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TWO ESSAYS ON WHOLE FARM MODELING AND CROP MARKETING IN WESTERN KENTUCKY

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TWO ESSAYS ON WHOLE FARM MODELING AND CROP MARKETING IN WESTERN KENTUCKY

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of
Master of Science in the College of Agriculture,
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By

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ABSTRACT OF THESIS

TWO ESSAYS ON WHOLE FARM MODELING AND CROP MARKETING IN WESTERN KENTUCKY

This thesis is composed of two essays that investigate whole farm planning and crop marketing in western Kentucky. In the first essay, contracting decisions between food corn producers and a mill are analyzed to observe factors affecting the bushel amount farmers contract. Unbalanced panel data containing seven years' worth of pricing and contract information are used with a fixed-effects model to generate parameter estimates and quantify their effect on bushels contracted. It was found that contract attributes, market condition, and relationship-specific assets had a significant effect on producers' food corn contracting decisions. The second essay utilizes mixed-integer programming to optimize resource allocation and marketing strategy for a hypothetical farm. Post-optimal analysis is performed to determine non-binding capacities for drying and storage equipment. The model is re-run with these non-binding capacities to observe changes in net returns as well as planting, harvesting, and marketing strategies. New equipment and associated costs are identified, and the change in net returns from the base case is used as net cash flow in a net present value investment analysis. Results of the investment analysis indicate increasing drying and storage capacity is a wise investment given the scenario modeled.

Keywords: Whole farm planning, mixed-integer programming, identity-preserved grain, grain drying, grain storage, crop marketing

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TWO ESSAYS ON WHOLE FARM MODELING AND CROP MARKETING
IN WESTERN KENTUCKY

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Chapter 1: Introduction

Grain producers' decision-making and management abilities are of utmost importance no matter whether the market is in an up or down cycle. Whether diversifying to new crops, making capital improvements, or determining a marketing strategy, ample thought should be put into decisions that affect operations well into the future. Numerous resources are available to aid in these decisions: university extension, crop advisers, or the trusted advice of an experienced neighbor. No matter the means, there will always be uncertainty given the variable nature of farming enterprises. Having a well-defined strategy for an upcoming growing season and marketing year can provide clarity in this often hectic environment. Taking stock of land, labor, and capital resources and allocating them in the most efficient manner is a difficult task knowing most farmers' time is spent on the day to day tasks that keep the business running. However, doing so can potentially uncover opportunities to make the business more competitive in the long run.

A prime example of the intersection of practical farm planning and analytics like linear programming (LP) is the work of McCarl et al. (1977). In their paper, the authors introduce the "Purdue Top Farmer Cropping Model 'B'" and chronicle their experiences working with researchers, extension personnel, and farmers to create a linear programming model for repeated application. Developed in 1968, the model had been used by more than 5,000 producers at the time the paper was published in 1977. The authors detail the process by which they determined proper model specification. McCarl et al. note the key to successful design and implementation of the model was an extensive interaction between extension and research staffs. This allowed identification of the realworld problems grain farmers were facing and academic research to combine and form an LP model for practical use. Decision variables and constraint types are similar to what will be seen later in the current text. Decision variables constituting the farming activities in the model include land preparation, production, harvesting, marketing, labor hired, and the amount of land to rent. Constraint types are acreage, days suitable for fieldwork, labor, storage availability, and the rate at which activities like harvesting are completed.

Beyond use by actual farmers, the model has been employed in other research such as studying the effects of government programs and new equipment types or farming practices. Even the private sector took notice. International Harvester purchased the model to give dealerships and farmers a direct way of analyzing machinery complements and developing equipment solutions for customers. While use of McCarl et al.'s model was relatively widespread, the authors still acknowledge its limitations. Price, yield, and weather risks are not considered and intra-year adaptive management is not modeled either. The specification was designed for large commercial grain farms and does not have a livestock component. Finally, it is a single year model that excludes investments. Understanding shortcomings is imperative when interpreting model results. After all, models are simplifications of reality, and in the context of farming, a very unpredictable reality. Beyond technical aspects, the primary focus of McCarl et al.'s work is consistent with this study's focus, decision making at the farm-level.

In this thesis, two essays are presented that examine decision making at the farm level. Specifically, the analyses are performed in the context of western Kentucky grain production and marketing. In the first essay, a fixed-effects model is used to observe contracting choices and determine factors affecting the bushel amount of food-grade corn producers contract with a mill. This is carried out with firm-level data from a mill in western Kentucky. The data set contains information on contract specifications like bushel price and delivery period, as well as assets used by the farmer during the production process. With this information, variable coefficients are generated that provide insight into the choices of producers and their overall interaction with the mill. These parameter estimates are then utilized to draw conclusions and analyze possible implications to the broader principal-agent relationship taking place between the farmers and the mill.

The second essay of this thesis is a whole-farm model of a hypothetical grain farm in Henderson County, Kentucky. Naturally, this shares many elements with McCarl et al.'s model discussed above. Mathematical programming techniques are employed to determine optimal resource allocation and maximize returns above selected costs. The enterprise mix is typical of a commercial western Kentucky grain farm growing white food-grade corn, field corn, and soybeans. A planting and harvesting strategy is generated in the results to study the effect planting date has on the demand for drying and storage resources, hauling capacity, and labor hours available for fieldwork. Once the base case is optimized, post-optimal analysis is performed to determine whether additional cash flow can be obtained by expanding grain drying and storage resources. This additional revenue is mainly a function of new marketing opportunities afforded by additional storage capacity. The marginal value products of expanded drying and storage capacity are calculated until each equal zero and no additional revenue can be attained. Knowing the non-binding capacities of these two elements within the system allows for the identification and pricing of new equipment that meets the non-binding capacities. Finally, investment analysis is performed to determine the suitability of the investment in a new dryer and grain bins for the hypothetical farm. Although this procedure is not ready to be deployed for widespread use among farmers, it is envisioned that with time and certain modifications, the model will be utilized in the decision-making process.

The elements that connect these two essays are geographical location, identity-preserved (IP) grain production and marketing, and how access to drying and storage equipment affects farmers' strategic decision making. The information generated from these two essays provides insight to firm-level decision making inside the farm gate and at the second step of the marketing channel for food corn. The role of farmers as price takers and the principal-agent dynamic of the first essay enables empirical analysis of industrial organization in IP grain markets. In the second essay, the economic optimization model underscores microeconomic concepts such as theory of the firm and diminishing marginal returns. Further, the prices and finite resources included in the model allow for the analysis of competition among crops for those resources. Opportunities arise, and strategies change as resources are augmented. Practical investment analysis is undertaken to determine whether or not to pursue those opportunities. With a heightened understanding of the buyers and sellers of food grade corn, and how farms can optimize while producing IP and commodity crops, this subsection of the agricultural economy in western Kentucky is better understood.

Chapter 2: Determinants of Firm-Level Food Corn Contract Decisions

2.1 Abstract

Given the downturn in grain prices following a bullish market from 2007 - 2013, producers are seeking opportunities to improve margins for their farming operations. One such opportunity is the production of food-grade corn in lieu of a percentage of No. 2 feed-grade production, the sale of which is usually based on a contract with a specified premium. When producers and processors come together to execute these transactions, they agree on a delivery amount and time period. Factors such as premium price, access to drying and storage equipment, and the price of other grain types affect how much food corn is contracted within a growing season. This paper utilizes an unbalanced panel data set from 2010 – 2016 from a food corn processor in Kentucky to estimate determinants of contract volumes initiated by producers. Over this seven-year period, grain market fluctuations in the form of price movements and consumer preference for non-genetically modified ingredients influenced contracting decisions. Results indicate the aforementioned factors and other variables have a significant impact on the bushel amount producers are willing to contract. Implications of these decisions will be examined from an agribusiness and producer perspective to determine whether aspects of the transaction can be improved.

2.2 Introduction

Depressed prices for homogenous grains and an uptick in demand for quality attributes such as ingredients that do not contain genetically modified organisms (GMOs) have motivated producers to seek opportunities in the identity-preserved (IP) market. IP grains are differentiated from commodity or feed grains based upon physical or chemical characteristics valuable to the end-user. Due to these attributes, IP grains must be kept separate from the commodity supply chain from producer to end-user. A premium is placed on the bundle of attributes intrinsic to the grain type, also serving as an incentive to offset the additional costs, management, and risk incurred by the farmer and marketing channel. Examples of IP grains include high oleic acid soybeans, white food-grade corn, and grains produced according to USDA organic standards.

One motivation for farmers to enter the IP market is that it enables them to diversify and potentially improve margins for their operations. However, infrastructure and human capital investments may be needed. A number of assets utilized for producing feed-grade grains are transferable to IP corn and soybean production, but farmers may have to construct additional storage to segregate their IP and commodity crops. On top of this, they may experience inefficiencies due to excess storage capacity if the IP grain's yield performance is less than expected. Further, the inputs used and management of grain quality during harvest, drydown (if necessary), and storage is of major importance to buyers and presents additional costs to the farmer. As one can imagine, there is considerable effort both by farmers and agribusinesses to keep IP grains segregated from commodity grains throughout the supply chain all the way to the end-user.

With these grain quality and segregation issues at play, coordination between buyers and producers is of utmost importance and necessitates the use of contracts. If a broker or food company wants to ensure an adequate supply of grain, they must prospect and establish relationships with farmers who can meet their contract standards. Beyond meeting supply quotas for downstream demand, mills and food companies use contracts to establish the desired attributes and grain quality so that unprocessed grain and subsequent products retain their economic value. Given the need for this coordination, the price or pricing mechanism for a farmer's production is established through the contract. From the buyer's perspective, this allows a specified quantity and quality of grain to be procured at a certain price within a satisfactory timeframe. If a higher degree of risk management is part of the firm's strategy, offsetting positions in the futures market are possible after the original price for the grain is established. From the farmer's perspective, alleviating some of the uncertainty regarding what price will be received is valuable and incentivizes the use of contracts. Certainly, other risks are present in production agriculture, but identifying a price and possibly a premium before or during a growing season enables producers to be more accurate in their marketing strategy and cash flow planning.

Another function of contracts in the IP grain market is to specify when, where, and how much of a specialty grain will be delivered by the seller to the buyer. This specification is closely related to the buyer's supply quota mentioned above. Most IP contracts identify whether grain will be delivered during harvest or at a time following harvest, implying the need for storage on the producer's end. If storage is needed, then supply quotas, delivery timing, and a premium become even more correlated. Constructing storage facilities for most or all of the grain an elevator or mill receives in a given year would be a tremendous upfront expense and financially infeasible. Instead, buyers provide an incentive for producers to utilize existing storage or construct new facilities to possibly enjoy higher margins. This could be in the form of a fixed premium above a previously agreed upon bushel price, or one that increases with the amount of time the crop is stored on-farm. If delivery is specified to occur following harvest time, a condition called buyer's call is sometimes imposed. Under a buyer's call, the producer must deliver grain at the buyer's request at a specified time. Usually, a general timeframe or specific date is established, but the buyer reserves the right to request that the farmer holds the grain longer. While this may cause some inconvenience for the farmer, a higher premium is typically associated with buyer's call caveat.

The quality control aspect of a marketing contract in this instance is of great importance. After all, if there were no distinguishing features between No. 1 and No. 2 corn, there would be no need for hierarchal designation. If the flow of quality grain is not scheduled correctly, a shortage could occur, and a bottleneck would arise. For example, if loads of food grade corn were continually received at high moisture and the grain had to be mechanically dried or refused altogether, a shortage of milled corn could occur for downstream processes. Thus, a contract is used to ensure the producer abides by quality standards outlined in the document, the impetus being discounts to the price received, or refusal to purchase the grain.

Given the interdependency between elevators/mills and the farmers that supply them with grain, in addition to various specifications within contracts that connect the two, this paper examines contracting decisions by producers in the form of contract volumes. That is, what factors cause farmers to increase or decrease their contract volume from one season to the next? Certainly, the firm-level demand of the mill will play a role, but the farmer remains autonomous in that s/he could choose not to produce at all. Does an increase in the premium offered induce farmers to contract more bushels with a mill? How much does access to assets like drying and storage equipment increase the amount a producer is willing to contract? From the buyer's perspective, this information is relevant to demand planning and how characteristics of the contracts they put forward, as well as economic factors larger than the transaction at hand, impact the amount producers intend to grow year to year. Contract and corresponding delivery data from a processor in Kentucky is utilized in the empirical study to evaluate local producers' contracting decisions. Further, implications of these decisions will be examined to determine what aspects of the transaction can be improved.

2.3 Literature Review

Literature on contractual arrangements is vast and derived from diverse sources, such as academic or law journals, as well as government publications, some of which narrow their focus to contract use in agriculture. Cheung's (1969) choice-based analysis to explain contractual behavior in land tenancy has little technical applicability, but great conceptual relevance to the current study. While it may seem commonplace today, Cheung introduces transaction costs and risks to do so. First, if a firm can increase production efficiency by employing the productive resources of more than one owner, a contract to combine both party's resources will prevail. In the case of food corn contracting, the mill employs the productive resources of the farmer, because vertical integration would be capital intensive and less efficient. Risk aversion is also incorporated into the study. While risk preferences are not the primary focus of the present study, the theory underlies part of the motivation for contract-based transactions between farmers and processors. Here, in general terms, both parties reduce risk by establishing a buyer (seller) and price to satisfy supply and demand needs. Finally, Cheung states that given transaction costs, risk aversion implies the value of productive assets and variance of income are negatively related. In other words, the valuation of productive assets (land on which the corn is grown, tractors, combines, grain bins) decreases as income variance increases. This would also imply that if a contract can secure a satisfactory price for the farmer's production, it would be beneficial for him or her to enter the agreement.

