UNDERSTANDING FARMER FINANCING PREFERENCES BY SEGMENTING THE AGRICULTURAL LENDING MARKET

by

Xavier A. Miranda-Colon

A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science

Agricultural Economics

West Lafayette, Indiana

May 2022

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Brady Brewer

Department of Agricultural Economics

Dr. Allan W. Gray

Department of Agricultural Economics

Dr. Scott Downey

Department of Agricultural Economics

Approved by:

Dr. Nicole J Olynk Widmar

This document is dedicated to Augusto Miranda, Julia Colon, Luis Miranda, and Alyzza Croissy.
I am truly thankful for all the support and encouragement.

ACKNOWLEDGMENTS

I want to thank Dr. Brady Brewer for his consistent patience, mentoring, and advice. He has guided and advised me at all stages of my graduate school journey.

I want to thank the rest of my committee members Dr. Scott Downey and Dr. Allan Gray for their encouragement and insightful comments.

I want to thank the faculty and staff of the college of agriculture at Florida A&M University that helped me get to this point. I am forever grateful of the guidance and mentorship of Dr. Michee Lachaud, Dr. Verian Thomas, and Tommeron Timmons.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Purpose - The goal of this study is to identify the current distinct market segments within the US agricultural credit lending market, predict segment membership based on readily available characteristics, and better understand farmer financing preferences.

Design/methodology/approach - A two stage clustering analysis was used to identify five distinct market segments. A multinomial logit regression was used to predict segment membership based on demographic and psychographic characteristics.

Findings - The segmentation analysis produced five distinct market segments. The identified segments are service, convenience, balance, price, and performance.

Practical implications - This information can aid credit lenders in segmenting the market and tailoring their sales approach to the different farmer segments.

Originality/value - This paper contributes to the literature in several ways. First, previous studies of farmer selection of lending institutions rely on supply side data (Brewer et al., 2019; Dodson & Koenig, 2004; Ifft and Fiechter, 2020). While these studies are useful in knowing how farmers may be segmented according to their choice set of particular lending institutions, what we cannot examine is why the farmer is choosing that choice set. Our study incorporates psychographic and buying preferences. Prior work has highlighted the trend away from demographics and socioeconomic characteristics towards psychographic characteristics as categories for customer segmentation (Sherrick et al., 1994). Secondly, as described above, much has changed in the agricultural lending markets concerning the lending institutions available to farmers and the technology that changes how farmers and lending institutions interact. Thus, this study updates the literature as farmers preferences may have changed due to the new market structure.

CHAPTER 1. INTRODUCTION

According to the Economic Research Service of the United States Department of Agriculture total farm sector debt is expected to reach $467.4 billion by 2022. How a farm operator sources credit is of utmost importance to the profitability and long-term sustainability of the business. Customers are seeking to maximize their value from transactions. Therefore, they will conduct transactions with firms they believe provide the highest value. As Sherrick, Sonka, and Monke 1994 state when a firm selects which market to enter, it also selects its customers and competitors. As such firms along the agricultural supply chain must continue to tailor marketing and services to their target segment to increase the customer's perception of value.

These firms will need to successfully contend with the consolidation trends in agricultural production which include larger producers having increased capital good and expendable item purchasing power. As a result of increased consolidation among farming operations there are fewer customers with increased purchasing power for capital and input dealers and credit lenders (Roucan-Kane et al., 2011). These larger producers can be considered commercial producers which are defined as a producer with annual sales of $1,000,000 or greater (Alexander et al., 2005). As these larger producers account for a majority of capital and agricultural input purchases it is imperative that firms along the agricultural supply chain successfully meet their needs. This can in turn increase the firms market share and improve customer retention.

Traditionally the available options for farm operators seeking credit have been loans from the Farm Credit System (FCS) and commercial banks. Recently another option has risen in popularity which is dealer or vendor financing commonly referred to as nontraditional lending (e.g., John Deere Financial, Case ® Credit) (Fiechter & Ifft, 2020b). This shift to nontraditional lenders is at the expense of traditional lending sources such as the FCS and commercial banks. Understanding how farmers are wanting to interact with their lending institution(s) will help all lending institutions provide better and more targeted product offerings to their farmer customers. Additionally, it will allow for the examination of key characteristics of borrowers that use particular types of agricultural credit. This deeper understanding of farmer preferences can be applied to identify which attributes (e.g., interest rate, convenience, relationship with loan office) most influence their credit sourcing decisions. This information can aid credit lenders in segmenting the market and tailoring their sales approach to the different farmer segments.

Furthermore, this study will provide an update to the agricultural finance literature of changes to farmer preferences when conducting business with credit lenders.

Nontraditional credit lenders are companies who primarily focus on selling other goods or services but also provide in house financing for their customers purchase (Sherrick, Sonka, and Monke 1994). It has been previously estimated that nontraditional lenders hold between 10 percent to 15 percent of all farm debt (Brewer et al. 2019; Fiechter and Ifft 2020a). Prior work on attribute preferences has focused on understanding which attributes most influence farmers capital and expendable input supplier choice (Alexander et al., 2005; Gloy & Akridge, 1999; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010). However, the question of what attributes most influence farmers credit decisions has not been analyzed using a psychographic data set. Through psychographic data, we can explore a farmers' attitude, interest, and opinions on different credit lending decisions. Through this exploration we will gain a better understanding of farmers preferences for credit lenders. This paper will examine which attributes are important in a farm operators' decision to use non-traditional credit and how that may differ from the choice to use a commercial bank or FCS institution. This study will utilize these farmer preferences to segment the US agricultural credit lending market and identify farmer preferences and usage tendencies towards nontraditional lenders.

This study aims to identify the distinct market segments for agricultural credit lending present within U.S. commercial agriculture. This study uses data collected during the 2021 Large Commercial Producer (LCP) survey conducted by The Center for Food and Agricultural Business at Purdue University. To determine this, we will begin by conducting a two-stage clustering analysis. First Ward's method will be conducted to estimate the number of clusters in the data. This is used as the starting point for the non-hierarchical k-means algorithm. A multinomial logistic regression model will be used to estimate which segment respondents are most likely to belong too. Using a two-stage clustering strategy paired with a multinomial logit will produce meaningful customer segments that are likely to express similar behavior patterns. The purpose of segmenting the market is to gain a better understanding of farmer preferences towards products, services, and information. As stated in Alexander, Wilson, and Foley (2005) in order to successfully target customers, one must first segment the market into smaller, like mined customer groups, profile these groups, determine which group to pursue, and lastly develop the marketing mix that best suits the target group. It will produce value for credit lenders in the form of knowing what these groups prioritize and what drives these customer segments to conduct business. Credit lenders can apply these behavior patterns to better attract and retain their target customers.

This paper contributes to the literature in several ways. First, previous studies of farmer selection of lending institutions rely on supply side data (Brewer et al., 2019; Dodson & Koenig, 2004). The supply side data prior studies used contains detailed financial and demographic data for borrowers. In the case of Brewer et al., 2019 individual farm loan data from the Kansas Farm Management Association was used. The study by Dodson & Koenig used data from the Agricultural Resource Management Survey (ARMS) and the Farm Costs and Returns Survey. While these studies are useful in knowing how farmers may be segmented according to their choice set of particular lending institutions, what we cannot examine is why the farmer is choosing that choice set. Our study incorporates psychographic and buying preferences. Prior work has highlighted the trend away from demographics and socioeconomic characteristics towards psychographic characteristics as categories for customer segmentation (Sherrick et al., 1994). Secondly, as described above, much has changed in the agricultural lending markets concerning the lending institutions available to farmers and the technology that changes how farmers and lending institutions interact. Thus, this study updates the literature as farmers preferences may have changed due to the new market structure.

CHAPTER 2. LITERATURE REVIEW

This section will cover related literature pertaining to the credit lending market, key trends in the marketplace, clustering methods, and prior work on the Large Commercial Producer (LCP) Survey conducted by Purdue's Center for Food and Agricultural Business (CAB). The discussion on credit lenders will include traditional lenders such as the Farm Credit System and commercial banks as well as nontraditional lenders such as vendor/ retailer financing. The clustering methods discussed in this section are partition, hierarchal, fuzzy, density, and distribution-based clustering methods. The discussion of the past literature on the LCP survey includes analyzing the findings of prior LCP segmentation analysis namely (Alexander et al., 2005; Gloy & Akridge, 1999; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010).

2.1 Credit Lenders

Historically the Farm Credit System (FCS) and commercial banks have dominated the agricultural credit lending sector. Traditionally when a farm operator wanted to secure financing there were two options either the Farm Credit System (FCS) or a commercial bank (CB). Traditional agricultural lenders such as the Farm Credit Service and commercial banks combined have supplied about 80% credit to US agriculture within the past two decades (Nadolnyak and Hartarska 2021). Commercial banks and the FCS have dominant positions in the real estate and short-term lending (Ifft et al., 2017a). However, the two options are not able to satisfy the financing needs of all customers. A reoccurring issue that credit lenders often face is accurately rating a borrower's risk. This can lead to borrowers that do not possess favorable risk profiles to have insufficient access to credit. Primarily because of customer selection preferences and criteria (e.g., credit history, collateral requirements, etc.) leading to increased selection in established farms. Are strict criteria imposed in the form of collateral requirements, credit history, and other credit worthiness factors? If so, there will be a segment of credit seekers who will be unable to secure financing this segment is composed of younger farm operators with a developing farm. Younger credit seekers may not have as much credit as they would like because they may have low credit scores and insufficient credit history, paired with fewer assets (Baldini & Divringi, 2016). This notion is supported by previous works which have found that the most likely customer of traditional lenders are larger farm operations with access to more capital (Brewer et al., 2019; Briggeman & Kenkel, 2008; Dodson & Koenig, 2004; Ifft et al., 2017a). Smaller less established farms face more difficulty in acquiring credit from traditional lenders because they may not meet the lending criteria that traditional lenders operate on. The literature points to farms that have been established for under ten years facing additional difficulty (Nadolnyak et al., 2017). As a result, less established farms are more likely to seek credit from multiple lenders including non-traditional lenders. This form of capital-based market segmentation finds support in federal regulations that require the FCS to select more established farmers (Dodson & Koenig, 2004).

