
| | (255.4) | (36.23) |
| Input Prices$_t$ | -1206.3*** | -1.551 |
| | (257.0) | (25.90) |
| Machinery Value on Farms$_t$ | 28.8 | -70.43 |
| | (46.3) | (102.9) |
| Net Farm Income$_{t-1}$ | 38.6** | 16.39 |
| | (22.4) | (13.40) |
| Acreage$_t$ | 1232.9 | 132.4 |
| | (2549.6) | (110.2) |
| Labor Costs$_t$ | -433.0*** | 214.7** |
| | (126.5) | (96.45) |
| Farm Assets$_t$ | 15.6*** | 9.959* |
| | (4.1) | (5.617) |
| Constant | 2,397,952 | -12,561 |
| | (Not listed) | (28,843) |
| Observations | 32 | 42 |
| R-squared | .95 | 0.753 |
| F-statistic | Not provided | 12.58 |

Note: The dependent variable for Cromarty (1959) was a derived quantity by taking the ratio of the value of manufacturers' farm machinery sales by an index of wholesales farm prices. The dependent variable for the modernized model is the annual units sold of two-wheel-drive farm tractors with at least 100 horsepower. Standard errors are in parentheses. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

One concern regarding Cromarty's original model specification is potential over-identification since he included input prices, output prices, and lagged net farm income in the model. Inclusion of input and output prices serves as a proxy for net farm income. Cromarty addressed this by lagging net farm income one period. This concern remains when re-evaluating the model with modern data. The models listed in section 4.1.2 attempt to address these potential problems and are displayed and discussed below.

### 5.1.2 Alternative Annual Models

Table 10 lists the results from the regressions discussed in section 3.1.2. The modernized model discussed above is listed in the first column for easier comparison. All estimations omit machinery value on farms for reasons discussed in the methodology section. Henceforth, models are titled with following nomenclature: a number indicating the order in which the model appears. If the model features annual data, the number will be followed by a letter "A," indicating that the model consists of annual data. If the model features quarterly data, the number indicating the original model will be followed the letter "Q" and a number, or numbers, indicating which of the quarterly dummy variables are used in that model. For example, model 3A indicates the annual model which appears third in the order, and model 3Q24 consists of the same set of independent variables as 3A, but with quarterly data and features quarterly dummy variables of Q2 and Q4.

Models 1A and 2A, shown in Table 10, attempt to correct for the potential over-identification in Cromarty's model. Model 1A drops the lagged net farm income variable, and the $R^2$-value and F-statistic increases slightly, this model has marginally better statistical fit than the modernized model. No coefficients flip signs, and only machinery prices, crop and livestock prices, and acreage have statistical significance. Model 2A omits prices received for crops and livestock and prices paid for inputs but retains lagged net farm income. The $R^2$-value falls slightly while the F-statistic increases moderately. The farm assets variable becomes statistically significant at the 1% level in Model 2A.

Models 3A, 4A, and 5A deviate more from the modernized model than models 1A and 2A. Model 3A includes crop and livestock prices received and prices paid for inputs, but omits lagged net farm income and labor costs. Model 4A omits crop and livestock prices received, prices paid for inputs, and labor costs, but includes lagged net farm income. Model 5A omits labor costs but includes lagged net farm income, prices received for crops and livestock, and prices paid for inputs. For all models, the F-statistic increases considerably, 28.77, 29.66, and 24.39, respectively, from 12.58 in the modernized model. The higher F-statistics indicate that the alternative models have better statistical fit than the model adapted strictly from Cromarty's original model. Again, the null hypothesis that all of the independent variables are equal to zero is more confidently rejected. The $R^2$ values increase a moderate amount as well, reinforcing that models 3A, 4A, and 5A have slightly better statistical fit than models 1A and 2A.

All variables in model 3A, excluding input prices, are statistically significant. While the input prices variable has a negative coefficient, which aligns with the hypothesis that if input prices increase farmers will have fewer resources to purchase machinery, it does not have statistical significance. The lack of statistical significance indicates that there is no certainty that an increase in input prices will result in a decrease in the quantity demanded of farm tractors with 100 HP and above. In model 4A, all explanatory variables have statistical significance at the 1% level, except for lagged net farm income. However, lagged net farm income still has statistical significance at the 10% level. Results for model 5A are similar to results from the estimation of model 3A.

Similar to 3A, input prices paid is the only variable in model 5A that is not statistically significant but does show the correct sign. Again, as the variable is not statistically significant at the 10% level, the correct sign for the respective coefficient, no confidence can be placed in this result holding in the future. The crop and livestock prices variable is only statistically significant at the 10% level, slightly lower than in model 3A, where it is statistically significant at the 5% level. All models include the average effective interest rate for farm machinery loans, and this variable is statistically significant at the 1% level. This level of statistical significance suggests that interest rates are indeed an essential factor in regards to sales of farm tractors with 100 HP and above, and the model should include it.

These models all indicate that when farm machinery prices increase, the quantity demanded of farm tractors with 100 HP and above will decrease. This result is consistent with the fundamental theory of the downward sloping demand curve in economics. The variable for farm machinery prices is statistically significant at the 1% level for all models.

Models 1A, 3A, and 5A include the variable for crop and livestock prices. Each estimation results in a positive coefficient for this variable, indicating that as farmers receive higher prices for their commodities, farmers will have increased monetary resources to purchase machinery leading to an increase in demand. Once again, this result matches the hypothesis that changes in prices received by farmers for their outputs impact the quantity demanded of farm tractors with 100 HP and above. Again, 5A includes crop and livestock prices received, prices paid for inputs, and lagged net farm income. The results from this estimation align closely with the results from model 3A and as lagged net farm income is not statistically significant in 5A, indicating that the effect of income was captured by including only prices received from crops and livestock and prices paid for inputs.

Table 10: Regression Results for Alternative Annual Models, 1978-2019.