In 2003, Sykuta and Parcell surveyed producers with IP soybean contracts sponsored by DuPont Specialty Grains from 1999 to 2002. They intended to classify contract structure for IP crops based upon three essential components of economic transactions: the allocation of decision rights, value, and risk. Parsing the different contracts revealed that management efforts to preserve the identity trait and preventing comingling through harvest, storage, and shipping was the vital source of value underlying each contract, in addition to delivery timing. The authors suggest that if the option to choose delivery timing is valuable to the buyer, then the buyer should be able to compensate producers for the transfer of value related to the change in delivery options. While this assertion is fundamental to contract and price theory, the value derived from a delivery timing mechanism is a function of all three economic underpinnings on which the study is based. Sykuta and Parcell's study is void of statistical analysis. However, the authors pose many questions for future research.

Given the focus of the current study, one in particular stands out: What factors affect the rate at which producers buy into a contract programs in a given crop year?

Hudson and Lusk (2004) used a choice-based experiment to observe contract choices by two groups of producers in Texas and Mississippi to estimate marginal utilities of contract attributes. Variables from both principal-agent and transaction cost models considered theoretically important are incorporated. Although the authors did not explicitly study IP grains as the product being contracted, many of their observations are relevant. They found that increases in expected income from a given contract were significantly related to increases in the probability of that contract being chosen, i.e., income has a positive marginal utility. Further, they observed that the producers derived significant disutility from investment in relationship-specific assets, which suggests producers would prefer to invest in assets with multiple uses to avoid rent appropriation by the buyer. These findings are intuitive and motivate the current study since premium levels and the use of more efficient grain dryers affected producers' contracting decisions.

Moving away from contract specifications and focusing specifically on premiums, Heiman and Peterson (2008) used hedonic pricing models to evaluate factors determining premiums for organic crops. Similar to the current study, the authors used firm-level data from an organic grain cooperative in Kansas to complete their analysis. Premiums were computed as the difference between the price the producer received and the monthly national average price from USDA's Agricultural Marketing Service (AMS) for the equivalent conventional crop. The premium was then regressed on variables including the type of buyer,

buyer/producer location, contract quarter, shipping quarter, contract volume, and contract length. They found estimates for type and location of buyers for organic feed grade soybeans were not statistically significant, suggesting a more mature and integrated market for organic feed grade soybeans. Further, seasonality was identified among price premiums; crops under longer contracts and crops put under contract during the fourth quarter commanded higher premiums compared to others. While the theoretical model differs from the current study, the variables are related and deserve acknowledgment. These include contract quarter, contract volume, and what quarter shipment takes place.

In addition to journal articles, there are well-developed government publications from USDA/ERS worth citing not only for their analyses of trends but also the application of economic theory and examination of diverse markets. McDonald et al. (2004) begin their report on contract use in agriculture by quantifying the prevalence of specific characteristics of marketing contracts for field crops using data from the 2001 ARMS and NASS data for average prices. Variation in contract prices likely reflects differences in contract terms, such as delivery, storage, or differences in product characteristics is a key result. From the buyer's perspective, the contract is considered a bundle of attributes, and more utility is derived as more value-added processes are incorporated. This information is captured in variables such a corn color, non-GMO, and premium level in the current study. Next, the authors point out that the range in contract volumes is quite surprising. Twenty-five percent of corn contracts were 5000 bushels or less, while contract volumes at the 75^{th} percentile were for 21000 bushels or more. Asset specificity and its relationship to the use of contracts in agriculture is also discussed. They cite Williamson's (1985) definition of asset specificity as durable investments undertaken in support of particular transactions. Physical asset specificity could include devoting the current use of, or purchasing new, drying and storage equipment for food corn production. While this is not as obvious as other examples, if food corn production is of higher value than other undifferentiated grains, the redeployment of those assets solely for feed grains would cause a decrease in their value. The authors further describe the tendency of food processors to be located in high production areas, introducing the concept of site specificity for both the farmer and mill, since compensating producers to haul long distances would be costly and inefficient. Reflecting on both forms of asset specificity, a more in-depth relationship between buyer and seller is recognized. Their observation also quantifies that 74.4 percent of IP corn was produced under contract in 2001. They note that contracts are utilized because few nearby buyers exist, and because higher costs of production expose producers to risks of holdup in the spot market. A final and germane observation put forth in the McDonald, et al. ERS report is the amount of turnover among producers selling IP corn to processors. Thirty percent of producers in 2000 did not return in 2001, and 27 percent of producers in 2001 did not return in 2002. Again, while this data is not current, a similar pattern of turnover among producers was seen year-to-year in the data used for the current study.

Elbehri (2007) details market structure and trends specifically for IP crops. Elbehri notes that overall cost structure for IP grains differs with the degree of segregation required. Additionally, price premiums for many trait-specific crops rise or fall depending on supply conditions of their commodity equivalent. He also states that the premium is the critical factor which draws producers into and out of IP corn production, and that farm surveys show a high degree of entry and exit each year because of yield performance and quality issues. This pattern is also indicative of higher fluctuations of supply and demand for differentiated grains than their commodity counterparts.

While a wealth of information regarding market structure for IP crops has emerged over the past two decades, econometric analyses are scant within the literature. Thus, this paper serves to help fill that gap and provide insight into contracting decisions between producers and buyers of specialty crops. The characteristics and length of the panel provide the opportunity to analyze such firm-level interactions since this type of data is not usually available. However, it is noted that applicability may only prevail amongst the mill and producers in that area. As will be seen, many hypotheses contained in this paper were derived from assertions or underlying theory of previous works.

2.4 Materials and Methods

Principal-agent theory provides the framework for this analysis. In this instance, the mill (principal) employs the farmer (agent) to take actions which ultimately affect the well-being of the milling enterprise. Naturally, these actions include the production of food grade corn subject to quality standards and the successful segregation of that production to preserve its economic value. Difficulties in principal-agent relationships arise when two situations occur: 1) the objectives of principal and agent are unaligned, and 2) actions taken by the agent or information possessed by the agent are hard to observe (Besanko, 2010). In this case, the volume producers are willing to contract year-to-year, if any, is difficult for the mill to determine. The statistical analysis in this paper was performed to shed light on this issue.

Since every producer does not return to contract each year, the panel is unbalanced. Because of this irregularity during the seven years of transactions, a fixed-effects model is chosen to quantify variables affecting producers' annual buy-in to the contract program. Further, the fixed-effects model controls for the unobserved factors that are constant, and those which vary over the seven-year period. The theoretical fixed-effects model is as follows:

$$y_{it} = \beta_0 + \delta_0 D_t + \beta_1 x_{it} + a_i + u_{it}\,, \;\; t = 1, 2, \ldots, \mathrm{T}$$

Following the notation, i signifies a single contract by an individual farmer in period t. D_t is a vector of dummy variables that equal zero when the period of the dependent variable is not congruent with that of the dummy, and one when it is. This allows for different intercepts over time, given unobserved changes that take place over time. While unrealistic, if every producer increased their acreage of IP corn to increase contract volumes from one year to the next, and that change went unmeasured, the unique intercept generated by the period dummy would help account for that alteration in the producers' decision making. The variable a_i captures all of the unobserved factors that do not vary over time. Hence, it is not indexed by subscript t, and is the fixed effect(s) affecting the value of y_{it}. For instance, if the on-farm storage capacity of each producer went unchanged over the seven-period, but were unobserved, the fixed-effects variable would account for that. Finally, u_{it} is the idiosyncratic error that represents unobserved factors that do change over time. Usually, the unobserved effect and the idiosyncratic error are combined to create a composite error, $v_{it,}$ where $v_{it} = a_i + u_{it}$.

Since the focus is observing factors that influence farmers' contracting decisions over time, the empirical model follows the fixed-effects framework. This allows for changes that went unobserved within individual years, but still influenced bushel amount per contract, to be considered when generating results. The following is the empirical model and variable definition used in the analysis of contract transactions between producers and the mill from 2011 – 2016:

$$volume_{it} = \beta_0 + \delta_0 D_t + \beta_1 white_{it} + \beta_2 nongmo_{it} + \beta_3 deliver_{it} + \beta_4 premium_{it}$$
$$+ \beta_5 corn_{it} + \beta_6 beans_{it} + \beta_7 market_{it} + \beta_8 con_{it-1} + \beta_9 disc_{it-1} + \beta_{10} nonyear_{it}$$
$$+ \beta_{11} tower_{it} + \beta_{12} stack_{it} + \beta_{13} inbin_{it} + \beta_{14} quart2_{it} + \beta_{15} quart3_{it}$$
$$+ \beta_{16} quart4_{it} + v_{it}$$

$i = 1, 2, 3, \ldots, 1135$

$t = 1, 2, 3, \ldots, 7$

Where:

i = individual contract by farmer

t = contract year

Volume = Contract volume in bushels

White = corn color; white = 1, yellow = 0

Non-GMO = GMO designation; non-GMO = 1, GMO = 0

Deliver = time of delivery; harvest = 1, storage = 2

Premium = premium above CME December futures price

Corn = CME December corn futures price on contract date

Beans = CME November soybean futures price on contract date

Market = Whether the transaction took place from 2010 – 2013, or 2014 – 2016
2014 – 2016 = 1, 2010 – 2013 = 0

Con = previous year contract volume in bushels of specific corn type

Disc = previous year discounts in bushels of specific corn type

Nonyear = year when mill did not contract GMO corn;
2010-2011, 2015-2016 =1, 2012-2014 = 0

Inbin = 1 if in bin dryer used by producer and 0 otherwise

Stack = 1 if stack dryer used by producer and 0 otherwise

Tower = 1 if tower dryer used by producer and 0 otherwise

Quart2 = 1 if corn contracted during the second quarter and 0 otherwise

Quart3 = 1 if corn contracted during the third quarter and 0 otherwise

Quart4 = 1 if corn contracted during the fourth quarter and 0 otherwise

The firm-level data used in this study comes directly from a milling enterprise in which 52 individual producers contracted IP corn production over a seven-year period, signing 1,135 contracts that serve as observations on contract volumes. Descriptive statistics for the variables utilized in this study may be seen in Table 2.1. As previously mentioned, the data is an unbalanced panel because many producers do not return to contract with the mill every year from 2010 to 2016. While the original data set obtained from the mill contained observations for color, non-GMO, delivery, premium, corn, and previous contract variables, daily soybean prices were gathered from Commodity Research Bureau's

Commodity Perspective (Commodity Research Bureau, 2016). Specific contract dates contained in the data mentioned above allowed for classification of contracts by fiscal year quarters. Additional data related to the delivery and quality analysis of the contracted corn enabled the calculation of previous year discounts as well as the type of dryer used by the farmer to dry the corn to proper moisture for storage. Finally, the standard contract used to complete these transactions was also provided by the mill and used to gain further insight into the transactions being studied.

The dependent variable, *volume*, is the total number of bushels contracted of a particular corn color, non-GMO (GMO) status, and delivery period by a single producer on a particular day. In the raw data obtained from the mill, some producers executed multiple but identical contracts in terms the aforementioned attributes. It is hypothesized that this was for traceability reasons so the mill could know where each bushel of contracted corn was grown. Because no difference in price occurred across these contracts with a given set of attributes, producers that signed multiple contracts in a single day were summed so they had one single observation for that day.

Corn color is a critical factor in the premium over the Chicago Mercantile Exchange (CME) December futures price that will be received by the farmer once the corn is delivered. Only yellow and white food-grade corn are purchased by the mill over the seven-year period, with white corn commanding a higher premium. This difference between corn colors is captured in the *white* variable and is constructed as a dummy variable where white corn equals one and yellow equals zero. Since white corn has higher production cost (Pritchett, 2000), it is hypothesized that producers allot smaller bushel amounts to these contracts. Over the seven-year period, 46 percent of all contracts were for white corn. Related to the color attribute is whether the production under contract is a genetically modified organism (GMO) or not. To be clear, both white and yellow corn contracts allow GMO production during the years when GMO grains were accepted. Again, this designation contributes to the premium. Since the majority of corn produced in the United States is GMO (ERS, 2017), non-GMO corn is given a higher premium because of its higher production cost, differentiated nature, and lower yield potential (Greene, 2016). From a producer's standpoint, the higher production cost associated with non-GMO corn could deter them from growing more of it compared to GMO corn, resulting in a higher per contract bushel amount of GMO corn. Because the choice to grow GMO or non-GMO corn is binary, a dummy variable is employed where non-GMO corn equals one, and GMO corn equals zero.

Whether corn is delivered to the mill during harvest, or if it is stored on the farm and delivered at a later date, contributes to the premium and varies among contracts. If the mill can avoid having to store all the corn themselves, as well as the fixed cost and risk associated with the amount of storage required to do so, it makes sense that the mill would pay a higher premium to have the farmer utilize their assets to store grain. To quantify the effect this decision has on individual contract volumes, the *deliver* variable is used. One could expect that a farmer with limited on-farm storage might allocate a large amount of bushels to a contract(s) with harvest delivery, and a much smaller amount requiring storage. While this should not be construed as a proxy for storage resources of the individual farmers, it serves to measure why farmers elect to grow more corn for a contract with certain stipulations. Again, the decision to deliver during harvest or sometime after harvest is binary when completing a contract. Therefore, it is included as a dummy in the model where harvest time delivery equals one, and a later delivery date associated with on-farm storage equals zero.