2.1.1 Traditional Credit Lenders

The Farm Credit System

The Farm Credit System (FCS) is a government sponsored enterprise (GSE) that was established by congress through the Federal Farm Loan Act of 1916 with the purpose of providing a reliable source of credit for farmers and rural Americans. Clients of the FCS benefit in numerous ways such as having access to a consistent line of credit in both good and bad years, potential tax benefits (i.e., tax-exempt bonds) and patronage programs. These financial incentives paired with the well-established reputation of the FCS have played a substantial role in its dominant position in the agricultural credit market.

The FCS offers benefits such as tax exemptions and patronage programs to its clients. The GSE status of the FCS allows for the interest earned from farm credit debt securities to be exempt from state, local, and municipal taxes. Since the FCS is a network of cooperative style lending institutions, they are allowed to distribute profits back to member owners through patronage programs. Patronage programs are popular among members and have the potential to attract more non-traditional loan customers (Briggeman & Kenkel, 2008). For example, customers of the East Central Farm Credit of Oklahoma have been reported to prefer an increase in patronage payments over lower interest rates (Jorgensen, 2007).

Commercial Banks

The term commercial banks (CB) is used to describe a for profit financial institution (e.g., Bank of America, Chase, Wells Fargo, etc.) that offers basic financial services such as loans, saving & checking accounts. They provide customers with essential services through local branches and remotely via online banking. They also help facilitate the creation of capital and liquidity within the market. CBs help maintain market liquidity by loaning customer deposits in the form of interest generating loans. Customers are attracted to CB savings accounts because they are insured by the Federal Deposit Insurance Corporation and the money in the savings accounts can be easily withdrawn. CBs generate revenues by providing interest earning loans, service charges, and fees. A common practice is using the deposits of clients to provide loans and in turn earn interest from the loans they provide. Commercial banking as an industry is heavily regulated by a country or regional central bank. In the United States CBs are regulated by the Federal Reserve which imposes regulations like reserve requirements. Reserve requirements require CBs to hold a percentage of their customer deposits at the central bank as a contingency in case the general public rushes to withdraw funds. Commercial banks are an essential component to the credit lending market and provide capital creation and liquidity.

2.1.2 Nontraditional Credit Lenders

The market imperfections in the credit market that drove the United States government to create the FCS in 1916 also attributed to the rise of nontraditional credit lending. In times of financial prosperity credit is plentiful and terms are favorable, conversely in economic downturns credit is scarce, and the terms are unfavorable. These conditions have forced farmers to adapt their credit sourcing strategies and in part led to the increased usage of nontraditional lending (e.g., John Deere® Financial, Case ® Credit).

Currently there has been research on the credit profile of farm operators who seek non-traditional credit (Brewer et al., 2019; Dodson & Koenig, 2004). The segmentation, composition, and status of the agricultural credit lending market has also been explored (Fiechter & Ifft, 2019; Kilkenny & Jolly, 2005; Moss et al., 1997). Prior work has highlighted the trend away from demographics and socioeconomic characteristics towards psychographic characteristics as categories for customer segmentation (Sherrick et al., 1994). Research has been conducted on estimating the size and composition of the nontraditional credit lending market (Fiechter & Ifft, 2020a, 2020b). The question of which attributes such as interest rate, product features, and convenience as it relates to a farmer's decision to use nontraditional credit lenders has not been fully explored.

Nontraditional lenders are firms whose primary business is selling a physical product or service and in order to enhance sales they offer in house financing or trade credits (Fiechter & Ifft, 2020a; Sherrick et al., 1994). The use of non-traditional credit lenders has been increasing, specifically input dealers financing the sale of implements (Brewer et al., 2019; Ifft et al., 2017a; Stevens, 2021). However, loans provided by non-traditional lenders are unlikely to be direct substitutes for loans provided by traditional lenders, but they may fill niches within agricultural credit markets (Nadolnyak and Hartarska, 2021). The driving force behind this increased use is currently unknown. However, previous studies point toward non-traditional credit lenders offering competitive interest rates, often at rates that are not sustainable in efforts to differentiate themselves (Brewer et al., 2019). (B. C. Briggeman & Kenkel, 2008) find that interest rates are perceived to be the most important factor in obtaining new loans from non-traditional customers. One of the reasons nontraditional lenders can offer highly competitive interest rates is they have less overhead cost. Understanding why some farm operators have increased their usage of non-traditional lending provides insight into which attributes most influence their credit sourcing decisions. There is an opportunity to further define which attributes lead to the increased use of non-traditional lenders.

Nontraditional lenders have been defined as creditors other than the FCS, commercial banks, FSA and other government supported lending agencies (Nadolnyak and Hartarska, 2021). In (Fiechter & Ifft, 2020b) an updated definition for nontraditional lenders is proposed. They suggest a definition that goes beyond the type of credit lender and includes how the credit is delivered. Specifically, they define nontraditional lenders as lenders that operate outside of the usual loan officer and local lender branch model (Fiechter & Ifft, 2020b). They breakdown nontraditional lenders into three categories high volume (e.g., MetLife, PGIM), vendor (e.g., John Deere Financial, Nutrien Financial), and collateral based (FarmOp, ARM). First the high volume branchless lenders such as MetLife and PGIM are specialized agricultural lenders that are targeting the top end of the market (Fiechter & Ifft, 2020b). These lenders attempt to gain a competitive edge in the market by providing competitive interest rates. Then vendors who finance such as John

Deere Financial which can be described as point of sale financing (Fiechter & Ifft, 2020b). Vendor financing offers competitive interest rates and according to vendor and lender reports this form of lending has a trend of fast repayment (Fiechter & Ifft, 2020b). The most common source of nontraditional credit is vendor provided financial services, such as John Deere Financial and Case ® Credit providing loans (Ifft et al., 2017a; Stevens, 2021). Lastly collateral based lenders which are nonbank institutions that make lending decisions based on the value of collateral. Collateral based lenders such as ARM, AgriFinancial, and Conterra provide competitive rates but can also take on riskier clients (Fiechter & Ifft, 2020b).

Accurately estimating the current share of nontraditional lending in the agricultural sector has proven to be difficult. The reasons for this may include a farmers' financial account usage pattern, lack of data, and credit sourcing trends. Nontraditional lenders are used less frequently as a customers' main account, instead customers prefer to limit their holdings to lower maintenance accounts such as credit accounts (White and Nteli 2004). Two well know estimates of the size of nontraditional lending market are the estimates in (Fiechter & Ifft, 2020a; Sherrick et al., 1994). According to Sherrick et al., 1994 in 1994 the share of non-real estate debt held by non-traditional lenders was between 18 to over 20 percent. A recent estimate by (Fiechter & Ifft, 2020a) estimates that nontraditional lenders hold between 10 to 15 percent of all farm debt. Nontraditional lenders offer an important credit source to small and medium sized enterprises (Martin Boyer & Gobert, 2009). Often these smaller operations are interested in purchasing machinery and equipment via loans. This niche is the area where nontraditional lenders thrive. Up to 1/3 of all machinery and equipment loans are provided by implement dealers (Ifft et al., 2017b). Equipment and machinery dealers have a major role in nonreal estate long term financing (Ifft et al., 2017b). The USDA ERS projects that total farm sector debt will reach $467.4 billion by 2022. Therefore, the conservative end of the projections estimates nontraditional lenders will hold $46.74 billion by 2022.

2.2 Age Trend

There are four generations coexisting in the agricultural credit marketplace today, from Baby Boomers to Generation Z. With this generational diversity comes differences in preferences for technology, communication, and financing. As farmers age they tend to consolidate their debt and reduce their lending relationships (Brewer et al., 2014). Whereas younger farmers place less importance on reducing or consolidating debt as compared to farmers in the above 40 age group

(Wise & Brannen, 1983). The average debt for farmers that are 60 years old or older is lower than for all younger age groups (Wise & Brannen, 1983). This supports the notion that older farmers are more likely to pay or have paid off their loans. These trends combined with an influx of younger farm operators joining the market presents an opportunity to further explore the changing credit needs and wants. Furthermore, this may warrant revisiting and potentially further expanding the credit consumer typology as described in (Briggeman & Boehlje, 2006).

Younger farmers may be more willing to acquire more lines of credit because their operations have unmet capital needs such as machinery. Inversely it can also be considered that older farmers have less debt because their operations have minimal capital needs. The older farmers have gone through the stage of acquiring multiple lines of credit and indebtedness. Generally, clients of financial institutions can be characterized by age, because as their position in the life cycle is interpreted in terms of age, which determines their current needs and their loyalty to an institution (Fernández-Aguirre et al. 2003). The median debt for borrowers increases as they reach middle age (35-54) and then decreases as they become older (55-84) (Baldini & Divringi, 2016). This trend, combined with an influx of younger farm operators joining the market, presents an opportunity to further explore the changing credit needs and wants. Furthermore, this may warrant revisiting and potentially further expanding the credit consumer typology as described in (Briggeman & Boehlje, 2006). These changes in credit needs and wants may cause credit lenders to redefine their lending criteria. Less established farms, which are often operated by younger farmers, face more difficulty in financing all their credit needs from traditional lenders. Beginning farmers and ranchers and female operators are likely to be the most credit constrained groups (Griffin et al., 2020; Katchova & Dinterman, 2018; Nadolnyak & Hartarska, 2021; Schmidt et al., 2021). However, some studies have found the FCS is a more likely supplier for young and beginning farmers (Dodson & Koenig, 2004). These preferential changes have encouraged banks to develop features such as e-banking, paperless statements, and other features that improve the overall user experience.

2.3 Clustering Methods

Clustering is the process of grouping a set of observations in a way that observations in the same segment are more similar with each other than observations in other segments. Clustering also referred to as cluster analysis has a myriad of uses such as market segmentation, social network analysis, search result grouping, medical imaging, image segmentation, and anomaly detection. Commonly used clustering algorithms include partition, hierarchal, fuzzy, density, and distribution-based clustering methods.

Partition based clustering algorithms work by regarding the center of data points as the center of the corresponding cluster (Xu & Tian, 2015). Within partition-based clustering two of the most popular methods are K-means and K-medoids. The K-means method works by updating the center of data points which represents the center of the cluster, then the process iterates until the convergence criteria is met (Xu & Tian, 2015). K-medoids is an improved version of the K-means algorithm that deals with discrete data. The advantages of partition based clustering methods are relatively low time complexity and high computing efficiency (Xu & Tian, 2015). The disadvantages are partition based algorithms are sensitive to outliers, the number of clusters need to be specified by the researcher, can be drawn easily to local optimal, and the clustering result is sensitive to the number of clusters the research specified (Xu & Tian, 2015).