| VARIABLES | Modernized | 1A | 2A | 3A | 4A | 5A |
|---|---|---|---|---|---|---|
| Machinery $Prices_t$ | -921.5*** | -825.8*** | -625.3*** | -621.6*** | -674.6*** | -632.3*** |
| | (271.6) | (274.9) | (176.6) | (87.39) | (65.25) | (89.24) |
| Crop and Livestock | 64.07* | 69.44** | | 54.73** | | 50.17* |
| $Prices_t$ | (36.23) | (33.55) | | (25.98) | | (26.92) |
| Input $Prices_t$ | -1.551 | -1.872 | | -13.16 | | -13.20 |
| | (25.90) | (26.54) | | (19.01) | | (19.15) |
| Machinery Value | -70.43 | | | | | |
| on $Farms_t$ | (102.9) | | | | | |
| $Assets_t$ | 16.39 | 10.40 | 22.06*** | 23.05*** | 24.99*** | 23.39*** |
| | (13.40) | (10.84) | (4.173) | (5.900) | (3.065) | (5.960) |
| Net Farm $Income_{t-1}$ | 132.4 | | 237.9** | | 135.6* | 56.07 |
| | (110.2) | | (91.46) | | (74.05) | (78.02) |
| $Acreage_t$ | 214.7** | 203.1** | 235.5** | 267.3*** | 297.9*** | 269.4*** |
| | (96.45) | (97.90) | (97.58) | (77.45) | (80.78) | (78.04) |
| Labor $Costs_t$ | 9.959* | 8.962 | 2.024 | | | |
| | (5.617) | (5.732) | (4.118) | | | |
| Machinery Interest | | | | -2,415*** | -2,196*** | -2,309*** |
| $Rate_t$ | | | | (469.1) | (517.8) | (495.1) |
| Constant | -12,561 | -16,134 | -1,835 | 9,538 | 19,831 | 9,515 |
| | (28,843) | (29,596) | (28,990) | (23,639) | (24,304) | (23,804) |
| Observations | 42 | 42 | 42 | 42 | 42 | 42 |
| R-squared | 0.753 | 0.723 | 0.709 | 0.831 | 0.805 | 0.834 |
| F-statistic | 12.58 | 15.23 | 17.54 | 28.77 | 29.66 | 24.39 |

Note: The dependent variable for all models is the annual units sold of farm tractors with 100 HP and above. Standard errors are in parentheses. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Variations of models 3A, 4A, and 5A using the debt-to-asset and debt-to-equity ratios, retrieved from the USDA's Economic Research Service's Balance Sheet, were also estimated. These ratios were substituted for total farm assets in the models as they provide alternative measures of borrowing capability. These substitutions resulted in the sign for crop and livestock prices received turning negative, and the sign for input prices paid to turn positive for all models estimated with debt-to-assets and debt-to-equity ratios instead of total farm assets. For these reasons, total farm assets appears to provide a better measure of farmers' borrowing capability.

Models were also estimated using total farm equity as a measure of borrowing capability instead of total farm assets. This substitution resulted in very little change for both models. The lack of change comes as little surprise as total farm assets and total farm equity have a correlation coefficient of 0.999. For this reason, total farm assets appears to provide the best measure of farmers' borrowing capability.

Models 3A, 4A, and 5A are selected as the best performing annual models as their statistical fit are comparatively high, their variables all have correct signs, and most of their independent variables having statistical significance at the 10% level or higher. These models are used to estimate elasticities in section 5.1.3, conduct out-of-sample forecast evaluations in section 5.1.4, forecast 2020 tractor sales in section 5.1.5, and, finally, provide the basis for estimating quarterly demand models of farm tractors with 100 HP and above in section 5.2.

### 5.1.3 Elasticities Calculated from Annual Models

Models 3A, 4A, and 5A from Table 10 are used to derive the elasticities for each variable with respect to sales of farm tractors with 100 HP and above. The mean of each variable from 1978-2019 is used to calculate its respective elasticity. According to these results, the quantity demanded of farm tractors with 100 HP and above is most responsive to changes in farm machinery prices and crop acreage. Table 11 provides elasticity estimates for each model.

According to these results, a 1% increase in machinery prices results in a roughly 4% decrease in the quantity demanded of farm tractors with 100 horsepower and above. A 1% increase in crop and livestock prices results in a 1.5-1.7% increase in quantity demanded. Conversely, a 1% rise in inputs prices was associated with the quantity demanded falling 0.7% during the estimation period, although prices paid for inputs is not statistically significant in either of the models. The models indicate that quantity demanded increases by about 1.5% if farm assets increase by 1%. Sales of farm tractors with 100 HP and above seem to be very responsive to acreage changes as a 1% increase in acreage will increase quantity demanded slightly more than 3%. Changes in the interest rates paid on loans for farm machinery elicits less of a response as the quantity demanded decreases slightly less than 1% when the interest rates rise 1%. Changes in lagged net farm income seem to have little impact in sales of farm tractors with 100 HP and above as a 1% increase only indicates a 0.30% increase in the quantity demanded farm tractors with 100 HP and above. Additionally, lagged net farm income is only statistically significant in 4A at the 10% level and does not statistical significance in 5A.

Table 11: Demand Elasticities for Annual Sales of Farm Tractors with ≥100 HP, 1978-2019.

| Variables | 3A Elasticities | 4A Elasticities | 5A Elasticities |
|---|---|---|---|
| Machinery Prices$_t$ | -3.93*** | -4.27*** | -4.00*** |
| Crop and Livestock Prices$_t$ | 1.66** | N/A | 1.52* |
| Input Prices$_t$ | -0.72 | N/A | -0.72 |
| Farm Assets$_t$ | 1.43*** | 1.55*** | 1.45*** |
| Acreage$_t$ | 3.07*** | 3.42*** | 3.09*** |
| Machinery Interest Rate$_t$ | -0.89*** | -0.81*** | -0.86*** |
| Net Farm Income$_{t-1}$ | N/A | 0.30* | 0.12 |

Note: Each elasticity is calculated using the mean of the respective variable. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

### 5.1.4 Out-of-Sample Estimations for Annual Models

An additional way to evaluate the robustness of the models is to evaluate and compare the various models' out-of-sample forecast performance. Models 3A, 4A, and 5A are estimated again, but only including data beginning in 1978 through 2014. This process is repeated four more times with one additional year of observations in each iteration, ending with the data from 2018, for a total of five iterations. Table 12, Table 13, and Table 14 highlight the results of each iteration of models 3A, 4A, and 5A, respectively.

Overall, the models' performances seem stable. None of the explanatory variables flip signs. The variable for prices received for crops and livestock loses statistical significance for the first two iterations of models 3A and 5A. However, there is statistical significance at the 10% level for the last three iterations. Lagged net farm income sees borderline significance in model 4A, which aligns with the previous model estimations. The $R^2$-values and F-statistics change little.

Table 12: Regression Results for Out-of-Sample Estimations of Model 3A.

| VARIABLES | 3A (1978-2014) | 3A (1978-2015) | 3A (1978-2016) | 3A (1978-2017) | 3A (1978-2018) |
|---|---|---|---|---|---|
| Machinery Prices$_t$ | -669.6*** | -630.6*** | -620.7*** | -629.7*** | -629.8*** |
| | (92.43) | (86.19) | (86.43) | (86.70) | (85.45) |
| Crop and Livestock | 31.20 | 47.89 | 59.89** | 62.43** | 61.36** |
| Prices$_t$ | (31.76) | (28.27) | (26.68) | (26.78) | (25.68) |
| Input Prices$_t$ | -1.714 | -12.29 | -15.69 | -13.12 | -12.90 |
| | (21.03) | (18.94) | (18.87) | (18.87) | (18.56) |
| Farm Assets$_t$ | 24.62*** | 25.08*** | 23.30*** | 20.62*** | 20.82*** |
| | (6.565) | (6.583) | (6.466) | (6.112) | (5.916) |
| Acreage$_t$ | 280.7*** | 285.4*** | 291.5*** | 306.3*** | 304.6*** |
| | (80.37) | (80.63) | (81.07) | (80.67) | (78.89) |
| Machinery Interest | -2,376*** | -2,433*** | -2,514*** | -2,609*** | -2,594*** |
| Rate$_t$ | (489.6) | (489.2) | (488.3) | (485.2) | (470.5) |
| Constant | 13,356 | 7,217 | 2,680 | -785.2 | -179.5 |
| | (25,003) | (24,521) | (24,414) | (24,409) | (23,814) |
| Observations | 37 | 38 | 39 | 40 | 41 |
| R-squared | 0.859 | 0.853 | 0.847 | 0.842 | 0.843 |
| F-statistic | 30.41 | 29.93 | 29.52 | 29.27 | 30.42 |