Indeed, the premium above the CME December futures quote is what motivates producers to grow IP corn in the first place. In other words, it is the price signal the mill uses to attract local farmers to produce food-grade corn. As has been discussed, what color the corn is, whether it is GMO or not, and when it will be delivered all factor into the value of the premium. For example, in 2012 the mill paid a $0.25 premium for GMO yellow corn delivered at harvest. During the same year, a $0.70 premium was paid for non-GMO white corn stored on the farm and delivered after harvest. Further, premiums for all corn types increase over the seven-year period. The same white corn contract that fetched $0.70 in 2012 had a premium of $0.90 in 2016. Given the premium is a price signal, the expectation is formed that an increase in premium will increase the quantity contracted.

The *corn* variable is the CME December futures quote on the day the contract was made. This information is included because it is the price a premium is added to that determines the overall price received by the farmer. Additionally, the December price of No. 2 corn on the day the contract is completed is the broader economic point of reference the producer has for the corn market. If prices are low, it is easy to imagine a producer would reduce their corn acreage (food grade or not) and substitute it with a crop that has the potential to be more profitable. This action could decrease the bushel amount a farmer would contract. Therefore, the price of soybeans is also included in the model. This is accomplished by using the November soybean futures price from the same day the food corn contract was made. November futures are chosen because this is price signal for the new crop of soybeans to be harvested, as are December futures for corn.

Market is a dummy variable used to indicate whether the transaction took place during 2010 – 2013 or from 2014 – 2016. This variable is utilized to reflect distinctly different grain market conditions during the seven-year period. It is well known that grain prices increased rapidly from 2010 to 2013 and decreased rapidly after that (ERS, 2016). Thus, a mechanism is implemented to account for altered decision-making during market upswings and downturns. The expected relationship between the overall commodity market and contract volumes for IP corn can go both ways. A hypothesis can be made that a down market would entice producers to seek opportunities in IP markets that have the potential to increase margins. However, if the premiums offered do not cover the added cost, management, and risk associated with IP grains, a negative relationship could occur when commodity prices are low. In the data, transactions occurring between 2010 and 2013 equal zero, and those executed from 2014 to 2016 equal one.

The previous year's contract volume(s) and quality discounts have the potential to influence a producer's decision making in the current year, so the *con* and *disc* variables are included in the model. While the producers were able to enact many contracts in a single year, i.e. the entirety of their white or yellow corn production could be spread across multiple contracts with varying stipulations, the previous year's contract volumes were aggregated by corn color, GMO/non-GMO, and delivery time. Previous year discounts are derived from the second data set of delivery information and quality analysis. Following the methodology for aggregating contract volumes in period $t - 1$, previous discounts are calculated by summing the number of bushels rejected per delivery of corn contracted by color, GMO/non-GMO, and delivery time. Although it is difficult to determine an expected relationship between a prior year's contracting decisions and the current one, one can assume an increase in a previous year's discounts will result in a decrease in contract volume in the current period.

Nonyear is a dummy variable employed to determine whether the mill was accepting both GMO and non-GMO corn during a particular year, or only non-GMO corn. In the data, there are years where the mill purchased only non-GMO corn. The years in which this selective buying took place were 2010 and 2011, as well as 2015 and 2016, and equal one. Being limited to only planting non-GMO seed could have prevented certain producers from expanding or maintaining the same contract volumes as in prior years, because of the higher production cost associated with non-GMO corn. Instead, they could opt to grow more of another crop, like GMO feed grade corn or soybeans, ultimately decreasing the number of bushels they contract with the mill.

Inbin, *stack*, and *tower* represent different dryer types that can be utilized to dry corn to fifteen percent moisture, making it suitable for storage. Because asset specificity is a concept inherent of principal-agent theory, as well as having access to this unique data, the question was posed whether the use of grain dryers would cause the producers to allot more bushels per contract. *Inbin*, *stack*, and *tower* indicate whether the dryer was a tower, stack, or in bin configuration. The alternative to mechanical drying is to let the grain dry naturally in the field over time, which is the reference group for the other variables. Under the hypothesis that the use of dryers has less value when deployed for drying less valuable, non-IP grains, an expectation is formed that, on average, contract volumes will be higher when the farmer intends to utilize mechanical drying during the production process. However, IP grains make less efficient use of the dryer than commodity grains because lower temperatures are required to maintain grain quality. It should also be recognized that having a mechanical dryer on the farm could be indicative of larger farms with more resources (land, labor, and capital), enabling those farmers to grow more IP corn. Unfortunately, data on farm size to control for this effect was unavailable and is recognized as a limitation.

Finally, what quarter the producer chose to put the bushel amount grown for the mill under contract is modeled through *quart2*, *quart3*, and *quart4*, with the first quarter as the reference group. The timing of contract agreements affects what price per bushel is received since the mill uses daily December corn futures to price grain. Thus, the usual temporal transmission of grain prices could cause producers to price more of their IP corn away from harvest time when stocks have decreased, and prices are higher. Conversely, producers could wait to see how strong their yield is before pricing a crop, causing them to price the corn closer to harvest when prices are lower, but avoiding any obligation to the mill for production shortfalls. Thus, variables to measure the timing of the agreement's effect on bushel amount are included and derived from the specific date each contract was made.

2.5 Results

Results of the fixed-effects model to estimate influences on contract volumes in an IP corn contracting program were generated using STATA (StataCorp, 2013). Results may be viewed in Table 2.2. Overall, the model is significant according to the *F*-statistic. With one exception, sign relationships between variables and the per contract bushel amount the farmers contracted are as expected. A Hausman test was conducted for specification between fixed-effects and random-effects models. Based on the results of the test, the null hypothesis that the covariates and unique errors were not correlated was rejected. Additionally, Variance Inflation Factor (VIF) values were examined to test the presence of multicollinearity between the variables. No evidence of severe collinearity was found.

Whether the contract was for yellow or white corn had an impact on the number of bushels specified in the contract. The *white* regressor exhibits a negative relationship with contract volume with a *p*-value of 0.082. The negative association between *color* and contract volume is consistent with the hypothesis that higher production cost decreases the bushel amount producers are willing to contract. If a producer chose to initiate a white corn contract, that contract would contain 2,496 fewer bushels than the same contract for yellow corn. The qualitative variable *nongmo* also reveals a negative relationship with contract volume. With an associated *p*-value of 0.000, the parameter indicates that contracts for non-GMO corn will be 7001 bushels less than the same contract for GMO corn. This confirms the expectation that the higher production cost associated non-GMO corn limits the number of bushels contracted compared to GMO corn. Indeed, the premium received for producing IP corn influences the bushel amount contracted. A *p*-value of 0.000 supports the hypothesis that this price signal gets producers in the door and has a positive effect on their buy-in to the contracting program. On average, if a premium for a particular contract increases by $0.10, the volume obligated to that contract is expected to increase by 1,956 bushels, *ceteris paribus*.

The overall condition of the grain market from 2010 – 2016 had a significant effect on contract volumes. The downturn in the corn market from 2014 – 2016 and its effect on contracting decisions is evident in the coefficient for the *market* variable. During this period of depressed prices, 4,404 fewer bushels were marketed per contract relative to 2010 – 2013. No distinct hypothesis was formulated for this variable because of the many unobserved decisions that could've been made during either period. However, it is possible that premiums were not covering the added cost and risk of producing IP crops, and producing commodity crops had higher relative profitability for some operations.

Another variable related to market condition and demand is whether the mill was accepting both non-GMO and GMO corn during a particular year, or only non-GMO corn. The relationship between the *nonyear* variable and dependent variable is not as expected. A decrease in contract volumes for years when more selective buying took place did not occur. Instead, an increase of 4,220 bushels per contract occurred during years when only non-GMO corn was accepted at the mill. This result contradicts the notion that limiting producers to only one kind of seed technology would induce a decrease in their buy-in to those contracts. Including variables like *premium* interacted with *market* or *nonyear* could provide more detail as to how the mill's price signal affected contract volumes during these distinct time periods. However, different model specifications that included such terms returned estimates with severe multicollinearity, or statistical insignificance, giving preference to the specification chosen for this essay.

Only one type of mechanical dryer returned a statistically significant result. However, this result had the largest impact on contract volumes. Compared to natural field drydown, the use of a stack dryer in the production process is associated with an 8,675 bushel increase in contract volume. This outcome is consistent with the expectation that prior investment in a mechanical dryer would result in larger contract volumes of IP corn. Stack dryers fall into the category of high-temperature grain dryers, making them more efficient than an in bin, low-temperature method of drying. If a farmer can efficiently dry and store value-added grain ahead of other undifferentiated grains during harvest, they may be inclined to initiate larger contracts to generate more income from their enterprise mix. Regardless of motivation, an association is observed between dryers and larger contract volumes, pointing towards some degree of asset specificity.

The last of the statistically significant variables are the quarters in which the corn was contracted and ultimately priced. The third quarter resulted in 2,797 more bushels contracted compared to the first quarter, and the fourth 2,965 more bushels. An expected relationship between when corn is contracted, and the bushel amount per contract was not defined due to the many factors affecting pricing decisions. However, it is possible to observe that contract volumes increase once better yield potential information is available during the summer months of the third quarter, and once yields are realized during the fourth quarter.

2.6 Conclusion

Through the firm-level analysis of contracting decisions between producers and a mill, insight has been gained into factors that affect how much IP corn is put under contract in a single transaction, but what are the implications? Many questions regarding the farmers in this relationship have been answered. From the mill's perspective, having an understanding of these factors can lead to better decisions in supply procurement. The majority of this conversation centers on the price premium, with additional implications for the principal-agent relationship and relationship-specific drying equipment. If the agribusiness decides in subsequent years to accept GMO corn again, what premium should be set to attract buy-in from producers and ensure adequate bushels for the markets they are supplying? The results indicate that farmers will produce more corn per contract relative to non-GMO corn and that small premium increases have a significant effect on the number of bushels per contract. Too low of a premium could result in low buy-in, not only because it is an unattractive price signal, but because of switching costs incurred by the farmer from year to year when certain grain types are accepted, and others are not. If this were to materialize, the mill could experience a shortage and have to make up for that shortage by buying grain from another elevator or broker at a potentially higher cost.

The condition of the commodity markets should also play a role in decision making with regards to premium levels. It was observed that a depressed market decreases producers' willingness to contract larger volumes of IP corn given the premiums offered by the mill in that period. Although it was seen in the data that as corn prices fell, premiums increased, but what is the strategy when the market strengthens, and prices increase? Should a premium be lowered to improve the bottom line of the milling enterprise and risk losing buy-in from producers, or should it remain the same to reduce turnover among producers and ensure adequate supply? Of course, these questions can be partially answered by analyzing the result of the premium variable, but observing other factors like market volatility compounds information and allows for better decision making.

If the mill continues to buy only non-GMO corn into the future, steps should be taken to ensure producers are satisfied with their business relationship. While the results indicate that larger contract volumes occur during years when only non-GMO corn is purchased, the overall number of contracts in these years is markedly lower. If a producer discontinued their business with the mill from one year to the next, they could experience a substantial loss of corn. Either a new producer who could produce the same amount of corn would have to be identified, or the remaining producers would need to grow more corn. Each situation could result in search cost or an increase in coordination effort, respectively.

Given previous ERS studies and the pattern seen in the data used for this study, turnover among producers in the IP corn market is most relevant. Just as businesses experience costs with high employee turnover, so would a mill that uses contractual arrangements with farmers to supply them corn. If year after year the mill loses producers and has to search for others to meet supply quotas, in addition to onboarding those producers and educating them about quality standards, etc., transaction cost significantly increases. In this sense, it would be in the interest of the mill to engage producers and receive feedback before one, or a handful of farmers stop contracting altogether, recognizing there are costs associated with this too.

Finally, drying equipment should be a consideration if the mill needs to prospect new producers to meet demand or expand the enterprise. Higher efficiency dryers allow producers to increase throughput during harvest. When considering the result of the stack dryer variable, producers with this type of dryer choose to contract more grain per contract. Attracting producers with these assets may ensure an adequate supply of grain stored past harvest and delivered by buyer's call, not subject to the yield loss and quality issues associated with natural drydown in the field. However, the use of high-temperature drying puts the grain at risk for stress cracks, which could cause discounts when the corn is delivered. If the mill decided to prospect for new producers with high-temperature dryers, they may have to provide education on drying IP corn to maintain quality, which would come at a cost and increase coordination effort.

This study serves as an empirical, firm-level study to quantify variables surrounding contracting decisions among farmers producing IP corn. The unique data set allowed econometric analysis of firm-level interactions not often available to researchers. Further, this inquiry fills a void in the economic literature on IP grains that lacks quantitative methods and is focused on industrial organization. Using a fixed-effects model, statistical analysis was performed on seven years of contract and pricing data to generate results and provide insight to the principal-agent relationship taking place between the mill and numerous producers. Yet, it is recognized that these results may only be applicable to the producers and mill in question, and not the broader IP corn market. Utilizing the results, aspects of the contractual arrangements that have the potential to impede the course of business are analyzed. With this understanding, a better principal-agent relationship may be forged, and better business decisions can be made.