Hierarchical based clustering algorithms work by constructing hierarchical relationships among data points to determine a cluster solution. Each point can be considered a cluster, then the closest two clusters are merged into a cluster until one cluster is left. The advantages of this clustering algorithm include easily detected hierarchical relationship among clusters, relatively high scalability, and suitability for data with arbitrary shape (Xu & Tian, 2015). The drawbacks are requires the number of clusters to be preset, high time complexity (Xu & Tian, 2015).

Clustering algorithms based on fuzzy theory work by changing the discrete value of the belonging label, {0,1}, into the continuous interval [0,1], to describe to better describe the belonging relationship (Xu & Tian, 2015). The advantages of this method are high clustering accuracy and increased likelihood of giving the probability of belonging (Xu & Tian, 2015). The drawbacks are low scalability, the number of clusters has to be preset, and the clustering solution is sensitive to the preset cluster values (Xu & Tian, 2015).

Density based clustering algorithms determine clusters by clustering the data that is in a high density region of the data space into the same cluster (Xu & Tian, 2015). These methods are known for high lustering efficiency and are suitable for data with an arbitrary shape (Xu & Tian, 2015). The drawbacks include low quality clustering solutions when the density of the data space is not even, large computer memory is required with large sets of observations, and the clustering solution is highly sensitive to the parameters (Xu & Tian, 2015).

The concept behind distribution based clustering algorithms is that the data are generated from the same distribution belong to the same cluster if multiple distributions exist in the original data set (Xu & Tian, 2015). The advantages of distribution based clustering algorithms include having a realistic chance of an accurate probability of belonging and high scalability by changing distributions and the number of clusters (Xu & Tian, 2015). The disadvantages include the parameters have a significant influence on the clustering solution and high time complexity (Xu & Tian, 2015).

2.4 Prior LCP Research

Early segmentation research has yielded three segments in which managers and sales representatives have historically segmented producers into (Downey et al., 1999). There are business buyers who use perceived value as the basis for their decision making. Then there are economic buyers who seek to minimize cost. Lastly, there are relationship buyers who make purchasing decisions based on the trust they have with sales representatives.

Further refinement of the customer segments came with (Gloy & Akridge, 1999) which found four distinct segments based on convenience, balance, price, and performance in the 1998 Large Commercial Producer Survey. Where members of the balance and performance segments can be categorized as business buyers, members of the price segment are part of the economic buyer segment, and the convenience segment most closely resembles the relationship buyers (Alexander et al., 2005). The work by (Alexander et al., 2005) revealed a fifth segment in contrast to the four found by Gloy and Akridge in 1999. This fifth segment was labeled service buyers and they fall into the relationship buyer category according to (Alexander et al., 2005).

Prior studies have conducted a clustering analysis of the respondents of the Large Commercial Producer Survey namely (Alexander et al., 2005; Gloy & Akridge, 1999; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010). The studies by (Gloy & Akridge, 1999; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010) have used a two-stage clustering analysis and found four distinct segments based on convenience, balance, price, and performance in the 1998 and 2008 LCP Survey respectively. This clustering analysis includes first conducting Ward’s method to determine the appropriate number of clusters for the data which will be used as seed values for the k-means, nonhierarchical algorithm. This work was extended by (Alexander et al., 2005) which used the same two stage clustering analysis and added the use of a multinomial logit model to predict segment membership based on demographic, behavioral, and business factors. In the study by (Alexander et al., 2005) behavioral segmentation was used in the analysis which resulted in five distinct consumer segments based on balance, price, performance, service, and convenience. Behavioral segmentation was chosen over demographic segmentation because the later has been contended to have less predictive power. A concern with the results of prior clustering analysis studies is producing clusters in which consumers’ preferences are one dimensional (Baker & Burnham, 2001). That is, no cluster represents consumers whose preferences are split between multiple factors. However, prior LCP research has yielded a balance segment in which consumers value all attributes equally.

CHAPTER 3. CONCEPTUAL MODEL

A firms' main objective is to maximize profit and an agricultural enterprise is no different. Profit is commonly defined as generating revenues that exceed costs. In order for a farm to earn revenues it must have capital goods and expendable inputs to produce its product. This leads the farm operator to the age-old question of "what is the optimal capital good and expendable input purchasing and financing strategy?". Although there are countless viable strategies one of the most common is to purchase items using credit. Purchasing capital and expendable items using credit can help farm operators manage their cash flows, develop a credit history, and gain access to increased financing and better terms. A farm operator can source credit from the Farm Credit System, commercial banks, and nontraditional lenders (e.g., dealer/vendor credit). The optimal strategy will differ depending on whether the farm operator is purchasing capital goods or expendable inputs. A farm will use capital goods such as tractors and mechanical implements that aid in harvest, spraying, and planting. Traditionally, when making a large purchase such as a tractor or land, farm operators have opted to finance the acquisition using a loan from a traditional lender. A large portion of FCS loans are long term mortgages secured by farmland, whereas the CBs deal more in short term loans and credit lines (Turvey et al., 2021). Farms will consume inputs such as fertilizer, seed, and feed in the production process. Historically farm operators have chosen to apply a combination of the full or partial cash purchase and some form of a short-term advance (under 30 days) from the vendor (Sherrick et al., 1994). Within the past decades the agricultural lending market has witnessed increased competition stemming from the adoption of non-traditional credit. As reported by (Sherrick et al., 1994) in 1994 the share of non-real estate debt held by non-traditional lenders was between eighteen to over twenty percent. More recently the share of non-real estate debt held by nontraditional lenders is estimated to be between ten to fifteen percent of all farm debt (Fiechter & Ifft, 2020a). This increase in adoption has afforded farm operators more flexibility in determining their optimal capital good and input purchasing strategy.

A farm operator enters the credit market looking to finance some aspect of their operation. On the other side credit lenders are seeking prospective clients to conduct business with. Decisions in the agricultural credit marketplace are jointly dependent on the lender and farmer coming to an agreement. (Sherrick et al., 1994) states that, as a firm selects which market to enter, it also selects its customers and competitors. The farmer seeks the best deal to minimize cost. Meanwhile, lenders seek to maximize profits by lending in accordance to their risk appetite. This dynamic decision-making process is influenced by farmers' perception of interest rates, product features, and convenience that are available in the agricultural credit marketplace. Credit lenders must remain competitive without compromising profitability. These market conditions may lead farmers to use more lines of credit. The presence of asymmetrical information dilutes the lending relationships and increases the difficulty the lender faces in accurately gauging the farmer's default risk (Sherrick et al., 1994).

A common assumption is that farmers are rational utility maximizers and as such seek to maximize their utility when selecting credit lenders. When a farmer enters the credit lending market, they are searching for their optimal combination of desirable credit lender attributes. The combination and weight placed on these attributes changes on a case-by-case basis. Some farmers will prioritize getting the cheapest price and as such will focus on securing the lowest interest rate possible. Whereas some farmers will prefer convenient transactions and familiarity and will conduct business with lenders and vendors they are familiar and comfortable with. Some farmers prioritize the product features (term, guarantee, sweep account, etc.) of a financial product when choosing credit lenders. There is no universally optimal solution and as such each individual farmer will have their own attribute rankings (Brewer et al., 2014).

Farmers may prioritize different attributes depending on the lender they are conducting a transaction with. When dealing with traditional lenders farmers may be more interested in securing the lowest interest rate possible because they perceive less differences in the product features and convenience among lenders in this category. Whereas when dealing with nontraditional lenders such as an agricultural retailer farmers may prioritize the product performance of the chemical or seed, they are purchasing over securing the lowest interest rate. These differences in attribute preferences based on lender type create nuances in the marketplace where the same farmer may consider different attributes the most important based on who they are dealing with. This can make a lenders job of attracting and retaining customers more difficult.

Given this conceptual framework, this study aims to segment a representative sample of large commercial producers into meaning groups based on shared attitudes and preferences towards credit lenders. Then the objective is to quantify the impact of product attributes (e.g. interest rate, convenience, lender relationship, product features, and perceived service quality) on the way the segments approach credit lender decisions.

CHAPTER 4. DATA

This study uses data collected during the 2021 Large Commercial Producer (LCP) survey conducted by The Center for Food and Agricultural Business at Purdue University. The survey is targeted at mid-size and large commercial producers of corn/soybean, wheat/barley, cotton, potatoes, tomatoes, dairy, swine, and beef. The 2021 LCP survey was distributed online to customers of various retailers, manufacturers, and lenders (e.g., BASF, Nutrien, and Syngenta). The LCP survey is conducted every four years and 2021 marks its seventh iteration. The LCP survey is a comprehensive survey of large commercial agricultural producers and is designed to elicit the concerns, preferences, behaviors, and attitudes of commercial producers as they interact with firms in the agricultural supply chain. The LCP survey data provides key insights into the current concerns, preferences, and behaviors of farmers and ranchers. These insights are crucial to efficiently target and serve these farmers and ranchers.

The LCP survey is designed to gain a deeper understanding of Producer Strategies, Buying Preferences, E-Commerce, Information and Salesperson Preferences, and Data/Tech Adoption and Sustainability. This study focuses on the buying preferences portion of the survey. The survey questions regarding this topic were designed to investigate the impact of attributes such as price, quality of service, and relationship/trust on farmer preferences. By analyzing this data we can better understand where potential tradeoffs might be for consumers and customize the sale approach to increase the success rate.

Within the 2021 LCP survey questions 7 & 8 are critical to the credit lending market segmentation analysis. Question 7 is specifically designed to measure the amount of dealer/retailer financing farmers use for capital and expendable items. Meanwhile, question 8 is designed to measure what attributes respondents most value when dealing with different lenders, e.g., Banks, Farm Credit, Agricultural Retailers, and other.

Question 7 is one of the key questions in this analysis and asks respondents to roughly estimate how much of their total financial needs are met through dealer/retailer financing. The question is stated as:

> About what percentage of your total finance needs are met through financing provided by your dealer/retailer?

The respondents can answer question 7 for capital and expendable items in the following categories none, 1% - 25%, 26% - 50%, 51% - 75%, and 76% - 100%.

