Nontraditional agricultural equipment lending trends in the Agricultural Resource Management Survey and Uniform Commercial Code data

by

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B.S., University of Wyoming, 2020

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2022

Approved by:

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Abstract

The U. S. Department of Agriculture's official farm debt estimates are a vital source of information on the financial characteristics and conditions of farms nationwide and support the economic stability of the farm economy. Farm sector debt estimates are used by government officials and agricultural sector stakeholders to inform policy and financial decisions. Farm debt is categorized by both the debt type (real estate or nonreal estate) as well as the lender. The Agricultural Resource Management Survey (ARMS) serves as the main data source for agricultural lending not subject to public reporting, referred to in official debt estimates as "Individuals and Others." One lender type that often falls in this category is nontraditional lenders, such as vendor finance divisions and collateral-based finance companies. Recent studies have suggested that nontraditional lending volumes and market share may be increasing, but this increase may not be reflected in official farm sector debt estimates. The unique role of ARMS data in official farm debt estimation motivates analysis of the accuracy of its measurement of nontraditional lending.

This study makes use of data from Uniform Commercial Code (UCC) filings, which contain agricultural equipment liens. Given that nearly all loans secured by equipment, or with a lien on farm equipment, have an associated UCC filing, this dataset provides a population measure of agricultural equipment debt levels. This study introduces UCC lien filing data as a corroborative resource for farm debt analysis and statistically analyzes the differences in the measurement of debt sourced from nontraditional lenders between UCC lien filing data and ARMS. The research question is whether ARMS underestimates nontraditional lending volume and market share. The primary finding is that nontraditional debt reported in ARMS is biased downward. This downward bias is large and is consistent across time and region. ARMS data may have limited value in informing the “Individuals and Others” lending category in official U.S. farm debt estimates.

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Acknowledgements

There are many people I would like to acknowledge and thank who were instrumental in helping me complete this thesis in both professional and personal capacities. Dr. Jennifer Ifft has not only served me as my major professor, but also as my primary research advisor for nearly the past two years, often with great patience and always with encouraging and constructive guidance. Without her help, my thesis and research endeavors would not have been a success. I also want to acknowledge Dr. Jisang Yu and Dr. Brian Briggeman, who served on my graduate committee. Their assistance to my research and the compilation of my thesis were always valuable and timely, and their willingness to participate in this process with me was very generous. Special thanks are due to Noah Miller, who repeatedly offered much of his time to research collaboration with me and provided the ARMS data used in this thesis' analyses.

I also would like to express my appreciation for the USDA Office of the Chief Economist, which provided the funding for this research through a cooperative agreement. Equipment Data Associates of Randall-Reilly provided lien data through Uniform Commercial Code databases and offered data troubleshooting assistance, for which I am very grateful. I also want to thank Carrie Litkowski for providing feedback on the preliminary research in this area that served as the groundwork for this thesis, as well as the participants in the 2021 AAEA annual meeting and 2022 SCC-76 conference who also provided helpful feedback.

I owe a great deal of thanks to my parents, Sam and Kristin Byers, and my girlfriend Rachel, as well as other family and friends who were always incredibly encouraging to me throughout this process. I love you, and I could not have done this without you. Finally, I want to give honor and thanksgiving to God, of whose guidance and support in composing my thesis and in my life I am not ashamed.

Chapter 2 - Introduction

The ability of farm sector stakeholders, financial regulators, and policymakers to track the financial health of the farm sector relies on accurate, consistently measured data and information on farm debt levels. The majority of farm debt is held by traditional lenders: Farm Credit System lenders and commercial lenders; other institutions such as the Farm Service Agency also play a substantial role. Today, however, a growing number of "nontraditional lenders" provide agricultural credit. Nontraditional lenders are a diverse group of lenders that operate outside the traditional banking relationship model conducted at a local branch (Sherrick, Sonka, and Monke, 1994; Fiechter and Ifft, 2020a). Some of these lenders, such as life insurance companies and vendor-originated finance held by commercial banks, are subject to public reporting of debt volumes. Others, such as private lenders (non-deposit taking), are subject to different (and often less stringent) regulations, including no public reporting of their debt volumes (Barry, 1995).

A few studies have considered the growth of nontraditional lenders' role in agricultural finance. Brewer et. al. (2014) and Brewer et. al. (2019) analyze farms that participate in the Kansas Farm Management Association and use multiple lenders and show significant growth in nontraditional lending for this group of farms. While farm management survey data is especially useful for analysis of the relationship between farm-level characteristics and debt use, these data sets only cover a subset of commercial farms at the state-level (Kuethe et. al., 2014). Ifft, Kuethe and Patrick (2017) analyzed the growth of implement dealing lenders, a type of nontraditional lender, from 2003-16 using ARMS data. This study found substantial growth in implement dealer market share in long-term non real estate debt, but no observable differences in financial characteristics of farms using implement dealer financing. Fiechter and Ifft (2020c) find that feed manufacturers are a major creditor for New York dairy farms during low milk price periods.

In cases of no public reporting, official estimates of U.S. farm debt rely on responses to the Agricultural Resource Management Survey (ARMS) (Briggeman, Koening and Moss, 2012). The use of data from ARMS is crucial to the estimation of official debt estimates in the lender category of "Individuals and Others." Briggeman, Koenig, and Moss (2012) also suggest that some features of the survey may generate confusion among responses and lead to survey incompleteness and information loss, contributing to potential compromises of data accuracy in the lender categories for which ARMS serves as a unique source in official farm debt estimation.

Studies that evaluate national farm debt estimates are limited, largely due to a lack of data. Briggeman, Koening and Moss (2012) note that ARMS is the only source of information for (most) nontraditional lenders used by USDA to estimate total farm sector debt and provides several suggestions for improved data collection. Nonresponse (as well as incorrect responses) may influence debt estimates that use ARMS data (Morehart, Milkove, and Xu, 2014). Ahrendsen et. al. (2016) caution that some FSA loan recipients (10-13 percent) indicate on ARMS that they have no outstanding farm debt.

This thesis first explores categories of farm sector debt that present unique challenges to estimation using ARMS data. This coincides with previous research in trade credit and vendor finance theory and research on ARMS debt collection and estimation efficacy, which are discussed in the literature review chapter. A novel dataset on farm equipment lending is introduced that allows for analysis of trends in volume and lender type for a population of farm loans. This approach concentrates the scope of analysis to nonreal estate equipment lending in the agricultural sector. Such a narrower focus allows for reliable internal validation of the data set used for this empirical comparison. Kuethe et al (2014) also compare ARMS with alternative data sources, but these sources are from state farm management associations, meaning that similarities and differences between data sets may not produce definitive conclusions on the performance of ARMS data in reflecting true debt levels. The Uniform Commercial Code (UCC) lien filing data, which is used as the basis of comparison in this study, has unique qualities that aid the conclusiveness of the empirical results, namely its inclusion of agricultural collateral equipment value on all liens in its specified geographic region. In other words, the UCC data set reflects nearly all loans for agricultural equipment, as equipment is typically self-collateralized and filing of liens is a standard lending practice.

The objective of this thesis is to empirically compare the reflection of UCC equipment collateral value data in ARMS nonreal estate equipment debt data between lender types, specifically between traditional and nontraditional lenders. The analysis uses UCC data to analyze farm equipment lending trends from 2001-2019. This data set has all publicly registered liens filed on farm equipment primarily suitable for field crop production, with tractors under 100 horsepower excluded, across major field crop state: Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, Oklahoma, South Dakota, Texas, and Wisconsin. Based on USDA Agricultural Resource Management Survey (ARMS) data, these 14 states contribute over half of both farm equipment asset value and debt nationally. A literature review is followed by a description of the data characteristics and identification of key trends. Information on lender type and collateral value is then used to compare the trends in farm equipment lending described by the UCC data with long-term nonreal estate lending data from (1) official USDA farm sector balance sheet estimates and (2) farm loan data available in ARMS.

Several empirical models are constructed and estimated to evaluate how the reflection of UCC data in ARMS differs when loans belong to nontraditional lender categories versus traditional lender categories. Alternative models are posed and estimated to provide robustness checks for the parameters of interest. These models, conceptually and empirically, also seek to account for differences in measurement between current-period debt acquisition in UCC data and outstanding debt volumes in ARMS, as well as differences between equipment value and loan value as debt measures.

This study provides novel information and analysis of U.S. farm lending. No other study in accessible circulation has used data from a population[1] of farm lending data to assess debt volumes, shares, and growth for different types of farm lenders. Lien data of this kind as a data source for research on other economic sectors is also scant (e.g., Murfin and Pratt, 2019, Gopal and Schnabl, 2020). The advancement of knowledge concerning the role of nontraditional lenders in farm equipment credit provision is a key intention of this study, specifically as it relates to the measurement of nontraditional lending on nonreal estate equipment loans in ARMS data. This study also provides information on the suitability of UCC data for future research, including localized or regional analysis of changes to lending volumes or lender type.

[1] By population, this mean that the data set arguably covers all liens within specified categories

Chapter 3 - Background and Literature Review

2.1 USDA Farm Debt Estimation

U. S. history indicates a need for the consistent, accurate estimation of national farm debt. The effects of economic expansion and recession, which are often exacerbated in the domain of debt financing, generate momentous swings in the patterns of borrowing and lending. These effects are important for lenders and policymakers to monitor with farm debt estimations to engage agricultural markets with appropriate financial measures.

Examples persist throughout the decades. In the 1970's, low real interest rates and high export demand suggested an impending growth in farm income nationwide, spurring the agricultural sector on toward large volumes of borrowing. The end of the decade, however, ushered in monetary policy changes aimed at subduing the inflation rate, crippling the farm boom. Similarly, the 2008 financial crisis was marked by rising input costs and negative profit margins among livestock producers, eventually culminating in a crash with tighter credit standards, national output reductions, and sector departures (Briggeman, Koening, and Moss, 2012).

The United States Department of Agriculture (USDA) makes annual estimates of total U.S. farm sector debt using various data sources. Two major components of farm sector debt are considered in USDA's estimation process: debt that is publicly reported and debt that is not. Publicly reported agricultural debt primarily includes debt held by commercial banks and the farm credit system. ERS performs a trim on the volume of publicly reported debt from these two sources to ensure the capture of farm business debt while excluding extraneous debt categories (Briggeman, Koenig, and Moss, 2012). The characteristics of the trim have historically been identified through data retrieved from surveys like Agricultural Economics and Land Ownership Survey (AELOS), which was targeted towards estimating agricultural real estate debt by surveying both farm operators and non-operator farmland owners. AELOS was discontinued after 1999 (Briggeman, Koenig, and Moss, 2012). Between 2000 and 2013, no official survey from USDA was administered that captured data from non-operator owners, but the TOTAL survey rebooted the endeavor in 2014 (Bigelow, Borchers, and Hubbs, 2016).

This study focuses on debt that is **not** publicly reported, referred to as debt from "Individuals and Others" in farm sector debt estimates. The USDA has long sought effective methods of tracking the patterns of farm debt, with varying degrees of success and continuity (Briggeman, Koenig, and Moss, 2012). Initial approaches emerged through the Census of Agriculture and Farm Finance Surveys, but the groundwork for contemporary farm debt surveys was laid in the mid-1980's. Currently, the Agricultural Resource Management Survey (ARMS) is USDA's primary source of information for estimating farm debt that is not publicly reported. This includes nontraditional lenders that do not publicly report debt and are thus classified as "Individuals and Others".

2.2 ARMS Data for Debt Estimation

The Agricultural Resource Management Survey is a survey that has been administered by the National Agricultural Statistics Service (NASS) annually since 1996. Surveys are dispensed to approximately 30,000 farms and offer questions regarding financial and production information. NASS seeks to administer surveys to farms of a broad range of sizes and gathers information through various surveying approaches and phases. Initial screening of farms begins with phone calls (Phase I), and once viable survey targets are identified, surveys are administered either in person or by mail about field production and applications (Phase II) and subsequently farm finance information (Phase III) (Weber, Clay, 2013).

ARMS surveys are administered through their three phases over the course of seven to ten months. Mail interviews and personal visits are divided roughly in half, and a select group of close to one sixth of the personally visited farms proceed to the second phase of the survey. The two latter phases of the survey are informationally linked. Farm financial data is gathered in consideration production and operational data. Phase II can be completed without Phase III, but Phase III cannot be completed without Phase II, implying that Phase III results are from the smallest sample size of the three phases (Kuethe and Morehart, 2012). After 2013, the survey was adjusted to be completed by mail, with optional enumerator assistance (USDA Economic Research Service, 2022).

ARMS is administered nationwide, but some states have higher sampling rates, for the purpose of supporting state-level statistics. For the time period 2003-2019, nine of the fourteen states in the UCC database were sampled at rates sufficient to support state level estimates (these are often referred to as “ARMS states”). In all other states, where survey participation is not sufficient for state-level statistics, ERS reports survey statistics at the regional or multi-state level.

ARMS data on debt can be subset and grouped according to sector specifications, such as real estate and nonreal estate debt, and by lender categories, such as commercial banks or farm credit system lenders. In ARMS, data collected on debt depends on the descriptive rigor of the respondent. ARMS includes a “loan table” where respondents record loans with a column requiring the identification of a loan’s lender category with its corresponding four-digit code.

Figure 3-1 Agricultural Resource Management Survey (2018), Section J

SECTION J FARM DEBT

1. Was debt used in funding the operation of this farm/ranch in 2018, including any loans obtained in earlier years? *(**Include** seasonal production and other loans taken and repaid during 2018.)*

1080 1 ☐ **Yes -** *Continue* 3 ☐ **No -** *Go to Section K*

2. What was the total amount repaid on farm business loans taken out in 2018? (Record any outstanding balances of loans taken out in 2018 in Item 3.) *(**Include only** seasonal production and other short term farm loans.)* . . . . 0890 None ☐ Dollars $ .00

3. To estimate the financial position of farms correctly and their ability to service debt and to categorize debt by types, we need to list loans this operation had on December 31, 2018, including any line of credit. *(**Include** farm/ranch loans, debt on the producer's house if owned by the operation, and multi-purpose loans used for both farm and non-farm purposes. **Exclude** CCC commodity loans and any loans used exclusively for non-farm purposes.)*

1	2	3	4	5	6	7	8	9
Who is the lender? *[From Lender Codes Below.]* (Code)	What was the balance owed on January 1, 2018 including outstanding principal plus unpaid interest? (Dollars)	What was the balance owed on Dec. 31, 2018 including outstanding principal plus unpaid interest? (Dollars)	What was the interest rate on Dec. 31, 2018? *[Report in hundredths of a percent. **Example: 9% = 09.00**]* (Percent)	What is the type of loan? *[From Loan Type Codes Below.]* (Code)	What year was it obtained? *[For refinanced loans, report year refinanced]* (Year) (YYYY)	What is the original term of the loan? (Number of Years)	What percent is for operating expenses, capital expenditures, or other expenses of the farm operation? (Percent)	What is the primary farm purpose of this loan? *[From Loan Purpose Codes Below.]* (Code)
1001	1050 $ .00	1002 $ .00	1003 .	1004	1005	1008	1006	1007
1010	1051 $ .00	1011 $ .00	1012 .	1013	1014	1017	1015	1016
1019	1052 $ .00	1020 $ .00	1021 .	1022	1023	1026	1024	1025
1028	1053 $ .00	1029 $ .00	1030 .	1031	1032	1035	1033	1034
1037	1054 $ .00	1038 $ .00	1039 .	1040	1041	1044	1042	1043

If more space is needed, please use a separate sheet of paper.

Lender Codes (*Column 1*)

Lender	Code
FARM CREDIT SYSTEM	1
USDA Farm Service Agency (FSA)	2
Small Business Administration (SBA)	3
State & county government lending agencies	4
Savings and loan associations, residential mortgage lenders	5
Commercial banks	6
Life insurance companies	7
Implement dealers and financing corporations	8
Input suppliers	9
Co-ops and other merchants	10
Contractor	11
Individuals from whom any land in this operation was bought under a **mortgage or deed of trust**	12
Individuals from whom any land in this operation was bought under a **land purchase contract**	13

Lender Codes (*Column 1*) (continued)

Lender	Code
Any other individuals	14
Any other lenders	15
Credit cards	16
Farmer Mac	17
Credit Union	18
Other debts (*such as unpaid bills, etc.*)	19

Loan Type Codes (*Column 5*)

Type	Code
One year or less production or other loans	1
Non-real estate loan more than one year	2
Real estate loan more than one year for producer's dwelling	3
Other real estate loans more than one year	4

Loan Purpose Codes (*Column 9*)

Purpose	Code
Purchase real estate (*land & its attachments*) ➢ farm and home improvements ➢ building construction ➢ construction of livestock and poultry facilities ➢ grove development and rehabilitation	1
Purchase feeder livestock	2
Purchase other livestock	3
Other current operating expenses ➢ current crop production ➢ care and feeding livestock including poultry ➢ labor, feed, seed, fertilizer, grove caretaking, repair and maintenance	4
Farm machinery and equipment	5
Debt consolidation	6
Other	7

4. If you had farm loans **in addition to the five recorded above**, what is the total amount of debt from these loans owed on December 31, 2018? *(**Include** farm/ranch loans and debt on the producer's house if it is owned by the operation. **Exclude** any loans exclusively for non-farm purposes that are secured by assets of the farm/ranch.)* . . . . 1047 None ☐ Dollars $ .00

5. How much of the total debt owed on December 31, 2018 (*reported in Items 3 and 4 above*), was for the producer's dwelling? *(If the producer's dwelling is owned by the operation debt should be included here and above. **Exclude** producer's dwelling if not owned by the operation.)* . . . . 1057 ☐ $ .00

0999 **Office Use Only**

Source: USDA, National Agricultural Statistics Service and Economic Research Service, 2018. Agricultural Resource Management Survey.

The respondent's internal method of specifying lenders is based on distinctions the respondent makes between lenders that directly affect the operations of his or her enterprise. Depending on the personal and/or financial considerations of a respondent toward various loans, including the process of applying for financing or the nature of the relationship between borrower and lender, one respondent may categorize a loan through a vendor capital division as nontraditional while another may categorize the same kind of loan as through a commercial bank. John Deere Financial is organized as a commercial bank, but per the economic incentives it considers, it operates as a nontraditional lender (Meltzer, 1960). That is to say, ARMS lender categorization interprets the acquisition of debt from the borrowers' perspective.

The surveying obstacle arises when one seeks to examine the categorization of lenders from the lender perspective. The main difference between these two perspectives is the categorization of nontraditional loans and commercial bank loans. Consensus between borrowers and lenders on the categorization of farm credit system loans is likely stronger. A respondent may view his or her experience applying for credit through a large equipment vendor capital division more akin to applying for credit through a bank than to a conventional trade credit account, but from an economic standpoint the vendor capital division perceives the relationship inversely. There is a tradeoff to the designation of some loans to the commercial bank category that are, from the lender perspective, nontraditional. Loans categorized differently between borrower and lender perspectives may create variations in evaluating loans' terms of credit, though some of this information is collected in the ARMS loan table. Pervasive differences make possible the attenuation of self-collateralized agricultural equipment debt estimates. The extent to which these differences pervade ARMS data, however, is inconclusive.

Presence of attenuation in agricultural debt estimation via understatement of nontraditional lending communicates several novel observations about the condition of respondents' enterprises. Nontraditional lenders are often willing to offer more favorable terms of credit to farmers for equipment than banks, meaning lower interest rates and lower down payments (Peterson, 1995). The negative implication is that farmers are marginally less capable of making down payments and periodic payments on equipment loans through operational cash flow than is depicted in ARMS. Furthermore, the down payments farmers make through nontraditional lenders are smaller than they are through banks, decreasing the value of counterfactual equipment for which loans are sought, ceteris paribus. Being as debt, not equipment value, is estimated in ARMS, differences in loan-to-value ratios raise the question of ARMS debt volume underestimation.

Other studies have considered issues with farm survey debt estimation from other perspectives. Morehart, Milkove, and Xu (2014) further conclude that ARMS debt volumes may be biased downward due to current imputation procedures for nonresponse, but comparison to alternative data sources remains a challenge. Briggeman, Koenig, and Moss (2012) discuss the underestimation of farm debt from the perspective of a related survey's impact on publicly reported debt estimates. Prior to 2000, combined public reporting of farm real estate debt from commercial banks and the farm credit system falls significantly short of USDA farm sector real estate debt estimates. Coincident with the discontinuation of AELOS, the combined public reporting statistic and the USDA estimate begin to converge after 2000, when ARMS remained the primary farm debt estimation survey tool. This indicates no obvious estimation issue since publicly reported data receives volume trims, but the breadth of aids in evaluating the characteristics of the trim decreases with the discontinuation of AELOS.