Note: The dependent variable for all models is the annual units sold of farm tractors with 100 HP and above. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 13: Regression Results for Out-of-Sample Estimations of Model 4A.

| VARIABLES | 4A (1978-2014) | 4A (1978-2015) | 4A (1978-2016) | 4A (1978-2017) | 4A (1978-2018) |
|---|---|---|---|---|---|
| Machinery Prices$_t$ | -662.4*** | -660.3*** | -666.8*** | -675.8*** | -678.0*** |
| | (62.52) | (63.90) | (66.70) | (66.68) | (65.69) |
| Farm Assets$_t$ | 30.94*** | 28.97*** | 26.47*** | 24.75*** | 24.38*** |
| | (3.801) | (3.666) | (3.604) | (3.322) | (3.169) |
| Net Farm Income$_{t-1}$ | 6.175 | 29.56 | 83.10 | 135.0* | 143.3* |
| | (88.74) | (89.43) | (89.23) | (78.32) | (74.99) |
| Acreage$_t$ | 265.4*** | 280.6*** | 296.0*** | 313.9*** | 319.2*** |
| | (83.18) | (84.46) | (87.90) | (87.15) | (85.25) |
| Machinery Interest | -2,193*** | -2,228*** | -2,247*** | -2,254*** | -2,276*** |
| Rate$_t$ | (501.1) | (511.8) | (534.8) | (538.0) | (529.3) |
| Constant | 26,372 | 23,345 | 20,495 | 16,399 | 15,488 |
| | (23,947) | (24,402) | (25,460) | (25,380) | (24,994) |
| Observations | 37 | 38 | 39 | 40 | 41 |
| R-squared | 0.844 | 0.832 | 0.812 | 0.807 | 0.807 |
| F-statistic | 33.66 | 31.74 | 28.59 | 28.36 | 29.29 |

Note: The dependent variable for all models is the annual units sold of farm tractors with 100 HP and above. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 14: Regression Results for Out-of-Sample Estimations of Model 5A.

| VARIABLES | 5A 1978-2014 | 5A 1978-2015 | 5A 1978-2016 | 5A 1978-2017 | 5A 1978-2018 |
|---|---|---|---|---|---|
| Machinery $Prices_t$ | -667.4*** | -630.7*** | -625.7*** | -640.5*** | -640.2*** |
| | (94.86) | (89.51) | (89.93) | (88.53) | (87.26) |
| Crop and Livestock $Prices_t$ | 31.32 | 47.88 | 58.57** | 58.33** | 56.87** |
| | (32.29) | (28.89) | (27.56) | (27.53) | (26.61) |
| Input $Prices_t$ | -1.488 | -12.29 | -15.49 | -13.29 | -12.94 |
| | (21.42) | (19.25) | (19.16) | (19.01) | (18.69) |
| Net Farm $Income_{t-1}$ | -15.12 | 0.282 | 22.09 | 57.54 | 54.80 |
| | (88.44) | (87.77) | (86.26) | (77.95) | (76.18) |
| $Assets_t$ | 24.79*** | 25.07*** | 23.12*** | 20.86*** | 21.16*** |
| | (6.746) | (6.772) | (6.600) | (6.164) | (5.977) |
| $Acreage_t$ | 278.6*** | 285.5*** | 294.1*** | 309.3*** | 306.4*** |
| | (82.63) | (82.78) | (82.93) | (81.33) | (79.50) |
| Machinery Interest $Rate_t$ | -2,392*** | -2,433*** | -2,485*** | -2,507*** | -2,489*** |
| | (506.7) | (507.7) | (508.7) | (507.6) | (495.8) |
| Constant | 13,971 | 7,209 | 2,206 | -1,104 | -157.9 |
| | (25,670) | (25,073) | (24,848) | (24,583) | (23,985) |
| Observations | 37 | 38 | 39 | 40 | 41 |
| R-squared | 0.859 | 0.853 | 0.847 | 0.844 | 0.845 |
| F-statistic | 25.23 | 24.83 | 24.58 | 24.82 | 25.77 |

Note: The dependent variable for all models is the annual units sold of farm tractors with 100 HP and above. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

The regression equations parameter estimates provided in tables 12, 13, and 14 are used to evaluate how well the models forecast the subsequent year. Predicted values are estimated using each model iteration and the data from the year following the respective iteration's end. For example, model 3A's predicted value for 2015 is calculated using the 3A iteration, which ended in 2014 and the 2015 observations for each variable. The predicted values are then compared to the actual units sold to judge accuracy. Tables 15, 16, and 17 show the predicted values for each out-of-sample iteration of model 3A, 4A, and 5A, respectively. All models tend to overestimate the units sold from 2015-2017 substantially. Models 3A and 5A better predict units sold in 2018 but then substantially underestimates units sold in 2019. Model 4A continues to overestimate the units sold in 2018 and underestimates units sold in 2019. However, while model 4A underestimates 2019 sales, it is much closer to the actual sales number than models 3A and 5A.

The out-of-sample estimations' lack of accuracy suggests that the models are over-emphasizing the weight certain explanatory variables have in regards to farm tractor sales. Judging by the elasticities examined in section 5.1.3, model 3A and model 5A seem to be over-emphasizing the impact falling prices received for crops and livestock have on farm tractor sales. Similarly, model 4A seems to be over-emphasizing the impact rising prices of machinery have had on farm tractor sales historically.

The models' poor performance for predicting 2019's sales can also be partly explained by 2019 being an anomaly. Poor planting conditions in the spring of 2019 resulted in the fourth-fewest acres harvested during this study's timeframe. While these acres were not harvested in 2019, they remain in the crop rotation. Had the acreage data for 2019 been the same as 2018, model 3A would have resulted in an estimation of 12,942 units sold, model 4A would have estimated 18,017 units sold, and model 5A would estimate 13,015 units sold. Using the 2018 acreage data to estimate the units sold in 2019 significantly reduces each model's prediction error. The prediction error for model 3A is still relatively large, underestimating sales by over 5,000 units. Model 4A only underestimated sales by 577 units or by about 3%. The last line in tables 15, 16, and 17 show the out-of-sample predictions for 2019, by model, when using the 2018 acreage data.