Question 8 is one of the key questions in this analysis and asks respondents to rank the listed attributes (interest rate, product features, and convenience) in order of importance when borrowing money from lenders. The question is stated as:

> When borrowing money from various lenders, please rank he listed attributes in order of importance to you, where 1 means "most important' and 3 means "least important". [There are columns for the following lenders: bank, farm credit, ag retailer, and other.]

The survey defined product features as term, guarantee, sweep accounts, etc. The definition of convenience was left to the respondent's interpretation.

Table 4-1 Demographic Variables

Demographic Variables	Observations	Frequency	Percentage	Std. Dev
Male	1,541	1,378	89.42%	.31
Female	1,541	82	5.32%	.22
Age	1,475	--	54.86	12.72
Crop	1,541	1,401	90.91%	.29
Livestock	1,541	140	9.09%	.29
High School or Less	1,233	231	18.73%	.36
Associate Degree	1,233	288	24.36%	.39
Bachelor's Degree	1,233	670	54.34%	.50
Graduate Degree	1,233	44	3.57%	.17

Our sample is comprised mainly of male large commercial producers that grow crops. The majority of our respondents have some form of education with approximately 15%, 19%, 43%, and 3% of our respondents having a high school diploma, associate degree, bachelor's degree, and graduate degree respectively.

Table 4-2 Farm Size Breakdown

Farm Size Breakdown by Revenue				
Farm Size	Observations	Frequency	Percentage	Std. Dev
Small	1,528	58	3.8%	.19
Midsize	1,528	533	34.88%	.48
Large	1,528	937	60.32%	.49

The respondents of the LCP survey were categorized into three farm size categories based on revenues. The three farm sizes used in this study are small, midsize, and large and they were defined using USDA ERS categories. Small farms are defined as operations with less than $350,000 in gross cash farm income. Midsize farms are defined as operations with gross cash farm income between $350,000 and $999,999. Large farms which will also be referred to as commercial producers are defined as operations with gross cash farm income larger than $1,000,000. Revenue figures were not explicitly asked in the 2021 LCP survey. Instead, they were estimated using the crop/livestock type, acres farmed, and USDA estimates of revenue per acre for the different crop/livestock types. The majority of our respondents, approximately 61% operate farms with revenues above $1,000,000. It is evident from Table 4-2 that our sample is mainly comprised of larger farms with higher revenues. This is in line with the target sample of this survey which is commercial producers.

Table 4-3 Capital Item Vendor/Dealer Financing Breakdown

Capital Item Vendor/Dealer Financing Breakdown	Observations	Frequency	Percentage	Std. Dev
No dealer/vendor capital item financing	1,541	663	43.02%	.50
1% – 25% dealer/vendor capital item financing	1,541	392	25.44%	.44
25% – 50% dealer/vendor capital item financing	1,541	225	14.60%	.35
50% – 75% dealer/vendor capital item financing	1,541	155	10.06%	.30
75% – 100% dealer/vendor capital item financing	1,541	106	6.88%	.25

Overall, from Table 4-3 it is evident that the single largest group of respondents (43%) uses no nontraditional financing for capital item financing. However, approximately 56.98% or 878 respondents use some nontraditional capital item financing. After the 25% - 50% category the rate at which usage decreases remains fairly constant. This could be because as farmers get accustomed to using nontraditional financing, they become more willing to use more. In general, a higher percentage of our sample uses some nontraditional lending in their capital item financing strategy.

Table 4-4 Expendable Item Vendor/Dealer Financing Breakdown

Expendable Item Vendor/Dealer Financing Breakdown	Observations	Frequency	Percentage	Std. Dev
No dealer/vendor expendable item financing	1,541	653	42.38%	.49
1% – 25% dealer/vendor expendable item financing	1,541	420	27.26%	.45
25% – 50% dealer/vendor expendable item financing	1,541	222	14.41%	.35
50% – 75% dealer/vendor expendable item financing	1,541	147	9.53%	.29
75% – 100% dealer/vendor expendable item financing	1,541	99	6.42%	.25

Overall, from Table 4-4 it is evident that the single largest group of respondents (42%) uses no nontraditional financing for expendable item financing. However, approximately 57.62% or 888 respondents use some nontraditional capital item financing. After the 25% - 50% category the rate at which usage decreases remains fairly constant. This is the same case as in the capital item nontraditional financing and could be because as farmers get accustomed to using nontraditional financing, they become more willing to use more. In general, a higher percentage of our sample uses some nontraditional lending in their expendable item financing strategy.

From the contents of tables 4-3 and 4-4 it is evident that the usage patterns for capital and expendable items are almost the same among our respondents. The majority of respondents use some nontraditional financing for capital or expendable items. However, due to the nature of the cross-sectional data and one-time survey used trends could not be identified.

CHAPTER 5. METHODS

This study follows the clustering and econometric methodologies set forth in (Alexander et al., 2005; Gloy & Akridge, 1999; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010). The first step is selecting which variables to cluster on. Variable selection is one of the most important steps in a cluster analysis because it will directly affect the likelihood of determining the true market segments. Past studies have segmented samples based on sales, acreage, age, and similar demographic and financial factors. Demographic variables such as age and education may influence the preferences of the segments. However, the objective is to segment respondents based on the similarities of their attitudes towards lending strategies. Segmenting customers into meaningful groups and subgroups is beneficial because the groups are likely to have similar behavior patterns. Subsequently demographic characteristics will be used to describe the segments composition.

In a similar manner to prior work (Alexander et al., 2005; Gloy & Akridge, 1999; Howcroft et al., 2007; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010) this study uses a two-step clustering analysis process. Notable advantages of using cluster analysis include minimizing the research bias by not specifying segments based on preconceived notions, increases in the validity of the segments by allowing the data to determine the groups, and increased efficiency in recognizing the multivariate relationships among class variables (Rosenberg & Turvey, 1991). Cluster analysis serves as a method that facilitates the pattern recognition and simplifies and portrays the true structure of a data set (Howcroft et al., 2007).

Prior to conducting the two-step clustering analysis, the data was normalized. The data was normalized using 0 to 1 normalization. Normalizing the data is the process of transforming the data so it appears on the same scale. The data points that are normalized are the responses to question 8. Question 8 asks the respondents to rank the listed attributes in order of importance to them, where 1 means “most important’ and 3 means “least important”. Normalizing data is useful when applying an algorithm that does not assume the distribution of the data such as k-nearest neighbors. Normalizing the data increases the probability of accurately clustering the data patterns by making the variables lie within a similar range and reducing the chances of variables being attributed more importance as predictors due to having a larger values (de Souto et al., 2008).

First Ward's method is conducted to determine the appropriate number of clusters for the data which will be used as seed values for the k-means, nonhierarchical algorithm. Ward's method is an agglomerative heuristic that starts with all data points as individual clusters, it continuously merges two clusters at a time to form a clustering with one less cluster (Großwendt et al., 2019). Ward's method minimizes the variance within clusters by finding the nearest neighbor for each observation. Ward's method attempts to maximize within cluster homogeneity while maximizing between cluster heterogeneity. The measure of similarly for the Ward's method is the Squared Euclidean distance. This is shown in the equation below,

(1) $$d_{ij} = d(\{X_i\}, \{X_j\}) = \|X_i - X_j\|^2$$

where the distance between two observations is the squared Euclidean distance between the points. Because Ward's method is minimizing the within cluster variance, it can be used to determine the optimal number of clusters. Once these clusters are found, they are used as a starting point for the K-means algorithm. This is advantageous since the K-means methodology is a nonhierarchical algorithm and thus cannot be used to determine the number of clusters within the data, so it must be predetermined. The k-means algorithm is applied and works as follows: given a set of n observations in real dimensional space, $\mathbb{R}^d$,and an integer k, it determines a set of k points in $\mathbb{R}^d$, called centers, then it works to minimize the mean squared distance from each observation to its nearest center (Kanungo et al., 2000). The K-means algorithm is as follows:

(2) $$\underset{S}{arg\ min} \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2$$

where S is the number of clusters and μ_i is the cluster mean.

The final process in the clustering analysis is validating the predicted segments. There are several measures that can be evaluated to determine the correct number of clusters. This study evaluates the pseudo T^2 and pseudo-F statistic values to determine the number of segments. Additionally the dendrograms and agglomeration schedule from the Ward's method were examined to determine the appropriate number of clusters similarly to (Howcroft et al., 2007). This analysis suggested that a five-cluster solution is the most appropriate for the data. The pseudo T^2 is a measure of the difference in the ratio between cluster variance to within cluster variance. The interpretation of the pseudo-F statistic is a ratio of between cluster variance to within cluster variance (Caliński & Harabasz, 1974). The pseudo-F statistic can be used to measure how separate the clusters are. The pseudo T^2 , pseudo-F statistic and the general rules that are associated with them have been shown to recover the true cluster structure of the data (Gloy & Akridge, 1999; Milligan & Cooper, 1985; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010). Based on the pseudo T^2 , pseudo-F statistic we have identified 5 natural segments for agricultural credit lender selection behavior.

To make the determination of how many clusters were present in the Ward's Method output two indices were used. The Calinski and Harabasz index and Duda and Hart index. In a prior study these indices have been found to provide excellent cluster recovery within artificially generated data (Milligan & Cooper, 1985).

The Calinski and Harabasz index is computed as follows

(3) $$\frac{\left[\frac{trace\ B}{(k-1)}\right]}{\left[\frac{trace\ W}{(n-k)}\right]}$$

where n is the total number of items and k is the number of clusters (Milligan & Cooper, 1985). Where B is the between and pooled within cluster sum of squares and W is the cross products matrices (Milligan & Cooper, 1985).

The Duda and Hart index is computed as follows

(4) $$\frac{Je(2)}{Je(1)}$$

where Je(2) is the within cluster sum of squared errors when the data is partitioned into two clusters and Je(1) is the squared errors when there is only one cluster (Milligan & Cooper, 1985).

The output from the K-means algorithm is used to define the categories of a multinomial logit. A multinomial logistic regression is used to predict segment membership based on psychographic and demographic factors following the following formula:

(5) $$y_i = \beta X_i + \theta\gamma_i + \varepsilon_i$$

where y_i is the segment, the farmer belongs to, X_i is a vector of demographic variables and γ_i is a vector of psychographic variables. The variables that were used for the multinomial logistic regression are gender, education level, operation type (Crop or Livestock), revenue level, capital item financing level, and expendable item financing level.