Formerly, the volume gap between the publicly reporting amount of debt and the USDA estimate was attributable to real estate debt held by nontraditional lenders, but more recently the gap has virtually disappeared, without market indications of nontraditional lending subsiding (Briggeman, Koening and Moss (2012). It is possible that the farm debt estimate shrinkage includes a shrinkage in nontraditional debt estimates. Briggeman, Koening and Moss (2012) point out that this shrinkage is observed in nonreal estate debt estimates, where nontraditional lenders are significant debt holders, in addition to real estate debt estimates.

An important objective of ARMS' administration of surveys is the collection of data from a representative cross-section of U.S. farms. Weber and Clay (2013) point out, however, that often ARMS data collection can be impacted by nonresponse patterns. ARMS response rates are highest among the smallest farms and gradually decrease with farm size. In other words, ARMS' largest targeted farms are of a smaller sample size proportion of all responses than largest farms are proportional of all farms (Weber, Clay 2013). Farm debt estimations must be made with fewer observations of large farms to draw from relative to smaller farms. While this does not necessarily implicate farm debt underestimation, sample size discrepancies avail debt estimates to the possibility of variations in robustness.

Aside from nonresponse patterns and lender categorization incongruities, Briggeman, Koenig, and Moss (2012) highlight that the structure of the survey may appear confusing to many respondents. The wording of some questions is described as being presented in nonintuitive ways and the ordering of questions is described as discordant with the survey's thought flow, citing questions 3, 4, and 5 in Section J of the ARMS Phase III questionnaire. They also indicate that question 6 of Section J, where outstanding loans are enumerated explicitly in a loan table, some column prompts are unclear about what information they are requesting.

Coupled with limited space for loan information in the table, respondents may forgo eliciting some information about certain loans and forgo all information about others.

Briggeman, Koenig, and Moss suggest focusing the loan table on the elements of farm debt most fundamental and accessible to respondents: information on lender, loan type, and loan terms, as well as on remaining principal, interest, and interest rate. Reframing the order and the wording of other questions may also aid the cognitive stamina of the respondents and the completeness of the survey.

2.3 Trade Credit Literature Review

Many firms selling intermediate or final goods and services make purchases from their suppliers with trade credit accounts, where inputs and capital assets change hands at point of sale but are paid for a later date. Agricultural vendors often engage in the same kind of short-term financing relationships with farmers.

Being a pioneer of trade credit literature, Meltzer (1960) introduces concepts that distinguish credit extension from traditional lending. Whereas banks and other traditional financial institutions evaluate their prospects by risk, suppliers weigh their customers' risk against the goals of their sales accounts. Credit offerors are aware of the risk of lost sales when customers' credit repayment ability is limited, so often rather than recoiling at credit risk they may extend credit that meets the unique needs of the buyer in times of tight money.

Meltzer (1960) measures this effect by combining interest rates and money tightness into an index representing credit repayment ability and marginal willingness of customers to purchase on credit. Two major effects were observed that reflect the financial marketplace for agricultural equipment. One is that suppliers are incentivized to extend credit to encourage sales. Another is that the larger a firm is in its assets, the greater its propensity to extend more generous lines of credit. An extension of the latter observation is that the rate of expansion in credit extension is greater among large suppliers than among small suppliers. Suppliers also possess protection against credit risk that traditional lenders do not. Suppliers are better equipped to liquidate collateral upon default than traditional lenders, as they have better market access for resale.

Like Chod (2017), Meltzer (1960) asserts that the largest firms are supplied credit primarily by non-bank sources, though Chod (2017) elaborates on lender-borrower relationship dynamics by firm size. Furthermore, manufacturing corporations play prominently in credit lending to non-manufacturing companies, mirroring the relationship between farmers and nontraditional lenders.

Although focusing on the manufacturing sector, Chod (2017) cites several factors determining the makeup of debtors' credit decisions that characterize agricultural equipment trade credit markets. Relative firm sizes influence the breadth of credit source diversification. Purchasing firms larger than their suppliers predominantly source their credit through trade credit accounts with their suppliers, as they possess negotiating leverage and pose a greater risk to suppliers if the account is lost. The inverse is true with agricultural equipment: farms are much smaller in assets than their equipment vendors. It follows that farms diversify their credit sources both across their enterprises' financial spectra and within equipment financing, though nontraditional lenders still dominate equipment financing.

Chod (2017) also remarks that trade credit accounts advantage firms when a plurality of assets are financed through one supplier. Multi-asset credit sourcing signals account vitality to a supplier, concentrating a supplier's credit extension toward diversified accounts. While this effect may be evident in perennial input and operating notes, this is difficult to support for agricultural equipment, considering the infrequency of large equipment purchases by farms and the scarcity of differentiated products offered alongside equipment by vendors. The relative smallness of and purchasing infrequency by farms reduces incentive for suppliers' account management, creating varying degrees of relational apprehension by farms toward large trade credit suppliers. Rather than minimizing their role, this only impedes nontraditional lenders from overtaking agricultural equipment finance altogether.

Trade credit accounts aid the flow of capital assets when macroeconomic conditions undergo dramatic changes. When commercial bank lines of credit are limited from tight money, firms' suppliers may extend relatively favorable credit terms to retain customer firms by absorbing initial impacts of financial disruptions. Small firms are targets for credit-extending suppliers due to expensive external financing sources and greater susceptibility to periods of credit constraining (Murfin and Njoroge, 2015). Agricultural equipment lending is characterized by suppliers much larger than borrowers, lending to itself the expectation of dense trade credit financing activity relative to other sectors. Initial observations of the data employed in this study reflect these conclusions.

Firm investment and capital growth are also affected by buyer and supplier size in trade credit relationships. Investment increases are most strongly observed in small suppliers offering generous credit terms to large buyers, whereas trade credit financing for smaller buyers is not implicative of enterprise growth (Murfin and Njoroge, 2015). This further suggests that extensive supplier equipment financing by farms is indicative of greater financial stress than if financed through traditional lines of credit.

2.4 Liens as a Data Source

The use of liens as a data source presents an opportunity to examine measurements of agricultural equipment trade credit from a novel perspective. Most loans made to finance agricultural production, equipment, machinery, or real estate are self-collateralized or self-liquidating (Office of the Comptroller of the Currency, 2018). In other words, the borrower pledges the item being financed as collateral for the lender. If the borrower cannot or does not repay the loan, the lender can collect the collateral in lieu of repayment. Thus, when a loan is made, the borrower will typically file a “lien” on the collateral, which provides legal documentation that specific property has been pledged as loan collateral. In the case of bankruptcy or other legal proceedings, such as lawsuits filed between borrowers and lenders, liens provide substantiation for lenders to legally collect or possess loan collateral. Filing a lien with the respective Department of State for loan collateral is a standard process for new loans. This study takes advantage of (1) lien data being publicly available and (2) liens arguably being filed on *all* loans that are secured by farm equipment (Gopal, Schnabl, 2020).

2.4.1 UCC History

UCC data reflects over a century of legal and political efforts to address inconsistent governance of economic transactions across U.S. states. Since the nineteenth century, measures to standardize commercial law were introduced in state and federal legislatures across the United States. After several iterations, a `Uniform Commercial Code' was ratified by the Uniform Law Commission in 1953. It was introduced to individual state legislatures and has since been universally adopted. The Uniform Law Commission is an organization comprised of attorneys, judges, legislators, and other legal professionals commissioned by the federal government to draft laws for the purpose of uniform adoption by state legislatures across the United States, (Virginia Division of Legislative Services, 2020)

The "Uniform Commercial Code" is a collection of laws that determine the conduct of commercial transactions in a way that can be applied to state law across the United States. The use of UCC data is ideal for national-level research, because the procedures and regulations governing these financial transactions are standardized from state to state. In other words, individual state commercial law need not be considered to consistently analyze financial activities across the U.S. Furthermore, liens filed with the UCC have the weight of the law behind them: UCC liens are filed through each U.S. State's Department of State. Liens provide legal substantiation for the posting of collateral on loans to the secured party, preserving the integrity of the transactions to which borrowers are liable.

2.4.2 UCC Data Novelty

The UCC lien filing database is a novel data source, and the literature indicates that its use in research has been very limited. Gopal and Scnhabl (2020) use a data set of UCC lien filings in a study on evolving lending practices to small business by finance and fintech companies since the 2008 financial crisis. Murfin and Pratt (2019) use UCC lien data on equipment manufacturer captive finance subsidiaries to study how captive finance affects resale values by equipment manufacturers where equipment is posted as collateral. In agricultural economics research specifically, however, UCC data has not yet been used to analyze equipment lending. The database is marketed as a tool for manufacturers and dealers to aid their industry pursuits, so it presents itself as an object of unique fascination with wide-ranging possibilities for research purposes.

Chapter 4 - Data Sets: ARMS and UCC

3.1 ARMS Data

The ARMS data used in this study consists of farm debt estimates that are organized into multiple subsets according to regional and sector concentrations. Nonreal estate debt is estimated as distinct from real estate debt and equipment debt is estimated as a subset of nonreal estate debt. Nonreal estate equipment debt includes data from a shorter time period (2005-2018) than overall nonreal estate debt (2003-2019) Both nonreal estate debt and nonreal estate equipment data debt are discussed in this study, but the latter provides the basis for the primary empirical analysis, as overall nonreal estate debt includes data on operating debt.

Data of both levels of specification are divided into two additional data sets according to state-level data publication status. UCC lien filing data includes data from fourteen states, so state-level ARMS data is initially restricted to those fourteen states. Of those fourteen, however, only nine are among states selected for the publication of state-level debt estimates. An additional data set is formulated by further restricting the fourteen-state ARMS data set into a nine-state data set including only data from states whose state-level data ARMS publishes. The fourteen-state data set is used foremostly to increase the size of the data set and bolster the conclusiveness of empirical results.

For each state in each year, ARMS data elements are allocated into five lender categories, numbered 1, … ,5 and labelled: “FCS”, (Farm Credit System), “FSA” (Farm Service Agency), “Comm. Banks” (Commercial Banks), “Implement Dealers”, and “Others”. These five categories were consolidated into two to expedite the testing of the empirical hypothesis. “FCS”, “FSA”, and “Comm. Banks” were aggregated into a new category, labelled “Traditional”, and “Implement Dealers” and “Others were aggregated into a separate new category, labelled “Nontraditional”. The latter new category is intended to reflect the basis derived from ARMS for the estimation of the “Individuals and Others” category of farm debt in official U. S. farm debt estimates.

3.2 UCC Data

3.2.1 Data Source

The UCC lien filing data used in this study was purchased from Equipment Data Associates (henceforth, EDA) of Randall Reilly. EDA compiles large data sets on equipment liens to assist businesses in their marketing efforts. UCC data for equipment used across multiple industries is collected from the UCC lien filing database in each state, compiled to be uniform across states, and supplemented with additional information on equipment characteristics.

UCC data compiled by EDA provides market information to large equipment vendors and lenders, but also has many research applications. These UCC lien databases have been used in finance research (e.g., Murfin and Pratt, 2019) to observe and interpret the relationships between the forms of property registered to secure loans, the characteristics of borrowers, and the characteristics of lenders in an effort to detect and predict patterns of behavior in secured loan markets.

3.2.2 Variables

The variables in the data Table 3-6 are organized into four major components: (1) lender (secured party information, (2) buyer information, (3) equipment information, and (4) UCC filing information. The first three components explain information about the parties that are secured, the parties that are borrowing, and the items in the transactions. The UCC filing information provides information about when the lien was filed with the UCC and how the lien was classified, whether it was a sale, a lease, or otherwise.

Several variables show how EDA designates observations to various secured party classifications, including unique lender identification numbers, lender classification numbers representing lender type, lender names, and separate variables for states and cities where lenders are based. EDA's lender classification numbers and lender names are used to code a new variable designating observations to a secured party classification method more analytically useful. Lender classifications include bank lenders, Farm Credit System lenders, Farm Service Agency (FSA), nontraditional (including implement dealers/manufacturers) and other. The additional lender variables are used as guides to ensure this designation's conformity to specified classification method, which proves useful when ambiguity arises about classifying lenders with similar names and/or EDA classification numbers.

Like the variables pertinent to lenders, buyer variables also include unique buyer identification numbers and states where liens are filed. Less important to this particular study, but included in the data, are separate variables for county names, ZIP codes, and FIPS codes. Because liens are filed in the states where buyers' enterprises are established, the buyer state variable is used as a condition to analyze the distribution of equipment value on liens across the states represented in the data and to analyze the trends of that distribution over time.

Financed values of loans are not recorded in the data set. EDA does, however, include equipment values either recorded on the lien or estimated by EDA (only 3 percent of UCC liens disclose the actual value of the equipment). While equipment values cannot be interpreted as loan values, they can be used as indicators of trends in loan volume and market share by lender type and as indicators of variation in lender composition by equipment type. Equipment information variables provide context to the applications of this study: equipment types, manufacturers, makes, models, serial numbers, and sizes. In this study, total equipment values are estimated according to several specified features: by state and year, by secured party classification and year, by equipment type and year, and by secured party classification for each equipment type.

3.2.3 Scope of Data

Analysis is restricted to 14 states where row-crop or field crop production is predominant. In states with more specialty crop or livestock is predominant, unique or small equipment may be more common. Data includes equipment classified as agricultural by EDA, and additional restrictions is imposed for types of equipment that were highly likely to be used in field crop production (see Table 3-1). This includes a restriction that all tractors be over 100 horsepower. While this data restriction thus excludes small horsepower tractors or vehicles that may be used for field crop production, it strengthens the likelihood that the data covers farm equipment only. For example, field crop farms might use small tractors, but this equipment is just as or more likely to be used for non-farm purposes such as yard maintenance. The types of farm equipment in this study are listed in Table 3-1.

Table 4-1 UCC Data Agricultural Equipment Types

Type
Misc Attachments
Global positioning systems
Irrigation Equipment
Utility Tractors
Utility tractor
Utility loader
Utility tractor loader backhoe
4-Wheel Agriculture Tractors
4-Wheel drive agriculture tractor
Harvesters
Beet harvester
Combines
Combine
Agricultural Implements
Corn head
Platform head
Grain cart
Grain wagon
Grain dryer
Agricultural Implements
Planter
Air seeder
Grain drill
Grain bin
Sprayer
Plow/disk
Utility vehicle
Performance side by side

Source: Equipment Data Associates data on select equipment for 14 states, 2000-2020

Table 4-2 Number of Liens Filed by State

Year	IA	IL	IN	KS	MI	MN	MO	ND	NE	OH	OK	SD	TX	WI
2001	12,287	12,650	3,975	6,185	5,205	6,562	6,979	4,788	5,227	6,449	8,929	2,433	30,504	4,762
2002	12,139	12,741	8,915	2,719	8,974	8,441	14,283	4,832	3,216	10,615	12,491	3,402	31,260	7,768
2003	11,504	12,275	9,617	6,109	8,833	10,874	12,510	4,699	4,222	10,495	12,733	3,860	32,525	7,443
2004	12,706	12,890	10,090	8,016	9,147	11,596	14,905	5,133	7,190	9,924	13,138	4,907	34,286	7,427
2005	11,377	11,830	9,121	7,779	7,942	10,593	13,396	4,607	7,566	9,016	13,091	3,304	32,483	7,241
2006	11,829	12,050	8,898	7,168	7,601	10,344	12,879	4,493	7,035	9,675	12,010	2,680	32,869	6,831
2007	14,119	13,111	9,451	8,367	8,484	11,318	14,186	5,025	8,347	10,299	13,940	3,206	43,280	7,575
2008	15,495	13,821	10,267	11,326	8,841	12,568	15,442	5,808	9,063	11,145	13,412	4,415	38,218	8,683
2009	19,625	14,131	14,123	11,729	9,711	16,114	19,347	8,019	11,827	13,743	13,770	5,990	41,550	10,444
2010	27,194	17,926	16,630	15,267	11,363	20,724	23,555	10,988	16,600	17,460	17,131	5,888	46,925	12,065
2011	28,390	19,293	15,458	15,528	12,228	19,621	24,422	12,139	17,120	18,218	15,341	6,490	42,173	13,456
2012	28,926	19,757	14,015	16,131	13,549	18,070	24,494	13,292	16,946	18,199	15,007	8,509	45,677	15,023
2013	28,940	21,200	14,946	17,974	13,769	18,973	27,262	14,170	18,408	19,211	14,333	9,532	46,650	16,620
2014	23,042	18,295	12,929	15,786	14,294	16,201	28,383	11,908	15,708	18,112	14,349	8,107	46,416	17,260
2015	19,880	16,065	11,704	14,429	12,485	20,685	28,275	9,824	13,186	16,572	13,518	7,707	47,284	17,134
2016	17,970	13,663	10,491	13,737	12,181	21,669	29,527	8,466	12,380	16,425	12,275	6,734	48,241	18,697
2017	17,566	11,928	11,582	13,474	12,721	21,290	30,510	8,516	12,214	15,256	11,674	7,396	50,092	20,313
2018	17,328	16,607	14,193	13,601	13,124	22,156	31,851	8,367	12,365	13,785	11,498	7,597	49,300	22,155
2019	17,293	19,656	12,986	14,229	12,929	23,540	33,752	8,934	12,096	13,176	11,919	7,247	51,964	23,494

Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019

Table 3-2 shows the number of liens per equipment per year by state. Table 3-5 shows total collateral value by state by year. A lender typically files liens within the year that credit is extended; hence this data provides information on new loans. Based on regulatory data reported by John Deere, the largest contributor of UCC collateral value, John Deere Capital Corporation held nearly $13 billion in "loans to financial agricultural production and other loans to farmers" at the end of 2019 in the U.S. Several considerations are warranted in interpreting collateral values. First, lenders typically do not provide a loan that is equivalent to the full value of the collateral. Several farm lenders and experts were consulted on typical loan to value ratios (LTV) as a part of this study. Several commercial bank and Farm Credit lenders (traditional lenders) reported a typical loan to value ratio of about 65-70%, with maximums at or below 80%. LTV ratios are typically higher for nontraditional or implement dealer lenders and many advertisements offer 0% down payment[2] on farm equipment loans (see Table 3-4). The highest advertised average down payment for an implement dealer-based lenders that was observed was 24%, which is still lower than many traditional lenders' maximum (see Table 3-4). These observed values, both gathered from lenders directly as well as online, are all anecdotal. However, the information collected was consistent among various sources of information and this type of confidential loan information is not publicly available. Given these typical loan-to-value ratios, it is likely that collateral value data overstate the share of equipment debt held by traditional lenders. Further, traditional lenders may file blanket liens on various loans, such as operating loans, on farm property beyond what the loan is intended for. For example, lenders may put a lien on land or equipment to secure an operating loan. On the other hand, most nontraditional lenders in the data are equipment manufacturers (Table 3-3, plus John Deere

[2] 1-downpayment \% = LTV ratio

Financial (JDF) and CNH) who are likely extending loans for the farm equipment that they sell *only*. Use of blanket liens further suggests that UCC data may overstate the role of traditional lenders in equipment lending.