Table 15: Out-of-Sample Predictions for Model 3A for 2015-2019.

| Years Used in the Model | Year Predicted | Actual Sales | Predicted Values | Prediction Error |
|---|---|---|---|---|
| 1978-2014 | 2015 | 23,920 | 31,180 | +7,260 |
| 1978-2015 | 2016 | 18,542 | 26,018 | +7,476 |
| 1978-2016 | 2017 | 17,026 | 24,216 | +7,190 |
| 1978-2017 | 2018 | 17,958 | 16,914 | -1,044 |
| 1978-2018 | 2019 | 18,594 | 8,540 | -10,054 |
| 1978-2018 | 2019 | 18,594 | 12,942* | -5,652 |

Note: Actual Sales refers to the units sold of farm tractors with 100 HP and above. Superscript * indicates the result is from the model estimation that used the acres harvested for corn, cotton, hay, rice, sorghum, soybeans, and wheat in 2018 to estimate 2019 farm machinery sales.

Table 16: Out-of-Sample Predictions for Model 4A for 2015-2019.

| Years Used in the Model | Year Predicted | Actual Sales | Predicted Values | Prediction Error |
|---|---|---|---|---|
| 1978-2014 | 2015 | 23,920 | 33,169 | +9,249 |
| 1978-2015 | 2016 | 18,542 | 30,894 | +12,352 |
| 1978-2016 | 2017 | 17,026 | 25,422 | +8,396 |
| 1978-2017 | 2018 | 17,958 | 20,685 | +2,727 |
| 1978-2018 | 2019 | 18,594 | 13,404 | -5,190 |
| 1978-2018 | 2019 | 18,594 | 18,017* | -577 |

Note: Actual Sales refers to the units sold of farm tractors with 100 HP and above. Superscript * indicates the result is from the model estimation that used the acres harvested for corn, cotton, hay, rice, sorghum, soybeans, and wheat in 2018 to estimate 2019 farm machinery sales.

Table 17: Out-of-Sample Predictions for Model 5A for 2015-2019.

| Years Used in the Model | Year Predicted | Actual Sales | Predicted Values | Prediction Error |
|---|---|---|---|---|
| 1978-2014 | 2015 | 23,920 | 31,354 | +7,434 |
| 1978-2015 | 2016 | 18,542 | 26,014 | +7,472 |
| 1978-2016 | 2017 | 17,026 | 23,486 | +6,460 |
| 1978-2017 | 2018 | 17,958 | 16,326 | -1,632 |
| 1978-2018 | 2019 | 18,594 | 8,584 | -10,010 |
| 1978-2018 | 2019 | 18,594 | 13,015* | -5,579 |

Note: Actual Sales refers to the units sold of farm tractors with 100 HP and above. Superscript * indicates the result is from the model estimation that used the acres harvested for corn, cotton, hay, rice, sorghum, soybeans, and wheat in 2018 to estimate 2019 farm machinery sales.

Root-mean-square error values (RMSE) are calculated for each model to compare the out-of-sample model performance. As Table 18 shows, Model 4A has the highest RMSE value out of the three models indicating that it has the worst forecasting performance. Models 3A and 5A have similar RMSE values, but 5A's RMSE is slightly lower than 3A's, indicating that it has the best out-of-sample forecasting performance. As model 5A has the lowest RMSE value, it is used to forecast 2020 the quantity demanded of farm tractors with 100 HP and above.

Table 18: Out-of-Sample RSME Values for Models 3A, 4A, and 5A.

| Model | RSME |
|---|---|
| 3A | 7,245 |
| 4A | 8,282 |
| 5A | 7,151 |

### 5.1.5 Forecast for 2020 Sales

Having a forecast for the quantity demanded of farm tractors with 100 HP and above is useful for decision-makers in the farm machinery production sector. This section estimates several forecasts for 2020 sales using model 5A and with varying assumptions regarding the independent variables. It is necessary to make a forecast of the independent variables as most of the variables are contemporary and, thus, are not known with certainty at the time of the forecast. Each forecast shows how changes in individual explanatory variables impact the quantity demanded of farm tractors with 100 HP and above.

To begin, the forecast for the monetary variables, machinery prices, crop and livestock prices, input prices, the interest rate for farm machinery loans, and the estimated value of farm assets is done by taking the average year-to-year percentage change and adding that value to the 2019 observation. The annual average percent change over the estimation period serves as a rough proxy for inflation. For example, to forecast 2020 machinery prices, the absolute value of the year-to-year percentage for machinery prices is calculated for each annual observation. The average of these year-to-year percent changes is 3.11%. The forecast for the 2020 machinery prices variable is made by taking the 2019 machinery prices observation and multiplying it by 1.03. In other words, the 2019 observations for these variables are multiplied by its average annual percentage change to forecast the 2020 observation. As for the acreage variable, it is a physical variable, not a monetary one, and is thus not impacted by inflation. The number of acres harvested in 2018 replaces the 2019 observation in the 2020 forecast due to the 2019 acreage being abnormally low because of adverse weather conditions. As net farm income is lagged one year in model 5A, it is known at the time of each forecast. Table 19 lists the assumptions for the foundational forecast.

Table 19: Assumptions for 2020 Foundational Forecast Variables.

| Variable | Assumption | Percentage Change or Value Used |
|---|---|---|
| Machinery Prices$_t$ | 2019 value plus the average annual % change | +3.11% |
| Crop and Livestock Prices$_t$ | 2019 value plus the average annual % change | +1.65% |
| Input Prices$_t$ | 2019 value plus the average annual % change | +3.26% |
| Farm Assets$_t$ | ERS's estimate | ERS's 2020 estimate |
| Net Farm Income$_{t-1}$ | ERS's estimate | 2019's Net Farm Income |
| Acreage$_t$ | Returns to 2018 acres harvested | 2018 Acres Harvested |
| Machinery Interest Rate$_t$ | 2019 value plus the average annual % change | -0.51% |

These baseline assumptions result in a 2020 forecast for sales of farm tractors with 100 HP and above of 11,195 units sold according to Model 5A. There will be an all-time low in sales of farm tractors with 100 HP and above if this forecast materializes. This forecast seems unlikely as the past four years have had an average of about 18,000 units sold. Table 20 lists changes made to the foundational forecast's assumptions and the resulting forecasts. These forecasts include scenarios such as farm assets increase more than expected by the ERS, crop and livestock prices increase more than the historical average, the average effective interest rate for farm machinery loans is 5%, machinery prices rise less than the historical average, and input prices rise 5%. The first row in Table 20 lists results from the foundational forecast for easier comparison.

According to this model, if farm assets increase at the historical average, which would be over twice the percentage change that ERS is estimating, sales of farm tractors with 100 HP and above will be around 1,500 units higher than the foundational forecast predictions. If crop and livestock prices increase more than the historical average and all remaining variables align with the foundational forecast, the quantity demanded of farm tractors with 100 HP and above in 2020 will be lower than 2019 by approximately 6,000 units, according to model 5A. The average effective interest rate for farm machinery loans was 5.73% in 2019. If 2020 has an average interest rate of 5% for farm machinery loans, the model predicts sales increasing by around 1,500 units from the foundational forecast.