To interpret the beta coefficients of the multinomial logistic regression marginal effects were computed using the mfx command in Stata. The marginal effects are calculated as follows,

(6) $$Marginal\ effect\ of\ x = -\frac{\partial f(\cdot)}{\partial x}$$

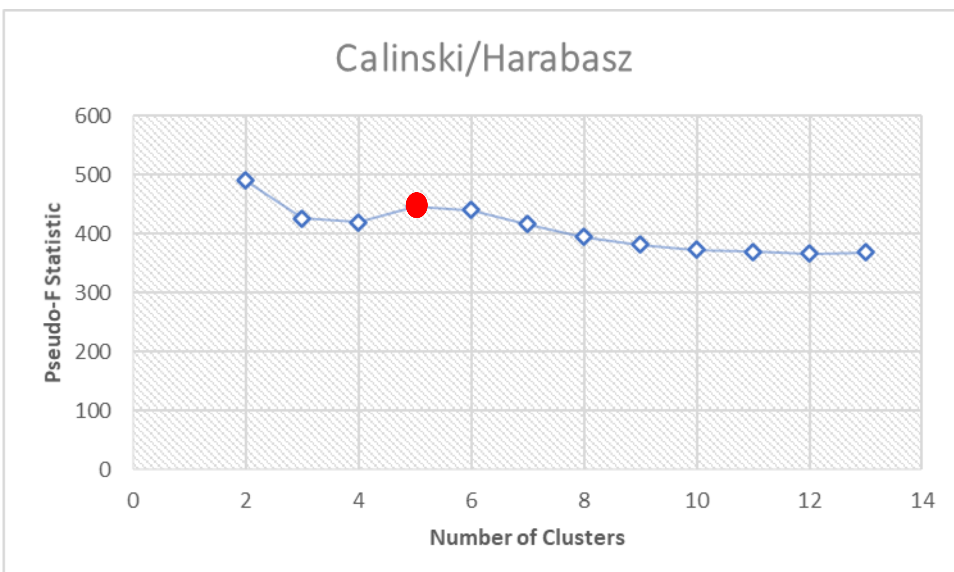
where the marginal effect of an independent variable x is the partial derivative, with respect to x of the prediction function $f(\cdot)$ (Boggess, 2022).

CHAPTER 6. RESULTS & DISCUSSION

6.1 Ward's Method Results

First Ward's method is conducted to determine the appropriate number of clusters for the data which will be used as seed values for the k-means, nonhierarchical algorithm. Subsequently the clustering solution was verified. There are several commonly used measures to verify the number of clusters. For the purposes of this study the pseudo T^2 and pseudo-F statistic values from the Calinski/Harabasz and Duda/Hart indices were used. Using the pseudo T^2 and pseudo-F statistic values to determine the number of clusters present in the data is commonly used in the literature and has been used in the following studies (Alexander et al., 2005; Gloy & Akridge, 1999; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010).

Figure 6-1 The Pseudo-F Statistic for the Calinski/Harabasz index



The rule of thumb for analyzing the Calinski/Harabasz index is to look for the highest Pseudo-F Statistic value. From figure 6-1 we can conclude that the most probable number of clusters in the data is 5.

Figure 6-2 The Duda values for the Calinski/Harabasz index

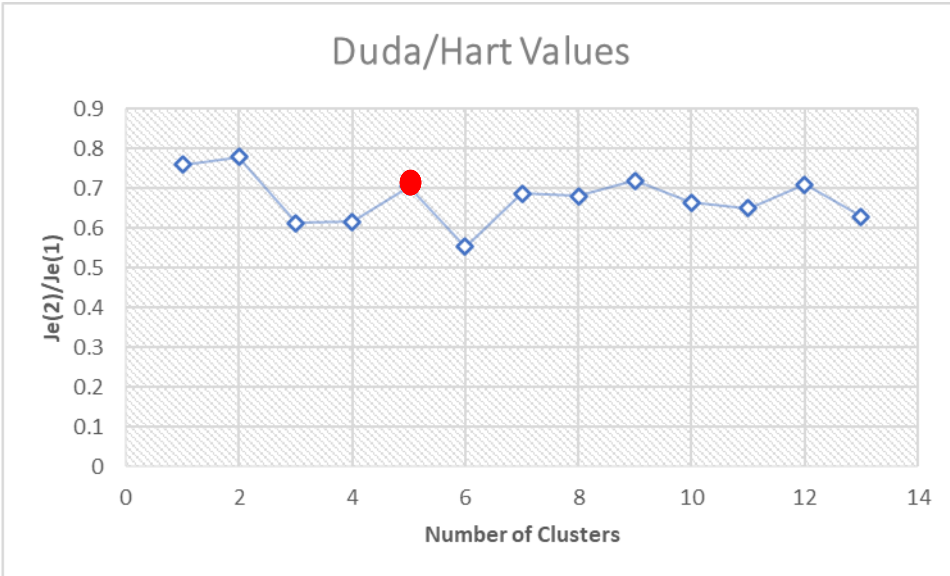
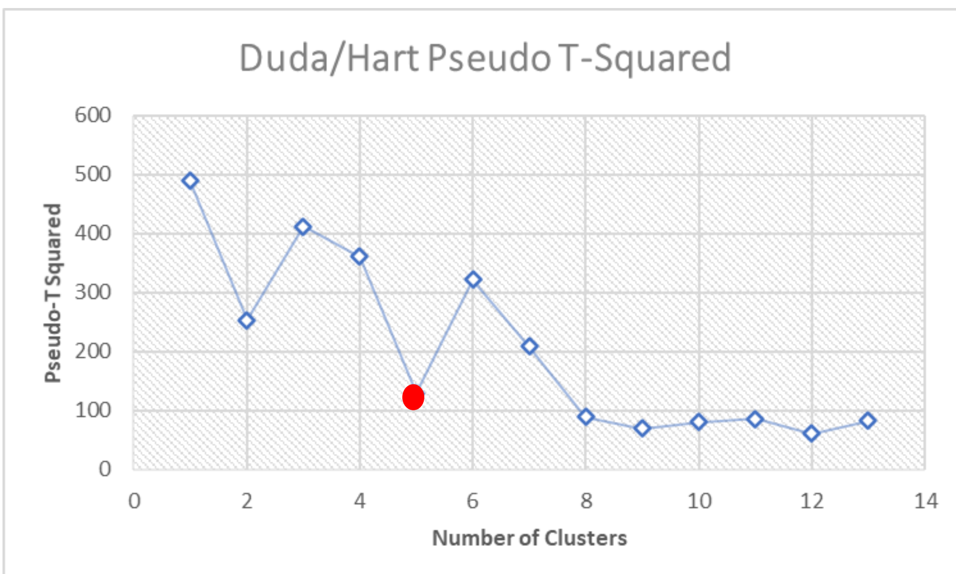


Figure 6-3 The Pseudo-T Squared values for the Duda/Hart index



The rule of thumb for interpreting the Duda-Hart index is to find the combination of highest Duda values that correspond to a reasonably low Pseudo-T squared. From figures 6-2 and 6-3 the observation can be made that a 5-segment clustering solution is appropriate for the data. In figure 6-2 segment 5 corresponds with the highest Duda/Hart value. Then in figure 6-3 the Pseudo-T squared values for a 5-segment clustering solution are reasonably low when compared to the alternatives. This indicates that the data is more likely to contain 5 segments.

Therefore, based on the interpretations of figures 6-1,6-2, and 6-3 we can verify the Ward's method clustering solution of 5 clusters. However, there are no reliable statistical tests to directly identify the solution and these statistics are widely used general rules of thumb (Gloy & Akridge, 1999). These methods have been previously shown to be effective at recovering the true group structure of the data in Monte Carlo experiments (Gloy & Akridge, 1999; Milligan & Cooper, 1985).

Figure 6-4 Ward's Method Cluster Analysis Dendrogram

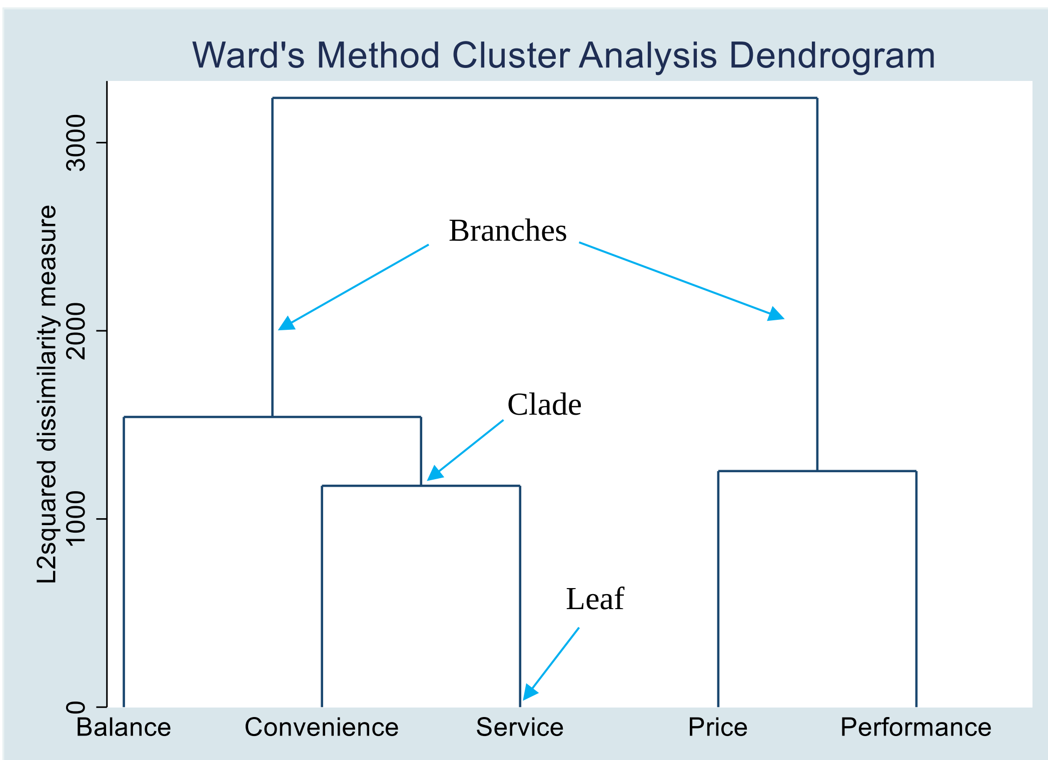


Figure 6-4 is a dendrogram with 5 leaves and 3 clades. The arrangement of the clades indicates the level of similarity between the leaves. The height of the branches indicates how similar or different the segments are. The greater the height the larger the difference between segments. The convenience and service segments are similar to each other and therefore are close.