Table 4-3 Types of Nontraditional Lenders (excluding JDF and CNH)

	Type	Liens	Value ($)
Kubota Credit Co. USA	Manufacturer	442,487	9,353,252,204
Agco Finance (IA)	Manufacturer	97,648	7,242,501,488
Agricredit Acceptance (IA)	Vendor finance company	54,500	1,609,035,380
Mahindra Finance USA	Manufacturer	37,336	789,807,444
Co-Alliance (IN)	Cooperative	10,734	524,743,259
CLAAS Financial Services, Inc.	Manufacturer	6,127	741,515,878
RDO Equipment Co.	Implement dealer	5,113	482,831,930
American Honda Finance Co.	Manufacturer	4,428	52,188,612
Great Plains Acceptance Corporation	Manufacturer	3,625	139,980,288
Titan Machinery, Inc.	Implement dealer	3,515	246,475,870
Caterpillar Financial Service Corporation	Manufacturer	3,390	288,980,341
Ziegler Inc. (IA)	Implement dealer	2,295	230,424,400
T-L Irrigation Corporation (NE)	Manufacturer	2,199	313,514,716
Mid-State Group, Inc. (WI)	Implement dealer	1,569	27,794,745
Randall Brothers (OH)	Implement dealer	1,460	120,643,422
Mid-State Equipment (WI)	Implement dealer	1,410	83,460,286
Trimble Financial Services	Manufacturer	1,274	3,866,157
Butler Machinery Company (ND)	Implement dealer	1,252	95,628,719
Vetter Equipment Company (IA)	Implement dealer	1,238	81,518,905
Kanequip, Inc.	Implement dealer	1,229	72,681,553

Source: EDA data on select equipment for 14 states, 2000-2019, Inflation-adjusted for 2000$

Table 4-4 Equipment Loan Offers

Lender	Equipment Type/Name	Ave. Down Payment	Link
JDF	5045E Utility Tractors	0%	https://www.deere.com/en/finance/offers-discounts/shared/tractors/utility-tractors/5e-series/5045e-offers/
JDF	5055E Utility Tractors	0%	https://www.deere.com/en/finance/offers-discounts/shared/tractors/utility-tractors/5e-series/5055e-offers/
JDF	5065E Utility Tractors	0%	https://www.deere.com/en/finance/offers-discounts/shared/tractors/utility-tractors/5e-series/5065e-offers/
JDF	5075E Utility Tractors	0%	https://www.deere.com/en/finance/offers-discounts/shared/tractors/utility-tractors/5e-series/5075e-offers/
JDF	6 Series M & R Tractors	0%	https://www.deere.com/en/finance/offers-discounts/shared/tractors/6-family-tractors/
JDF	Balers and related equipment	0%	https://www.deere.com/en/finance/offers-discounts/shared/hay-forage/round-balers/
Case IH	AFS Connect Steiger Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=404
Case IH	AFS Connect Magnum Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=385
Case IH	Optimum Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=373
Case IH	Puma Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=363
Case IH	Maxxum Series Tractor	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=364
Case IH	Vestrum Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=384
Case IH	Farmall 100A Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=365
Case IH	Utility Farmall U Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=370
Case IH	Utility Farmall C Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=368
Case IH	Farmall Utility A Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=366
Case IH	Compact Farmall C Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=369
Case IH	Farmall V Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=371
Case IH	Farmall N Series Tractors	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=372
Case IH	Axial-Flow 150 Series Combines	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=391
Case IH	Axial-Flow 250 Series Combines	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=390
Case IH	Corn Heads	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=387
Case IH	Draper Heads	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=388
Case IH	Flex Auger Heads	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=382
Case IH	Grain Heads	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=389
Case IH	Pickup Heads	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=381
Case IH	Speed-Tiller High-Speed Disks	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=386
Case IH	True-Tandem Disk Harrows	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=401
Case IH	True-Tandem Vertical Tillage	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=398
Case IH	Heavy-Offset Disk Harrows	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=396
Case IH	Nutri-Tiller	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=400
Case IH	Ecolo-Tiger Series Disk Rippers	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=397
Case IH	Ecolo-Tiger Series In-Line Rippers	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=402
Case IH	Tiger-Mate Series Cultivators	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=399
Case IH	Flex-Till Chisel Plow	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=403
Case IH	Early Riser 2000 Series Planters	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=383
Case IH	Early Riser 1200 Series Planters	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=392
Case IH	Precision Disk Series Air Drills	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=395
Case IH	Precision Air Air Carts	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=393
Case IH	Flex Hoe Air Drills	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=394
Case IH	Patriot Series Sprayer	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=346
Case IH	Titan Series Floaters	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=348
Case IH	Nutri-Placer Pull-Type Fertilizer Applicators	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=350
Case IH	Trident Combination Applicator	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=351

Table 3-4 (Continued) Equipment Loan Offers

Lender	Equipment Type/Name	Ave. Down Payment	Link
Case IH	RB455A Round Balers	24%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=353
Case IH	Small Square Balers	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=355
Case IH	Large Square Balers	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=356
Case IH	Rotary Disc Mower	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=361
Case IH	Pull-Type Disc Mower	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=357
Case IH	Rotary Disc Mower Conditioner	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=358
Case IH	Sicklebar Mower Conditioner	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=359
Case IH	Windrower	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=377
Case IH	Draper Headers	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=378
Case IH	Sicklebar Header	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=363
Case IH	Rotary Disc Headers	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=379
Case IH	Wheel Rakes	20%	https://www.caseih.com/northamerica/en-us/Pages/Disclaimer.aspx?idOffer=376
JDF	Sprayer Performance Upgrades Kits	20%	https://www.deere.com/en/finance/offers-discounts/shared/performance-upgrade-kits/sprayer-deals/
JDF	Air Seeding Tools and Carts	20%	https://www.deere.com/en/finance/offers-discounts/shared/seeding-equipment/air-seeding/
JDF	Box Drills	20%	https://www.deere.com/en/finance/offers-discounts/shared/seeding-equipment/box-drills/
JDF	Planters	20%	https://www.deere.com/en/finance/offers-discounts/shared/planters/planter-deals/
New Holland	Tractors and Telehandlers	0%	https://agriculture.newholland.com/nar/en-us/about-us/buying-services/pre-sale/offers-promotions/special-offers
New Holland	Haytools and Spreaders	0%	https://agriculture.newholland.com/nar/en-us/about-us/buying-services/pre-sale/offers-promotions/special-offers

Table 4-5 Total Equipment Collateral Value[3]

Year	IA	IL	IN	KS	MI	MN	MO	ND	NE	OH	OK	SD	TX	WI
2001	670	628	108	207	93	273	147	236	217	155	108	92	357	125
2002	638	580	281	84	187	348	275	231	119	233	139	132	345	201
2003	563	504	253	189	139	432	231	226	183	198	153	154	371	170
2004	676	627	308	294	161	466	300	265	350	233	172	216	426	172
2005	505	497	243	275	127	374	246	239	295	184	149	125	342	157
2006	498	475	220	237	123	359	225	221	277	200	114	55	298	127
2007	618	520	256	274	159	394	256	227	351	222	149	68	461	149
2008	734	563	295	457	174	482	315	311	422	229	156	124	462	178
2009	1,060	713	439	506	209	708	438	466	624	305	182	197	520	242
2010	1,573	981	571	671	293	947	600	586	965	417	226	186	647	281
2011	1,583	1,005	509	653	305	834	587	654	930	440	220	168	578	306
2012	1,645	1,053	444	696	370	709	593	718	900	469	220	313	616	352
2013	1,821	1,091	576	839	381	793	685	796	1,084	515	224	369	785	401
2014	1,453	881	497	724	390	622	680	649	973	468	211	311	738	378
2015	1,199	768	406	671	287	829	595	549	804	417	188	382	709	346
2016	1,052	597	330	642	239	818	533	476	781	397	166	385	664	342
2017	1,021	536	393	598	263	749	513	448	757	353	162	412	653	336
2018	1,065	876	523	636	219	770	540	445	833	278	154	437	647	332
2019	1,119	1,020	427	670	227	801	573	527	850	284	164	424	719	351

Source: Equipment Data Associates data on select equipment for 14 states, 2000-2019, Inflation-adjusted for 2019$

[3] Values in terms of $Millions

A second major consideration is that the loans may not be extended to farm operators or used for a farm operation. Landowners, family members, local implementer dealers, etc. may hold for equipment loans. This consideration is more relevant to the interpretation of the data in relationship to official statistics than its reflection of financial risk in the agricultural sector. USDA farm sector debt estimates assume that some publicly reported farm loan data is not held by farm operators and make adjustments for this (Briggeman, Koening, and Moss, 2012). Likewise, estimates of farm sector debt account for potential non-farm uses of loans extended to finance agricultural production (Briggeman, Koening, and Moss, 2012). However, to the degree that policymakers are concerned with financial risk in the agricultural sector, the total value of farm equipment used as collateral is of interest. Comparisons between UCC data and official farm sector debt estimates will reintroduce these considerations.

3.3 Data Manipulation Methods

3.3.1 Data Files

The UCC data set is broken into three separate files: “KansasState_UCCTransactionData_Line1_20201104 (1)”, “KansasState_UCCTransactionData_Line3_20201104”, and “KansasState_AgBlanketLien_Line2_20201104”. The reason that there is a “(1)” after the first line such that it is labelled differently from the other two files is because there was originally an importing error with this file such that a duplicate copy was required to be imported. The reason that the “AgBlanketLien” file is listed as “Line2” is because that is the order in which the purchased data files from Equipment Data Associates of Randall Reilly were received as enumerated on the receipt of the purchase. Furthermore, the AgBlanketLien file's observations cover a time period encompassed by both Line1 and Line3, so it is reasonable that it should be labelled between the two other files.

3.3.2 Data Content

For the purposes of this study, only Line1 and Line3 were used. Line3 data covers observations of liens filed with the buyer's state's Department of State via the Uniform Commercial Code for the time period 06/01/2000 – 06/01/2010. Line1 data covers observations of liens filed with the buyer's state's Department of State via the Uniform Commercial Code for the time period 06/01/2010 – 06/01/2020. Each data file consists of 27 variables, identical across both files, listed and described as follows from an index document included with the purchase of the data from EDA:

Table 4-6 UCC Lien Filing Data Variable Descriptions

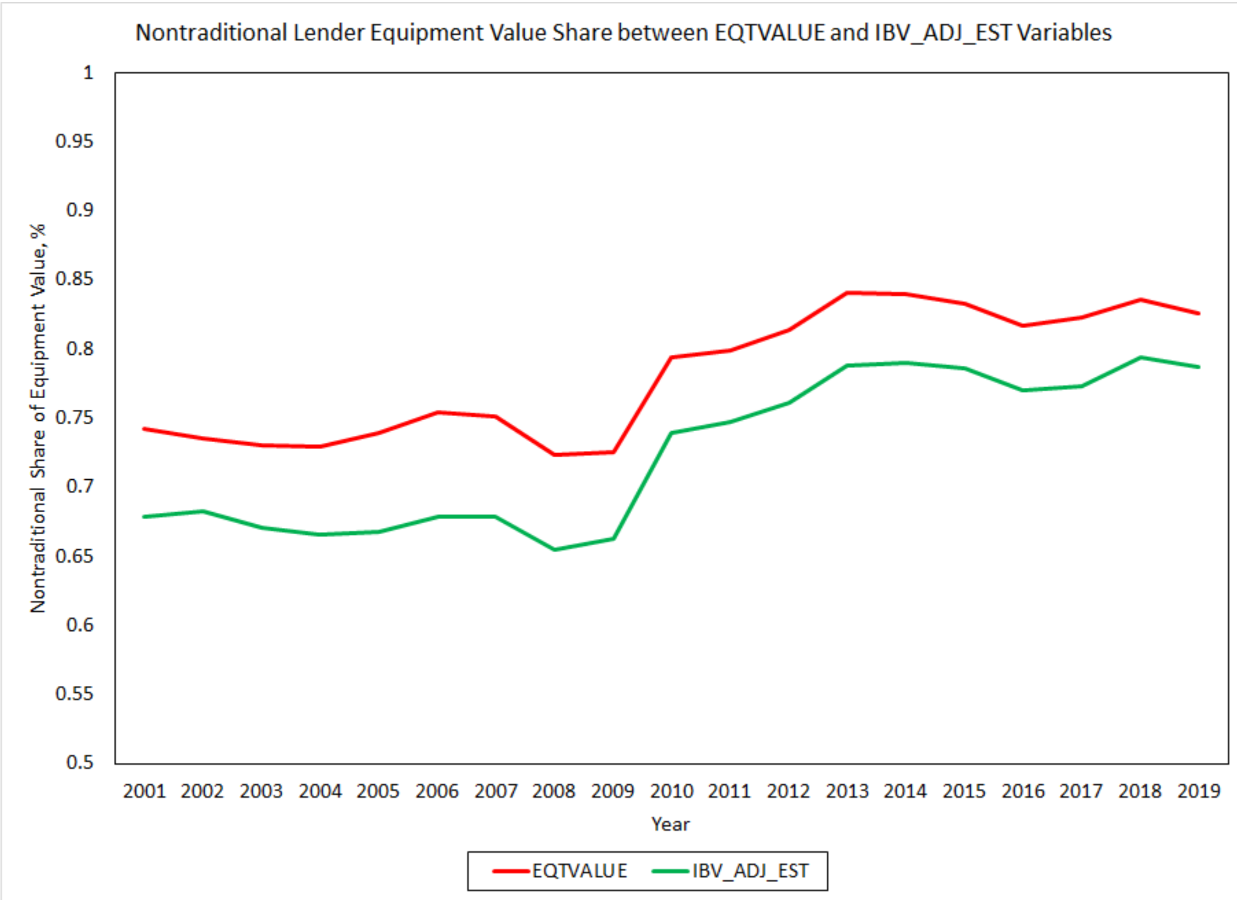
Variable	Description
BUYID	EDA's seven-character, alphanumeric buyer ID. Each buyer location in EDA's database is assigned a unique BUYID
BUYSTATE	Buyer's state
BUYZIP	Buyer's zip code
BUYFIPS	Known as a FIPS code, the buyer's county number is similar to a zip code for counties
BUYCTY	Buyer's county
UCCID	An incremental number assigned by EDA to every processed UCC. Used for internal tracking
UCCDATE	The date the UCC was received and led by the Secretary of State's office
UCCSTATUS	The financing status of the collateral in the UCC (e.g. Sale, Lease, Rental, etc.), appended by EDA
SPID	A unique EDA number assigned to the Secured Party for internal tracking
SPCLASS	EDA Secured Party classification
SPCOMP	Secured Party, typically the lender
SPCITY	Secured Party city
SPSTATE	Secured Party state
EQTUNIT	Used for EDA internal tracking, this number corresponds to the order in which the collateral appeared on the UCC filing

Table 3-6 (Continued)	**UCC Lien Filing Data Variable Descriptions**
Variable	Description
EQTUCCYR	Displays equipment's year of manufacture as it appears in the UCC filing
EQTNU	Indicates if the equipment is new or used
EQTMAN	The equipment manufacturer
EQTMODEL	The manufacturer's model designation
EQTDESC	A standardized description of the equipment, appended by EDA
EQTCODE	EDA-assigned numerical code representing the equipment category
EQTSN	The equipment serial number as shown on the UCC filing. When the serial number is not provided on a UCC, this field is populated with NSN and a tracking number
EQTSZ	Appended by EDA, this letter (A-Z) corresponds to the size classification for the model. The size is typically based on a physical attribute (e.g. horsepower)
EQTEDAYR	The estimated year of manufacture determined by EDA. This is used in place of the actual year of manufacture when not provided on the UCC
EQTATTACH	This field lists any attachments included in the purchase of the equipment
EQTVALUE	The value of the equipment, either actual or estimated. Actual values are provided by the secured party on less than 3% of UCCs
EQTAE	Indicates whether the value of the equipment is actual or estimated (A or E)
IBV_ADJ_EST	For equipment codes with multiple size categories, EDA has applied an estimated value to "new" equipment based on the model's specific size category.

Despite differences in equipment value evaluation bases, the IBV_ADJ_EST variable and the EQTVALUE variable have similar equipment value distributions and shares by lender type aggregations. One of the advantages of using the IBV_ADJ_EST variable in analysis is its virtual elimination of zero-value equipment value elements from the UCC data set. Additionally, it depicts nontraditional lenders as having a more conservative share of collateral equipment value, bringing clarity to the significance of the study's empirical results.

The selection of the variable to be representative of equipment value was a subject of extended debate. The IBV_ADJ_EST variable is comprised of values imputed according to the makes, models, and sizes of the equipment on liens, whereas the EQTVALUE variable's values are imputed according to bases not specified by EDA in detail. A trivial number (less than 3%) of liens include equipment value data, so discrepancies in the extent of equipment value imputation between variables give the EQTVALUE variable no significant empirical advantage. In the chapter on conceptual and empirical models, references to EQTVALUE in the models refer to the IBV_ADJ_EST measurement of equipment value.

Figure 4-1 Nontraditional Lender Equipment Value Share of EQTVALUE and IBV_ADJ_EST Variables



Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019

3.3.3 Categorization Tests

Line3 has approximately 1,610,000 observations, while Line1 has approximately 2,860,000 observations. Because of their identical variables, the two data sets were able to be bound together by their corresponding columns to create one large data set of approximately 4,470,000 observations. From there, a series of tests were performed on the data to evaluate the extent to which certain variables provided significant indication as to the category of lender into which the observations could be sorted. The two most promising variables were SPCOMP and SPCLASS.

The name of the lender (SPCOMP) gave strong indication as to which category of lender observations could be sorted, especially considering that the organizational structure of lender categories was based on assignment of lenders to categories prior to analysis of the data. For example, having already resolved that “Farm Credit” was to be its own lender category, observations that were identifiable by their lender description as being farm credit institutions were easily placeable into this category.

The five-digit lender classification number (SPCLASS) assigned by EDA also gave strong indication as to which category of lender observations could be sorted. For example, when all combinations of five-digit numbers in this variable that appeared in the data set were tabulated, a conclusion was that the five-digit number “26000” was the one and only number to include lender names such as “John Deere Industrial Credit”, “John Deere Financial”, and other similar names indicating that the lender was the financial division of the John Deere company. Furthermore, no observations classified with the “26000” had any descriptions other than lender names indicating that the lender was the financial division of the John Deere Company. Finding this pattern at work in other relevant lender categories, it became evident that this five-digit number from the SPCLASS variable was strongly indicative of the category of lender into which observations fell.

3.3.4 Categorization Functions

After testing the variables in the data set and concluding the overwhelming reliability of SPCOMP and SPCLASS to indicate lender category, two functions were encoded –one using

SPCLASS, the other using SPCOMP— to loop through the observations in the data set and assign them a descriptor in a new column based on corresponding character strings between the variable indicating the lender category (SPCLASS or SPCOMP) and the character strings defined via the new columns created by the functions. These columns were created by a series of simple binary logical tests, summarized as: if the character string in the observation matches any of the character strings identified by the vector of character strings for a given new variable described by the function, assign to the observation its corresponding label (Farm Credit, Nontraditional, etc.) in a new column, and if not, leave the observation's new column cell blank.

With the SPCLASS function, nine new columns were created, one for each lender category, using SPCLASS character strings: **Insurance, Nontraditional, Individual, Trust, Credit Union, Farm Service Agency, Case New Holland, John Deere**, and **Corporate Financial Leasing**. With the SPCOMP function, three new columns were created using SPCOMP character strings: **Farm Credit, Commercial Bank,** and **Rural Bank**.

Having these lender categories encoded, the columns were collapsible into one master column, UCCCAT ("Uniform Commercial Code Categories"), and removed the columns with only the binary results of each of the individual logical tests, making the data set wieldier and streamlining further analysis performed to safeguard the integrity of the categorization scheme.

3.3.5 Uncategorized Observations

Naturally, there were some observations that did not receive an allocation into a specified category based on the functions encoded to categorize them. Largely, this was due to observations withheld from the master column, namely those with SPCLASS number "60000", of which the vast majority appeared to be a kind of bank. Being as a subsidiary research intention was to subcategorize banks into rural and commercial banks, the common SPCLASS number between rural and commercial banks did not suffice to accurately delineate between the two classifications as they had been defined: commercial banks being banks that are publicly traded, and rural banks being all others. Furthermore, since there was no discernable pattern to how commercial and rural banks might be distinguished from one another within SPCLASS "60000" other than by the name of the lender, the SPCOMP variable was a necessary resort.

An undergraduate student employee manually sifted through all the observations filtered for SPCLASS "60000" that had not already been classified and listed each unique name of a commercial bank when able to verify its public status (the number of unique commercial bank names was is intuitively lower than the number of unique rural bank names, making the identification of unique commercial banks a more expeditious task). In the meantime, all the observations which fell into the SPCLASS "60000" group were reserved as blank, the blank description serving as an indicator of a bank (in general) for the purpose of constructing graphical analyses later. Having received back the complete list of commercial bank names, the code is prepared to create a defined commercial bank variable to include in the master column, provided a thorough evaluation of the remaining observations and a confident conclusion that the remainder are indeed overwhelmingly rural banks.

3.3.6 Overlapping Categories

Because both SPCLASS and SPCOMP were used in the functions to place observations into categories, there was the potential for observations to be placed into multiple categories if they happened to meet the criteria defined for both the SPCLASS function and the SPCOMP function. Because entries are only given one SPCLASS five-digit number and "Commercial

Bank” and “Rural Bank” were temporarily withheld from the master column –not the entries, but only the unique labels that bank entries would later receive—, it was only possible for multiple category placements to occur on account of matching criteria across both variables and not from matching multiple criteria within the same variable. Regardless, a simple data query revealed where the placement of entries into multiple categories was occurring.

In short, the only categories for which entries may have been doubly assigned were “Farm Credit” and “Corporate Financial Leasing”. “Farm Credit” was assigned based solely on whether the SPCOMP variable had character strings in it that indicated a farm credit lender, such as the character string “farm credit” and so forth. “Corporate Financial Leasing” was assigned based on its corresponding SPCLASS number given by EDA, “72000”. The issue arose when just under 5,000 observations emerged with a 72000 SPCLASS that also had character strings indicating their classification as liens secured by the farm credit system.

I encoded a subset of the data consisting only of entries with both categories and performed a second data query to assess the unique contents of the entries in the SPCOMP variable, concluding that the entries with character strings relevant to the Farm Credit category were indeed rightfully categorized as Farm Credit and not as Corporate Financial Leasing. From there, a duplicate of the function assigning entries by character strings within the SPCOMP variable reran the function on a subset of data consisting only of entries with the 72000 SPCLASS, redefining the doubly classified entries so that each observation was categorized only as either “Farm Credit” or “Corporate Financial Leasing” based on the scheme within that subset. Then, the 72000 SPCLASS subset was remerged with the rest of the UCC data and performed a final data query to ensure that the problem of overlapping categories had been resolved and that there were no remaining entries with double classifications.