2.7 Chapter 2 Tables and Figures

Table 2.1 Descriptive statistics of factors affecting food corn contract volumes

Variable	Mean	Std. Dev.	Min	Max	Expected Sign
Volume	12674.49	14052.95	332	150000	
White	0.460793	0.49868	0	1	-
Non-GMO	0.681938	0.465929	0	1	-
Premium	0.608546	0.211762	0.25	1.2	+
Deliver	0.352423	0.477935	0	1	+/-
Corn	4.970152	1.183247	3.2275	8.3525	+
Beans	11.64391	1.804131	8.7275	17.4575	-
Market	0.399119	0.489933	0	1	+/-
Con	22663.35	26118.85	0	190000	+
Disc	378.714	722.2195	0	68240	-
Nonyear	0.536564	0.498881	0	1	-
Tower	0.081057	0.273043	0	1	+
Inbin	0.555066	0.497178	0	1	+
Stack	0.120705	0.325928	0	1	+
Quart2	0.225551	0.418129	0	1	+/-
Quart3	0.206167	0.40473	0	1	+/-
Quart4	0.295154	0.456313	0	1	+/-

N = 1135

Table 2.2 Fixed-effects estimates of factors affecting food corn contract volumes

Variable	Parameter	Standard Error
Constant	7740.819	5214.018
White	-2496.096*	1433.245
Non-GMO	-7001.134***	1688.937
Premium	19563.33***	4702.485
Deliver	-2203.357	1395.865
Corn	1203.409	893.975
Beans	-915.320	618.515
Market	-4404.617***	1473.577
Contract	0.0248	0.020
Discount	-1.048	0.689
Nonyear	4220.931***	1657.432
Tower	3741.9	3107.667
Stack	8675.599***	2619.216
Inbin	769.962	1525.38
Quart2	-1278.34	1409.348
Quart3	2797.041*	1653.287
Quart4	2965.572*	1538.322
$F = 0.0000$		

Chapter 3: Optimizing Planting, Storage, and Marketing Strategies for Identity Preserved and Commodity Crops

3.1 Abstract

This essay utilizes mixed-integer programming to optimize resource allocation and a marketing strategy for a hypothetical farm. Post-optimal analysis is performed to determine non-binding capacities for drying and storage equipment. The model is re-run with these non-binding capacities to observe a change in net returns in addition to planting, harvesting, and marketing strategies. New equipment and associated costs are identified, and the change in net returns from the base case is used as net cash flow in a net present value investment analysis. Results of the investment analysis indicate increasing drying and storage capacity is a wise investment given the crop prices used in the model.

3.2 Introduction

Considerable capital improvements are sometimes necessary for a row crop farm to realize increased profitability. Oftentimes decisions regarding these improvements are made without careful analysis of the entire system and what effect their addition will have on other components. An obvious example is when the capacity of a machine or machinery complement is undersized relative to throughput and a bottleneck occurs, reducing the efficiency of the overall system. Suboptimal performance of a whole farm system can occur during each stage of the production process from planting to delivering grain at an elevator. A component of this system that is of both logistical and economic importance is the capacity and efficiency of drying and storage equipment. Yet, it would be a mistake to assume every other aspect of production, for instance, the date a crop is planted, would not affect the demand for drying and storage equipment. Moreover, the specifications of grain drying and storage equipment affect subsequent marketing strategy and prices received, which in turn affect net returns.

The purpose of this essay, therefore, is to determine optimal drying and storage equipment for a typical western Kentucky grain farm growing white food grade corn, field corn, and soybeans. Further, a marketing strategy will be determined based on the optimal equipment size that maximizes whole farm net returns. White corn is included in the enterprise mix to observe if the model prioritizes it over the other grain types for harvest, drydown, and storage operations given its economic value. Mathematical programming is employed to determine both optimal equipment size and marketing strategy, utilizing AIMMS software as the development environment to construct the model. Proper programming methodology (e.g., integer, linear programming) will be discovered during the experimentation process.

The context of the analysis is a farm business with preexisting drying and storage equipment that is interested in determining limiting factor(s) within harvest, drydown, and storage logistics and the effect that has on marketing strategy and net returns. Once net returns are maximized in the base case, bottleneck(s) will be identified through binding constraints. If the capacity constraint of the dryer, grain bins, or both, are binding, capacity will be augmented until no additional contribution to net returns can be made. Following post-optimal analysis, net present value investment analysis will be performed to determine the suitability of investing in expanded drying and storage resources.

While the primary objective of this essay is optimal equipment selection, it will also serve to demonstrate the interdependencies of operations within an entire growing season and marketing year and how those relationships affect the profitability of a farming operation. With this degree of understanding, optimal decision levels can be discovered and implemented with greater ease.

3.3 Literature Review

Several farm management studies related to livestock and crop production have been performed which utilize mathematical programming for optimization. Methodologies and objectives of previous investigations span a range of formulations and topics. In 2011, Shockley, Dillon, and Stombaugh examined the effects of automatic section control technology on whole farm net returns, risk, and production practices using a mean-variance quadratic programming resource allocation model. Morrison, et al. (1986) selected integer programming to determine optimal land use between crop and pastureland. In doing so, biological, financial, and technological interactions that drive optimal decision making were demonstrated. These are just two of many examples which employ mathematical programming techniques to explore optimal decision levels for agricultural production.

As the focus is narrowed to machinery selection, a collection of literature becomes relevant to the current study. Danok, McCarl, and White (1980) chose mixed integer programming (MIP) to select optimal tillage, planting, and harvesting equipment sets amidst weather variability. They selected mixed integer programming to represent integer characteristics of machinery decisions, the stochastic nature of weather, the relationship between machinery set and crop mix, and selection of machinery sets as opposed to individual machines or implements. To demonstrate the usefulness of MIP in this context, a particular machinery set was assumed and alternative sets were generated after the base case was run. Shadow prices from the base case indicated the system was characterized by excess plowing and tractor capacity, and insufficient planter and harvest capacity. When the model was reformulated and could choose among sets of equipment, a complement with less tractor capacity and more harvesting capacity was chosen. This result demonstrated the ability of the MIP formulation to evaluate possible modifications to existing sets, in addition to choosing new sets. An overarching concept of Danok, et al.'s paper applicable to the study at hand is that shadow price information supports machinery set characterization and modification by the decision maker.

Reid and Bradford (1987) used a multiperiod mixed integer programming model to determine optimal equipment investment strategy over 15 "decision periods" for three different beef backgrounding systems, each requiring different levels or forage production, weight gain, and herd size. Their formulation included constraints pertinent to Net Present Value (NPV) methodology to identify optimal machinery replacement, investment, or disinvestment decisions. Their results indicate shadow prices of binding constraints within a less profitable production system must reach a certain level before investment in larger equipment and a switch to a more profitable system will take place. Additionally, tax implications and the opportunity cost of new equipment purchases factor into these decisions as per the NPV approach to investment analysis. Once again, Reid and Bradford's study demonstrates the importance of binding constraints and their shadow price as the starting point for machinery selection and associated analysis.

Bender, Kline, and McCarl (1990) implement a postoptimality algorithm based on the formula by Mills (1956) into the REPFARM linear programming model (McCarl and Pheasant, 1983) to improve upon the shadow price approach for identifying bottlenecks caused by undersized machinery. The authors note that problems can arise when the acquisition of a machinery resource changes the coefficients within some related constraints. They propose that relevant shadow prices need to be aggregated to accurately reflect the single marginal value of a resource. To illustrate this approach, Bender, et al. implement a case study on Texas A&M University's research farm to analyze different machinery complements. Their algorithm returned information that gave the value of a machine if its capacity was increased by one percent. Ultimately, the field capacity of the disc was found to be limiting the productivity of the case farm. However, the authors did not discover this through a shadow price since results were interpreted as labor hours for particular machinery operations. In fact, shadow prices for "preparation hours" were zero across all machinery complements. Rather, their technique of a comparison of annual returns, added cost, and value indicators for each equipment set was employed to determine the disc implement was stifling productivity. When the authors extended their study to other farms in Texas, they found the prediction error of the objective function value to be less than 10% when machinery capacity was increased by 100% or less. While an explicit algorithm for post-optimal analysis is not part of the current study, Bender, et al.'s work is a prime example of how comprehensive post-optimal analysis can lead to better understanding of linear programming solutions.

Ekman (2000) employs Discrete Stochastic Sequential Programming (DSSP) to evaluate the economics of alternative tillage and cropping systems for cereal grain and oilseed production. DSSP is a technique which enables modeling of dynamic and stochastic processes and allows random coefficients both in constraints and objective function. Ekman's results show a major tradeoff between conventional, high capital, high labor tillage systems and their associated higher yields and low capital, low labor direct drilling with lower expected yields. Adding to this tradeoff are lower timeliness costs for the direct drilling system since less field work is required prior to planting. When sensitivity analysis is performed on farm size, the optimal tillage system changes from chisel plowing to direct drilling between 120 and 150 hectares. This observation demonstrates how changing parameters can affect optimal decision making, which is an objective of the current study- a change in marketing strategy as a result of a change in drying and storage resources.

While math programming literature as it relates to farm management and machinery selection is of obvious importance, it would be a mistake to forego acknowledgment of agricultural engineering works that examine principles of on-farm drying and storage operations. Loewer et al. (1980), include both economic and engineering information to demonstrate the tradeoffs experienced by a farm with drying and storage equipment and one that does not. Their results illustrate the relationship between pre-harvest losses from waiting for grain to dry in-field when drying and storage resources are not present, and the benefits associated with an earlier harvest and subsequent drying and storage. For instance, as harvest time increases by one day, net returns to drying and storage decreases at an average rate of $0.00258/bu for corn. Harvest, drydown, and storage are the only tasks considered; upstream operations such as planting date are not considered factors of the demand for drying and storage equipment by Loewer, et al (1980).

Loewer, Kocher, and Solaimanian (1989) developed a computer simulation model to identify bottlenecks within grain harvesting, delivery, handling, drying, and storage systems. While they provide insight for the inquisitive modeler by explaining that increasing capacities of upstream processes along with the bottleneck itself results in increased overall capacity, again, no discussion takes place on how operations or environmental conditions prior to harvest affect demand for drying and storage. Since no economic information was modeled, implications of bottlenecks on values such as net returns are not discussed. Nevertheless, the model demonstrates the interdependencies of machine capacities between harvesting, drying, and storing operations.

Finally, general economic and extension literature relating to drying and storage must be considered to acquire a basic understanding of the underlying problem within this study. For example, Nichols (1985) presents formulas and analyzes the costs of on-farm corn drying in three categories: overhead, operating, and shrinkage/loss expenses. Maier and Watkins (1998) outline best practices for maintaining the quality of white corn during the drying of white corn. Edwards (2015) designed a spreadsheet calculator to determine the monthly costs of storing grain, a discount used in this study, while Smith (2013) formulated a similar calculator for hauling costs. To end, enterprise budgets like Halich (2017) provide detailed information for estimating per acre costs of production for grain crops. While extension publications and decision aids may be void of sophisticated mathematical or statistical techniques, they assist in estimating parameters and help the analyst understand the problem they seek to accurately model.

3.4 Materials and Methods

The framework for this study includes the production environment, the whole farm economic optimization model, and resource endowment of the hypothetical farm at the focus of this inquiry. These subsections are addressed individually to establish context on which results will be based.

3.4.1 The Production Environment

Planting date and yield interactions are considered an important driver of demand for drying and storage resources during harvest. Yield estimates for the hypothetical farm are calculated by detrending historical data to obtain an average yield for each crop. These average yields are then multiplied by a curve representing specific plant dates and yield as a percentage of yield potential. In this case, yield potential is the abovementioned average yield of each crop.

Average yields for corn and soybeans from 1996 – 2015 in Henderson Co., KY (NASS, 2015) are detrended to establish an overall average yield for each crop. Per acre, average yields are 136 bushels for white corn, 156 bushels for corn, and 52 bushels for soybeans. Detrending the data is necessary to establish technical coefficients independent of production advances that took place during the 20-year period. While there was no data available for white corn yield, white corn is estimated to have 87% of the yield potential of field corn. This is determined by taking the ratio of white corn average yield to average field corn yield from the Kentucky Hybrid Corn Performance Test (Kenimer, Kurd, and Lee, 2015). The planting date yield curve upon which average yields are constructed comes from a 13-year study by Beck's Hybrids in Henderson Co., KY (Beck's, 2017). When applied to the average yield of each crop, the curve provides a penalty for planting too early or too late around the optimum plant date. These values range from -15% to +10% for corn and -26% to +7% for soybeans. The complete array of yield penalties and advantages can be seen in Table 3.1. To end, it is assumed harvest can begin 23 weeks after planting a given crop.

3.4.2 The Economic Model

Linear and mixed-integer programming are employed to determine optimal resource allocation for the hypothetical farm. The use of mixed-integer programming (MIP) allows for logical sequencing of operations such as planting and harvesting as a farmer would tend to perform them. Further, sequencing will enable analysis of labor requirements during planting and harvesting and the feasibility of segregation measures between IP and commodity crops. Although shadow prices of the MIP case are uninterpretable, drying and storage resources will be ranged until no additions to net returns are made. The difference in objective function value between the base case and non-binding drying and storage capacities will be motivate an investment analysis.

The objective function to be maximized is net returns above selected costs. The mathematical representation of the economic decision-making model is located in the appendix. Selected costs include variable input costs per acre such as seed, fertilizer, and herbicide, as well as operating costs like fuel, lubricant, repairs, and interest on operating capital. As will be seen, drying and storage costs are intentionally excluded from per acre costs of each enterprise and instead subtracted from the price of contracted bushels. Since land and labor costs are not incorporated, the objective function value is interpreted as returns to land, labor, and management.

The economic model includes decision variables, constraints, resource endowments, and technical coefficients. Decision variables include acres devoted to the production of each enterprise by plant date and harvest, bushels harvested by enterprise and harvest week obligated to either cash or contract sales, and trucks needed each harvest week to haul grain to on-farm storage or a commercial elevator. Given finite land, labor, and capital resources, constraints are enforced to determine optimal decision variable levels and maximized net returns.