The price and performance segments are similar to each other. The balance segment is most similar to the convenience and service segments. Based on the height of the branches there is a significant difference between the clade connecting the price and performance segments and the clade connecting the balance, convenience, and service segments.

Figure 6-5 Ward's Methods Segments

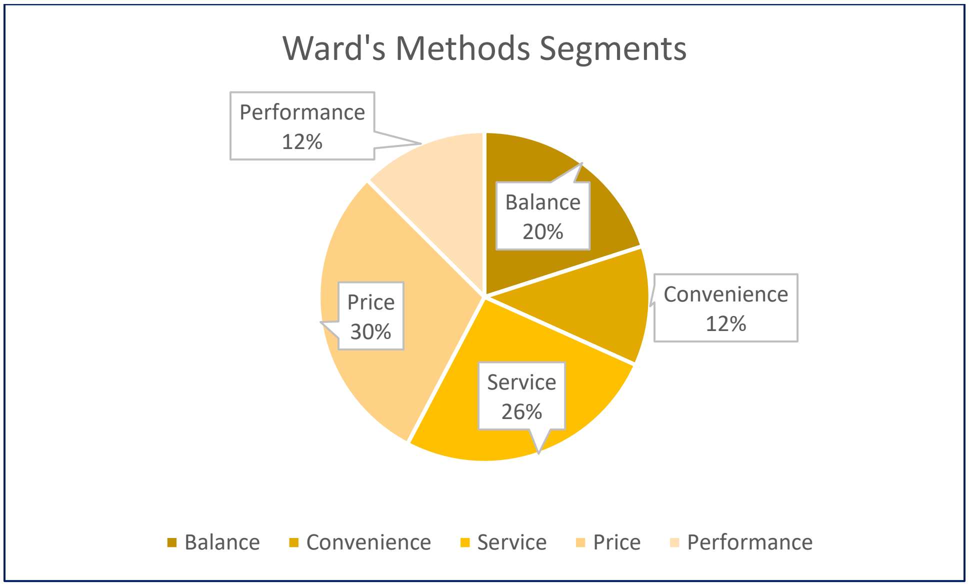


Figure 6-5 breaks down the sizes of the segments within the sample of 1,541 observations. The 5-segment solution from the Ward's method has three large clusters and two considerably smaller clusters. Based on figures 6-1, 6-2, 6-3, and 6-4 the LCP data set can be interpreted as having 5 segments. This is a sensible interpretation which suggest the existence of 5 segments in the respondents of the LCP survey that are based on how respondents prioritize interest rate, product performance, and convenience when dealing with the different credit lenders. This 5 segments Ward's method solution will be used as the starting point for the K-means clustering algorithm.

6.2 K-Means Results

Figure 6-6 K-Means Segments

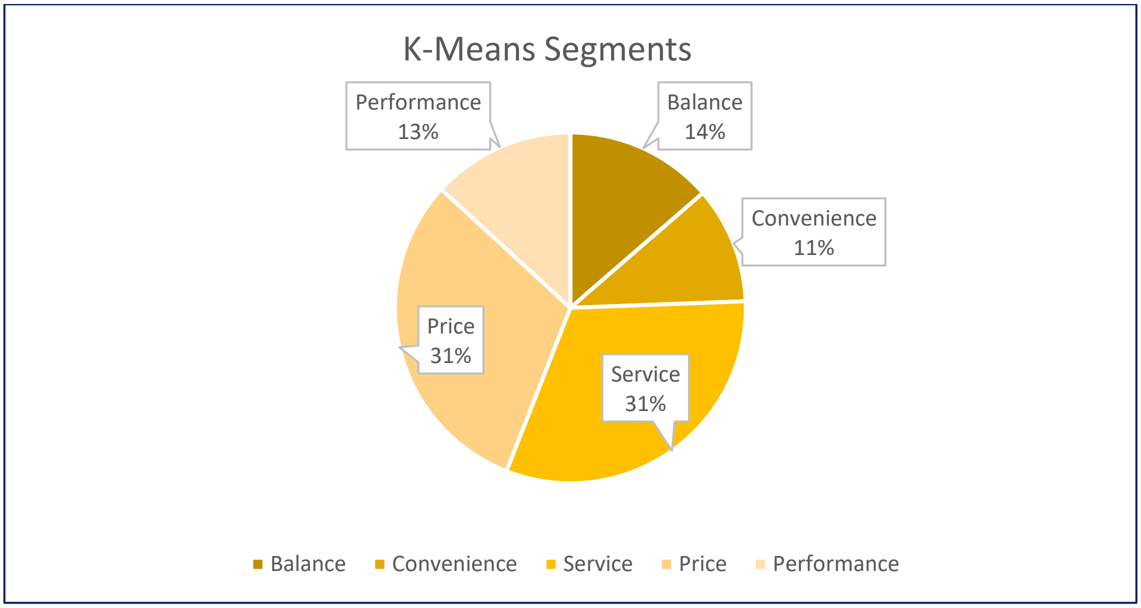


Figure 6-6 illustrates the breakdown of the K-means algorithm. The K-means algorithm changed the sizes of the clusters that were defined by the Ward's method. Notably the balance segment decreased in size and the service segment increased in size. A relatively small change such as this is to be expected based on how the Ward's method and K-means minimize distance. The Ward's method defines every observation in the data as an individual point and the merges two segments at a time until only one segment remains. Where the K-means uses the starting points as centroids and assigns all observations to their nearest centroid. Then it moves the centroid to the average of all the data points assigned to it. After it again moves all the observations to the nearest centroid. The process iterates until no observation changes centroid. This difference in how they minimize distance accounts for the changes we see in the Ward's method and K-means clustering solutions.

Table 6-1 K-Means Segment Psychographic Breakdowns

K-Means Segment Psychographic Breakdown					
	Balance	Convenience	Service	Price	Performance
Commercial Bank Interest Rate	0.16	0.55	0.08	0.04	0.57
Commercial Bank Product Performance	0.82	0.88	0.96	0.5	0.04
Commercial Bank Convenience	0.57	0.06	0.46	0.96	0.89
Farm Credit Interest Rate	0.06	0.56	0.02	0.02	0.53
Farm Credit Product Performance	0.66	0.87	0.93	0.51	0.08
Farm Credit Convenience	0.77	0.07	0.55	0.97	0.89
Ag Retailer Interest Rate	0.82	0.47	0.04	0.04	0.48
Ag Retailer Product Performance	0.3	0.86	0.93	0.52	0.29
Ag Retailer Convenience	0.38	0.17	0.52	0.94	0.73

Table 6-1 breaks down segment members attribute (e.g., interest rate, performance, convenience) preferences. In question 8 respondents were asked to rank attributes from 1 to 3 where 1 means “most important’ and 3 means “least important”. The responses were normalized using 0-1 normalization. This means that the preference most often ranked “1” will be closest to zero. While the preference most often ranked “3” will be closest to one. For example, for the Balance segment when dealing with commercial banks interest rate was most often ranked “1”. In contrast to product performance which was most often ranked “3”. Another example is when looking at the attribute preferences of the Performance segment for FCS lenders one can conclude that product performance was most often ranked “1”. Whereas the convenience attribute was most often ranked “3”. Table 6-3 helps plainly illustrates how each segment prioritizes the attributes when dealing with the different lenders. Based on the segment preferences towards these attributes the segment names were designated.

In Figure 6-4 it is evident that convenience and service segments are similar to each other based on the clade that connects them as well as the proximity of their leaves. Using the convenience and service columns in Table 6-1 we can explain their locations on the dendrogram. In the convenience column of Table 6-1 it shows that for the convenience segment the convenience attribute was on average ranked first most often followed by interest rate and lastly performance. In the service column of Table 6-1 it shows that in the case of the service segment the interest rate attribute was on average ranked fist most often followed by convenience and lastly performance.

Therefore, in Figure 6-4 the convenience and service segments are closed based on how they rank the convenience attribute. Similarly, the proximity of the price and performance segments on the dendrogram in Figure 6-4 can be explained. The price segment on average ranks interest rates first followed by performance and lastly convenience as is evident in Table 6-1. Whereas the performance segment on average ranks performance first followed by price and lastly convenience as is evident in Table 6-1. Therefore, in Figure 6-4 the price and performance segments are close in proximity to each other based on how they rank the product performance attributes. The balance segment leaf in Figure 6-4 is most similar to the clade which connect the convenience and service segments. That is the combination of the service and convenience segments. The balance column in Table 6-1 shows that the balance segment has shifting priorities based on which credit lender they are dealing with. This explains the balance segments distance from the other 4 segments. In general Table 6-1 and Figure 6-4 can be used to explain the differences and similarities between the five segments.

Table 6-2 K-Means Segment Breakdown

K-Means Segment Breakdown

Variables	Balance	Convenience	Service	Price	Performance	Total Observations
Members	210	166	486	476	203	1541
Membership Percentage	14%	11%	32%	31%	13%	--
Female	15%	1%	21%	43%	21%	82
Age	57.60	51.77	53.81	55.34	56.07	1475
Crop	14%	11%	31%	31%	13%	1401
Livestock	8%	9%	34%	32%	17%	140
Small Farming Operation	21%	16%	31%	24%	9%	58
Midsize Farming Operation	13%	11%	31%	31%	15%	533
Large Farming Operation	14%	10%	32%	32%	13%	937
High School or less	15%	9%	36%	29%	12%	231
Associate Degree	19%	13%	28%	32%	8%	288
College Degree	12%	12%	31%	31%	14%	670
Graduate Degree	16%	11%	45%	18%	9%	44
No dealer/vendor capital item financing	14%	11%	32%	30%	13%	663
Dealer/vendor capital item financing	13%	11%	31%	31%	14%	878
No dealer/vendor expendable item financing	13%	10%	33%	34%	11%	653
Dealer/vendor expendable item financing	14%	12%	31%	29%	15%	888

6.2.1 Balance Segment

The first segment in Figure 6-4 was determined to be the balance segment based on the preferences of the segment members. Balance segment members prioritize interest rates first followed by convenience and lastly product performance when dealing with commercial banks. When balance segment members are dealing with the FCS, they prioritize interest rates followed by performance and lastly convenience. When balance segment members are dealing with agricultural retailers, they prioritize product performance followed by convenience and lastly interest rates. Therefore, since on average segment members have different attribute preferences depending on which lender, they are dealing with this segment was determined to be the balance segment. It should be noted that the rest of the segments have stable preferences across all lenders.