3.3.7 Filtering Duplicate Entries

Upon creating some initial visualizations from the data to examine the progress of the categorization process, it became evident that the fact that two separate .csv files were combined to create the complete data set may have been affecting the analysis of the time period in which the two data sets may have overlapped. The number of liens filed and the total value of the corresponding collateral equipment in the year 2010 appeared artificially inflated discordantly from the otherwise intuitive trends illustrated in the initial data visualizations, despite the fact that the .csv file documentation from EDA stipulated that Line3 concluded on 06/01/2010 and Line 1 began on 06/01/2010.

A test for duplicate entries by year in the combined data set revealed that, almost unilaterally, duplicated entries were appearing in the 2010 lien filing year. By encoding the removal of only the duplicated entries in the data set, visualizations on number of liens filed and total collateral equipment value in 2010 returned to snug concord with the illustrated trends from across the time period.

3.3.8 Parsing Nontraditional Entries

Up until this point, much of the analysis was done with consideration to Case New Holland and John Deere as their own respective lender categories, the usefulness of which was not dispensed with so as to understand the significance of their role in self-collateralized agricultural equipment lending trends. Nevertheless, for the purpose of garnering a broader view of the role of major equipment manufacturers and implement dealers in this sector, observations of major equipment manufacturers and implement dealers were partitioned from within the broader Nontraditional category and consolidated with the John Deere and Case New Holland categories so that the general category of nontraditional lenders –through which John Deere, Case New Holland, and Nontraditional were all analytically interpreted— were reorganized into two new categories: Major Equipment Manufacturers and other Nontraditional.

As a disclaimer, this reorganization did not necessarily preclude the use of the John Deere and Case New Holland categories in the code, but the delineation between Major Equipment Manufacturers and other Nontraditional outside of the John Deere and Case New Holland categories was encoded with the expectation that John Deere and Case New Holland entry data could be seamlessly aggregated with Major Equipment Manufacturer data analytically without any need to parse either category in the code itself.

The method by which Major Equipment Manufacturer (and implement dealer) entries were distinguished from other Nontraditional entries was raw, inducing minor attenuation as to mildly understate the significance of the lender types for which primary analyses were conducted. Aggregations of numbers of liens filed and total value of collateral equipment according to SPCOMP descriptions within the original Nontraditional category was organized into a table and exported as a unique file. SPCOMP descriptions with over 1,000 liens in the whole data set were selected from the table. These selected descriptions were then manually differentiated as major equipment manufacturers and implement dealers or others.

Qualifying SPCOMP descriptions comprised a new variable via the SPCOMP lender categorization function, making, in the variable creation commands, a list of acceptable descriptions to search for by the function in creating the new variable. Equipment manufacturers or implement dealers with fewer than 1,000 liens in the data set were deferred to categorization in the other Nontraditional category. While this deferment of manufacturers and dealers under

1,000 liens to other Nontraditional attenuated aggregations in the combined Major Equipment Manufacturers category, it only improved the surety of analytical results by imposing a comparatively higher threshold of confidence for the conclusion of significance to the results, since Major Equipment Manufacturers were a lender category of specific interest. Furthermore, this encoded deferment to other Nontraditional did not cause any entries categorized in the original Nontraditional category to fall outside of the Nontraditional category at large.

3.3.9 Nontraditional vs. Major Equipment Manufacturers

The coding process for recategorizing the original Nontraditional category into Major Manufacturers and other Nontraditional followed a similar pattern to the recategorization of entries that fell into both the Farm Credit and Corporate Financial Leasing categories. SPCOMP descriptions matching the list of manufacturers and dealers with over 1,000 liens filed had their character strings listed in a new variable created by the SPCOMP function, temporarily called New Nontraditional. Thus, because the original Nontraditional category was categorized according to the matching character strings in SPCLASS and the New Nontraditional category was categorized according to the matching character strings in SPCOMP, entries that were captured by the SPCOMP function into the New Nontraditional variable necessarily overlapped with the original Nontraditional label.

All entries that overlapped between the original Nontraditional and the New Nontraditional categories were reassigned to the label Major Equipment Manufacturers and then remerged with the rest of the data set. Running the code, the output produces four different ways of categorizing liens filed with Nontraditional lenders, but this would prove useful for analytical purposes because different combinations of Nontraditional subcategories revealed important interpretive nuances to the questions of the study.

3.3.10 Equipment Type Categorization

Categorizing liens by the equipment type followed a very similar pattern to the process of categorizing liens by lender type. In fact, categorizing by equipment type was slightly simpler. In addition to the variable index document, another document was included in the purchase of the data sets from EDA called “Agriculture_Eqt_Codes”. This document indexed nine major categories of equipment, and within each category were various subcategories of equipment that were groupable by their function in agricultural production. Each subcategory was designated a unique four-digit number by which each entry in the data set was categorized.

I created a new function in the code using the EQTCODE variable that would create new variables based on character strings that matched between entries and specified lists in each new variable. These specified lists of character strings corresponded to the lists of four-digit numbers given in the Agriculture_Eqt_Codes document, so that the new variables created through the function likewise corresponded to the nine major categories in the document. These variables were binary variables: from looping through the data set, the function would assess whether entries’ EQTCODE four-digit strings matched any of the specified four-digit strings in the variable, placing the name of the category in the new variable’s column if matching and leaving it blank otherwise.

Like in the case of lender categories, columns having undergone binary tests collapsed into a master column with the binary columns removed from the data set for conciseness. Because all entries were categorized by EQTCODE, no four-digit strings matched between newly created variables, and all four-digit strings listed in the Agriculture_Eqt_Codes document were used, no entries were left uncategorized and no entries overlapped in equipment type categories. The categories created were as follows: **Balers, Combines, Harvesters, 4-Wheel Drive Agriculture Tractors, Utility Tractors, Irrigation Equipment, Miscellaneous Attachments, Agriculture Implements 88** (heads, carts, wagons, augers), and **Agriculture Implements 89** (plows, discs, seeders, planters).

3.3.11 Horsepower Data Consultation

During the analysis, EDA provided several additional files upon request, comprised of the same data as the initial files received but with the inclusion of additional variables, most importantly a variable detailing the horsepower of the equipment used as collateral on the lien. The purpose of identifying the horsepower of the equipment on each lien was to use a proxy variable to ensure that the entries used for analysis were equipment used primarily for agricultural purposes. These new files were not initially in an importable format, so the new files were converted via an FTP Client into .csv format.

From the first line (entries from 6/1/2000 - 6/1/2010), there were 1,882,650 total entries, which was close to the number of total entries from the previous .csv files EDA sent us, but not identical. Of those ~1.8mil, 33,228 failed to load into R due to a parsing error. An additional 73,576 were dropped from the data set because of a misinterpretation of the comma separation within the data during importation that occurred in the horsepower variable. To elaborate, there were commas used as part of the description in the horsepower variable that were interpreted as separating variables. For example, if the description of the horsepower variable was meant to read: “Payload Capacity Under 1,000 lbs”, it ended up reading: “Payload Capacity Under 1” and the “000 lbs” was shifted over into the next column, offsetting the columns on those ~74k entries. Fortunately, by identifying all the unique descriptions in the horsepower variable, it was discernable that all these entries read either: “Payload Cap 1,000 lbs” or “Payload Cap Under 1,000 lbs”, indicating that these entries would likely not have fallen into the category of farm equipment over 100 horsepower. Even in a rare case where they did, that would not be something discernable from the data, because those entries unilaterally lacked information about horsepower itself.

There were 302,053 entries where, in the horsepower variable, it read: “Insufficient Information Available” and an additional 113,636 that read: “No Model Given”. Another 47,044 did not explicitly state the horsepower either and 19 were dropped due to other errors. Of the original ~1.8mil, 1,313,094 provided a number for either horsepower or kilowattage, roughly 70% of the whole data set. Of the ~1.3mil, 596,181 entries were listed as having less than 100 horsepower (or 75KW), about 45%. 717,000 had 100+ horsepower (~55%).

There were 569,556 total entries that did not mention horsepower or kilowattage. Of these, the ~74k with the comma separation error would not have fit into the category of 100+ horsepower, leaving the remaining amount at 495,980. To determine how to incorporate the remaining entries, entries with identified horsepower received correlation tests between equipment size (EQTSZ) and the horsepower variable.

The overall correlation between horsepower and equipment size, was 0.82. Filtering out the observations of less than 100 horsepower, equipment in sizes J-Z (on an A-Z scale) were nearly perfectly correlated with corresponding horsepower (100-300hp). Equipment sizes A-I were also very closely correlated with corresponding horsepower (100-300hp), but not perfectly. Among equipment sizes A-I, the imperfect correlation was found to be fully attributable to differences in equipment types. All entries that had both horsepower information and an equipment size from A-I were partitioned according to equipment type. When these partitions were made, entries with size A-I were almost perfectly correlated with horsepower under 100 unless they were categorized under one of the two following equipment categories: “Combines” or “4-Wheel Drive Agriculture Tractors”. The new data files from EDA were pervaded by a litany of technical problems, so once the scheme by which the data could consist of entries strictly over 100 horsepower, the new restrictions in the code were applied to the original data set

3.4 Equipment Lending Trends

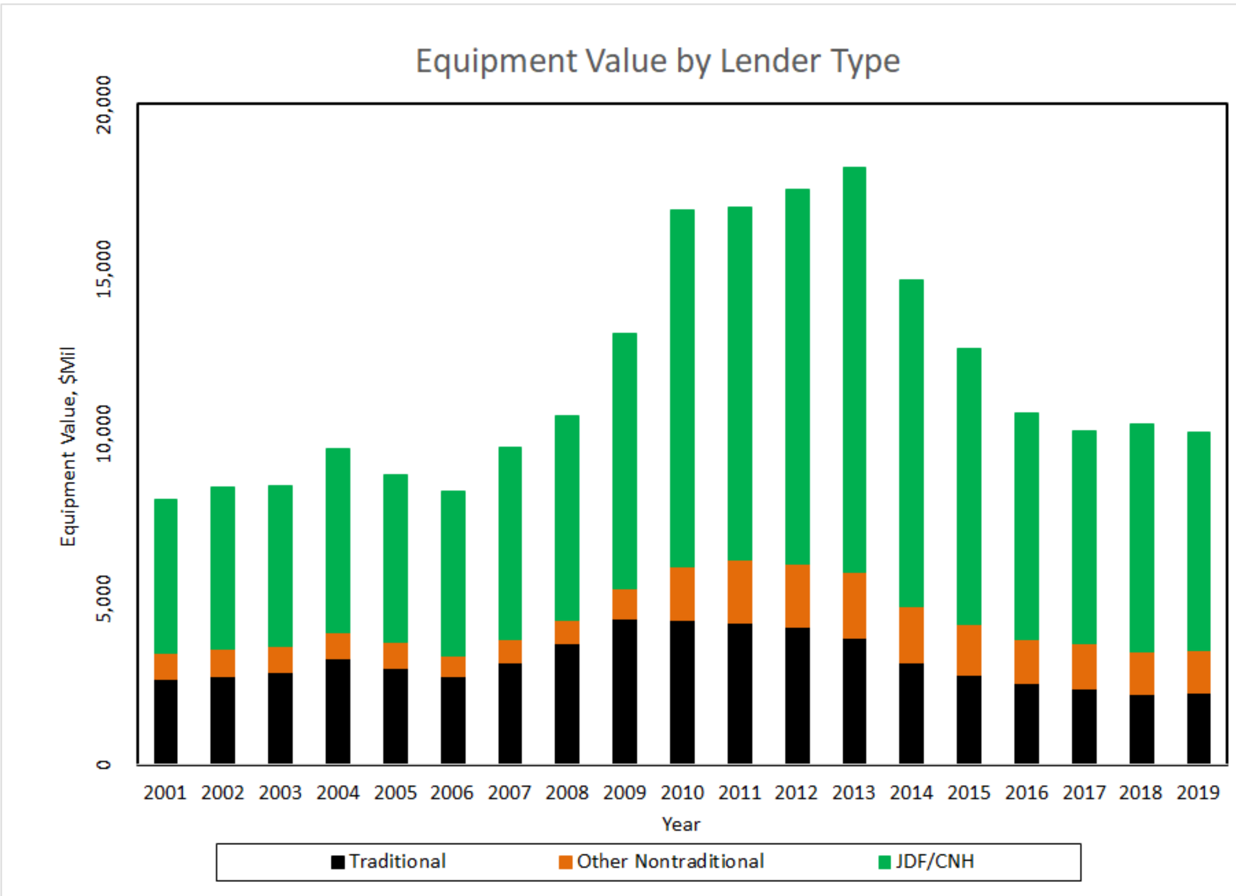
3.4.1. Overview

Overall trends in collateral value by lender type are the initial focus of examination. Total value of new farm equipment collateral was around $8 billion annually from 2001-2006 (Figure 3-2) in the 14 study states. After this, aggregate collateral value increased to nearly $18 billion in 2013. Recently, annual collateral value has leveled off at around $10 billion, consistent with broader trends in farm income. Banks appear to have maintained a steady volume of equipment lending throughout the study period. While Farm Credit System collateral values peaked in 2009, collateral levels have decreased recently to 2001 levels. Starting around 2006, John Deere Financial (JDF, which is organized as a commercial bank) has dominated farm equipment lending. CNH[4] has also increased lending and is currently a larger farm equipment lender than all

[4] CNH Industrial Capital is the captive financial services provider for the CNH Industrial family of brands, which includes Cash IH and New Holland

Farm Credit System lenders combined. Other nontraditional lenders increased their market share around 2009 and have largely maintained 2011/12 collateral levels, near the current volume of all banks (Figure 3-6).

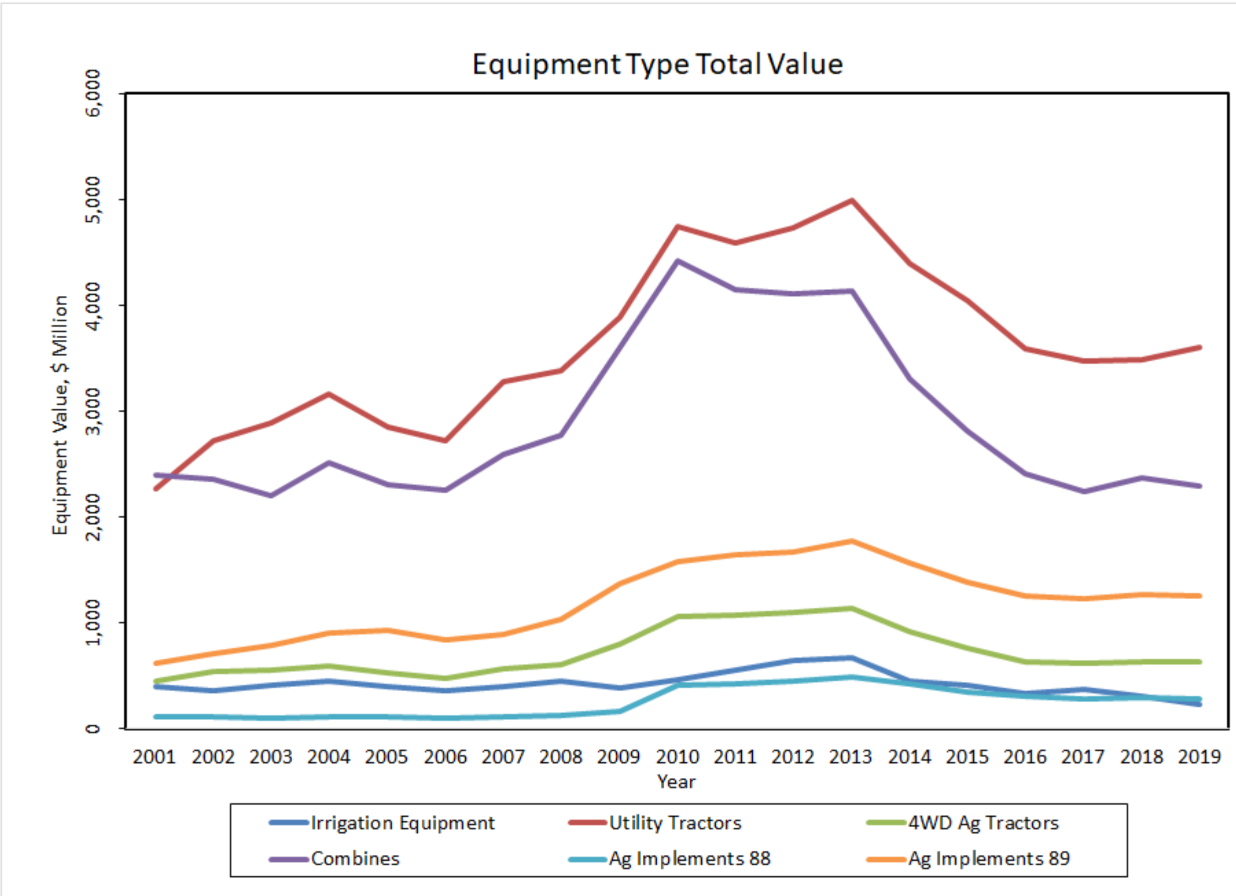
Figure 4-2 UCC Equipment Value by Lender Type



Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019, inflation-adjusted for 2019$

The increase in machinery collateral value from 2007-13 appears to have been for all major machinery classes. Combines and utility tractors account for the vast majority of loan collateral, which is not surprising given their size and importance in field crop production (Figure 3-3). While most lenders hold collateral for all equipment types, CNH and JDF do not hold meaningful quantities of collateral for irrigation equipment. This is likely out of their line of business and also suggests that traditional lenders may play a larger role in financing nonstandard equipment or equipment that is not sold by major manufacturers.

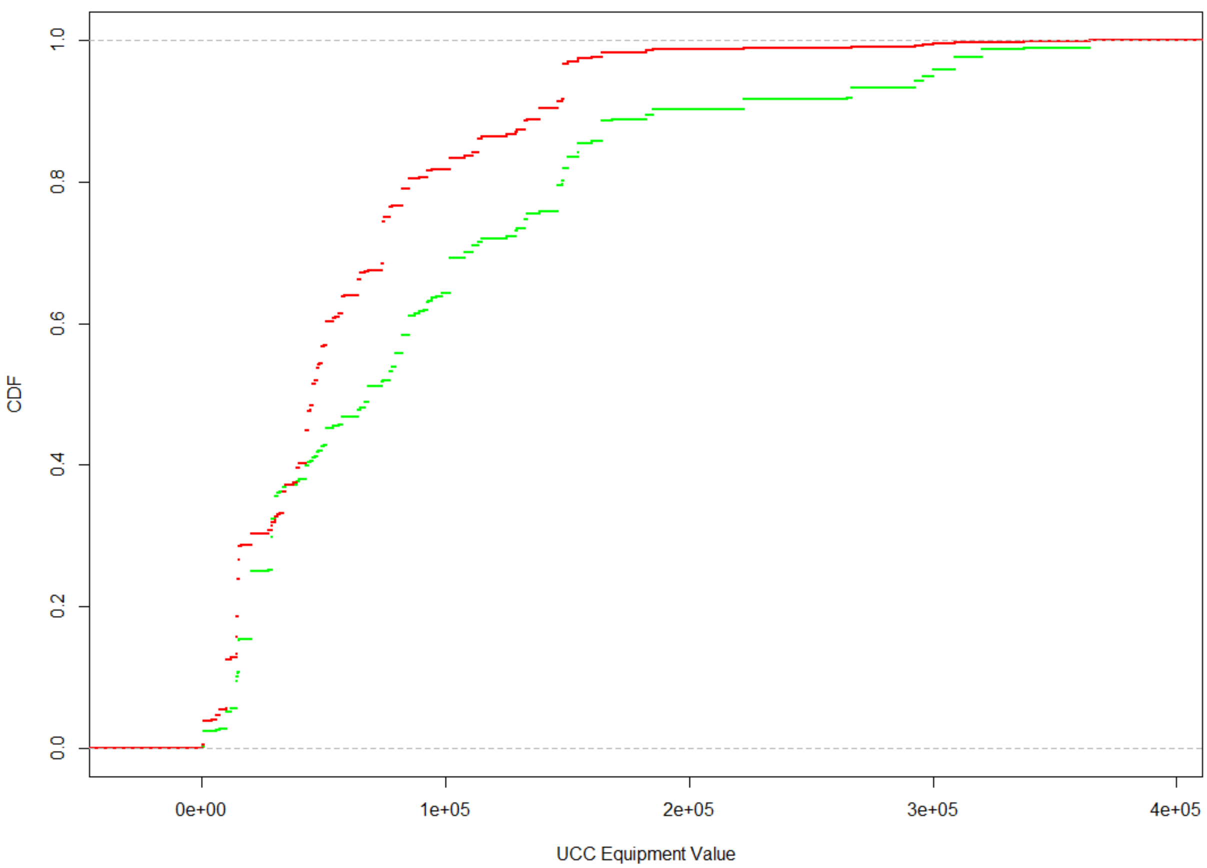
Figure 4-3 UCC Equipment Type Total Value by Lender Type



Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019, inflation-adjusted for 2019$

The size of the UCC data set creates a barrier to examining the whole data set in detail, so the distribution of equipment value is examined according to various categorical stipulations to confirm the data's conformation to a hypothesized normal distribution. UCC equipment values appear to take a normal distribution overall, but nontraditionally sourced equipment values have a normal distribution with a higher mean than traditionally sourced equipment values. This indicates that nontraditional loans, on average, are larger than traditional loans. In other words, for larger debt acquisition endeavors, farmers are more likely to resort to nontraditional credit sources, deferring smaller debt acquisition to traditional sources. The Kolmogorov-Smirnov Test was employed to measure the difference in distribution between traditional and nontraditional sources, finding that their distributions did not significantly deviate from one another or a normal distribution.