Constraints imposed in both the LP and MIP models include land available for cultivation, weekly hours suitable for fieldwork, a marketing limitation, a white corn production contract, crop rotation, weekly hauling capacity to either on-farm storage or a commercial elevator, weekly drying capacity, and total on-farm storage capacity. The land constraint ensures that total crop production does not exceed the assumed acreage available. Suitable field hours by week constrain the planting and harvesting operations taking place in the model. The marketing constraint limits total sales to actual bushels produced by each enterprise in individual harvest weeks. A white corn contract of 40,000 bushels dictates the production level and is assumed stored on the farm and delivered after harvest. Crop rotation is imposed to reflect sound agronomic practices. This constraint requires 50% of available acres be planted to white corn or field corn, and 50% to soybeans. Weekly per truck hauling capacities to on-farm storage or a commercial elevator, multiplied by the optimal number of trucks, restricts the number of bushels per week that can be transported to either facility. Finally, weekly drying capacity limits the amount of white corn or corn bushels dried in a week, and total storage limits the amount of grain that can enter on-farm storage.

Constraints specific to the MIP case are imposed to require completion of planting as well as harvesting operations for a given crop before another crop can begin. First, constraints are included requiring that the decision to plant (harvest) on a given planting date (in a given harvest week) must be made (a value of one for the respective binary variable) before any positive level of crop production acreage occurs. The next set of constraints dictates that the planting (harvesting) of each crop will continue until it is completed. A concurrent constraint is imposed to allow planting (harvest) of another crop to begin only if the first crop's planting (harvest) is completed during the said week.

In addition to constraints, establishing technical coefficients, right-hand sides, and other assumptions are required to complete the model. These include labor hours, prices, and costs. Labor requirements for producing corn and soybeans are based on the field efficiencies of planting and harvesting equipment. Field efficiency data are derived from a prior whole farm analysis by Shockley, Dillon, and Stombaugh (2011). For all three crops, planting requires 0.049 hrs/A. Harvesting requires 0.219 hrs/A for white corn and corn, and 0.102 hrs/A for soybeans. Suitable field hours for the planting and harvesting windows are estimated by taking the 50th percentile of suitable field days per week for Kentucky from 1996 – 2016 (Shockley and Mark, 2016) and multiplying them by an assumed 12-hour workday.

Crops can be sold in the cash market or hedged on the futures market. Thus, two sets of prices for each enterprise are available for the model to select an optimal marketing strategy amidst drying and storage constraints. The contract price for field corn is December futures priced in week 14 (late March, early April). This strategy was determined by analyzing daily Chicago Mercantile Exchange (CME) December futures prices from 2014 – 2017 (Commodity Research Bureau, 2017) to determine which Julian week had the highest average price. 2014 – 2017 data is used to reflect current grain market conditions. Corn contract price equals $4.22 before selected costs are subtracted. White corn is priced using the same strategy as stipulated in the mills contract that daily CME December futures and a fixed premium are used to determine pricing. Fortunately, access to the mill's pricing data from 2011 – 2016 was available to determine the premium applied to white corn (Confidential, 2016). Over the seven years of data, the average premium for non-GMO white corn delivered after harvest was \$0.73. The contract price for soybeans is January futures priced in week 37 (mid-September). Again, this strategy follows the methodology for corn. CME January soybean futures from 2014 – 2017 were analyzed to determine week 37 had the highest average price of \$9.60.

Hauling, drying, and storage costs are subtracted from contracted white corn and corn bushel prices. A \$0.12/bu hauling cost was calculated using University of Tennessee Extension's Grain Hauling Cost Calculator (Smith, 2013). This estimation assumes a 15-mile trip from field to on-farm storage. An additional \$0.17 is subtracted to reflect transportation cost from the farm to a commercial elevator when the grain is delivered, assuming a 20-mile trip from storage to market. Drying and storage costs are also subtracted from the bushel price of contracted white corn and corn. Together, drying and storage costs total \$0.32 per bushel. This discount was calculated with Iowa State University Extension's Monthly Cost of Storing Grain decision tool (Edwards, 2015) and assumes 10-point moisture removal. An additional \$0.0034 per bushel per week opportunity cost and quality discount are subtracted once grain enters storage. This was also estimated using Edwards' storage cost decision tool and includes interest cost and quality deterioration. Hauling and storage costs are subtracted from the bushel price of contracted soybeans. These were also calculated with Smith's and Edwards' decision tools and equal \$0.25 and \$0.05, respectively. Associated opportunity cost and quality discount per bushel per week equal \$0.01.

Cash prices are weekly averages from 2014 – 2017. Price data during harvest weeks is the average spot price of 12 western Kentucky elevators. Using Smith's (2013) calculator, a $0.22 hauling cost is deducted from the weekly average bushel price of both corn and soybeans. This assumes a 60-mile round trip from field to the commercial elevator. An additional 10% moisture dockage also discounts the cash price of each corn bushel since no drying takes place before delivery.

Finally, per acre costs are adapted from the University of Kentucky enterprise budgets for western Kentucky no-till corn and soybeans (Halich, 2017) and total $396.42 for white corn, $368.42 for corn, and $234.73 for soybeans. The difference in costs between white corn and corn is due to increased seed and herbicide cost (Reinbott, 2018) since white corn production is assumed non-GMO and requires a different herbicide package.

3.4.3 The Hypothetical Farm

The hypothetical farm in this study was parameterized to represent a commercial grain farm in Henderson County, Kentucky. The 2,300 acre farm size (operator tillable acres) corresponds with the upper one-third of all farms in management returns represented by net farm income in the Ohio Valley region of Kentucky where Henderson County is located (Pierce, 2017). Specifications of the machinery complement relevant to this study include a 16-row split row no-till planter and a 300-hp combine with an 8-row header for corn, and a 25-ft flex header for soybeans. As previously mentioned, field efficiencies of the planter and combine represent the technical coefficient of labor for planting and harvesting. The study by Shockley et al. (2011) from which the field efficiencies are taken from the Mississippi State Budget Generator (MSBG) to determine equipment specifications. MSBG complies with the American Society of Agricultural and Biological Engineering Standards (Laughlin and Spurlock, 2007).

Dryer and storage capacities are modeled to analyze whether these systems cause binding constraints and if there is an opportunity to increase net returns by increasing capacity. The weekly capacity of the dryer totals 12,740 bushels for white corn and 25,480 for field corn. Weekly drying capacity was determined by multiplying the 260 hourly bushel capacity of the GSI 1108 portable dryer (GSI Grain Systems, 2016) by a 14-hour workday and 7-day workweek. This capacity represents 10% moisture removal to align with the drying costs subtracted from the bushel price of white corn and corn. The 50% reduction in capacity for white corn (unpublished dryer and cycle time analysis, 2016) is representative of the need to dry at lower temperatures to maintain the grain quality requirements of most food corn contracts. On-farm storage capacity totals 100,000 bushels. This figure is derived from a large farm in Logan County, KY and is scaled to the 2,300 acre farm size used in the model.

Last, weekly hauling capacities to on-farm storage and a commercial elevator are included in determining the number of trucks needed to haul grain during harvest weeks. Cycle time data for trucks going to on-farm and commercial storage was taken from an ongoing study to determine weekly hauling capacities (unpublished dryer and cycle time analysis, 2016). For trucks delivering to on-farm storage, the cycle time is 1.2 hours, assuming a 17.5 minute unloading time at the pit and round trip of 30 miles. Since a workday is 12 hours long, one truck can complete approximately 9.6 cycles in a day. When multiplied by 1,000 bushels per load and a 7-day workweek, weekly hauling capacity to on-farm storage totals 67,264 bushels per truck. Cycle time to transport grain from the field to a commercial elevator is 2.6 hours, which includes a 50-minute waiting/unloading time and 60-mile round trip. Total weekly hauling capacity to a commercial elevator is 31,726 bushels per truck.

3.5 Results

Ultimately, two models were constructed to complete this investigation. A linear programming model was run to observe results of the least restrictive case and compare them to the results of the MIP model. As previously mentioned, the MIP model was assembled to sequence planting and harvesting operations in a logical order. Following post-optimal analysis of the MIP base case, the model was re-run with non-binding dryer and storage capacities to discern a change in net returns. This change in objective function value warranted investment analysis of new drying and storage equipment. For clarity, only results from the MIP base case and with non-binding drying and storage capacities are presented.

3.5.1 Base Case Results

Maximized net returns from the MIP base case solution total $495,561.08. For reference, net returns in the LP solution were maximized at $499,516.35. While possible, planting and harvesting activities in the LP model were sporadic amongst crops and did not follow a logical order in which a producer would perform them.

Decision variables include a planting strategy, a harvest and marketing strategy, and the number of trucks needed to haul grain during harvest. Ultimately, the model considers the planting date yield curve and resource endowments during harvest when allocating total acreage across crops and planting dates. White corn is the first crop planted on the hypothetical farm March 16th and March 23rd, albeit a small area of 14 and 94 acres, respectively. While these dates are toward the earliest limit of the planting window in Kentucky and would only be possible in a small percentage of growing seasons, this acreage could easily be incorporated into the following two weeks' activities given the amount of slack in hours suitable for fieldwork. White corn planting continues the week of April 1st at 88 acres and is concluded the week of April 8th with 87 acres.

The same week white corn planting ends, field corn begins. 242 acres are planted the week of April 8th, followed by 557 acres (across harvests 1 and 2) the week of April 16th. Field corn plantings are completed the week of April 23rd with 68 acres planted. Reflecting on the yield curve used to model plant date and yield combinations, the optimal time to plant all three crops is the week of April 16. However, as will also be seen in the harvest and marketing strategy, field corn takes precedence due to its relative profitability in both the cash and futures market. Finally, the planting of soybeans begins the week of April 23rd at 526 acres and ends the week of May 1st with 624 acres planted. This entire planting scheme may be viewed in sequential order in Table 3.2. In all, 1,150 acres are planted to white corn and corn, and 1,150 acres are planted to soybeans, satisfying the constraint that 50% of acreage is planted to a corn variety and 50% is planted to soybeans.

Optimal harvesting and marketing decisions are seen in Table 3.3. Following the order of crops planted, harvest begins with white corn and concludes with soybeans. Over weeks 35 – 38 (late August to mid-September), the entire 40,000 bushels of white corn devoted to the production contract are harvested. Since white corn is the first crop harvested, contamination issues between it and another crop are not considered. Harvest continues in week 38 with sales of 40,777 bushels of field corn in the spot market. Another 29,055 bushels of field corn are sold in the spot market the following week, as well as 25,480 bushels sold on the forward contract. This contracting decision repeats itself in week 40 with another 25,480 bushels stored and delivered in December. The bushel amount of forward contracted corn in weeks 39 and 40 are equal to the number of bushels that can be dried per week. When that capacity is met, bushels are sold in the spot market at an elevator to keep harvest moving. Hence, 15,575 bushels of corn are sold in the spot market during week 40. Field corn harvest is completed in week 41 with 2,398 bushels sold in the spot market and 9,040 hedged on the futures market. Finally, the harvest of soybeans takes place over weeks 41 – 42 for a total of 63,063 bushels sold exclusively in the cash market. The fact that no soybeans are sold in the futures market indicates that returns to storage are greater for corn. Thus, the model devotes the remaining 60,000 bushels of this resource to field corn after the predetermined 40,000 bushels of white corn are stored.

Knowing the number of trucks needed to haul grain is of great logistical importance during harvest. Idling combines or grain carts waiting to unload delays harvest and is an inefficient use of time and money. During the seven-week harvest period, three trucks are the maximum needed in a single week. A three-truck fleet is needed in week 38 when large amounts of grain are transported to both on-farm storage and the more distant commercial elevator. Two trucks are needed in weeks 39 – 42. Again, this capacity is needed to keep up with the flow of bushels headed to the elevator. In weeks when on-farm storage is the only destination (35, 36, and 37), one truck is required. The entire strategy for trucking capacity is contained in Table 3.4.

Constraint solutions relevant to this analysis include drying and storage capacities as well as labor hours suitable for fieldwork. In the base case, a binding dryer capacity limits how much grain can enter storage in a given week. The constraint solution for weekly dryer capacity may be seen in Table 3.5. Of the seven harvest weeks in which the dryer was running, five (36 – 40) are characterized by maximum capacity given the assumptions outlined in the previous section. While explicit shadow prices cannot be derived from a mixed-integer program, right hand side ranging of weekly dryer capacity allows for the identification of the non-binding dryer capacity within the system. After several runs of the model with capacity incrementally increased by 1,000 bushels, dryer capacity is determined non-binding at 83,584 bushels per week, an increase of 58,104 bushels per week from the base scenario. The point at which the marginal value product (MVP) of weekly dryer capacity becomes zero can be seen in Figure 3.1.

Maximum storage capacity is reached in week 41. Differences in the bushel amount accumulating in storage as harvest weeks progress equal the number of bushels harvested for contract sales by week. This accumulation of grain and the point at which capacity is reached may be seen in Table 3.6. As seen in the harvest and marketing strategy, no soybeans enter storage because of the higher returns to storing corn. Because total storage is binding, right hand side ranging is also performed to determine at which capacity storage becomes non-binding. Normally, tracing out this derived demand curve would entail holding all other elements constant in the base case and ranging the right hand side of storage. However, before storage capacity is ranged, the non-binding weekly dryer capacity is included in the model. This is because dryer capacity is a bottleneck upstream of storage in the base case. If storage capacity was ranged independent of the change in weekly dryer capacity, a true optimum would not be identified. Many iterations were performed increasing capacity by 10,000 bushels each run. Ultimately, storage capacity is non-binding at 252,080 bushels, a difference of 152,080 bushels from the base case. Because greater margins are achieved by pricing crops in the futures market and storing them for delivery after harvest, it is no surprise that the non-binding capacity equals the total number of bushels produced on the hypothetical farm. The MVP of storage over the range of capacities can be seen in Figure 3.2.