6.2.2 Convenience Segment

The second segment in Figure 6-4 was determined to be the convenience segment. As described by the name the members of the convenience segment on average prioritize convenience followed by interest rates and lastly product performance across all lenders. Therefore, based on segment members prioritizing convenience above the other attributes this segment is defined as the convenience segment.

6.2.3 Service Segment

The third segment in Figure 6-4 was determined to be the service segment. Members of the service segment on average prioritize interest rates followed by convenience and lastly product performance across all lenders. It should be noted that both the service segment and the price segment both prioritize interest rate over the other attributes. However, the main distinction between them is the second priority. In the case of the service segment the second priority most often was convenience. Whereas price segment most often chose product performance as the second priority. In addition, in Figure 6-4 the service segment is most similar to the convenience segment. So, it would stand to reason that the order of the priorities in this segment would indicate members to be service oriented. One potential interpretation is that service segment members are looking for the best combination of price and convenience.

6.2.4 Price Segment

The fourth segment was determined to be the price segment. Members of the price segment on average most often prioritized interest rates followed by product performance and lastly convenience across all lenders. As noted in the analysis of the service segment members in both the price and service segments most often prioritized interest rates first. In contrast to the service segment members of the price segment most often selected product performance as the second priority. This difference in the second priority is one of the reasons that in Figure 6-4 the price segment closest to the performance segment and is therefore the most similar to the performance segment. The choice of product performance as the second priority potentially indicates that price segment members are looking for the most “bang for their buck”.

6.2.5 Performance Segment

The fifth segment was determined to be the performance segment. Performance segment members on average prioritized product performance followed by interest rates and lastly convenience across all lenders. It should be noted that the performance and price segments are in close proximity to each other in Figure 6-4. A potential reason for this is the price segment prioritizing interest rate followed by product performance and lastly convenience. The only difference in the priorities of these two segments is the order of the product performance and interest rates. Therefore, based on segment members most often prioritizing product performance this segment was named the performance segment.

6.3 Multinomial Logistic Regression

Table 6-3 Multinomial logistic regression predicting segment membership

Variables	Balance	Convenience	Service	Price	Performance
Female	-0.0717	-2.716	-0.855**	0	0.0153
	(0.391)	(6.399)	(0.308)	(0)	(0.344)
Age	0.0182*	-0.0225**	-0.0122*	0	0.00614
	(0.00763)	(0.00742)	(0.00550)	(0)	(0.00749)
Crop	0.636	0.0177	0.336	0	-0.479
	(0.340)	(0.363)	(0.247)	(0)	(0.304)
Livestock	0.847**	0.229	-0.0448	0	-0.868**
	(0.312)	(0.328)	(0.242)	(0)	(0.292)
Small Farming Operation	0.412	0.174	0.0526	0	-0.328
	(0.278)	(0.288)	(0.204)	(0)	(0.227)
Midsize Farming Operation	1.089	0.907	1.038*	0	-0.252
	(1.071)	(1.406)	(0.495)	(0)	(1.905)
Large Farming Operation	0.554	0.132	-0.209	0	-0.481
	(0.424)	(0.400)	(0.254)	(0)	(0.288)
High School or less	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)
Associate Degree	-0.202	0.512	-0.399	0	13.65***
	(5.006)	(7.822)	(3.509)	(0)	(3.802)
College Degree	-0.936	0.0834	-0.583	0	13.96***
	(4.973)	(7.851)	(3.476)	(0)	(3.327)
Graduate Degree	-0.768	-0.0375	-0.59	0	13.70***
	(4.964)	(7.844)	(3.471)	(0)	(3.322)
No dealer/vendor capital item financing	0.156	0.168	0.132	0	0.16
	(0.201)	(0.204)	(0.145)	(0)	(0.196)
Dealer/vendor capital item financing	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)
No dealer/vendor expendable item financing	-0.428*	-0.346	-0.0842	0	-0.574**
	(0.206)	(0.205)	(0.155)	(0)	(0.196)
Dealer/vendor expendable item financing	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)
Constant	-1.995	0.0211	1.357	0	-14.01***
	(5.025)	(7.854)	(3.483)	(0)	(3.368)
N	1475				
Pseudo R^2	.0276				

Notes: Variable coefficients, standard errors in parentheses; *, **, *** represent 0.05, 0.01 and 0.001 levels of statistical significance, respectively

A multinomial logistic regression was used to predict segment membership. The segments from the clustering analysis were used as the bins or categories for the multinomial logistic regression. These segments are psychographic in nature due to the questions they are clustered on. This study clustered on the responses to question 8 which is psychographic by design since it asks respondents their opinions on a set of product attributes. Question 7 is the other question of interest and was not used to cluster on because it is not psychographic. Instead, it was used as a variable in the multinomial logistic regression. The independent variables that were used to predict segment membership are gender, age, operation type, operation size, education, and the level of nontraditional financing for capital and expendable items. This study uses data that lenders have access to or can easily access to predict segment membership for the respondents of the 2021 LCP survey. Identifying market segments and successfully predicting segment membership will improve a credit lenders ability to develop and tailor marketing programs. Specifically, credit lenders will have a better understanding of what attributes most influence a farmer’s credit sourcing decision. With this information they can more efficiently target customers of interest.

Tables 6-3 and 6-4 display the coefficients of the multinomial logistic regression and the marginal effects respectively. One notable observation is that the age variable is statistically significant in the balance, convenience, and service segments. The age variable is the variable that is statistically significant across the most segments. In this case the age variable was found to have the most predictive power this was also the case with past LCP segmentation research namely Roucan-Kane et al., 2010. However, the marginal effects for age are miniscule. As seen in table 6-4 the marginal effects for the age variable for the balance, convenience, and service segments are .3%, -.2%, and -.3% respectively. Therefore, although the age variable is statistically significant the magnitude of the variable is small.

Within the balance segment age, associate degree, and no nontraditional expendable item financing are the only statistically significant variables. The associate degree variable has a marginal effect of approximately 11% on table 6-4. This can be interpreted as if a respondent’s highest level of education is an associate degree, they are 11% more likely to be a member of the balance segment. The no dealer/vendor expendable item financing variable had a marginal effect of -3%. This means that if a respondent uses no nontraditional expendable item financing they are 3% less likely to be a member of the balance segment as compared to the base segment (price).

The variables that are statistically significant within the service segment are female, age, and the midsize operation size. The marginal effect for the female variable is -8%. This can be interpreted as if a respondent is female, they have an 8% decrease in the probability that they are a member of the service segment as compared to the base segment (price). The marginal effect for the midsize operation size is -66% which can be interpreted as if a respondent operates a midsize farm, they are 66% less likely to be a member of the service segment as compared to the base segment (price).

The performance segment had the livestock, no nontraditional expendable item financing, and all farm size variables as statistically significant. The no dealer/vendor expendable item financing variable had a marginal effect of -5%. This means that if a respondent uses no nontraditional expendable item financing, they are 5% less likely to be a member of the performance segment as compared to the base segment (price). The marginal effect for the small operation size is 157% which can be interpreted as if a respondent operates a small farm, they are 157% more likely to be a member of the performance segment as compared to the base segment (price). The marginal effect for the midsize operation size is 163% which can be interpreted as if a respondent operates a midsize farm, they are 163% more likely to be a member of the performance segment as compared to the base segment (price). The marginal effect for the large operation size is 160% which can be interpreted as if a respondent operates a large farm, they are 160% more likely to be a member of the performance segment as compared to the base segment (price)

Table 6-4 Marginal effects multinomial logistic regression predicting segment membership

Variables	**Balance**	**Convenience**	**Service**	**Price**	**Performance**
Female	.064 (.099)	-.231 (.607)	-.082 (.23)	.173 (.212)	.076 (.093)
Age	.003*** (.001)	-.002*** (.001)	-.003** (.001)	.001 (.001)	.001 (.001)
Crop	.077 (.044)	.019 (.035)	-.051 (.046)	.013 (.047)	(-.058) (.030)
Livestock	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Small Farming Operation	-.245 (.443)	-.126 (.680)	-.648 (.485)	-.551 (.79)	1.57*** (.311)
Midsize Farming Operation	-.319 (.441)	-.155 (.683)	-.655 (.48)	-.503 (.775)	1.63*** (.22)
Large Farming Operation	-.294 (.44)	-.165 (.684)	-.649 (.48)	-.494 (.773)	1.6*** (.219)
High School or less	.066 (.034)	-.012 (.037)	(.064) (.043)	-.038 (.045)	-.079* (.031)
Associate Degree	.108*** (.032)	.024 (.028)	-.016 (.043)	-.001 (.042)	-.115*** (.031)
College Degree	.047 (.029)	.014 (.025)	.002 (.036)	-.014 (.036)	-.049* (.023)
Graduate Degree	.072 (.12)	.039 (.134)	.153 (.121)	-.162 (.133)	-.102 (.210)
No dealer/vendor capital item financing	.007 (.021)	.007 (.018)	.009 (.027)	-.031 (.026)	.008 (.020)
Dealer/vendor capital item financing	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
No dealer/vendor expendable item financing	-.030 (.021)	-.016 (.018)	.035 (.028)	.061* (.027)	-.05* (.021)
Dealer/vendor expendable item financing	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
N	1475				

Notes: Marginal effects, standard errors in parentheses; *, **, *** represent 0.05, 0.01 and 0.001 levels of statistical significance, respectively

After the relationships between observable characteristics/variables and segment membership has been identified, credit lenders can calculate the probability that a farmer is a member of a segment. If the prediction is correct the use of a multinomial logit to predict segment membership will help credit lenders tailor their marketing approach to the farmer. One potential strategy is to identify common sets of needs within the segments and offer a tailored marketing mix that matches these needs (Roucan-Kane et al., 2010). However, this model may incorrectly predict the segment membership of a farmer. The effect of this error varies on the flexibility of the marketing program (Roucan-Kane et al., 2010). If the marketing program is flexible and offers customers multiple options, then the cost of the error will be lower. If the program is rigid and only offer one option per segment the cost of the error will be higher. Agricultural credit lender will continue to benefit from improvements in the understanding of customer segments.