Figure 4-4 Cumulative Distribution Functions of Traditional and Nontraditional Collateral Equipment Values

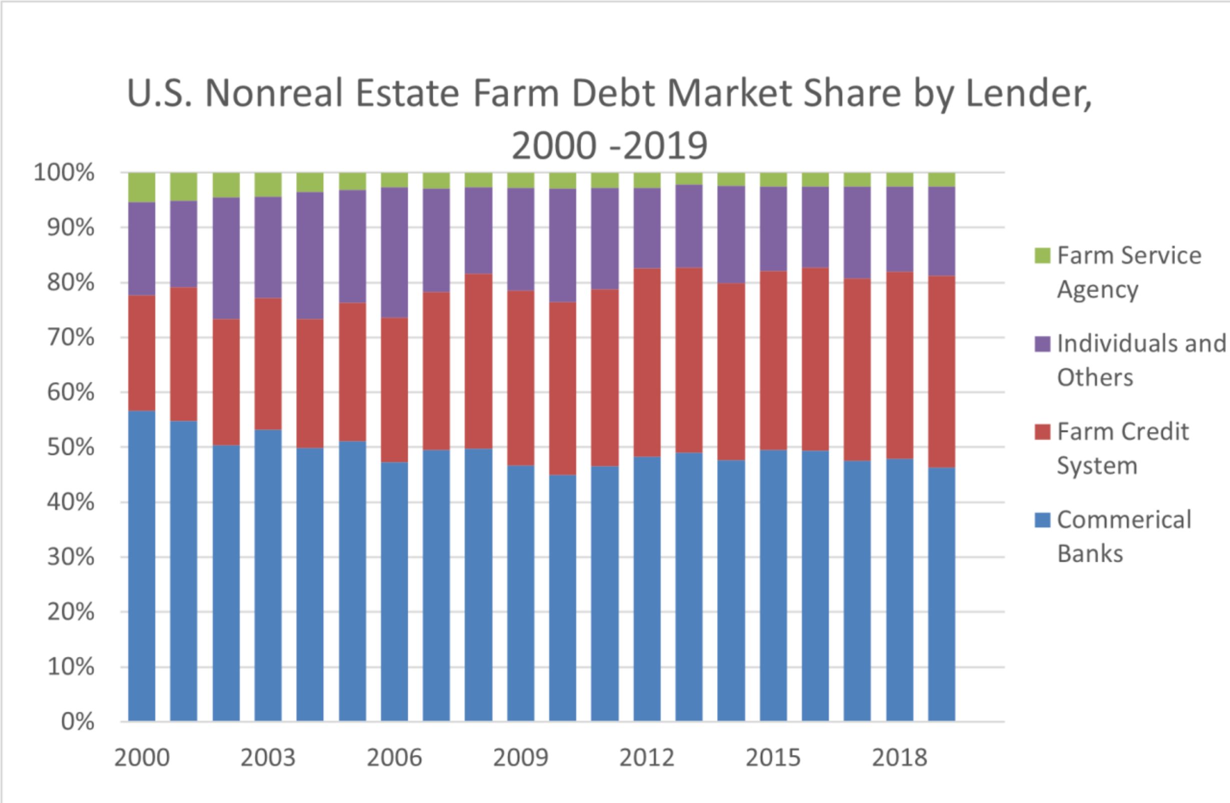


Source: Equipment Data Associates data on select equipment for 14 states, 2000-2020, $

3.4.2 Comparison with USDA data sources

The USDA Economic Research Service publishes estimates of total debt held by the U.S. farm sector. In short, these estimates are comprised of (1) publicly reported farm loan data from various lenders, adjusted to account for some share of these loans going towards nonfarm uses and (2) farm loan information provided by the Agricultural Resource Management Survey (ARMS). Farm sector debt is classified as real estate or nonreal estate debt; real estate debt is secured by real estate. Nonreal estate debt covers all debt that is not secured by real estate; this category would include loans secured by equipment as well as unsecured loans and loans secured by other property, i.e. personal wealth, livestock, crops. In 2019, 36% of U.S. farm sector debt was estimated to be non-real estate debt. This share is comparable to the level of short-term loans and long-term non-real estate debt relative to real estate debt estimated using ARMS, of about 20% each (Ifft, Novini, and Patrick, 2014). Thus while U.S. farm sector nonreal estate debt estimates include a large share of loans not secured by equipment, potentially up to 13% in recent years based on ARMS data, major equipment loan trends may be reflected in these estimates.

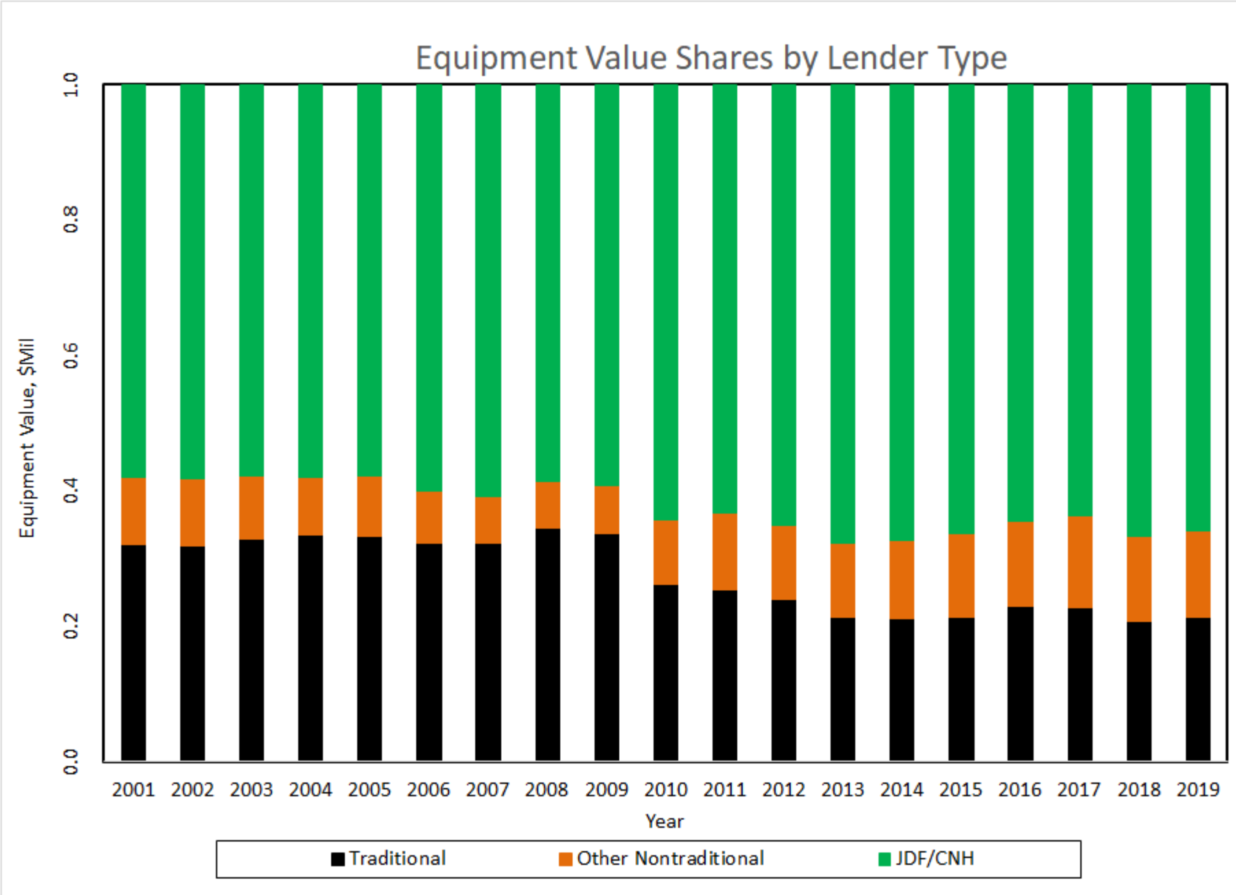
Figure 4-5 USDA Nonreal Estate Debt Share Estimates by Lender Type



Source: USDA, National Agricultural Statistics Service and Economic Research Service, 2000-2019. Farm Income and Wealth Statistics Balance Sheets

There are important distinctions between UCC data and farm sector (or ARMS-based) debt estimates, related to how UCC data reflects a flow of new credit and farm sector debt estimates reflects the stock of credit. UCC data measures the estimated value of equipment used as collateral on liens in the year the liens are filed. Thus, equipment value only appears in the data in the year in which the lien was filed but not in subsequent years. New credit is only a portion of equipment value recorded in UCC data and can only be approximated using standard loan-to-value ratios. Farm sector debt estimates, on the other hand, measure the value (or stock) of outstanding farm debt each year, or the outstanding balance from last year, less any repaid debt plus new debt. As previously discussed, it is possible that UCC data market shares may underestimate nontraditional lender market share.

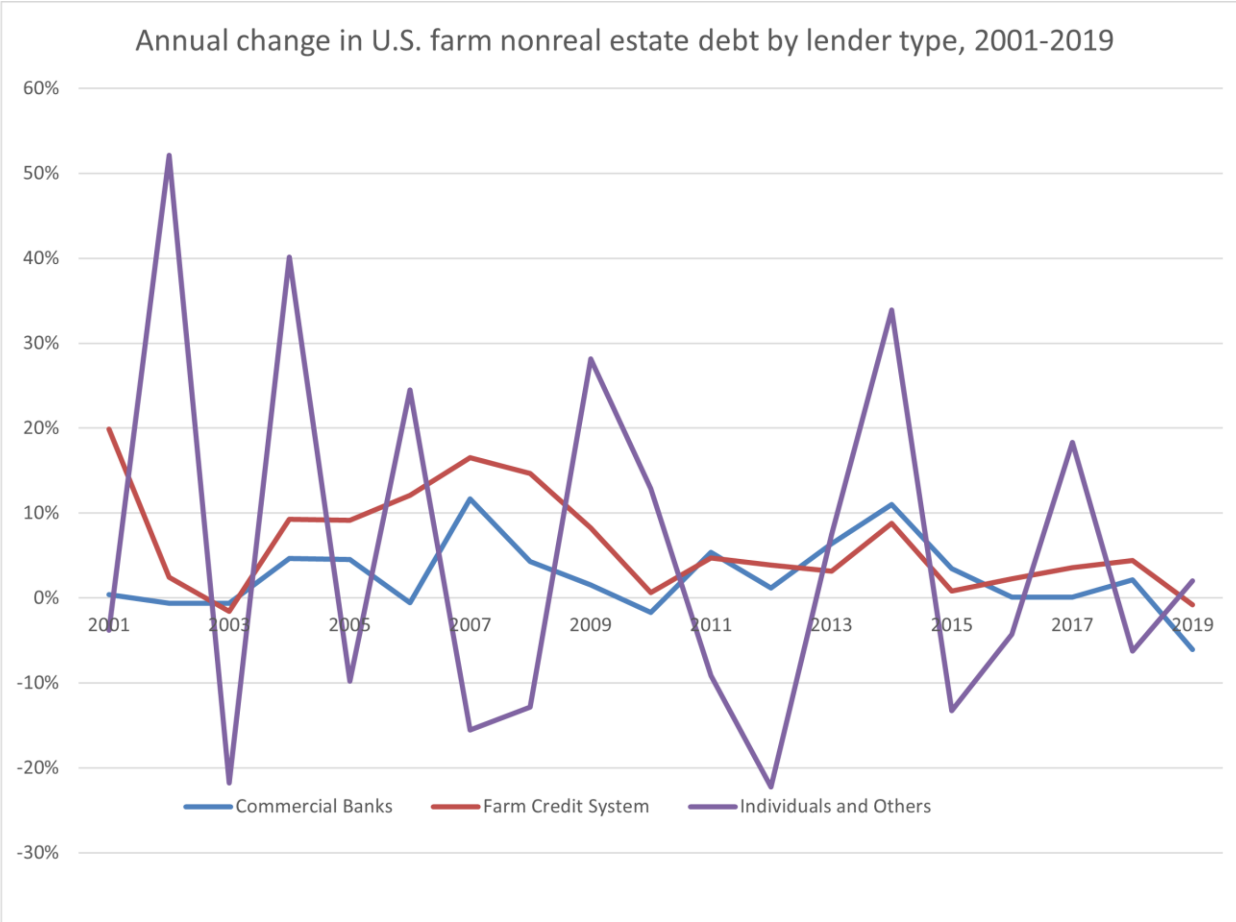
Figure 4-6 UCC Equipment Value Shares by Lender Type



Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019

With these caveats in mind, comparisons are made in trends in market share and loan/collateral growth by lender. Market shares in equipment lending (Figure 3-6) are first compared to U.S. nonreal estate debt market shares reported in Figure 3-5. USDA data suggests little growth in market share in loans from individuals and others (2000), which is very different from the growth in implement manufacturer and other nontraditional lending implied by UCC data (Figure 3-5). However, assuming that John Deere Credit is captured as a bank lender in USDA estimates, the difference is somewhat muted, although "Individuals and Others" market share (about 16%) is still substantially lower in the sector data than implied by equipment loan data (up to 40% for CNH, nontraditional and others). Another comparison is the changes in U.S. nonreal estate farm debt (Figure 3-7) to the value of new farm equipment loan collateral by year (Figure 3-8). First, Farm Credit System nonreal estate debt appears to be increasing in most years or stagnant in others (Figure 3-7), which is inconsistent with the decline in farm equipment used as collateral in other years (Figure 3-8). Likewise, commercial bank equipment collateral value was steady from 2001, with only a slight decline from 2010 (Figure 3-8). However, nonreal estate farm debt suggests a growth in commercial bank nonreal estate lending in most years (Figure 3-7). These trends may reflect growth in non-equipment lending by FCS system lenders and commercial banks. Changes in loans to individuals and others are highly volatile from year to year and do not correspond to equipment lending trends, even when JDF is classified as a commercial bank. Ultimately, these data sources are difficult to compare, as the USDA non real estate debt estimates includes additional states and loan types.

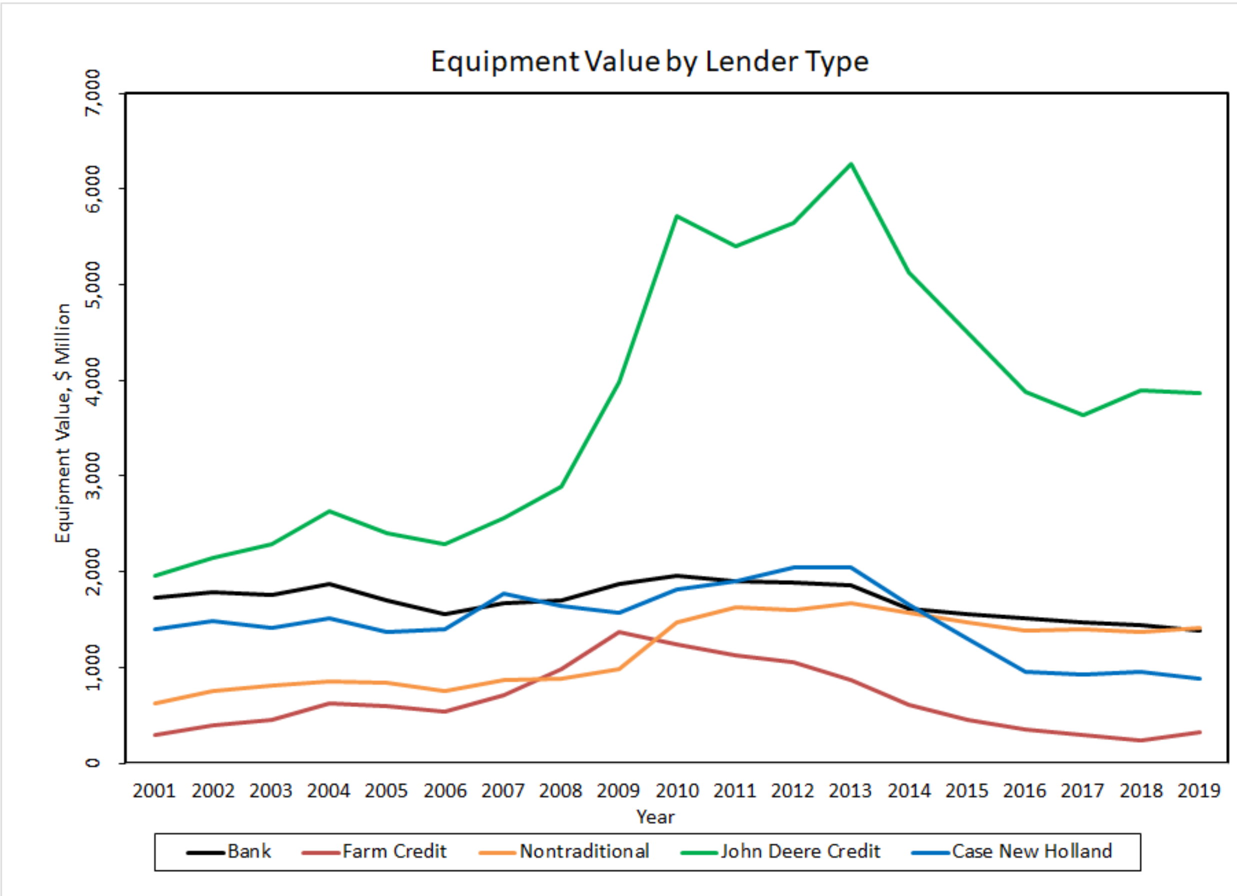
Figure 4-7 Annual Change in U.S. Farm Nonreal Estate Debt by Lender Type



Source: USDA, National Agricultural Statistics Service and Economic Research Service, 2000-2019. Farm Income and Wealth Statistics Balance Sheets

While it is evident that official U.S. farm sector nonreal estate debt estimates do not reflect the growth and predominance of nontraditional lenders in farm equipment lending across the 14 study states, stronger conclusions cannot be supported by UCC data. Focus hence turns to comparisons with ARMS data, where analysis is limitable to specific states, loan types, and loan uses. These comparisons are also useful because ARMS data is used to estimate loans from entities not subject to public reporting for farm sector debt estimates. These analyses inform the degree to which ARMS data reflects that growth and predominance of nontraditional lenders in farm equipment lending.

Figure 4-8 UCC Equipment Value by Lender Type



Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019, inflation-adjusted for 2019$

There are important distinctions between UCC data and ARMS data related to show UCC data reflects a flow of new credits and ARMS reflects the stock of credit. UCC data measures the estimated value of equipment used as collateral on liens in the year the liens are filed. Thus, equipment value only appears in the data in the year in which the lien was filed but not in subsequent years. ARMS data, on the other hand, measures the value (or stock) of outstanding farm debt each year, or the outstanding balance from less year less any repaid debt plus new debt. The relationship between equipment value recorded in UCC data and new credit is shown through the loan-to-value ratios that correspond to financing conventions of each lender type. Capturing the growth of market shares by lender type in each data set therefore becomes a useful starting point in isolating financing trends from these interpretive distinctions that obfuscate analytical clarity.