Having ample time to plant and harvest crops around select dates can increase yields. Therefore, it is essential to analyze the number of labor hours needed to complete the planting and harvesting strategies returned in the decision variables. Fortunately, there is enough slack in the base case that having enough time is not an issue. This is primarily driven by the field efficiency of the planter. Had a less favorable of percentile of suitable field hours been included in the model, slack in labor hours across planting weeks would decrease, and the size of the planter would not seem as large. During the eight weeks of harvest, seven weeks (38, 39, 41, and 42) have binding labor hour constraints. These results are not surprising considering the increase in suitable field hours from the planting to harvest window, as well as the lack of downstream constraints the model has to consider when selecting a harvest strategy. The full constraint solution for labor hours is seen in Table 3.7.

3.5.2 Non-binding Results

Since one of the objectives of this study is to analyze the effect increasing drying and storage capacities has on net returns, expanded capacities replaced the base case right hand sides, and the model was rerun. The following results are the product of capacities associated with the equipment that will be seen in the investment analysis. These total 71,140 bushels per week for drying, and 250,000 bushels for storage. While these figures are slightly below the true non-binding capacities, they are the next best case without grossly oversizing equipment. Hereafter, these results are referred to as 'non-binding'. Under these new resource endowments, whole farm net returns increase to $591,059.61, a difference of $95,498.54 from the base case. Decision variable and constraint solutions also change considerably. Most notably, all corn and most of the soybeans are priced with forward contracts and stored for post-harvest delivery. Below, changes in these solutions are analyzed to determine their causes within the model.

The total number of weeks planting takes place decreases from the base case, but on average, more acres are planted per week. White corn is planted first the week of April 1st for a total of 123 acres. White corn planting is completed the week of April 8th with 312 acres planted across harvests 1 and 2. Corn planting picks up the same week and is completed the week of April 23 for a total of 876 acres planted. With hours still available for fieldwork, soybean planting starts the same week corn ends and is completed the week of May 1 for a total of 1,150 acres. As in the base case, field corn is given priority for the optimal plant date of April 16th because of price and yield combinations above variable costs. The new planting strategy is compiled in Table 3.8.

Following the planting strategy, fewer harvest weeks are required, but the average number of bushels harvested per week is greater than the base case. White corn is the first crop harvested starting week 37 and completed in week 38. The reduction in harvest time from four to two weeks for white corn is a result of increased weekly drying capacity. Additionally, since white corn is still the first crop harvested under the new drying and storage conditions, contamination issues are not addressed. Corn harvest begins in week 39 and ends in 41. Finally, soybeans are harvested in weeks 41 and 42, with 2,618 bushels still being sold in the spot market due to the slight difference in true non-binding storage capacity and the one used in the model run. This harvest strategy and number of bushels harvested per week may be viewed in Table 3.9.

Trucks needed to haul grain during harvest decreases since only a small amount of soybeans are transported to an elevator. Instead, most trucks leaving the field are bound for on-farm storage. Under the assumptions used in the model, trucks going to on-farm storage can move about twice as much grain as those going to the elevator due to the distance traveled and wait times to unload. In this scenario, only one truck is needed weeks 37 – 41, and two are needed in week 42 when a relatively small number of bushels of soybeans are sold at the elevator.

Since drying and storage capacities were determined non-binding prior to the model run, it is known that no additions to net returns can be made by increasing them further. The last bushel enters storage in week 42 for a total of 250,000 bushels stored. Tables 3.10 and 3.11 provide full detail of dryer use and the accumulation of bushels in storage during harvest.

Since the number of planting and harvest weeks decrease, average time spent planting and harvesting within weeks increases compared to the base case. Thus, the average slack in labor hours decreases across weeks. However, the overall number of weeks where labor hours available are binding stays the same. In harvest weeks 39 – 42, the total amount of labor hours are used, respectively. The complete constraint solution for labor hours available may be seen in Table 3.12.

3.5.3 Investment Analysis

Quantifying a positive change in net returns as drying and storage capacities become non-binding is the first step to figuring out whether the hypothetical farm can pay for the proposed capital improvements. The second step is knowing what those improvements cost. Once these two numbers are identified, an investment analysis for expanded drying and storage capacities can be performed.

Sales quotes from two GSI grain systems dealers in western Kentucky were gathered to estimate the cost of additional drying and storage capacity. These quotes include the total equipment and labor cost to install the new grain bins and dryer. The dryer selected to meet the non-binding capacity is the GSI 1226 portable dryer with a 10-point moisture removal capacity of 730 bushels per hour (GSI Grain Systems, 2016) and a cost of $98,583.33. To add the additional storage capacity needed, a 100,000-bushel bin and a 50,000-bushel bin need to be built. The cost to construct these two bins totals $253,993.73. Collectively, the total investment is $352,577.06 to modify the current grain system. It should be noted variable costs of drying and storage are not considered since they are subtracted from bushel prices used in the whole farm model.

Recognizing most farms are not able to pay the total amount upfront, an amortization schedule was generated to represent financing of a seven-year loan with eight percent annual interest. The seven-year loan term is based on the Modified Accelerated Cost Recovery System (MACRS) which lists the useful life of grain bins at seven years (IRS, 2018). Annual equal total payments of $57,562.28 are calculated after an assumed 15% down payment. Utilizing the net present value (NPV) method, investment analysis is performed to determine NPV and internal rate of return (IRR) over the equipment's useful life. A 20 year useful economic life, 15% salvage value, and eight percent reinvestment rate are assumed to perform the analysis. If the increase in whole farm net returns remains at or above the expected level, repaying the loan in seven years is entirely feasible. In this instance, there is negative net cash flow after the annual payment in years one and two, but positive cash flows are realized in years three to seven of the loan term.

Once the loan is paid off, net cash flow reverts to the original expected change in net returns after adding capacity, $95,948.54. At the end of the grain system's useful economic life, NPV equals $552,211.46 with an IRR of 74%. Certainly, this is a wise investment, but one that should be made with caution due to the unpredictability of commodity prices.

3.6 Conclusion

As was shown through the whole farm model, an increase in drying and storage capacity can increase net returns. This increase is attributed to a change in how each crop is marketed. When these capacities are binding in the model, a portion of field corn and the entirety of soybeans are sold in the cash market during harvest. Historically, this is when prices are lowest throughout the year due to the influx of supply from producers. With increased storage, crops previously sold at harvest are forward contracted for higher prices. At the non-binding storage capacity, this strategy includes almost every bushel produced on the hypothetical farm. To get all these bushels into storage promptly and avoid delaying harvest, adequate drying capacity is needed. To feed the dryer and prevent downtime of combines and grain carts, a sufficient amount of trucks are needed to haul grain out of the field. As was seen, this number can increase or decrease depending on where the trucks are headed. While these logistical elements of grain harvest are the main focus of the study, they do not complete the picture.

Because optimization is inherent to the quantitative method employed for this inquiry, selection of planting dates for each crop maximized yield subject to the relative profitably of each crop. This combination of planting date and expected yield drove demand for drying and storage resources in the base case. Although it was known white corn would be stored, field corn commanded the remaining capacity due to its greater returns to storage than soybeans. After non-binding capacities of drying and storage equipment were identified and included in the model, not only did marketing strategy change, but planting did as well. Overall, net returns increased $95,498.54 after a 46,060 and 150,000 bushel increase in drying and storage capacity, respectively.

Being aware of this increase in net returns is of little value if the equipment needed to achieve it cannot be paid off in a reasonable amount of time. The investment analysis for the new dryer and grain bins proved practical over their useful economic life. Under the white corn, corn, and soybean contract prices used in the model, NPV totals $552,211.46 after 20 years with an IRR of 74%. When put into the context of debt capital, the increase in expected net returns is enough to realize a positive accumulated cash flow after three years. Just like any investment for grain production, net cash flows are subject to change along with commodity prices.

Through this analysis, it has been demonstrated that capital improvements can increase the profitability of row crop farms. Utilizing a systems approach, a thorough context is created that considers many factors affecting the focus of the investigation. Here, linear and mixed-integer programming were used to model a hypothetical commercial grain farm in Henderson County, KY. From the linear program, the presence of shadow prices for drying and storage capacity indicated binding constraints and provided motivation to run experiments with increased capacities. However, logical results for planting and harvesting operations were not returned from the LP model. Thus, binary variables and new constraints were implemented to sequence these activities. Once non-binding capacities were identified, the model was re-run to observe a change in net returns. Given this change was positive, investment analysis was performed to determine whether the capital improvements could be paid back over their useful life. Implementing these improvements proved possible given the prices used in the model. Within this developed framework, an analysis of the economics of planting date as well as drying and storage equipment is accomplished, and insights to more profitable decisions are gained.

3.7 Chapter 3 Tables and Figures

Table 3.1 Percent yield potential as a function of planting date

Plant Date	White Corn/Corn	Soybeans
March 16	0.93	0.81
March 23	0.995	0.91
April 1	1.06	1.01
April 8	1.08	1.04
April 16	1.1	1.07
April 23	1.085	1.06
May 1	1.07	1.05
May 8	1.03	1.025
May 16	0.99	1
May 23	0.92	0.98
June 1	0.85	0.96
June 8	0.85	0.85
June 16	N/A	0.74
June 23	N/A	0.74

Table 3.2 Planting strategy (base case)

Crop	Plant Date	Harvest	Acreage
White Corn	March 16	1	14
White Corn	March 23	1	94
White Corn	April 1	1	88
White Corn	April 8	1	87
Corn	April 8	1	242
Corn	April 16	1	318
Corn	April 16	2	239
Corn	April 23	2	68
Soybeans	April 23	2	526
Soybeans	May 1	2	624

Table 3.3 Harvest and marketing strategies (base case)

Crop	Week	Bushels	Market
White Corn	35	1780	Contract
White Corn	36	12740	Contract
White Corn	37	12740	Contract
White Corn	38	12740	Contract
Corn	38	40777	Spot
Corn	39	25480	Contract
Corn	39	29055	Spot
Corn	40	25480	Contract
Corn	40	15575	Spot
Corn	41	9040	Contract
Corn	41	2398	Spot
Soybeans	41	29019	Spot
Soybeans	42	34044	Spot

Table 3.4 Trucks required to haul grain (base case)

Harvest Week	On-Farm	Elevator	Total
35	1	0	1
36	1	0	1
37	1	0	1
38	1	2	3
39	1	1	2
40	1	1	2
41	1	1	2
42	0	2	2

Table 3.5 Dryer capacity constraint solution (base case)

Harvest Week	Bushels	Bound Status
35	1780	Non-binding
36	12740	Binding
37	12740	Binding
38	12740	Binding
39	25840	Binding
40	25840	Binding
41	9040	Non-binding

Table 3.6 Storage capacity constraint solution (base case)

Harvest Week	Bushels	Bound Status
35	1780	Non-binding
36	14520	Non-binding
37	27260	Non-binding
38	40000	Non-binding
39	65480	Non-binding
40	90960	Non-binding
41	100000	Binding
42	100000	Binding

Table 3.7 Labor hour constraint solution (base case)

Week	Hours	RHS	Slack	Bound Status
11	0.7	50	49.3	Non-binding
12	4.6	50	45.4	Non-binding
13	4.3	50	45.7	Non-binding
14	16.1	51.6	35.5	Non-binding
15	27.3	46.8	19.5	Non-binding
16	29.1	47.5	18.4	Non-binding
17	30.5	46.8	16.3	Non-binding
35	3.1	74.2	71.1	Non-binding
36	20.6	72	51.4	Non-binding
37	19.4	72	52.6	Non-binding
38	72	72	0	Binding
39	69.6	69.6	0	Binding
40	52.4	72	19.6	Non-binding
41	68.5	68.5	0	Binding
42	63.6	63.6	0	Binding

Table 3.8 Planting strategy (non-binding case)

Crop	Plant Date	Harvest	Acreage
White Corn	April 1	1	123
White Corn	April 8	1	151
Corn	April 8	1	161
Corn	April 16	1	318
Corn	April 16	2	329
Corn	April 23	2	68
Soybeans	April 23	2	526
Soybeans	May 1	2	624

Table 3.9 Harvest and marketing strategies (non-binding case)

Crop	Harvest Week	Bushels	Market
White Corn	37	17812	Contract
White Corn	38	22188	Contract
Corn	38	27163	Contract
Corn	39	54536	Contract
Corn	40	56416	Contract
Corn	41	11439	Contract
Soybeans	41	29019	Contract
Soybeans	42	31426	Contract
Soybeans	42	2618	Spot

Table 3.10 Dryer capacity constraint solution (non-binding case)

Harvest Week	Bushels	Bound Status
37	17812	Non-binding
38	49351	Binding
39	54536	Non-binding
40	56416	Non-binding
41	11438	Non-binding

Table 3.11 Storage capacity constraint solution (non-binding case)

Harvest Week	Bushels	Bound Status
37	17812	Non-binding
38	67163	Non-binding
39	121699	Non-binding
40	178116	Non-binding
41	218573	Non-binding
42	250000	Binding

Table 3.12 Labor hour constraint solution (non-binding case)