CHAPTER 7. CONCLUSION

A useful tool in a credit lenders toolbox is market segmentation and segment membership prediction. It generates the potential for targeted marketing campaigns, increased market share, and increased customer retention. The ability to accurately understand their customers' preferences and behaviors is essential to their success. The style of segmentation analysis used in this study can help lenders market their products more efficiently to a receptive target audience.

The single most important decision variable in this study was price. As seen in Table 6-1 the interest rate variable was most often ranked as the first or second priority across all lenders and segments. One potential reason for this is farmers are more interested in controlling their cost than the alternatives (e.g., increasing revenues). By a farmer getting the most competitive price for a loan product or input they can effectively lower and in turn control one part of their profit function. However, priorities like this will require the sales teams to accurately identify an individual farmers' priorities and deliver a complex message that targets what the farmer values.

There are several variables with noteworthy insights from Table 6-2 the K-Means segment breakdown. Among these are the female, crop, livestock, operation size, and education variables. The price segment had the largest percentage of female segment members at 43% of all female respondents. The price and service segments had the largest share of crop, livestock, small, midsize, and large operations. This breakdown is unsurprising as these are the two largest segments and combined account for 63% of the entire sample. In the case of the education variables 36% of all respondents that at most have completed a high school diploma are members of the service segment. The service segment also has 45% of all respondents that have obtained a graduate degree.

This study focuses on segmenting the current agricultural lending market and predicting segment membership. The question that was clustered on is psychographic and relates to credit lending. Whereas past LCP research focused on clustering based on a question regarding the influence of six factors on input supplier selection (Alexander et al., 2005; Gloy & Akridge, 1999; Roucan-Kane et al., 2011; Roucan-Kane et al., 2010). This studies psychographic segmentation strategy yielded 5 different segments based on attribute preferences: balance, convenience, service, price, and performance.

The limitations of this study include the ordinal nature of the variables that were used for clustering and the cross-sectional nature of the data. The responses to question 8 which were used for clustering are ordinal. Therefore, while the order of the categories is important the distance between the categories is unknown. However, both the Ward's method and K-means assume the distance between the points is known. The cross-sectional nature of the data set does not allow for the identification of changing trends and usage patterns throughout the years.

REFERENCES

Alexander, C. E., Wilson, C. A., & Foley, D. H. (2005). *Agricultural Input Market Segments: Who Is Buying What?* 20.

Baker, G. A., & Burnham, T. A. (2001). Consumer Response to Genetically Modified Foods: Market Segment Analysis and Implications for Producers and Policy Makers. *Journal of Agricultural and Resource Economics*, *26*(2), 387–403.

Baldini, N., & Divringi, E. (2016). A Mixed-Methods Exploration of Consumer Credit Trends by Age in the Third Federal Reserve District. *Beyond the Numbers*, 1–16.

Boggess, M. (2022, April 24). *Methods for obtaining marginal effects*. What Is the Difference between the Linear and Nonlinear Methods That Mfx Uses? https://www.stata.com/support/faqs/statistics/marginal-effects-methods/

Brewer, B. E., Bergtold, J. S., Featherstone, A. M., & Wilson, C. A. (2019). Farmers' Choice of Credit among the Farm Credit System, Commercial Banks, and Nontraditional Lenders. *Journal of Agricultural and Resource Economics*, 18.

Briggeman, B., & Boehlje, M. (2006). *Market Segmentation of Today's Agricultural Borrower*.

Briggeman, B., & Kenkel, P. (2008). Customer segmentation perceptions of farm credit associations. *Agricultural Finance Review*, *68*(2), 227–236. https://doi.org/10.1108/00214660880001227

Caliński, T., & Harabasz, J. (1974). A dendrite method for cluster analysis. *Communications in Statistics*, *3*(1), 1–27. https://doi.org/10.1080/03610927408827101 de Souto, M. C. P., de Araujo, D. S. A., Costa, I. G., Soares, R. G. F., Ludermir, T. B., & Schliep, A. (2008). Comparative study on normalization procedures for cluster analysis of gene expression datasets. *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, 2792–2798. https://doi.org/10.1109/IJCNN.2008.4634191

Dodson, C. B., & Koenig, S. R. (2004). Competition in farm credit markets: Identifying market segments served by the farm credit system and commercial banks. *Agricultural Finance Review*, *64*(2), 167–186. https://doi.org/10.1108/00214660480001161

Downey, D., Holschuh, M., & Jackson, M. (1999). *Agriselling Principles and Practices. Third Edition*. Doane LLC.

Fiechter, C., & Ifft, J. (2019). *Is Trade Credit Use Countercyclical? Evidence from the Northeast Dairy Industry*. 12.

Fiechter, C., & Ifft, J. (2020a). *How Big Is Nontraditional Finance?* 2.

Fiechter, C., & Ifft, J. (2020b). *What Makes Nontraditional Finance Nontraditional?* 3.

Gloy, B. A., & Akridge, J. T. (1999). Segmenting the commercial producer marketplace for agricultural inputs. *The International Food and Agribusiness Management Review*, *2*(2), 145–163. https://doi.org/10.1016/S1096-7508(00)00023-9

Griffin, B., Hartarska, V., & Nadolnyak, D. (2020). Credit Constraints and Beginning Farmers' Production in the U.S.: Evidence from Propensity Score Matching with Principal Component Clustering. *Sustainability*, *12*(14), 5537. https://doi.org/10.3390/su12145537

Großwendt, A., Röglin, H., & Schmidt, M. (2019). Analysis of Ward's Method. In *Proceedings of the 2019 Annual ACM-SIAM Symposium on Discrete Algorithms (SODA)* (pp. 2939–2957). Society for Industrial and Applied Mathematics. https://doi.org/10.1137/1.9781611975482.182

Howcroft, B., Hamilton, R., & Hewer, P. (2007). Customer involvement and interaction in retail banking: An examination of risk and confidence in the purchase of financial products. *Journal of Services Marketing*, *21*(7), 481–491. https://doi.org/10.1108/08876040710824843

Ifft, J., Kuethe, T., & Patrick, K. (2017a). *Nontraditional Lenders in the U.S. Farm Economy*. 23.

Kanungo, T., Mount, D. M., Netanyahu, N. S., Piatko, C., Silverman, R., & Wu, A. Y. (2000). The analysis of a simple *k*-means clustering algorithm. *Proceedings of the Sixteenth Annual Symposium on Computational Geometry*, 100–109. https://doi.org/10.1145/336154.336189

Katchova, A. L., & Dinterman, R. (2018). Evaluating financial stress and performance of beginning farmers during the agricultural downturn. *Agricultural Finance Review*, *78*(4), 457–469. https://doi.org/10.1108/AFR-08-2017-0074

Kilkenny, M., & Jolly, R. W. (2005). Are Rural Credit Markets Competitive? Is There Room for Competition in Rural Credit Markets? *Choices*, *20*(1), 25–29.

Martin Boyer, M., & Gobert, K. (2009). The impact of switching costs on vendor financing. *Finance Research Letters*, *6*(4), 236–241. https://doi.org/10.1016/j.frl.2009.07.001

Milligan, G. W., & Cooper, M. C. (1985). An examination of procedures for determining the number of clusters in a data set. *Psychometrika*, *50*(2), 159–179. https://doi.org/10.1007/BF02294245

Moss, L. M., Barry, P. J., & Ellinger, P. N. (1997). The competitive environment for agricultural bankers in the US. *Agribusiness*, *13*(4), 431–444. https://doi.org/10.1002/(SICI)1520-6297(199707/08)13:4<431::AID-AGR9>3.0.CO;2-#

Nadolnyak, D., & Hartarska, V. (2021). Nontraditional lenders and access to local agricultural credit markets by beginning and female farmers. *Agricultural Finance Review*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/AFR-06-2021-0073

Nadolnyak, D., Shen, X., & Hartarska, V. (2017). Farm income and output and lending by the farm credit system. *Agricultural Finance Review*, *77*(1), 125–136. https://doi.org/10.1108/AFR-03-2016-0020

Rosenberg, A., & Turvey, C. G. (1991). Identifying Management Profiles of Ontario Swine Producers through Cluster Analysis. *Applied Economic Perspectives and Policy*, *13*(2), 201–213. https://doi.org/10.2307/1349637

Roucan-Kane, M., Alexander, C., Boehlje, M. D., Downey, S. W., & Gray, A. W. (2010). Agricultural financial market segments. *Agricultural Finance Review*, *70*(2), 231–244. https://doi.org/10.1108/00021461011065265

Roucan-Kane, M., Alexander, C., Boehlje, M. D., Downey, S. W., & Gray, A. W. (2011). Large Commercial Producer Market Segments for Agricultural Capital Equipment. *International Food and Agribusiness Management Review*, *14*(4), 18.

Schmidt, C., Goetz, S. J., & Tian, Z. (2021). Female farmers in the United States: Research needs and policy questions. *Food Policy*, *101*, 102039. https://doi.org/10.1016/j.foodpol.2021.102039

Sherrick, B. J., Sonka, S. T., & Monke, J. D. (1994). Nontraditional Lenders in Agricultural Credit Markets. *Agribusiness*, *10*(4), 341–357. https://doi.org/10.1002/1520-6297(199407/08)10:4<341::AID-AGR2720100407>3.0.CO;2-C

Stevens, A. W. (2021). Nontraditional credit in the Wisconsin dairy industry. *Agricultural Finance Review*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/AFR-05-2021-0068

Turvey, C. G., Carduner, A., & Ifft, J. (2021). Market microstructure and the historical relationship between the US farm credit system, farm service agency and commercial bank lending. *Agricultural Finance Review*, *81*(3), 360–385. https://doi.org/10.1108/AFR-06-2020-0089

U.S. Department of Agriculture, Economic Research Service. Farm Sector Income & Finances: Assets, Debt, and Wealth, February 4, 2022.

Xu, D., & Tian, Y. (2015). A Comprehensive Survey of Clustering Algorithms. *Annals of Data Science*, *2*(2), 165–193. https://doi.org/10.1007/s40745-015-0040-1