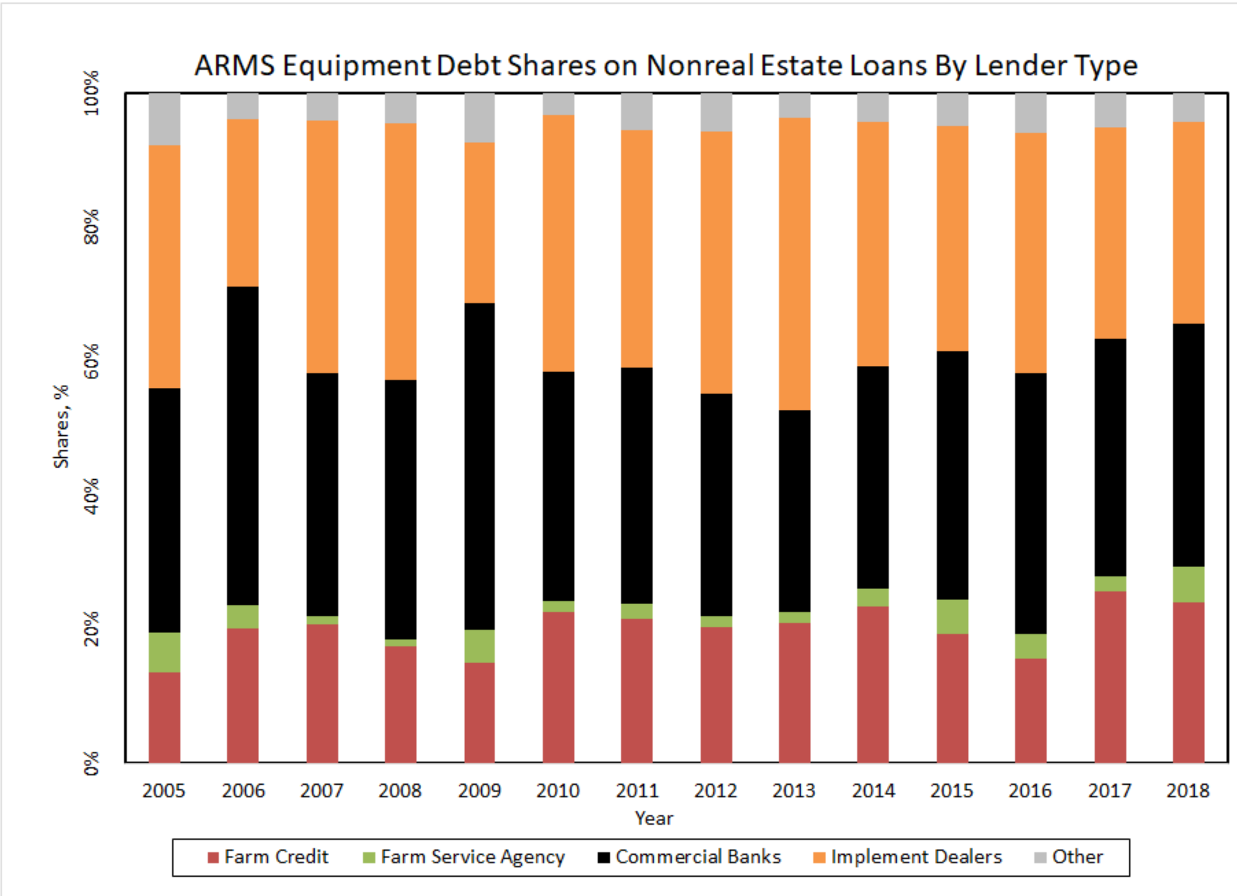
In future analyses, characteristics that contribute to the interpretive distinctions between UCC data and ARMS data may be able to be modelled in forms that recover statistical identification. Compounding interest support functions, principal down payment values, and loan durations may play important roles in aiding the interpretation of UCC equipment value data to rigorous comparisons with official statistics. Meanwhile, the trends indicated by UCC data as they compare to ARMS data are nonetheless substantive for their own fascination. Capturing the growth of market shares by lender type in each data set therefore becomes a useful starting point in isolating financing trends from these interpretive distinctions that obfuscate analytical clarity.

The data of interest comes from the ARMS' "loan table" in the Farm Debt section of ARMS, where producers typically report details on their five largest farm loans.[5] This information includes loan value, lender type, loan type, and loan use. Loan types include short term (one year or less production loans), long term nonreal estate loans, and long-term real estate loans. Loan uses include real estate, livestock, and operating expenses, machinery and equipment and debt consolidation. Data is only used from farms located in states where equipment lien data

[5] The number of loans reported varies in some years

is also available. Further, comparisons are made for states where farm equipment data is published at state level; that is, where ARMS data is sufficient for state-level estimates.[6]

Figure 4-9 ARMS Nonreal Estate Equipment Debt Shares by Lender Type



Source: USDA, National Agricultural Statistics Service and Economic Research Service, 2005-2018. Agricultural Resource Management Survey, non-real estate long term debt data (equipment use only) from 14 states.

Based on 2018 ARMS data, about 60% of long term non real estate debt in the 14-state study area is for equipment purchase. A trivial share (1% or less) of short term and real estate

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[6] These are often referred to as "ARMS states" and include Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, and Wisconsin

debt goes towards equipment purchases. Preliminary analyses consider lender types for all long term nonreal estate equipment loans in ARMS in Figure 3-9, for farms in the same states for which UCC data is available. Implement dealers had a generally expanded market share in the latter half of the study period (2010 onward) based on ARMS data, but overall trends in implement dealer lending remain indeterminate. The level of loans by others and FSA was generally small with significant fluctuation, while commercial banks held substantially more loans than FCS lenders (similar to UCC data). How John Deere Financial is treated by ARMS respondents has important implications for how the data is interpreted. While JDF originates loans similar to other nontraditional or implement dealer lenders, JDF is organized as a commercial bank that is subject to public reporting. Under the assumption that JDF is treated as a commercial bank, Farm Credit System market share is higher, commercial bank share is lower, and implement dealer/nontraditional is similar in ARMS relative to the UCC data. If it is assumed that ARMS respondents treat JDF as an implement dealer, nontraditional lending is significantly lower based on ARMS, while commercial banks are much larger. Given that nontraditional (non-JDF) market share has largely been steady in the UCC data, but implement dealer financing has shifted upward in ARMS concurrent with large growth of JDF lending in the UCC data, it is likely that ARMS implement dealer lender share to some degree picks up trends in JDF. This trend may create complications for how ARMS data is used inform farm sector debt estimates.

Chapter 5 - Conceptual and Empirical Models

4.1 Stock/Flow Theory and Conceptual Model

ARMS debt volumes reflect real-world information, including both debt levels from previous years and true new debt volumes indicated in UCC data. In the latter sense, ARMS debt volumes accumulate new debt each new year while simultaneously relinquishing existing debt from previous years. Each year in ARMS implicitly consists of terminal debt (debt being finished in payment in that period), new debt (debt being first taken out in that period), and intermediate debt (debt neither brand new nor being finished off). The gradual repayment of principal on old debt, both terminal and intermediate, may be expressed through a recursive, arithmetic sequence and translated into an explicit function.

Theoretically, these three components of ARMS estimates can be compressed into two: new debt and unpaid old debt. The extent to which old credit is outstanding can be represented as a function of the age of the debt. To begin, a linear function of debt repayment is suggested, such that old debt repayment status is proportional to the duration for which debt is taken out.

$$D_t = c_t + \sum_{i}^{n} \beta_i c_{t-i} \ , \qquad i = 1, \dots, n \tag{1}$$

Where:

$$c_t = debt\ acquired\ in\ time\ t$$

$$\beta_i = unpaid\ share\ of\ debt\ from\ i\ years\ ago$$

$$D_t = total\ debt\ in\ time\ t$$

Unpaid share parameters are larger in years more recent to time *t* and smaller in years more distantly past from time *t.* Under a linear model, these parameter values are distributed evenly between (0,1) in descending order according to the number of years for which loans are taken out. New debt has an implied unpaid share parameter value of 1. Thus, if loans are taken out for four years, for example, the parameter vector would be as follows.

$$\beta = (0.8, 0.6, 0.4, 0.2) \tag{2}$$

The linear model's parameter distribution pattern depicts the incrementally smaller volumes of debt retained in current outstanding debt as loan age recedes backwards in time from the current period. It can be represented generally through an explicit function for any loan length. Substituting this parameter function into the original equation creates a new linear expression for debt volumes.

$$\beta_i = 1 - (i)\frac{1}{n+1} \tag{3}$$

$$D_t = c_t + \sum_{i=1}^{n} \left[1 - (i)\frac{1}{n+1}\right] c_{t-i} \tag{4}$$

This expression illustrates the two components of ARMS' debt as a stock measurement in relation to UCC's measure of debt as a flow measurement. ARMS debt estimates each year are depicted in the left-hand side D_t elements, UCC aggregate values in the same year are depicted in the c_t elements, and UCC aggregate values in preceding years are depicted in the c_{t-i} elements from 1 year prior to the current year to *n* years prior.

UCC data in its rawest form is disaggregated to the lien level, whereas ARMS data at its most disaggregated estimates debt volumes for different lender types in unique states each year. As such, a state index is included. Furthermore, as UCC data shares equipment value from liens and not loan data, loan-to-value ratios may be imposed to create a more accurate depiction of the relationship between UCC and ARMS values. Variations in loan-to-value ratios across lender types are indexed by the same lender type index for ARMS debt observations. With these modifications in mind, a linear relationship between ARMS observations and UCC observations emerges.

$$D_{slt} = \sum_{j=1}^{J} \psi_l v_{sltj} + \sum_{i=1}^{n} \sum_{j=1}^{J} \left[1 - (i)\frac{1}{n+1}\right] \psi_l v_{sl(t-i)j} \tag{5}$$

Where:

$$v_{tj} = j^{th}\ equipment\ value\ observation\ for\ lender\ type\ l\ in\ state\ s\ at\ time\ t,\ \ 1, \dots, J$$

$$\psi_l = \frac{loan}{value}\ for\ lender\ type\ l$$

While the linear relationship displays the principle of decreasing retained debt values by debt age, it fails to capture a true functional form according to the amortization of loans. The true functional form will follow an amortization schedule while retaining the same conceptual structure.

$$D_t = New\ Credit + (Old\ Credit - Paid\ Principal) \quad (6)$$

Old credit appears in the equation as it would appear in the data with only the loan-to-value adjustment. New credit is represented identically to the linear expression. Paid principal is a function of old credit through amortization. There are two components to paid principal, the total value of repayment against a loan and its difference with the value of interest payments made on the loan that are not part of the original loan.

$$A = \left(\frac{r(P)}{1 - (1 + r)^{-n}}\right) \quad (7)$$

$$I = rP_k, \;\; k = 1, \dots, i - 1 \quad (8)$$

Where:

$$A = periodic\ payment\ amount$$

$$I = total\ interest\ paid$$

$$P = amount\ of\ principal$$

$$r = periodic\ interest\ rate$$

$$n = number\ of\ periods$$

An analogue to the linear expression can be made by substituting the variable definitions from the linear expression into the new expression with the amortization of old loans.

$$D_{slt} = \sum_{j=1}^{J} \psi_l v_{sltj} + \sum_{i=1}^{n} \sum_{j=1}^{J} (\psi_l v_{sl(t-i)j} - \left[\frac{r\psi_l v_{sl(t-i)j}}{1-(1+r)^{-n}}\right] - \sum_{k=1}^{i-1} r\psi_l v_{sl(t-i+k)j}) \qquad (9)$$

With each component of outstanding debt in the amortization functional form laid out, a simplification of the "true" representation of ARMS debt volumes by UCC values can be made.

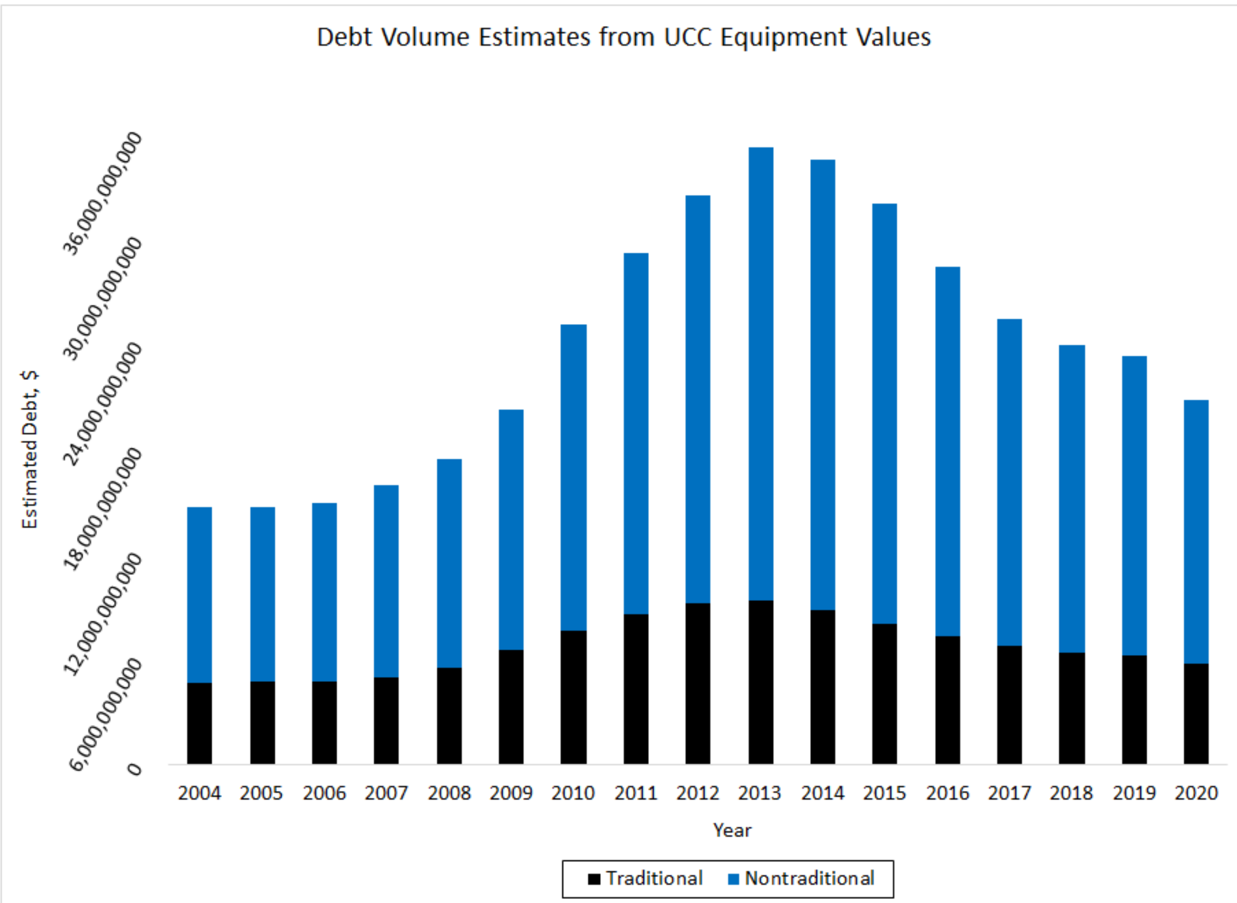
$$D_{slt} = \sum_{j=1}^{J} \psi_l v_{sltj} + \sum_{i=1}^{n} \sum_{j=1}^{J} \left[\left(1 - \frac{r}{1-(1+r)^{-n}}\right) \psi_l v_{sl(t-i)j} - \sum_{k=1}^{i-1} r\psi_l v_{sl(t-i+k)j}\right] \qquad (10)$$

Given flexibility in the identification of loan time horizons and interest rates, this "true" representation can be implemented to translate UCC equipment value data into rough measurement equivalents to ARMS debt volume data. With sufficient data, differences in loan length and interest rates may be indexable to the level of individual observations. Nevertheless, more restrictive assumptions can also offer general depictions of nonreal estate equipment debt through UCC data. For example, Figure 4-1 consists of UCC equipment value that has been transformed according to the conceptual model's debt volume representation by assuming that all loans for which liens are filed have a 5% interest rate and a length of five years. Liens are bifurcated between traditional and nontraditional secured parties, which are assigned loan-to-value ratios of 0.65 and 0.80, respectively.

As with implications from the preliminary visualizations and summary statistics examined in the initial data exploration, the indication here is that nonreal estate equipment debt has a higher annual value and nontraditionally sourced share than depicted in ARMS data.

Measurement trends between ARMS data and UCC transformed data do not pose strong indications about the performance of ARMS in capturing traditional lending, but ARMS data's reflection of UCC transformed in nontraditional lending is consistently low, ranging between 20% and 35% across the 2005-2018 period.

Figure 5-1 Nonreal Estate Equipment Debt Volume Estimates Calculated from UCC Collateral Equipment Values



Source: Equipment Data Associates data on select equipment for 14 states, 2000-2020

4.2 Empirical Models

4.2.1 ARMS as a Function of UCC data

The focus of the conceptual exercise is to show that there is some function that takes the lien collateral values of the UCC data set and transforms them into aggregates metrically comparable to the outstanding debt observed in the ARMS data. This function is represented as f_t, where $f_0 = 0$ such that d_0, being credit taken out zero years ago, is not transformed. Thus, the *t* indexes which function amortizes the collateral value with respect to the present period.

$$D_t = \sum_{t=0}^{n} f_t(d_t) \tag{11}$$

The function amortizing lien value must first be adjusted for loan-to-value ratio to represent the amount of credit taken out at the beginning of the loan. The two major categories of lender type, traditional and nontraditional, are the major points of demarcation between conventional loan-to-value ratios.

True representation:

$$D_t = \sum_{0}^{n} f_t(d_{Tt} + d_{mt}) \tag{12}$$

The "true" representation, dubbed so because the formula draws upon the UCC data set, which is a population data set if one makes a few very modest assumptions, also has a "true" function, in the theoretical sense, that accurately transforms the true new credit into a true value of outstanding debt. For the purposes of this analysis, the true form of this function is not essential, but it is important to consider the major components of the function described in the previous section, chiefly surrounding the question of how debt taken out in previous time periods is represented in outstanding debt in the time period of interest.

ARMS takes a different approach. The estimation of outstanding debt is done via survey, which in effect serves as the estimation "function". The true function of the UCC transforms adjusted lien values to outstanding debt, while the "function" for ARMS is the transformation of survey responses into outstanding debt data.

Observed representation:

$$D_{ARMS} = \sum_{0}^{n} g_t(d_{Tt} + d_{mt}) \tag{13}$$

The final metric is the same –outstanding debt— and the UCC lien values are true variables that are operated upon to estimate that final metric. Thus, if the outstanding debt estimated in ARMS is accurate, it will reflect the adjusted lien values that the final metric is supposedly based upon. The question then becomes: to what extent do ARMS nonreal estate equipment debt data reflect the credit patterns of the UCC data; and, more specifically: how do ARMS nonreal estate equipment debt data respond when there are changes in credit volumes according to lender category? In other words, does ARMS become less reflective of true debt (proxied in UCC data) when nontraditional lending takes a larger share of the market?

Model structure:

$$ARMS_{slt} = \beta_0 + \beta_1 d_{slt} + controls \tag{14}$$

Where d_{slt} refers to equipment values from the UCC database organized by state (s), time period (t), and lender category (l).

The parameter, β_1, estimates how much of ARMS debt estimates can be explained through UCC adjusted lien values. This analysis, however, need not exist in a vacuum. Various combinations of variables can be incorporated to see how various factors of interest do or do not play into the composition of ARMS estimates. For example, a dummy for nontraditional lender interacted with UCC equipment values, hypothetically, would have a negative parameter value, showing that ARMS has less explanatory power about true debt if debt is nontraditionally sourced as if it is traditionally sourced.

The measurement of interest is the extent to which ARMS debt volume estimates are captured by UCC equipment values under the traditional and nontraditional lending paradigms, respectively. ARMS debt volumes and UCC equipment values have important distinctions to consider in modelling their relationship. ARMS debt volumes measure a year's level of outstanding debt, whereas UCC equipment values measure the total value of equipment for which debt is acquired in that year. Thus, the ARMS variable may be viewed as a stock variable, and the UCC variable a flow variable. Equipment value, as it relates to outstanding debt, only measures the level of equipment value that flows into outstanding debt. Rates of repayment are unobserved, but their general structures are hypothesized in the conceptual modelling section.

As the relationship between the flow of equipment value and the stock of outstanding debt is defined linearly, a linear estimation of ARMS debt by UCC equipment value is appropriate, using ordinary least squares. A baseline model is created to identify the fundamental elements of UCC equipment value's relationship to ARMS debt with three key terms in addition to UCC equipment value itself: an indicator of nontraditional lending, a time trend, and an interaction term between UCC equipment value and nontraditional lender type dummy variable.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \varepsilon_{slt} \quad (15)$$

Where:

$$\eta_{slt} = [1 | l = \text{nontraditional}, 0]$$

$$trend_{slt} = t$$

The EQTVALUE variable measures how ARMS debt data are explained by UCC data as a proxy for new equipment debt. The trend variable captures the independent trajectory of ARMS debt volume estimation over time, and the interaction term measures how UCC equipment value's explanation of ARMS debt estimation differs whether loans are traditionally or nontraditionally sourced.