Week	Hours	RHS	Slack	Bound Status
13	6.1	50	43.9	Non-binding
14	15.3	51.6	36.3	Non-binding
15	31.7	46.8	15.1	Non-binding
16	29.1	47.5	18.42	Non-binding
17	30.6	46.8	16.2	Non-binding
37	27.1	72	44.9	Non-binding
38	68.4	72	3.6	Non-binding
39	69.6	69.6	0	Binding
40	72	72	0	Binding
41	68.5	68.5	0	Binding
42	63.6	63.6	0	Binding

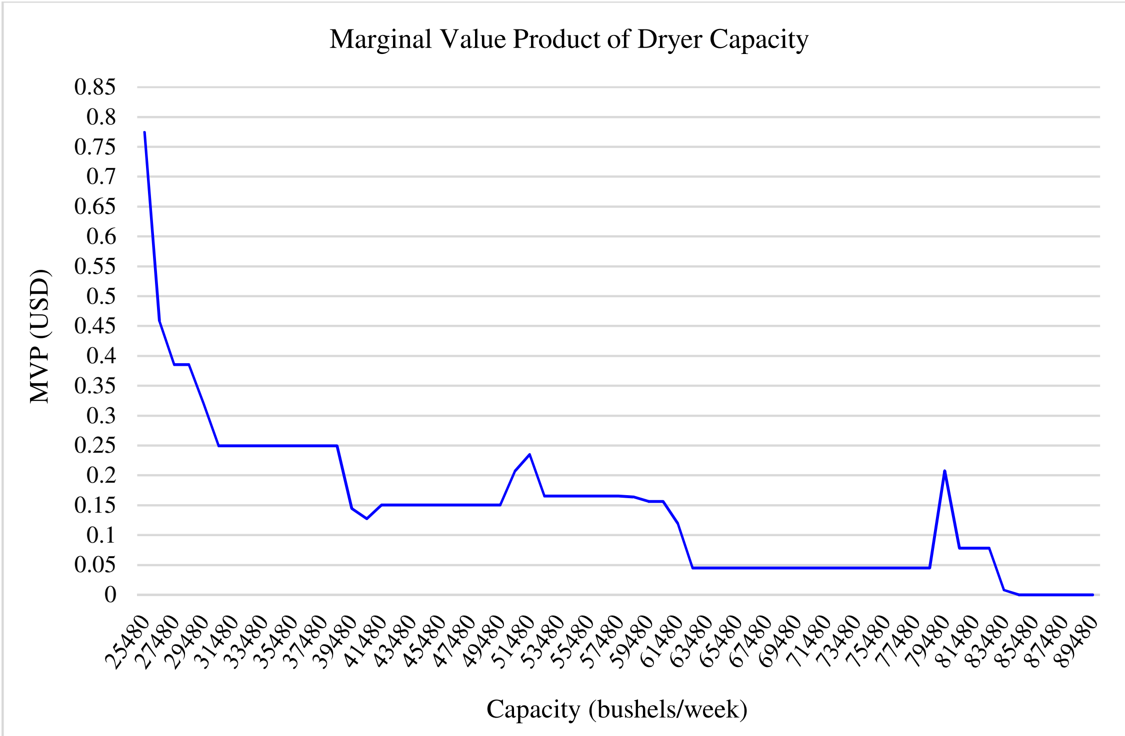

Figure 3.1 Marginal value product of weekly dryer capacity

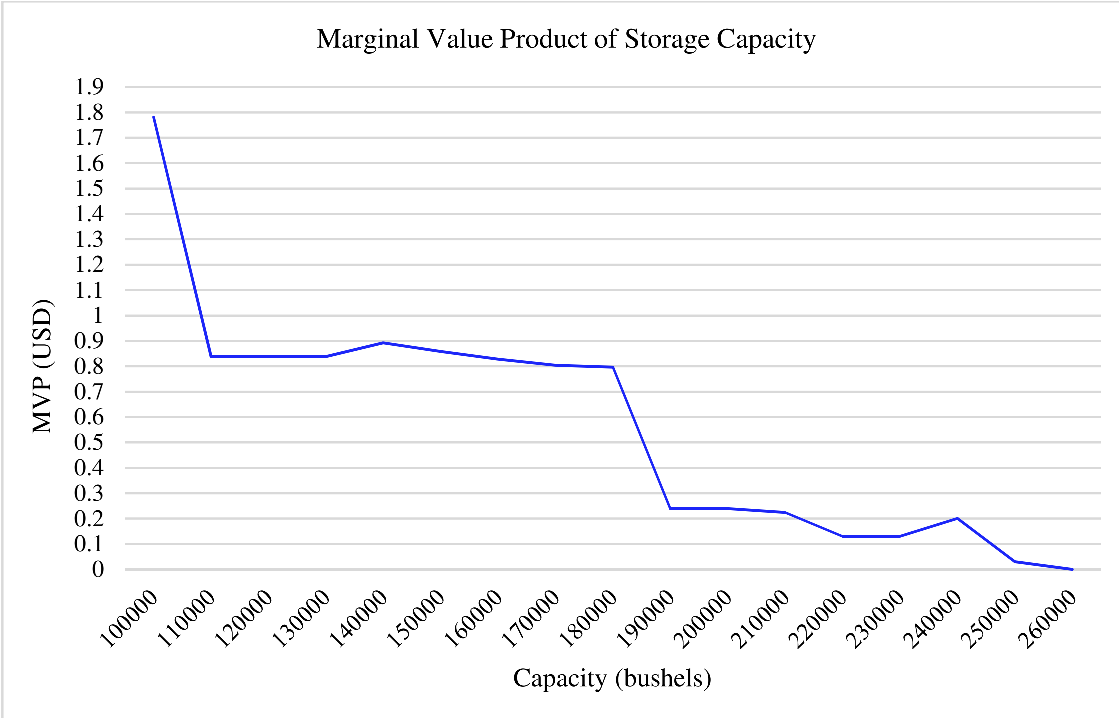

Figure 3.2 Marginal value product of storage capacity

Chapter 4: Summary

As has been seen, whole farm planning and crop marketing is a complex process laden with decisions requiring substantial thought. Having a greater understanding of this process at the farm-level and first point of sale can allow both producers and the buyers of their products make better decisions and potentially increase their bottom line. The two essays constituting this thesis emphasize the considerations that need to be made when planning the production and subsequent marketing of IP and commodity crops.

In the first essay, attention was given to contract attributes, market information, and relationship-specific assets that affect producers' food corn contracting decisions. An unbalanced panel comprised of seven years' worth of contract data and a fixed-effects model were used to estimate factors affecting producers' buy-in to a contracting program. Once these variables influence on contract volumes were quantified, implications to the farmer-mill relationship were considered.

Naturally, the premium over the commodity price had the greatest impact on contract volumes. Yet, the premium is subject to change year-to-year with the overall condition of the commodity market. Identifying the proper premium levels for different food corn types can mitigate turnover among producers dissatisfied with the mill's price signal. This, in turn, can reduce the transaction cost of identifying new producers to supply the mill with corn and educating them on quality control. Other contract/product attributes like corn color and whether it was non-GMO or not had an impact on the bushel amount producers were willing to grow for the mill. On average, producing a non-GMO variety of corn decreased contract volumes, likely due to the higher cost of production. However, in years when only non-GMO corn was accepted, bushels per contract increased, but total number of contracts decreased. Maintaining strong relationships with farmers that grow large amounts of non-GMO corn is important so that interruptions in supply does not occur.

White corn contracts decreased in volume versus yellow corn, possibly due to a decrease in yield potential and overall unfamiliarity with producing the crop. The condition of the commodity market played a role in producers' contracting decisions. The period of increasing prices from 2010-2013 saw farmers contract more bushels per contract than the period of decreasing prices from 2014-2016. During times of low prices, producers could've possibly been consolidating their businesses or realizing greater profitability with commodity crops. On the mill's end, ensuring premiums cover or exceed the marginal cost of food grade corn production could increase contract volumes if supply is not meeting their demand.

Use of stack dyers in the production process increased contract volumes. When prospecting for new growers, knowing the drying equipment available to farmers can help gauge their ability to supply the mill with grain. Being aware of this can also help the mill target education for maintaining grain quality during dry down. Finally, the quarter in which contracts were made returned significant results. Contracts initiated in the third and fourth quarters of the fiscal year saw increases in volume versus the first quarter. From a pricing perspective, this decision is confounding since higher commodity prices on which food corn price is based generally occur in the first and second quarter. However, this decision can be rationalized by farmers waiting to have a better handle on yields before entering into a contract they potentially could not fill.

In all, the first essay examines the principal-agent relationship of the farmers and the mill buying their product. Quantifying effects of the variables in the empirical model provides a better understanding of how farmers choose to market their crops in this subsection of the grain industry. With this understanding, better management of the farmer-mill dynamic can be achieved, and better business decisions can be made by both parties.

The second essay utilized a whole-farm model to optimize resource allocation and determine non-binding capacities of drying and storage equipment based on the production levels of three crops. Mixed-integer programming was selected to model planting and harvesting operations in a logical manner after a linear programming failed to do so. The results of the MIP base case indicated that drying and storage capacities were preventing the hypothetical farm from achieving greater net returns. This was due to the fact that a portion of field corn and the entirety of soybeans were sold during harvest in the cash market at a lower price. Once drying and storage capacities were increased, this production could be priced in the futures market and sold by forward contracting. In addition to a change in marketing strategy, the increase in drying and storage capacities caused the planting strategy to change. This change was based on the yield penalties associated with planting crops outside the optimum date, as well as the ability to dry and store crops at a faster rate during harvest weeks. The difference in net returns between the base case and non-binding case warranted an investment analysis to see if expanding drying and storage was a sound investment. Under the net present value method, it was determined that making the investment was advisable, recognizing this decision was subject to change with a change in commodity price. Nevertheless, the ability of whole farm modeling to uncover and quantify opportunities was demonstrated.

This second essay also demonstrates how a systems approach is needed to analyze the effect a change in one or two components can bring about in the overall model. Had a more modest method like partial budgeting been employed, a change in net returns could be quantified, but the implications for planting and harvesting logistics could not be identified. Thus, a greater understanding of the effect that increasing drying and storage has on other components is achieved. The range of variables, parameters, and constraints and their associated data or specifications underscore how complex a crop production and marketing system is. Certainly, more operations could be modeled, but potentially at the expense of concise study objectives. Just like McCarl et al.'s model described in the introduction, the model used in this study has limitations. Knowing these limitations such as the absence of risk or the exclusion of other marketing strategies aids the interpretation of model results and provides a focus for future research.

To end, the two essays comprising this thesis offer a better understanding of the decision making process behind crop marketing and whole farm planning in western Kentucky. Utilizing econometric and mathematical programming methods, insight has been gained into the intricacies of these two activities. Access to grain handling equipment and its effect on marketing strategy was emphasized across both essays, as well as the production and marketing of IP crops. With a heightened understanding of the economic interactions contained in these two essays, future research may be developed, and prescriptive analytics deployed for better decision-making at the farm-level.

Appendix

The economic decision-making model described in the text is depicted mathematically as follows:

Maximize:

$$(1)\quad NR = -\sum_{E}\sum_{PD}\sum_{H} VARCOST_E * PLANTINGS_{E,PD,H} + \sum_{E}\sum_{WK} CONPRICE_{E,WK} * CONSALES_{E,WK} + \sum_{E}\sum_{WK} CASHPRICE_{E,WK} * CASHSALES_{E,WK}$$

Subject to:

$$(2)\quad \sum_{E}\sum_{PD}\sum_{H} PLANTINGS_{E,PD,H} \leq ACRES$$

$$(3)\quad \sum_{E}\sum_{PD}\sum_{H} PLANTINGS_{E,PD,H} * LABOR_{E,PD,H,WK} \leq HRSSFW_{WK} \quad \forall\, WK$$

$$(4)\quad -\sum_{PD}\sum_{H} YIELD_{E,PD,H,WK} * PLANTINGS_{E,PD,H} + CONSALES_{E,WK} + CASHSALES_{E,WK} \leq 0 \quad \forall\, E, WK$$

$$(5)\quad \sum_{E} DRYTHRU_E * CONSALES_{E,WK} \leq DRYTPUT \quad \forall\, WK$$

$$(6)\quad \sum_{E}\sum_{WK} STORE_{E,WK,WKP} * CONSALES_{E,WK} \leq STORECAP \quad \forall\, WKP$$

$$(7)\quad CONSALES_{E,WK} - FARMCAP * FARMTRUCK_{WK} \leq 0 \quad \forall\, E, WK$$

$$(8)\quad CASHSALES_{E,WK} - ELEVCAP * ELEVTRUCK_{WK} \leq 0 \quad \forall\, E, WK$$

$$(9)\quad \sum_{WK} CONSALES_{E=\text{"WHITE CORN"},WK} = WCCON$$

$$(10)\quad \sum_{PD}\sum_{H} PLANTINGS_{E=\text{"WHITE CORN"},PD,H} + \sum_{PD}\sum_{H} PLANTINGS_{E=\text{"CORN"},PD,H} \leq CACRES * ACRES$$

$$(11)\quad \sum_{PD}\sum_{H} PLANTINGS_{E=\text{"}SOYBEANS\text{"},PD,H} \leq SACRES * ACRES$$

$$(12)\quad \sum_{H} PLANTINGS_{E,PD,H} - \mathrm{M} * IPLANT_{\ E,PD} \leq 0 \quad \forall\, E, PD$$

$$(13)\quad \sum_{PD}\sum_{H} YLDOCCURS_{E,PD,WK,H} * PLANTINGS_{E,PD,H} - \mathrm{M} * IHARVEST_{\ E,WK} \leq 0 \quad \forall\, E, WK$$

$$(14)\quad \sum_{PD} CONTPLANT_{E,PD,PDP,PI} * IPLANT_{\ E,PD} \leq 1 \quad \forall\, E, PDP, PI$$

$$(15)\quad \sum_{WK} CONTHARVEST_{E,WK,WKP,HI} * IHARVEST_{\ E,WK} \leq 1 \quad \forall\, E, WKP, HI$$

$$(16)\quad \sum_{E}\sum_{PD} INTRAPLANT_{E,PD,PDP} * IPLANT_{\ E,PD} \leq 3 \quad \forall\, PDP$$

$$(17)\quad \sum_{E}\sum_{WK} INTRAHARVEST_{E,WK,WKP} * IHARVEST_{\ E,WK} \leq 3 \quad \forall\, WKP$$