Dating back to 1978, machinery prices have risen at an average rate of 3.11% per year. Over the past five years, however, the average percentage increase has halved. If machinery prices increase at 1.5% instead of the historical average in 2020, the model estimates approximately 2,500 additional units demanded. Conversely, if the prices for inputs rise by 5% instead of the historical average of just over 3%, the model estimate about 500 fewer units demanded in 2020 than the foundational forecast estimates.

Table 20: Changes Made to Foundational Forecast Assumptions and Resulting Forecasts.

| Change to Foundational Forecast | Sales Forecast for 2020<br>5A |
|---|---|
| Foundational Forecast, no change | 11,195 |
| Assets increase at historical average, +3.58% | 13,785 |
| Crop and livestock prices increase more than average, at +4% | 12,287 |
| Machinery interest rate is 5% | 12,802 |
| Machinery prices only rise by 1.5% | 13,612 |
| Input prices rise 5% | 10,684 |

Note: Sales forecast refers to the estimate of units sold of farm tractors with 100 HP and above.

## 5.2 Quarterly Models

All previous studies on farm machinery sales focus solely on annual sales while there were no studies in the literature that focused on quarterly farm machinery sales. This section will evaluate quarterly models. Models 3A, 4A, and 5A are estimated again using quarterly data from 2009-2019 and analyzed. Elasticities are then estimated and interpreted.

### 5.2.1 Quarterly Re-estimation of Annual Models

Re-estimating the three best performing annual models, models 3A, 4A, and 5A, using quarterly data from 2009-2019, and including dummy variables to control for the seasonality in the data provides the OLS regression results seen in Table 21. Again, the nomenclature for the quarterly models is as follows: the first number indicates the annual model of which it is based, “Q” indicates the use of quarterly data. The number(s) following “Q” indicates the quarterly dummy variables represented in the respective model. The second quarter, Q2, and fourth quarter, Q4, are selected as the quarterly dummy variables as the dependent variable peaks in all but one year over this timeframe. Models are estimated twice, once with both quarterly dummy variables and once with just the Q4 dummy variable since sales of farm tractors with 100 HP and above peaked in Q4 in all but three years during this period.

A limitation in the quarterly models arises due to the variability in quarter-to-quarter sales of farm tractors over 100 HP and that several of the independent variables only change once a year. These variables include lagged net farm income, farm assets, and acreage. There is a noticeably higher variation in quarter-to-quarter farm tractor sales than there is in year-to-year sales. For example, there is an average of a 22% change in units sold between quarters compared to an average change of 14% between years for annual sales. This increased variability and lack of change in some of the explanatory variables likely results in the quarterly models having limited explanatory power.

Some differences arise between the quarterly models and their respective annual models. The variable for machinery prices loses statistical significance for models 3Q24, 3Q4, 5Q24, and 5Q4, but is statistically significant at the 1% level for models 4Q24 and 4Q4. Models 3Q24, 3Q4, 5Q24, and 5Q4 see the sign for the crop and livestock prices flip from positive to negative. The input prices paid variable becomes statistically significant in models 3Q24, 3Q4, and 5Q4, whereas it did not have statistical significance in the annual models. Acreage has a negative sign when it is expected to be positive for all six models and is only statistically significant at the 5% level in 4Q24 and 4Q4.

The machinery interest rate variable is no longer statistically significant across all models. This change could reflect interest rates being at historic lows during most of this timeframe, loosening the constraint higher interest rates would have had on sales of farm tractors with 100 HP and above. The $R^2$-values for the quarterly models are comparable to the values seen in the annual models. All models see a decrease in the resulting F-statistic.

Q4 is highly statistically significant, which aligns with expectations as this quarter had the highest number of two-wheel-drive farm tractors sold for all but three years from over the 2009-2019 timeframe. Q2 is only statistically significant at the 5% level in 3Q24 and 5Q24, having no statistical significance in 4Q24 despite often having the second-highest sales throughout the year.

The models that include the Q2 dummy variable only see a slight increase in the $R^2$-values in comparison to the models that feature only Q4 for a seasonal control. Additionally, 4Q24 sees a slight decrease in the F-statistic in comparison to the 4Q4. Q2 will be omitted in additional model estimations as its inclusion does not seem to benefit the models much, if at all.

Table 21: Regression Results for Quarterly Models, 2009 Q1-2019 Q4.

| VARIABLES | 3Q24 | 3Q4 | 4Q24 | 4Q4 | 5Q24 | 5Q4 |
|---|---|---|---|---|---|---|
| Machinery $\text{Prices}_t$ | -14.37 | -69.83 | -318.0*** | -362.7*** | -44.98 | -102.3 |
| | (98.21) | (102.6) | (102.1) | (100.2) | (99.42) | (102.7) |
| Crop and Livestock | -5.131 | -2.909 | | | -4.772 | -2.639 |
| $\text{Prices}_t$ | (7.578) | (8.066) | | | (7.485) | (7.913) |
| Input $\text{Prices}_t$ | -10.80* | -12.25** | | | -9.186 | -10.24* |
| | (5.552) | (5.918) | | | (5.602) | (5.947) |
| $\text{Assets}_t$ | 4.521* | 6.137** | 7.066** | 8.310*** | 4.481* | 5.975** |
| | (2.402) | (2.480) | (2.926) | (2.879) | (2.371) | (2.435) |
| $\text{Acreage}_t$ | -18.16 | -37.95 | -122.2** | -139.9** | -33.82 | -55.14 |
| | (44.95) | (47.43) | (52.11) | (51.98) | (45.78) | (47.81) |
| Machinery Interest $\text{Rate}_t$ | -321.0 | -27.01 | -202.4 | 31.62 | -173.5 | 127.2 |
| | (372.0) | (378.5) | (464.5) | (450.0) | (382.2) | (384.2) |
| Net Farm $\text{Income}_{\text{prior year}}$ | | | 42.84*** | 44.44*** | 14.99 | 17.80 |
| | | | (11.67) | (11.87) | (10.80) | (11.44) |
| Q2 | 855.6** | | 678.4 | | 804.6** | |
| | (339.8) | | (424.8) | | (337.4) | |
| Q4 | 1,928*** | 1,855*** | 2,247*** | 2,186*** | 1,982*** | 1,924*** |
| | (387.0) | (413.6) | (482.8) | (491.3) | (384.0) | (408.1) |
| Constant | 29,125 | 41,939* | 87,649*** | 97,858*** | 34,802 | 47,771* |
| | (23,679) | (24,781) | (26,531) | (26,283) | (23,727) | (24,593) |
| Observations | 44 | 44 | 44 | 44 | 44 | 44 |
| R-squared | 0.831 | 0.801 | 0.727 | 0.708 | 0.840 | 0.814 |
| F-statistic | 21.55 | 20.66 | 13.70 | 14.93 | 19.87 | 19.09 |

Note: The dependent variable for all models is the quarterly units sold of farm tractors with 100 HP and above. Standard errors are in parentheses. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

### 5.2.2 Elasticities Calculated from Quarterly Models

The models which only include the Q4 dummy variable as a seasonality control, models 3Q4, 4Q4, and 5Q4 from section 5.2.1, are used to estimate the elasticities of each variable. Table 22 displays the elasticities from each model. In comparison to the elasticities estimated from the annual models, the elasticities estimated from the quarterly models are much more extreme. Model 4Q4 indicates that a 1% increase in farm machinery prices results in a roughly 13% decrease in sales of farm tractors with 100 HP and above. However, 3Q4 and 5Q4 indicate a 1% increase in prices results in about a 3% fall in demand, aligning more closely with the elasticities estimated from the annual models.