Because UCC equipment value is presented as the true, population representation of agricultural equipment value, the result of the interaction term is the result specifically indicative of whether the empirical hypothesis is rejected or fails to be rejected. If the sign of the interaction term is negative, the estimate statistically significant, and the magnitude of the parameter reasonably financially meaningful, the null hypothesis will be rejected. If not, the null hypothesis will fail to be rejected.

A variant of this model includes a nuanced form of the regressand. ARMS data can be partitioned into three main components for each observation relative to other observations in the time series: new debt in the current period, less debt that has been repaid since the preceding period (dubbed "old debt"), and debt that is neither repaid since the previous period nor acquired in the current period (retained debt). In the current period, only new debt and retained debt are observed, as old debt is dropped after the previous period. In the previous period, only old debt and retained debt are observed, as new debt is not acquired until the current period.

$$ARMS_t = new\ debt + retained\ debt \tag{16}$$

$$ARMS_{t-1} = old\ debt + retained\ debt \tag{17}$$

The difference between debt in the current period and debt in the previous period can be expressed as:

$$ARMS_t - ARMS_{t-1} = new\ debt - old\ debt \tag{18}$$

The difference between "new debt" and "old debt" creates a version of a flow variable, though with a key distinction from the equipment value flow variable, namely the outflow of debt from ARMS estimates through repayment that is not observed in UCC data. This reconfiguration augments the interpretation of the time trend variable as it relates to the difference between ARMS estimates over time, capturing the trend in the relationship between "new debt" and "old debt" from the beginning to the end of the time series. Debt acquisition and repayment relationship patterns may not persist consistently across time and state, lending to the possibility of noisier results from models using the differenced dependent variable. The variant regression can be expressed as follows:

$$\Delta ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \varepsilon_{slt} \quad (19)$$

Various configurations of the baseline models affect the strength of the interpretations of each variable. Including an interaction term between UCC equipment value and a nontraditional dummy implies a theoretical model where the nontraditional dummy is estimated independently from the interaction term in a model without the interaction term, in addition to the model where both the independent nontraditional dummy and the interaction term are included.

The interaction term between the nontraditional dummy and UCC equipment value captures the reflection of new nontraditional debt between UCC data and ARMS data, implicitly delineating new debt from old debt. The nontraditional dummy and the time trend make no such distinctions. Thus, as the nontraditional dummy indicates the difference in ARMS debt between nontraditional and traditional sources, it captures debt volume changes comprised of both new debt and old debt. Similarly, as the time trend captures the yearly trends in ARMS debt, it captures trends in both new debt and old debt. Where the nontraditional dummy and time trend afford occasion for the interaction term to gain greater nuance to its interpretation, they also afford occasion for the interpretation to be weaker than an unnuanced interpretation. Furthermore, excluding the nontraditional dummy from models where the interaction term is included imposes the assumption of equivalent average debt values between traditional and nontraditional sources, compromising the accuracy of the empirical results.

4.2.2 Empirical Modelling

The approach to the empirical model undergoes consecutive iterations of progressive degrees of complexity. A rudimentary preliminary model is posed to highlight the key observable relationship between ARMS debt data and UCC lien data.

Baseline Model:

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \varepsilon_{slt} \tag{20}$$

An additional model is introduced to explain the relationship embedded within ARMS data between the average values of traditionally and nontraditionally sourced loans through a dummy variable. This model also incorporates a time trend variable to capture the pattern of year-to-year debt estimate differences over time.

Nontraditional Binary Model:

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \varepsilon_{slt} \tag{21}$$

An alternative to the nontraditional binary model adds an interaction term between the nontraditional dummy and UCC equipment value. Whereas the nontraditional binary model follows the principle of the empirical hypothesis, a regression with the interaction term in it conforms to the empirical hypothesis more closely. This model is the preferred model of the study to identify any discrepancies between ARMS nontraditional equipment debt estimates and true nontraditional equipment debt, indicated by UCC equipment values.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \varepsilon_{slt} \quad (22)$$

These three regressions comprise the system of models whose graduated levels of variable inclusion lead to the estimation of the combined model with state fixed effects. This model includes all the variables included in the three preceding models together in a single regression with the addition of state fixed effects for all states except Wisconsin.

UCC equipment value is organized by state by virtue of being a population of lien filings. ARMS, too, is organized by states through the collection of states selected for use in estimating state-level data. Even data from states not selected for state-level data publication are included in creating national ARMS debt level estimates. ARMS estimates are made from aggregating state-level data together, so to include state-level variables in ARMS regressions is empirically appropriate. While it is not the preferred model, this model serves illustrative purposes in investigating how variations in lending practices between states impact the interpretations of the variables of interest.

Combined Model with State Fixed Effects:

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) \quad (23)$$
$$+\beta_5 IA_{slt} + \beta_6 IN_{slt} + \beta_7 IL_{slt} + \beta_8 KS_{slt} + \beta_9 MI_{slt} + \beta_{10} MO_{slt} + \beta_{11} MN_{slt} + \beta_{12} ND_{slt} +$$
$$\beta_{13} NE_{slt} + \beta_{14} OH_{slt} + \beta_{15} OK_{slt} + \beta_{16} SD_{slt} + \beta_{17} TX_{slt} + \varepsilon_{slt}$$

Where:

$$IA_{slt} = [1|s = IA, 0]$$

$$IN_{slt} = [1|s = IN, 0]$$

$$IL_{slt} = [1|s = IL, 0]$$

$$KS_{slt} = [1|s = KS, 0]$$

$$MI_{slt} = [1|s = MI, 0]$$

$$MO_{slt} = [1|s = MO, 0]$$

$$MN_{slt} = [1|s = MN, 0]$$

$$ND_{slt} = [1|s = ND, 0]$$

$$NE_{slt} = [1|s = NE, 0]$$

$$OH_{slt} = [1|s = OH, 0]$$

$$OK_{slt} = [1|s = OK, 0]$$

$$SD_{slt} = [1|s = SD, 0]$$

$$TX_{slt} = [1|s = TX, 0]$$

After the establishment of the preferred model, modifications are made with additional variables to provide robustness checks. The first of these modified regressions is unique from the others, as it includes a dummy variable recognizing data elements after 2008-2009 (this could be a 2011 dummy with some easy adjustments) and before 2015, a period in which both financial and commodity market dynamics underwent dramatic changes nationwide. The inclusion of this regime dummy is to deliberately capture the effect of major shifts in ARMS and UCC data values gleaned from the macroeconomic context and reinforced by each data set's summary statistics. Multicollinearity problems arise between this dummy variable on financial market regimes and the time trend variable from the baseline model, so for this model only (and all ancillary models with the regime dummy) the time trend variable is excluded. The concentrated focus of the regime dummy on this period of marked debt growth is expected to return a coefficient of strong statistical significance and a magnitude greater than the time trend variable.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 \rho_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \varepsilon_{slt} \quad (24)$$

Where:

$$\rho_{slt} = [1|13 > t \geq 5, 0]$$

Two other modified regressions remove the regime dummy in favor of the time trend variable and include triple interaction terms to examine specific effects. In the first case, the triple interaction term is between the existing interaction term of UCC equipment value and the nontraditional dummy variable, and another dummy variable indicating if the debt is taken out from one of the four largest crop-producing states that appear in the data sets. These four states are Iowa, Illinois, Minnesota, and Nebraska which, along with California (not in the data sets) round out the top five crop-producing states in the United States. It is notable also that these four states produce similar crop varieties, reflecting comparable equipment purchasing patterns that justify their common grouping in the dummy variable. The measurement of interest with the triple interaction term is how the reflection of nontraditionally sourced UCC equipment values by ARMS differs based on the regional intensity of equipment use on cropland. If the estimates of this effect return significant, the expectation is that ARMS reflects nontraditionally sourced

UCC equipment value less in the region of crop-intensive states than in other states, meaning a negative parameter value.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \beta_5 (EQTVALUE_{slt} * \eta_{slt} * \tau_{slt}) + \varepsilon_{slt} \quad (25)$$

Where:

$$\tau_{slt} = [1|s = IA, IL, MN, or\ NE, 0]$$

In the second case, the triple interaction term is between the existing interaction term in the combined model and the time trend variable. The measurement of interest in this model is how the reflection of nontraditionally sourced UCC equipment values by ARMS changes over time. If this estimate returns significant, the expectation is that ARMS nontraditional debt estimation accuracy deteriorates over time as overall debt grows: the estimate would be negative.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \beta_5 (EQTVALUE_{slt} * \eta_{slt} * trend_{slt}) + \varepsilon_{slt} \quad (26)$$

The fourth supplementary model to the combined model is a simplification of the time trend triple interaction model. Rather than measure the change in ARMS' reflection of nontraditional UCC values over time, this model includes an interaction term that measures the change in ARMS' depiction of nontraditional lending over time. The interaction is between the time trend variable and the nontraditional dummy variable. A statistically significant estimate would suggest that ARMS estimates either a significantly higher or lower level of nontraditional debt over time, depending on the parameter's sign. A lack of statistical significance could cause the estimate to have an equally interesting interpretation: ARMS estimates no significant change in nontraditional debt volumes over time.

$$ARMS_{stl} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \beta_5 (\eta_{slt} * trend_{slt}) + \varepsilon_{slt} \quad (27)$$

Additional models address the question of ARMS debt volume's reflection of UCC equipment value according to loan origination period. If UCC equipment value is a valid proxy for new equipment debt, then ARMS debt data should be expected to partially house new UCC equipment value from past periods within an outstanding debt balance for a current year. The accompanying hypothesis to these amended models is that ARMS data are less reflective of nontraditionally sourced equipment loans taken out in periods prior to the period for which debt volumes are estimated.

These models are based on the combined model, but in addition to a UCC equipment value variable and its interaction with a nontraditional dummy include various arrangements of lagged UCC equipment values. The first of these lagged models adds only a one-year lagged equipment value variable and an interaction between the nontraditional dummy and lagged equipment value. This model's additions are implemented to capture the extent to which equipment value on loans taken out one year before the ARMS debt reporting year are reflected in that year's debt value, and the extent to which that effect differs between traditional or nontraditional debt, respectively. It is expected that the lagged equipment value variable be of a similar order of magnitude as that of the equipment value variable from previous models, though slightly lower, and that the added interaction have a negative coefficient to match the interaction term in previous models.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) \\ + \beta_5 EQTVALUE_{slt-1} + \beta_6 (EQTVALUE_{slt-1} * \eta_{slt}) + \varepsilon_{slt} \quad (28)$$

The second lagged model adds only a two-year lagged equipment value variable and an interaction between the nontraditional dummy and lagged equipment value. This model's additions are implemented to capture the extent to which equipment value on loans taken out two years before the ARMS debt reporting year are reflected in that year's debt value, and the extent to which that effect differs between traditional or nontraditional debt, respectively. The effect of these additions is anticipated to be similar to those of the one-year lagged equipment value model, but with a smaller coefficient magnitude in the lagged equipment value variable.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) \\ + \beta_5 EQTVALUE_{slt-2} + \beta_6 (EQTVALUE_{slt-2} * \eta_{slt}) + \varepsilon_{slt} \quad (29)$$

The third lagged model incorporates both the one-year and two-year lagged equipment value variables along with their corresponding interaction terms. This model's additions are implemented to capture the extent to which equipment value on loans taken out both one year and two years before the ARMS debt reporting year are reflected in that year's debt value, and the extent to which those effects differ between traditional or nontraditional debt, respectively. Because of the inclusion of multiple lagged equipment values to predict debt values of previous periods undergoing constant amortization, it is possible that the expected effects indicated from the two previous models encounter noisy or unintuitive results in its added coefficients, though results consistent with the general impressions garnered from previous models is expected to remain.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \beta_5 EQTVALUE_{slt-1} + \beta_6 (EQTVALUE_{slt-1} * \eta_{slt}) + \beta_5 EQTVALUE_{slt-2} + \beta_6 (EQTVALUE_{slt-2} * \eta_{slt}) + \varepsilon_{slt} \quad (30)$$

The fourth lagged model adds both lagged equipment value variables and interaction terms as well as state fixed effects for all states in the data set except Wisconsin. More than providing insight into the effects of any particular state, the inclusion of these state fixed effects is foremostly for the purpose of confirming the generality of the effects estimated from each of the previous models.

$$ARMS_{slt} = \beta_0 + \beta_1 EQTVALUE_{slt} + \beta_2 \eta_{slt} + \beta_3 trend_{slt} + \beta_4 (EQTVALUE_{slt} * \eta_{slt}) + \beta_5 EQTVALUE_{slt-1} + \beta_6 (EQTVALUE_{slt-1} * \eta_{slt}) + \beta_5 EQTVALUE_{slt-2} + \beta_6 (EQTVALUE_{slt-2} * \eta_{slt}) + \beta_7 IA_{slt} + \beta_8 IN_{slt} + \beta_9 IL_{slt} + \beta_{10} KS_{slt} + \beta_{11} MI_{slt} + \beta_{12} MO_{slt} + \beta_{13} MN_{slt} + \beta_{14} ND_{slt} + \beta_{15} NE_{slt} + \beta_{16} OH_{slt} + \beta_{17} OK_{slt} + \beta_{18} SD_{slt} + \beta_{19} TX_{slt} + \varepsilon_{slt} \quad (31)$$

Chapter 6 - Results and Analysis

5.1 Results and Analysis

Results are organized into three tables with results from four regressions apiece. Results from the primary models appear in Table 5-1 and robustness check results in Table 5-2. Discussion follows with interpretations of key parameters and how their results compare to each model's hypotheses. Results from models with lagged UCC equipment value variables then appear in Table 5-3 and receive similar discussion.

Overall, consistency in parameter sign, magnitude, and to a more modest extent, significance, persisted across the models. Many of the results confirmed the hypotheses posed from the discussion on model constructions. Exceptions, however, arose in some instances, namely among the regime dummy capturing ARMS debt from the 2009-2014 period and the equipment value variable and its corresponding interaction term among the models including lagged equipment value.

Perhaps one the most critical of hypothesis confirmations was gathered from the nontraditional dummy, which indicated that less equipment debt is nontraditionally sourced than traditionally sourced. This is sharply opposite to implications from UCC data and market intuition. The interaction term between UCC equipment value and the nontraditional dummy was also of import, modestly suggesting that ARMS reflects nontraditional equipment value less strongly than traditional equipment value.

Table 6-1 Regression Results for Primary Econometric Models of ARMS Nonreal Estate Equipment Debt Data for 2005 to 2018[7]

	Dependent Variable ($ARMS_{slt}$, \$)			
Variable	Baseline Model	Nontraditional Dummy Model	Combined Model	Combined Model, State FE
Intercept	355.1*** (27.47)	167.3*** (31.05)	107.1* (46.73)	204.8*** (55.73)
Equipment Value	0.2097*** (0.05401)	0.3753*** (0.04892)	0.6074*** (0.1434)	0.05042 (0.1579)
Nontrad. Binary		-298.9*** (29.22)	-221.6*** (53.56)	-176.2*** (48.23)
Time Trend		35.93*** (3.212)	35.81*** (3.205)	40.13*** (2.779)
Nontrad.* Equip. Value			-0.2613. (0.1519)	-0.05043 (0.1490)
RMSE	323.2	252.5	251.9	214.8
Adjusted R^2	0.03473	0.4108	0.4138	0.5735
Observations	392	392	392	392

Significance codes: '***'→ 0.001, '**'→ 0.01, '*'→ 0.05, '.'→ 0.1
The results of each amended regression are enumerated in Table 5-2.

[7] Intercept, nontraditional binary, time trend, RMSE in terms of millions

Table 6-2 Regression Results for Amended Econometric Models of ARMS Nonreal Estate Equipment Debt Data for 2005 to 2018[8]

	Dependent Variable ($ARMS_{slt}$, \$)			
Variable	Regime Dummy Model	Region Triple Interaction Model	Time Triple Interact Model	ARMS Averages Trend Model
Intercept	341.0*** (47.87)	103.6* (46.80)	81.48. (49.30)	22.94 (50.04)
Equipment Value	0.8126*** (0.1732)	0.6056*** (0.1434)	0.5936*** (0.1434)	0.5618*** (0.1409)
Nontraditional Dummy	-231.6*** (61.60)	-195.9*** (57.87)	-227.8*** (53.59)	-56.33 (65.81)
Regime Dummy	-45.21 (32.42)			
Time Trend		36.34*** (3.234)	39.71*** (4.022)	48.63*** (4.399)
Nontrad. * Equip. Value	-0.3510* (0.1782)	-0.3439* (0.1674)	-0.09521 (0.1838)	-0.1820 (0.1500)
Region Triple Interaction		0.07965 (0.06814)		
Trend Triple Interaction			-0.01830 (0.01145)	
Nontrad. * Time Trend				-26.13*** (6.280)
RMSE	288.9	251.7	251.3	246.7
Adjusted R^2	0.2285	0.4143	0.4161	0.4375
Observations	392	392	392	392

Significance codes: '***'→ 0.001, '**'→ 0.01, '*'→ 0.05, '.'→ 0.1

[8] Intercept, nontraditional binary, regime dummy, time trend, nontraditional time trend interaction, RMSE in terms of millions

The equipment value parameter has an important interpretation because loan-to-value ratio-adjusted equipment value is a conceptual component of ARMS debt volumes. In theory, the entirety of adjusted equipment value is nested within outstanding debt changes as new debt in the current period. The equipment value parameter, then, operates as an estimate of the proportion of new debt, as depicted in UCC data, that is reflected in ARMS. It follows that if ARMS reflects new debt from UCC data accurately the parameter will have a value that is significantly large in the range [0,1], roughly close to a conventional loan-to-value ratio while considering potential noise created by unobserved variables nested in the regressand.

This indicates the importance of including the interaction term between UCC equipment value and the nontraditional dummy as a unique measure of nontraditional debt. In each of the three models peripheral to the combined model, the estimate for the UCC equipment value variable suggests a relatively lower level of reflection in ARMS [~0.21,~0.50] than in the combined model. Each model represented among tables 5-1 and 5-2 that includes the interaction term suggests higher levels of UCC equipment value reflected in ARMS [~0.50,~0.81].

The change in value of the UCC equipment value parameter with the inclusion of the interaction term corresponds with the interaction term's own interpretation. The interaction term measures how ARMS' reflection of UCC equipment value changes if the equipment is nontraditionally sourced. While it would be too rudimentary to describe the interaction term parameter as a proportion, it is expectable that it is scaled similarly to the UCC equipment value parameter. With a magnitude range of [~(-0.26),~(-0.35)] from the models in tables 5-1 and 5-2 where the interaction term is included and its estimate significant to a reportable extent, it is safe to assert that the variable's measurement is financially meaningful, statistical significance notwithstanding. The parameter's magnitude in the combined model is ~(-0.26).

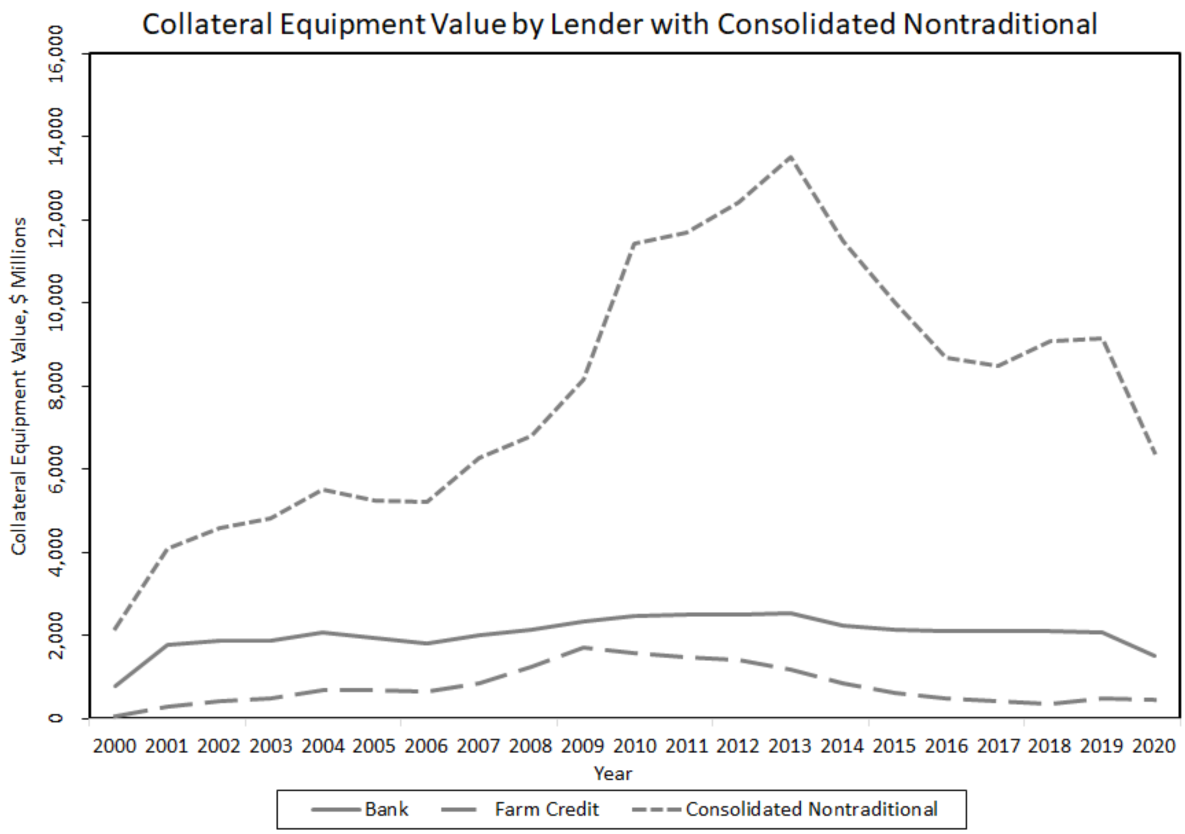
In other words, ARMS' estimation of new debt from nontraditional sources is less accurate that its estimation of new debt from traditional sources by a magnitude of ~0.26. For discussion's sake, though it is an interpretive overreach and not to be taken as an empirical conclusion, this is akin to saying that for every dollar of nontraditionally sourced new debt that is truly taken out, ARMS estimates twenty-six cents less of it than if the debt were traditionally sourced. Thus, excluding the nontraditional dummy/equipment value interaction term from the regression reduces the estimation of the reflection of UCC data in ARMS specifically in the domain of nontraditionally sourced debt.