Activities include:

NR = Whole farm net returns

$PLANTINGS_{E,PD,H}$ = Production in acres of enterprise E under planting date PD harvested during harvest H

$CONSALES_{E,WK}$ = Bushels of enterprise E harvested in week WK sold in contract market

$CASHSALES_{E,WK}$ = Bushels of enterprise E harvested in week WK sold in cash market

$FARMTRUCK_{WK}$ = Number of trucks needed to haul grain to on-farm storage in week WK

$ELEVTRUCK_{WK}$ = Number of trucks needed to haul grain to a commercial elevator in week WK

$IPLANT_{E,PD}$ = Binary variable to initiate planting of enterprise E under planting date PD

$IHARVEST_{E,WK}$ = Binary variable to initiate harvesting of enterprise E in week WK

Constraints include:

(1) Objective function

(2) Land resource limitation

(3) Labor resource limitation by week

(4) Marketing limitation by week

(5) Storage capacity in bushels

(6) Dryer capacity in bushels per week

(7) Trucking capacity to on-farm storage in bushels per week

(8) Trucking capacity to a commercial elevator in bushels per week

(9) White corn contract in bushels

(10) Corn rotation limitation

(11) Soybean rotation limitation

(12) Decision to start planting

(13) Decision to harvesting

(14) Continuous planting of an enterprise until completed

(15) Continuous planting of an enterprise until completed

(16) Ability to plant multiple crops in a given week

(17) Ability to harvest multiple crops in a given week

Coefficients include:

$VARCOST_E$ = Variable cost of enterprise E in dollars per acre

$CONPRICE_{E,WK}$ = Price of enterprise E sold in contract market during week WK in dollars per bushel

$CASHPRICE_{E,WK}$ = Price of enterprise E sold in cash market during week WK in dollars per bushel

$ACRES$ = Number of tillable acres on farm

$LABOR_{E,PD,H,WK}$ = Labor requirement for planting and harvesting enterprise E under planting date PD of harvest H in week WK

$HRSSFW_{WK}$ = Labor hours suitable for fieldwork in week WK

$YIELD_{E,PD,WK,H}$ = Expected yield of enterprise E under planting date PD of harvest H

$DRYTHRU_{E}$ = Percentage of dryer throughput required by enterprise E

$DRYTPUT$ = Dryer throughput in bushels per week

$STORE_{E,WK,WKP}$ = Storage requirement for contract sales of enterprise E in week WK, WKP

$STORECAP$ = On-farm storage capacity in bushels

$FARMCAP$ = Trucking capacity to on-farm storage in bushels per week

$ELEVCAP$ = Trucking capacity to a commercial elevator in bushels per week

$WCCON$ = White corn production contract in bushels

$CACRES$ = Percent tillable acres devoted to corn or white corn production

$SACRES$ = Percent tillable acres devoted to soybean production

M = Vector to remove artificial variables from optimal solution

$YLDOCCURS_{E,PD,WK,H}$ = Yield of enterprise E under planting date PD ready to harvest in week WK under harvest H

$CONTPLANT_{E,PD,PDP,PI}$ = Continuous planting of enterprise E under plant date PD, PDP in planting interval PI

$CONTHARVEST_{E,WK,WKP,HI}$ = Continuous harvesting of enterprise E in week WK, WKP in harvest interval HI

$INTRAPLANT_{E,PD,PDP}$ = Ability to plant enterprise E after previous enterprise E under plant date PD, PDP

$INTRAHARVEST_{E,WK,WKP}$ = Ability to harvest enterprise E after previous enterprise E in week WK, WKP

Indices include:

E = Enterprise (“$WHITE\ CORN$”, “$CORN$”, “$SOYBEANS$”)

PD = Planting Date

PDP = Planting date prime

PI = Planting interval

WK = Week

WKP = Week prime

H = Harvest

HI = Harvest interval

Bibliography

Mccarl, Bruce A., Wilfred Candler, Howard Doster, and Paul Robbins. “Experiences with Farmer Oriented Linear Programming for Crop Planning.” *Canadian Journal of Agricultural Economics/Revue Canadienne D'agroeconomie*, vol. 25, no. 1, 1977, pp. 17–30., doi:10.1111/j.1744-7976.1977.tb02862.x.

Cheung, Steven N.S. “Transaction Costs, Risk Aversion, and the Choice of Contractual Arrangements.” *The Journal of Law and Economics*, vol. 12, no. 1, 1969, pp. 23–42., doi:10.1086/466658.

Sykuta, Michael, and Joseph Parcell. “Contract Structure and Design in Identity-Preserved Soybean Production.” *Review of Agricultural Economics*, vol. 25, no. 2, 2003, pp. 332–350., doi:10.1111/1467-9353.00142.

Hudson, Darren, and Jayson Lusk. “Risk and Transactions Cost in Contracting: Results from a Choice-Based Experiment.” *Journal of Agricultural & Food Industrial Organization*, vol. 2, no. 1, June 2004, doi:10.2202/1542-0485.1046.

Heiman, Ross D., and Hikaru Hanawa Peterson. “Determinants of Premiums Received by Organic Field Crop Producers.” *Review of Agricultural Economics*, vol. 30, no. 4, 2008, pp. 729–749., doi:10.1111/j.1467-9353.2008.00443.x.

MacDonald, James M. “Contracts, Markets, and Prices: Organizing the Production and Use of Agricultural Commodities.” *Contracts, Markets, and Prices: Organizing the Production and Use of Agricultural Commodities*, U.S. Dept. of Agriculture, Economic Research Service, 2004.

Riordan, M., and Williamson, O. Asset specificity and economic organization. *International Journal of Industrial Organization.,* 3(4), 1985, 365-378.

Elbehri, Aziz. “The Changing Face of the U.S. Grain System: Differentiation and Identity Preservation Trends.” *The Changing Face of the U.S. Grain System: Differentiation and Identity Preservation Trends*, U.S. Dept. of Agriculture, Economic Research Service, 2007.

Besanko, David. “Performance Measurements and Incentives.” *Economics of Strategy*, 6th ed., Wiley, 2010, p. 402.

“Commodity Research Bureau - (CRB) - Commodity Perspective (CP).” *Commodity Research Bureau - (CRB) - Commodity Perspective (CP)*, www.crbtrader.com/.

Pritchett, James. *Specialty Corn and Soybeans: Production and Marketing in Indiana. Specialty Corn and Soybeans: Production and Marketing in Indiana.*

ERS, and Seth J. Wechsler. “Recent Trends in GE Adoption.”*Recent Trends in GE Adoption*, 12 July 2017. www.ers.usda.gov/data-products/adoption-of-genetically-engineered-crops-in-the-us/recent-trends-in-ge-adoption/.

Greene, Catherine. “Economic Issues in the Coexistence of Organic, Genetically Engineered (GE), and Non-GE Crops.” *Economic Issues in the Coexistence of Organic, Genetically Engineered (GE), and Non-GE Crops.*

Melton, Alex. “Inflation-Adjusted Price Indices for Corn, Wheat, and Soybeans Show Long-Term Declines.” USDA ERS , 12 Aug. 2016, www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=76964.

StataCorp. 2013. *Stata Statistical Software: Release 13*. College Station, TX: StataCorp LP

Shockley, Jordan, Carl R. Dillon, and Tim Stombaugh. "Whole Farm Analysis of Automatic Section Control for Agricultural Machinery." Precision Agriculture 13.4 (2011): 411-20. Web.

Morrison, David A., et al. “A Mathematical Programming Model of a Crop-Livestock Farm System.” *Agricultural Systems*, vol. 20, no. 4, 1986, pp. 243–268., doi:10.1016/0308-521x(86)90116-2.

Abdulla B. Danok, Bruce A. McCarl, T. Kelley White; Machinery Selection Modeling: Incorporation of Weather Variability, *American Journal of Agricultural Economics*, Volume 62, Issue 4, 1 November 1980, Pages 700–708, https://doi.org/10.2307/1239768

Reid, Donald W., and Garnett L. Bradford. “On Optimal Replacement of Farm Tractors.” *American Journal of Agricultural Economics*, vol. 65, no. 2, 1983, pp. 326–331. *JSTOR*, JSTOR, www.jstor.org/stable/1240883.

Bender, D. A., et al. “Postoptimal Linear Programming Analysis Of Farm Machinery.”*Transactions of the ASAE*, vol. 33, no. 1, 1990, pp. 0015–0020., doi:10.13031/2013.31286.

Ekman, Sone. “Tillage System Selection: a Mathematical Programming Model Incorporating Weather Variability.” *Journal of Agricultural Engineering Research*, vol. 77, no. 3, Nov. 2000, pp. 267–276.

Loewer, Otto J., et al. “The Influence of Harvesting Strategies and Economic Constraints on the Feasibility of Farm Grain Drying and Storage Facilities.” *Transactions of the ASAE*, vol. 23, no. 2, 1980, pp. 0468–0476., doi:10.13031/2013.34605.

Loewer, O. J., et al. "An Expert System for Determining Bottlenecks in On-Farm Grain Processing Systems." *Applied Engineering in Agriculture*, vol. 6, no. 1, 1990, pp. 69–72., doi:10.13031/2013.26347.

Nichols, T.E. *Economics of On-Farm Corn Drying*. *Economics of On-Farm Corn Drying*, http://corn.agronomy.wisc.edu/Management/pdfs/NCH21.pdf.

Maier, Dirk E, and Adam E Watkins. *Drying of White Food Corn for Quality*. *Drying of White Food Corn for Quality*.

Edwards, William. *Monthly Cost of Storing Grain*. Iowa State University, n.d. Web. 19 Oct. 2016. https://www.extension.iastate.edu/agdm/crops/html/a2-33.html.

Smith, Aaron. Grain Hauling Cost Calculator. University of Tennessee, n.d. Web. 19 Oct. 2016.https://extension.tennessee.edu/WebPacket/Pages/WP-2013-12 GrainCalculator.aspx.

Halich, Greg. *Western Kentucky Corn and Soybean Budgets*. University of Kentucky, Apr.2017.Web.http://uky.edu/Ag/AgriculturalEconomics/halich_greg_rowcropbudgets.php.

National Agriculture Statistics Service. *Quick Stats*, USDA, 2015. https://quickstats.nass.usda.gov/.

Kenimer, Richard C., Ron W. Kurd, and Chad Lee. 2015 Kentucky Hybrid Corn Performance Test. Rep. no. PR-692. College of Agriculture, Food, and Environment, University of Kentucky Cooperative Extension Service. 6-7. Web.

Practical Farm Research. Beck's Hybrids, 2017, *Practical Farm Research*, https://beckshybrids.com/PFR/PFR-Books-and-Videos.

Shockley, Jordan, and Tyler Mark. *Days Suitable for Fieldwork in Kentucky*. 2016, *Days Suitable for Fieldwork in Kentucky*.

"Commodity Research Bureau - (CRB) - Commodity Perspective (CP)." *Commodity Research Bureau - (CRB) - Commodity Perspective (CP)*, 2017. https://crbtrader.com/.

Confidential Source. "Food Corn Pricing Data." Henderson County, KY, 2016.

Smith, Aaron. 2013. *Grain Hauling Cost Calculator*. University of Tennessee, n.d. Web. https://extension.tennessee.edu/WebPacket/Pages/WP-2013-12-GrainCalculator.aspx.

Edwards, William. 2015. *Monthly Cost of Storing Grain*. Iowa State University, n.d. Web. https://extension.iastate.edu/agdm/crops/html/a2-33.html.

Halich, Greg. *Western Kentucky Corn and Soybean Budgets*. University of Kentucky, Apr. 2017. Web. http://uky.edu/Ag/AgriculturalEconomics/halich_greg_rowcropbudgets.php.

Reinbott, David. *2018 Crop Budgets*. University of Missouri Extension, 2017, *2018 Crop Budgets*, https://extension.missouri.edu/scott/crop-budgets.aspx.

Pierce, J.S. *Kentucky Farm Business Management Program: Annual Summary Data 2016.* Lexington, KY: University of Kentucky Cooperative Extension Service, 2017.

Laughlin, D.H. and S.R. Spurlock, Mississippi State Budget Generator v6.0, 2007.

GSI Grain Systems. *Portable Grain Dryers*. *Portable Grain Dryers*, 2016.

Unpublished Material. Montross, M, A Turner. 2016. “Miles Farms Analysis”. Unpublished, University of Kentucky Department of Biological and Agricultural Engineering.

Hanna, H. Mark and Jarboe, Darren H., "Effects of Full, Abbreviated, and No Clean-Outs on Commingled Grain during Combine Harvest" (2011). *Agricultural and Biosystems Engineering Publications*. 635.

Internal Revenue Service. “2017 Publication 946.” *2017 Publication 946*, 28 Feb. 2018. www.irs.gov/pub/irs-pdf/p946.pdf.

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Refereed Manuscripts

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Conference Presentations

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