Model 4Q4 indicates that a 1% increase in acreage results in a 6% decline in the quantity demanded of farm tractors with 100 HP and above. This result contradicts the hypothesis that as acreage increases, the quantity demanded of farm tractors with 100 HP and above will increase. This result might indicate that as farms continue to consolidate, increasing the average acreage per farm, farmers are spreading their machinery costs over more acres, which means that instead of two separate farmers using two separate tractors to farm a certain number of acres. When these farms consolidate, only one farmer cultivates the same number of acres with one tractor. Once again, Model 4Q4 estimates a much more extreme elasticity for acreage than the other two models. Models 3Q4 and 5Q4 estimate an elasticity of a roughly 2% fall in quantity demanded when acreage increases 1%.

According to these models, the quantity demanded of farm tractors with 100 HP and above is not highly responsive to changes in lagged net farm income, crop and livestock prices received, input prices paid, or machinery interest rates. These variables are all estimated to be inelastic with a 1% change resulting in a percentage change in the quantity demanded of farm tractors with 100 HP and above less than 1%. The models also indicate that a 1% increase in assets results in a 2.5% to 3.5% increase in the quantity demanded of farm tractors with 100 HP and above.

Table 22: Demand Elasticities for Quarterly Sales of Farm Tractors with ≥100 HP, 2009 Q1 – 2019 Q4.

| VARIABLES | 3Q4 | 4Q4 | 5Q4 |
|---|---|---|---|
| Machinery Prices$_t$ | -2.44 | -12.68*** | -3.57 |
| Crop and Livestock Prices$_t$ | -0.44 | N/A | -0.39 |
| Input Prices$_t$ | -3.83 | N/A | -3.19* |
| Net Farm Income$_{\text{prior year}}$ | N/A | 0.61*** | 0.24 |
| Assets$_t$ | 2.65** | 3.59*** | 2.58** |
| Acreage$_t$ | -1.71 | -6.29** | -2.48 |
| Machinery Interest Rate$_t$ | -0.02 | 0.03 | 0.10 |

Note: Each elasticity is calculated using the mean of the respective variable. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

## 5.3 Sentiment Data

Similar to how previous studies did not utilize quarterly data to model farm machinery sales, no previous research utilized farmer sentiment data in farm machinery demand models. This gap in the literature is not surprising as no data on farmer sentiment existed until October 2015 when the *Purdue University-CME Group Ag Economy Barometer* was first available. To evaluate whether including farmer sentiment data in the models improves their performance, models 3Q4 and 4Q4 are re-estimated over the timeframe in which the sentiment data is available, 2015 Q4 to 2019 Q4. The models are then re-estimated with the sentiment data included. The models which do not include sentiment data and the models that do include sentiment data are compared.

### 5.3.1 Re-estimating Quarterly Models over the Ag Economy Barometer's Timeframe

The results from the re-estimations of models 3Q4, 4Q4, and 5Q4 using quarterly data spanning from 2015 Q4 to 2019 Q4 obtains the OLS regression results seen in Table 23. The statistical significance, measured by the F-statistic, for each model substantially falls when estimated over this time. When estimated over the ten-year period, models 3Q4 and 5Q4 have F-statistics of around 20 and these values drop below 2.0 when estimated over the shorter period. Model 4Q4 tells a similar story, having an original F-statistic of just below 15 and falling to slightly above 2.0 when re-estimated.

Importantly, the variables for input prices, assets, acreage, and the interest rate on farm machinery loans rates all have signs that are inconsistent with economic theory. The fourth quarter seasonal dummy variable is statistically significant in models 3Q4 and 4Q4, but not in 5Q4. The F-statistic also falls substantially in comparison with the models in section 5.1.2. One consideration when comparing the annual models to the quarterly models is the fact that just 17 quarterly observations are available for model estimation, which could be a driving factor behind the decline in model performance. Despite the initial lackluster results, the quarterly models will be estimated again with sentiment variables included.

Table 23: Regression Results for Quarterly Models, 2015 Q4-2019 Q4.

| VARIABLES | 3Q4 | 4Q4 | 5Q4 |
|---|---|---|---|
| Machinery Prices$_t$ | -93.80 | -62.16 | -93.51 |
| | (121.5) | (135.7) | (153.0) |
| Crop and Livestock Prices$_t$ | 14.95 | | 14.97 |
| | (21.01) | | (23.00) |
| Input Prices$_t$ | 2.369 | | 2.381 |
| | (11.92) | | (13.06) |
| Assets$_t$ | -5.052 | -5.360 | -5.081 |
| | (9.034) | (9.338) | (12.53) |
| Acreage$_t$ | -52.84 | -83.00 | -52.83 |
| | (67.98) | (50.76) | (72.12) |
| Machinery Interest Rate$_t$ | 538.2 | 468.7 | 537.5 |
| | (779.0) | (732.1) | (851.0) |
| Net Farm Income$_{prior\ year}$ | | 12.23 | -0.131 |
| | | (30.59) | (36.82) |
| Q4 | 877.8* | 852.3* | 877.1 |
| | (422.2) | (418.7) | (485.3) |
| Constant | 31,994 | 54,367 | 31,979 |
| | (43,769) | (32,157) | (46,607) |
| Observations | 17 | 17 | 17 |
| R-squared | 0.605 | 0.574 | 0.605 |
| F-statistic | 1.97 | 2.24 | 1.53 |

Note: The dependent variable for both models is the quarterly units sold of farm tractors with 100 HP and above. Standard errors are in parentheses. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

### 5.3.2 Addition of Sentiment Data to Quarterly Models

Data that measures farmer sentiment, or the level of optimism or pessimism farmers have in the agricultural economy has the potential to improve model performance. The rationale behind this thought is that if farmers are more optimistic regarding their economic standing, they will be more likely to make large purchases and investments in items such as farm machinery. Studies using consumer sentiment data, or sentiment data regarding the entire U.S. economy, have found results that align with this idea in the consumer sector (Huth et al., 1994; Wilcox, 2007). However, the consumer sentiment data used by these researchers have a much longer history providing them with a much richer data set to use in their model estimation. In contrast, the agricultural sentiment data only dates back to October 2015, providing just 17 quarters of data. Table 24, 25, and 26 provide the $R^2$-values and F-statistics for each estimation of models 3Q4, 4Q4, and 5Q4 when the models include various measures of farmer sentiment. The first column lists the results from the estimations in section 5.3.1, the models which do not include sentiment data for easier comparison. The following columns show the same models with various sentiment variables, derived from the *Purdue University-CME Group Ag Economy Barometer* monthly survey, indicated in the column title. There is very little change in the $R^2$-values and F-statistics from one model to the next. No independent variables are statistically significant at the 10% level. All independent variable signs align with those seen in section 5.3.1, except for Assets in the iteration of model 4Q4 that included the *Index of Future Expectations*. These results indicate that including sentiment variables to the quarterly models does not improve the demand models' explanatory power.

Table 24: Results for 3Q4 Model with Sentiment Data Included, 2015 Q4-2019 Q4.

| VARIABLES | No Sentiment Data | Ag Economy Barometer Index | Index of Current Conditions | Index of Future Expectations | Farm Capital Investment Index |
|---|---|---|---|---|---|
| Machinery Prices$_t$ | -93.80 | -152.0 | -190.4 | -87.84 | -230.1 |
| | (121.5) | (133.8) | (187.3) | (122.3) | (158.7) |
| Crop and Livestock Prices$_t$ | 14.95 | 15.42 | 23.22 | 8.743 | 28.27 |
| | (21.01) | (20.95) | (24.71) | (22.12) | (22.83) |
| Input Prices$_t$ | 2.369 | 3.817 | 1.948 | 4.561 | 1.039 |
| | (11.92) | (11.97) | (12.29) | (12.21) | (11.57) |
| Assets$_t$ | -5.052 | 6.035 | 3.820 | 1.713 | 8.149 |
| | (9.034) | (14.08) | (15.82) | (11.56) | (13.53) |
| Acreage$_t$ | -52.84 | -27.73 | -32.88 | -37.36 | -13.31 |
| | (67.98) | (72.08) | (75.72) | (70.30) | (72.64) |
| Machinery Interest Rate$_t$ | 538.2 | 286.5 | 610.3 | 156.9 | 142.8 |
| | (779.0) | (814.7) | (809.2) | (880.8) | (814.2) |
| Q4 | 877.8* | 1,268* | 1,222 | 1,090* | 1,450** |
| | (422.2) | (567.4) | (659.8) | (479.9) | (605.8) |
| Ag Economy Barometer Index$_t$ | | -26.28 | | | |
| | | (25.64) | | | |
| Index of Current Conditions$_t$ | | | -13.15 | | |
| | | | (18.97) | | |
| Index of Future Expectations$_t$ | | | | -22.52 | |
| | | | | (23.77) | |
| Farm Capital Investment Index$_t$ | | | | | -50.97 |
| | | | | | (39.91) |
| Constant | 31,994 | 5,951 | 15,157 | 12,724 | 6,366 |
| | (43,769) | (50,501) | (51,210) | (48,493) | (46,827) |
| | 1.97 | 1.87 | 1.69 | 1.82 | 2.05 |
| Observations | 17 | 17 | 17 | 17 | 17 |
| R-squared | 0.605 | 0.651 | 0.628 | 0.645 | 0.672 |

Note: The dependent variable for all models is the quarterly units sold of farm tractors with 100 HP and above. Standard errors are in parentheses. Superscripts ** and * indicate statistical significance at the 5 and 10 percent levels, respectively.

Table 25: Results for 4Q4 Model with Sentiment Data Included, 2015 Q4-2019 Q4.

| VARIABLES | No Sentiment Data | Ag Economy Barometer Index | Index of Current Conditions | Index of Future Expectations | Farm Capital Investment Index |
|---|---|---|---|---|---|
| Machinery Prices$_t$ | -62.16 | -102.4 | -101.1 | -41.18 | -126.6 |
| | (135.7) | (144.2) | (190.5) | (136.7) | (162.4) |
| Net Farm Income$_{prior\ year}$ | 12.23 | 11.17 | 16.13 | 2.137 | 17.20 |
| | (30.59) | (30.92) | (34.49) | (32.00) | (31.92) |
| Assets$_t$ | -5.360 | 4.145 | -1.671 | 1.626 | 1.181 |
| | (9.338) | (14.19) | (15.48) | (11.49) | (12.83) |
| Acreage$_t$ | -83.00 | -62.93 | -81.06 | -55.65 | -75.74 |
| | (50.76) | (55.94) | (53.60) | (57.06) | (52.73) |
| Machinery Interest Rate$_t$ | 468.7 | 251.3 | 483.1 | 93.55 | 188.0 |
| | (732.1) | (778.1) | (769.1) | (814.5) | (833.7) |
| Q4 | 852.3* | 1,185* | 991.6 | 1,076** | 1,145* |
| | (418.7) | (562.7) | (630.6) | (469.8) | (574.8) |
| Ag Economy Barometer Index$_t$ | | -22.73 | | | |
| | | (25.34) | | | |
| Index of Current Conditions$_t$ | | | -5.401 | | |
| | | | (17.55) | | |
| Index of Future Expectations$_t$ | | | | -24.08 | |
| | | | | (23.25) | |
| Farm Capital Investment Index$_t$ | | | | | -28.47 |
| | | | | | (37.35) |
| Constant | 54,367 | 33,435 | 51,887 | 26,778 | 50,198 |
| | (32,157) | (39,990) | (34,669) | (41,669) | (33,304) |
| Observations | 17 | 17 | 17 | 17 | 17 |
| R-squared | 0.574 | 0.609 | 0.578 | 0.619 | 0.600 |
| F-statistic | 2.24 | 2.00 | 1.76 | 2.09 | 1.92 |

Note: The dependent variable for all models is the quarterly units sold farm tractors with 100 HP and above. Standard errors are in parentheses. Superscripts ** and * indicate statistical significance at the 5 and 10 percent levels, respectively.

Table 26: Results for 5Q4 Model with Sentiment Data Included, 2015 Q4-2019 Q4.

| VARIABLES | No Sentiment Data | Ag Economy Barometer Index | Index of Current Conditions | Index of Future Expectations | Farm Capital Investment Index |
|---|---|---|---|---|---|
| Machinery Prices$_t$ | -93.51 | -143.5 | -209.5 | -62.45 | -235.3 |
| | (153.0) | (162.1) | (235.2) | (157.7) | (190.4) |
| Crop and Livestock Prices$_t$ | 14.97 | 16.07 | 22.76 | 9.832 | 27.97 |
| | (23.00) | (23.12) | (26.54) | (23.82) | (24.90) |
| Input Prices$_t$ | 2.381 | 4.206 | 1.388 | 5.764 | 0.843 |
| | (13.06) | (13.25) | (13.61) | (13.65) | (12.78) |
| | -0.131 | -4.158 | 6.035 | -11.07 | 2.165 |
| | (36.82) | (37.21) | (39.27) | (38.91) | (35.91) |
| Assets$_t$ | -5.081 | 5.270 | 5.651 | -0.0324 | 8.659 |
| | (12.53) | (16.52) | (20.66) | (13.73) | (16.76) |
| Acreage$_t$ | -52.83 | -27.26 | -31.95 | -35.41 | -13.28 |
| | (72.12) | (77.11) | (81.03) | (75.04) | (77.64) |
| Machinery Interest Rate$_t$ | 537.5 | 260.2 | 647.8 | 57.33 | 153.7 |
| | (851.0) | (901.4) | (897.4) | (999.5) | (888.8) |
| Q4 | 877.1 | 1,252* | 1,272 | 1,055* | 1,462* |
| | (485.3) | (622.7) | (776.6) | (524.6) | (680.0) |
| Ag Economy Barometer Index$_t$ | | -26.63 | | | |
| | | (27.56) | | | |
| Index of Current Conditions$_t$ | | | -13.91 | | |
| | | | (20.83) | | |
| Index of Future Expectations$_t$ | | | | -24.78 | |
| | | | | (26.49) | |
| Farm Capital Investment Index$_t$ | | | | | -51.11 |
| | | | | | (42.71) |
| Constant | 31,979 | 5,143 | 14,870 | 9,547 | 6,540 |
| | (46,607) | (54,422) | (54,686) | (52,741) | (50,130) |
| Observations | 17 | 17 | 17 | 17 | 17 |
| R-squared | 0.605 | 0.652 | 0.629 | 0.649 | 0.672 |
| F-statistic | 1.53 | 1.46 | 1.32 | 1.44 | 1.60 |

Note: The dependent variable for all models is the quarterly units sold farm tractors with 100 HP and above. Standard errors are in parentheses. Superscript * indicates statistical significance at the 10 percent level.

# CHAPTER 6. CONCLUSIONS

This study analyzes the driving forces behind the quantity demanded of large two-wheel-drive farm tractors with 100 HP and above from 1978-2019. The literature on this topic dates back to the 1920s; however, there have been relatively few studies done since Powell's in 1929. The most relevant study was published by Cromarty (1959) in the *Journal of Farm Economics* and used broad measures of the agricultural economy's health to explain annual farm machinery demand. No past studies evaluate quarterly farm machinery sales. Instead, researchers focused their attention on modeling annual sales as a function of annual explanatory variables. In addition to exploring annual sales in a modern context, this study also attempts to learn whether farmer sentiment, as measured by the *Purdue University-CME Group Ag Economy Barometer* and several of its sub-indices, help explain variation in sales of farm tractors with 100 HP and above.

Using Cromarty's study as a guide, annual demand models are estimated using OLS regression models. A model is estimated with explanatory variables similar to Cromarty's with data from 1978 through 2019. Additional model estimations, such as omitting an interest rate variable and correcting for potential over-identification, attempt to address potential shortcomings in Cromarty's original model. The three best performing models are deemed to be those that model annual tractor sales as a function of farm machinery prices, prices received for crops and livestock, prices paid for inputs, total farm assets, acreage, interest rates, and lagged net farm income. Over 80% of the variation in past sales of farm tractors with 100 HP and above are explained using these models.

These models are then used to calculate elasticities and generate out-of-sample forecasts. The elasticities were all calculated using the sample mean of each variable and parameter estimates from the annual models. The elasticities calculated from these models reveal that the quantity demanded of farm tractors with 100 HP and above is most responsive to changes in machinery prices, acreage harvested, and farm assets. Reviewing the explanatory variables used in this study, the quantity demanded of farm tractors with 100 HP appears to be least responsive to changes in lagged net farm income.

The three best performing models, judged by each model's overall statistical fit and the statistical significance of the explanatory variables, were used to generate out-of-sample tractor sales estimates. The models' out-of-sample estimates for sales of farm tractors with 100 HP and above from 2015 to 2017 were much higher than the actual number of units sold. The models' forecasting performance improves for 2018, coming relatively close to the actual number sold. The models then greatly under-estimate sales for 2019. However, this is primarily due to the abnormal planting conditions in 2019, which resulted in a historically low number of acres harvested in 2019. When using the number of acres harvested in 2018 for the 2019 forecasts, the model performs better, but still underestimates sales. From the out-of-sample results, root-mean-square errors (RMSE) are calculated for each model. The model with the lowest RMSE value is deemed the best performing model to forecast the quantity demanded of farm tractors with 100 HP and above.

The best performing out-of-sample model, 5A, included machinery prices, crop and livestock prices received, input prices, lagged net farm income, farm assets, acreage, and the average effective interest rate for farm machinery loans. A baseline forecast for 2020 which assumes that the machinery prices, crop and livestock prices received, input prices, farm assets, and the interest rate variables all change at historical averages, the number of acres harvested returns to the 2018 number, and a forecast for total farm assets made by the ERS is first used to predict 2020 sales. Modifying the baseline forecast provides several additional scenarios for 2020. The model estimates that sales of farm tractors with 100 HP and above will hit a record low in 2020.

The same three annual models are modified so that they can be estimated using quarterly data beginning in January 2009, or 2009 Q1, to December 2019, or 2019 Q4. Dummy variables representing the second quarter and fourth quarter of each year control for the strong seasonality in sales of farm tractors with 100 HP and above. The quarterly models do not perform as well as their annual counterparts. In particular, signs on some variables coefficients, which matched expectations from economic theory in the annual models, changed in the quarterly models and some variables which were statistically significant in the annual models lost statistical significance when estimated in a quarterly framework. The quarterly models' lack of success can partly be attributed to some of the key explanatory variables, namely lagged net farm income, acreage, and farm assets, only being available annually which limited the models' sensitivity

Finally, the study evaluates the inclusion of farmer sentiment data. To do so, the quarterly models are estimated again over the timeframe that data from the *CME Group-Purdue University Ag Economy Barometer Survey*, October 2015 to December 2019, or 2015 Q4 to 2019 Q4 is available. This timeframe results in only 17 quarterly observations, significantly limiting each model's performance. Additionally, inclusion of annual explanatory variables in the quarterly models and quarterly tractor sales volume that's more variable than annual sales make it difficult to explain quarterly variation in tractor sales. Unsurprisingly, the statistical fit of each model and the statistical significance of all variables, except for the Q4 dummy variable, plummet.

One of this study's objectives was to evaluate whether inclusion of farmer sentiment in models that explain farm tractor sales volume improved model performance. Unfortunately, including the farmer sentiment variables did not improve model performance. However, it remains possible that when more observations of farmer sentiment become available including sentiment in future models might improve model performance. As the *Ag Economy Barometer Survey* gains additional observations, future studies could evaluate how annual farmer sentiment impacts sales of farm tractors with 100 HP and above. More definitive quarterly models can be estimated as well. In addition to farm machinery sales, future research can also explore how farmer sentiment impacts other parts of the agricultural economy, such as land values.

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