This interaction term's interpretation has implications that reverberate throughout the whole scope of ARMS data. ARMS estimates that agricultural equipment's share of total farm debt was roughly 12% in 2018. ARMS' weaker relative performance in nontraditional debt estimation implies that overall equipment debt estimates are lower than true equipment debt volumes. Equipment debt in that case constitutes a larger share of overall debt than ARMS estimates. This effect is reflective of the summary statistics and preliminary visualizations of the differences between ARMS' and UCC's depictions of debt shares held by nontraditional lenders.

The nontraditional dummy parameter implies a similar interpretation without the same rigor of empirical verification. It depicts how ARMS debt volumes differ between nontraditional and traditional debt. A negative and significant coefficient means that ARMS' estimation of nontraditional debt value is lower than that of traditional debt. While the coefficient itself says nothing specific about UCC data's reflection in ARMS, it contradicts the visual implication of UCC data that across time and between states equipment value from debt held by nontraditional lenders is consistently much greater than by traditional lenders. UCC data show that equipment value on liens filed with nontraditional lenders comprise between 65% and 80% of total equipment value from 2001 to 2019, with 20% to 35% held by traditional lenders by default. This is likely an underestimation of the share of debt held by nontraditional lenders due to differences in loan-to-value ratios between traditional and nontraditional lenders. The depiction of nontraditional lenders' debt share of total agricultural equipment debt from the ARMS nontraditional dummy variable is inverse of UCC data's depiction.

A similar interpretation, though less disconcerting for ARMS estimates, arises for the nontraditional dummy and time trend interaction term as for the nontraditional dummy. The negative coefficient and statistical significance in that interaction term indicates that ARMS predicts a divergence in the relative volumes of traditional and nontraditional debt, specifically that the relative volume of nontraditional debt decreases with time. UCC data suggests that the growth in overall debt for the period 2001-2019 is primarily concentrated in the growth of nontraditionally sourced debt. This interpretation is reinforced by the discrepancy in sign and concordance of significance between the time trend and the nontraditional/time trend interaction term.

Figure 6-1 UCC Collateral Equipment Value by Lender Type[9]



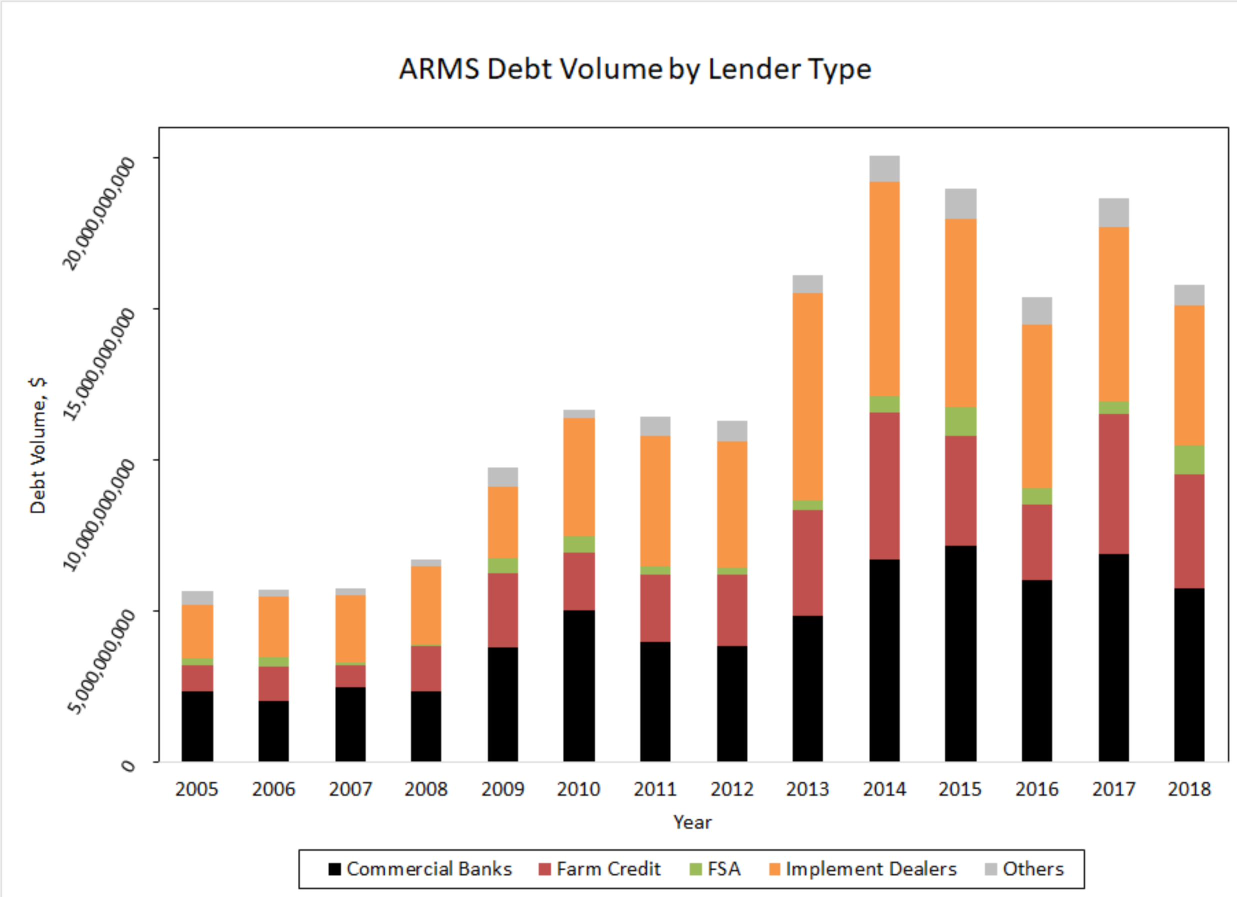
Source: Equipment Data Associates data on select equipment for 14 states, 2000-2020

The interpretations for the time trend variable and the financial market regime dummy go hand in hand. While the time trend parameter estimates in each model display strong statistical significance, they capture only the linear trend of ARMS debt volumes over time. UCC data indicate that the 2009 to 2014 period represents a period of unique growth in equipment debt, but the negative sign and lack of significance in the regime dummy coefficient indicate that this is

[9] "Consolidated Nontraditional" refers to John Deere Financial, Case New Holland, and all other lenders in the nontraditional category

not an effect strongly observed in ARMS debt data. Likely, this is attributable to relatively lower debt volumes depicted in the years 2009 through 2012 and no apparent alleviation of higher debt volumes from 2015 to 2018. It is possible, therefore, that the highest debt volumes reported in ARMS from 2013 to 2018 do eventually detect higher levels of new debt acquisition, but only from consecutive years of persistent debt accumulation patterns. Thus, the expected sign and magnitude of the regime dummy does not arise in the models where ARMS debt volume is left unaltered, but where it is differenced with the preceding years debt volume to depict changes in ARMS values. Tables where ARMS values are treated as "flow" variables in this way are enumerated in Appendix A.

Figure 6-2 ARMS Nonreal Estate Equipment Debt Volume by Lender Type



Source: USDA, National Agricultural Statistics Service and Economic Research Service, 2005-2018. Agricultural Resource Management Survey, non-real estate long term debt data (equipment use only) from 14 states.

Although the coefficient of the triple interaction term between UCC equipment value, the nontraditional dummy, and the region dummy has the sign expected from its inclusion in the model, the model does not return statistically significant results. This indicates that ARMS' reflection of nontraditional UCC equipment value is not significantly different between larger and smaller crop-producing states. Had statistical significance been observed, the sign of the coefficient would suggest that ARMS' reflection of nontraditional UCC equipment value is weaker in the larger states than in the smaller states. This would pose a follow-up question in subsequent studies on if the difference in ARMS' performance between lender types is negatively affected by higher levels of equipment debt. As it is, the performance of ARMS' nontraditional debt depiction is not uniquely weaker than nontraditional UCC equipment value according to region, but only generally. The diminished statistical significance of the baseline model's interaction term in the region triple interaction model owes itself to this conclusion.

The coefficient of the triple interaction term between UCC equipment value, the nontraditional dummy, and the time trend follows a similar interpretation. The coefficient lacks statistical significance and therefore fails to make its result conclusive. In short, ARMS' weaker performance of expressing nontraditional UCC equipment value compared to traditional is a general phenomenon across time and regions, not uniquely evident in certain times and places over others.

The theoretical structure of the relationship between periodic differences in ARMS stock data and UCC flow data is represented conceptually through the acquisition of new debt and the repayment of old debt. The arrangements of the empirical models whose results appear in tables 5-1 and 5-2 do not include data on debt acquired from previous periods; they constitute an unobserved component of ARMS debt estimate differences. The measurement of this component seems to appear in the intercepts of the regressions, indicated by the consistency in the sign, magnitude, and the significance of the intercepts.

Unobserved variables often demand instrumental variables, proxies, or other empirical methods to account for them. Without these methods, regressions may be characterized by omitted variable bias. A natural consequence of these methods is the loss of interpretation to the intercept and the error term. Seldom do regression intercepts contain unique interpretations, but in this case the intercept partially behaves as a parameter of the unobserved variable, the measurement of debt acquired in previous periods (old debt).

It is unlikely that old debt's unobserved property generates omitted variable bias among other parameter estimates because of consistency in measurement between old and new debt. All old debt expressed in an ARMS debt datum is a component of new debt from a previous ARMS year, of which UCC data from that previous year is a proxy. Old debt can be conceptualized as a theoretical dummy vector where every element in the vector has a value of 1, and the intercept is that variable's coefficient. Variations in old debt volumes are partially embedded in the value of the intercept, just as variations in new debt acquisition are embedded in the UCC equipment value parameter.

An important consideration in the interpretation of the intercept is the static nature of the intercept's estimate juxtaposed with the implied variations in old debt levels over time. As changes in ARMS debt data varies over time, these variations exist both in new and old debt. Depending on loan length, loan value from a past year of uniquely high debt acquisition may affect outstanding debt values if current-period debt acquisition is not also uniquely high. While loan values from a high-volume past year will be affected in all years where unpaid principal from that past year remains, amortization in true debt may cause unpaid principal from high-volume past years to be disproportionate from year to year.

The time trend variable, uncoupled from UCC data variable interactions, averages out the potential for old debt volume disproportionalities without regard for the time period in which debt is acquired or the lender category into which debt falls. Nevertheless, additional steps can be taken to control for old debt variations unaccounted for in the collection of primary models. The four models incorporating lagged UCC equipment values empirically evaluate the debt reporting relationships between lender types according to debt age. The results of these four models are enumerated in Table 5-3.

Table 6-3 Regression Results for Econometric Models of ARMS Nonreal Estate Equipment Debt Data with Lags for 2005 to 2018[10]

	Dependent Variable ($ARMS_{slt}$, \$)			
Variable	1-Year Lag Model	2-Year Lag Model	1-Year and 2-Year Lag Model	Combined Model, State FE
Intercept	114.2* (52.82)	112.1. (63.05)	121.7. (64.10)	254.2*** (70.61)
Equipment Value	-0.9155* (0.4517)	-0.3178 (0.2976)	-0.7452 (0.5359)	-1.351** (0.4.751)
Nontrad. Binary	-228.8*** (56.86)	-236.0*** (62.15)	-240.2*** (62.93)	-190.4** (57.54)
Time Trend	32.08*** (3.862)	30.55*** (4.779)	30.31*** (4.803)	35.22*** (4.148)
Nontrad.* Equip. Value	0.9729* (0.4701)	0.5194. (0.3031)	0.8365 (0.5576)	1.072* (0.4850)
1-Year Lagged Equip. Value	1.629*** (0.4475)		0.8129 (0.8404)	1.447* (0.7270)
Nontrad.* 1-Yr. Lagged Value	-1.297** (0.4631)		-0.5991 (0.8895)	-0.9563 (0.7645)
2-Year Lagged Equip. Value		1.117*** (0.2898)	0.7041 (0.5130)	-0.003961 (0.4555)
Nontrad.* 2-Yr. Lagged Value		-0.9020** (0.2914)	-0.5978 (0.5375)	-0.1992 (0.4688)
RMSE	252.2	254.6	254.8	217.6
Adjusted R^2	0.4237	0.4109	0.4100	0.5698
Observations	364	336	336	336

Significance codes: '***'→ 0.001, '**'→ 0.01, '*'→ 0.05, '.'→ 0.1

[10] Intercept, nontraditional binary, time trend, RMSE in terms of millions

The results of the regressions including lagged equipment values cast aspersions on focused interpretations of the coefficients. The equipment value parameter has a negative coefficient in each model, which is unintuitive considering the established relationship between equipment value and ARMS debt from previous models. Supplementary to this notion, several of the coefficients for lagged equipment value exceed 1. This implies that ARMS debt values contain over 100% of equipment value lent in a previous year, which is unrealistic. In theory, the coefficient of one-year lagged equipment value is close to a loan-to-value ratio but trimmed slightly due to the partial amortization of debt acquired in the previous year. The theoretical coefficient of two-year lagged equipment value follows the same intuition with a slightly larger amortization trim. The coefficient trim is exhibited between the coefficients of the one-year and two-year lagged models' coefficients, both in lagged equipment value and the nontraditional lagged equipment value interactions, but the coefficient magnitudes indicate confusing relationships with the current-year equipment value and interaction variables.

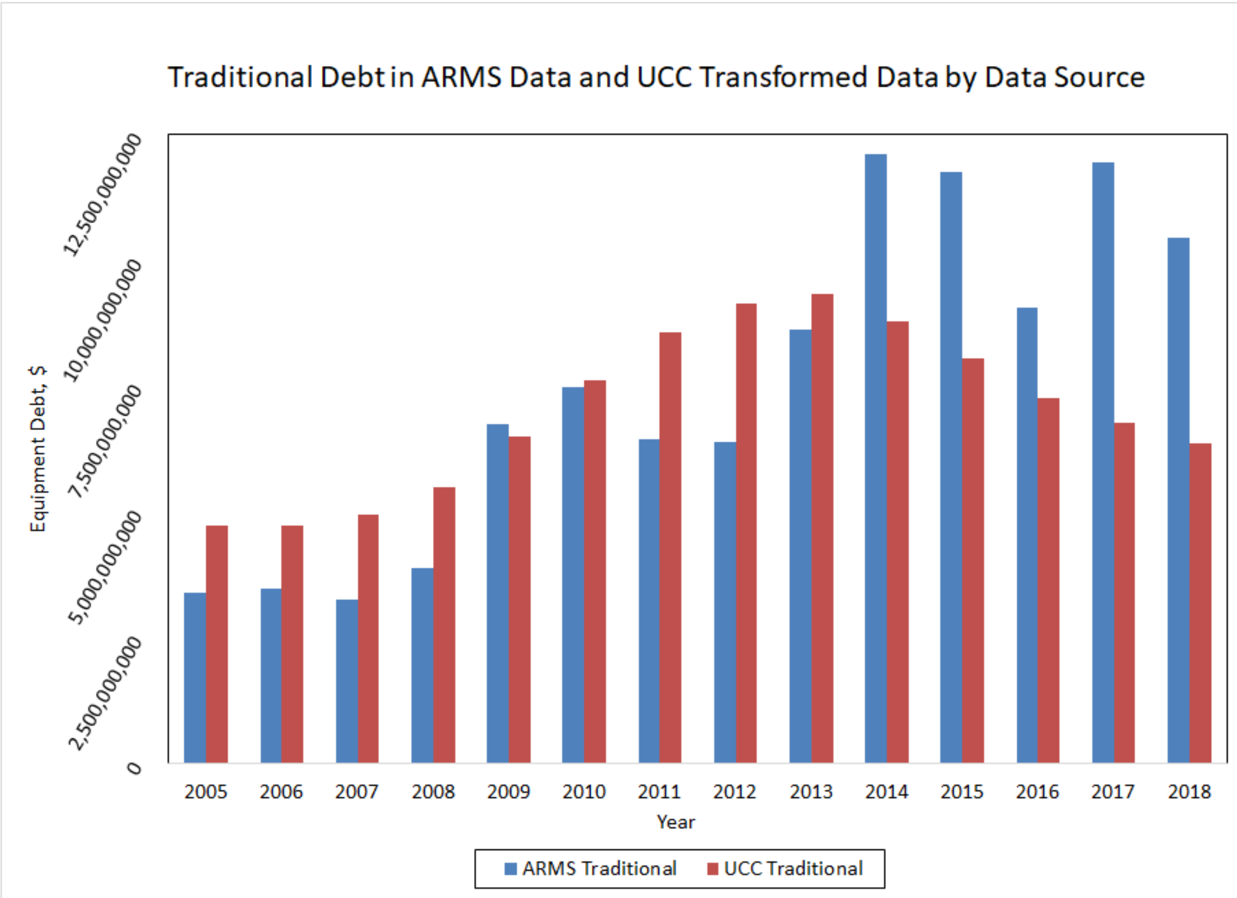
The lagged regressions do not possess the internal logic to allocate ARMS values to loan origination years in the same way as UCC equipment values. The outcome of each regression is instead the establishment of best fit according to the arrangement of variables. Obviously, these regressions suggest that lagged UCC equipment values provide better fit to ARMS values, such that these lagged values and interactions seem to absorb explanatory power from the current-year values and interactions, connoted through the inverted signs of the current-year UCC variable parameters relative to unlagged models. Lower levels of nontraditional equipment value reflection in ARMS remains an observed aggregate effect across UCC data variables. Statistical significance in the UCC data variables diminishes as more lagged equipment value is included, indicating that the divergence of traditional and nontraditional debt reporting in ARMS is an observation among old debt generally, not necessarily among old debt of a specific age. Comparative strength in significance and magnitude characterizes UCC data variables in lagged models to unlagged models. This suggests that, beyond general underrepresentation, nontraditionally secured equipment value's underrepresentation in ARMS is significantly attributable to reporting patterns of nontraditional debt originated in years prior to survey issuance.

Chapter 7 - Conclusion

UCC data provides a novel source of information on farm lending trends in an evolving credit market with an increasing diversity of lenders. As a population of lien filings on agricultural equipment, it represents actual annual acquisition of farm equipment debt. ARMS data is the predominant tool used by the USDA to estimate the volume of farm debt held by lenders in the category of "Individuals and Others." This includes equipment manufacturers and implement dealers, whose financial divisions comprise a substantial portion of the nontraditional lending category in agricultural equipment finance.

Empirical comparisons between the two sources of data return statistically significant discrepancies in the measurement of debt held by nontraditional lenders relative to that held by traditional lenders. These statistical discrepancies are further indicated by differences in proportions of farm equipment debt and collateral equipment value on nontraditionally sourced loans in ARMS and UCC data, respectively. The primary conclusion of this thesis is that ARMS systemically and significantly underestimates nontraditionally sourced nonreal estate farm equipment debt relative to traditionally sourced lending. Because of the different time frames and metrics that the two datasets use to measure debt, the precise extent to which underestimation occurs is inconclusive. However, estimation of the conceptual model provides a visualization of measurement discrepancies.

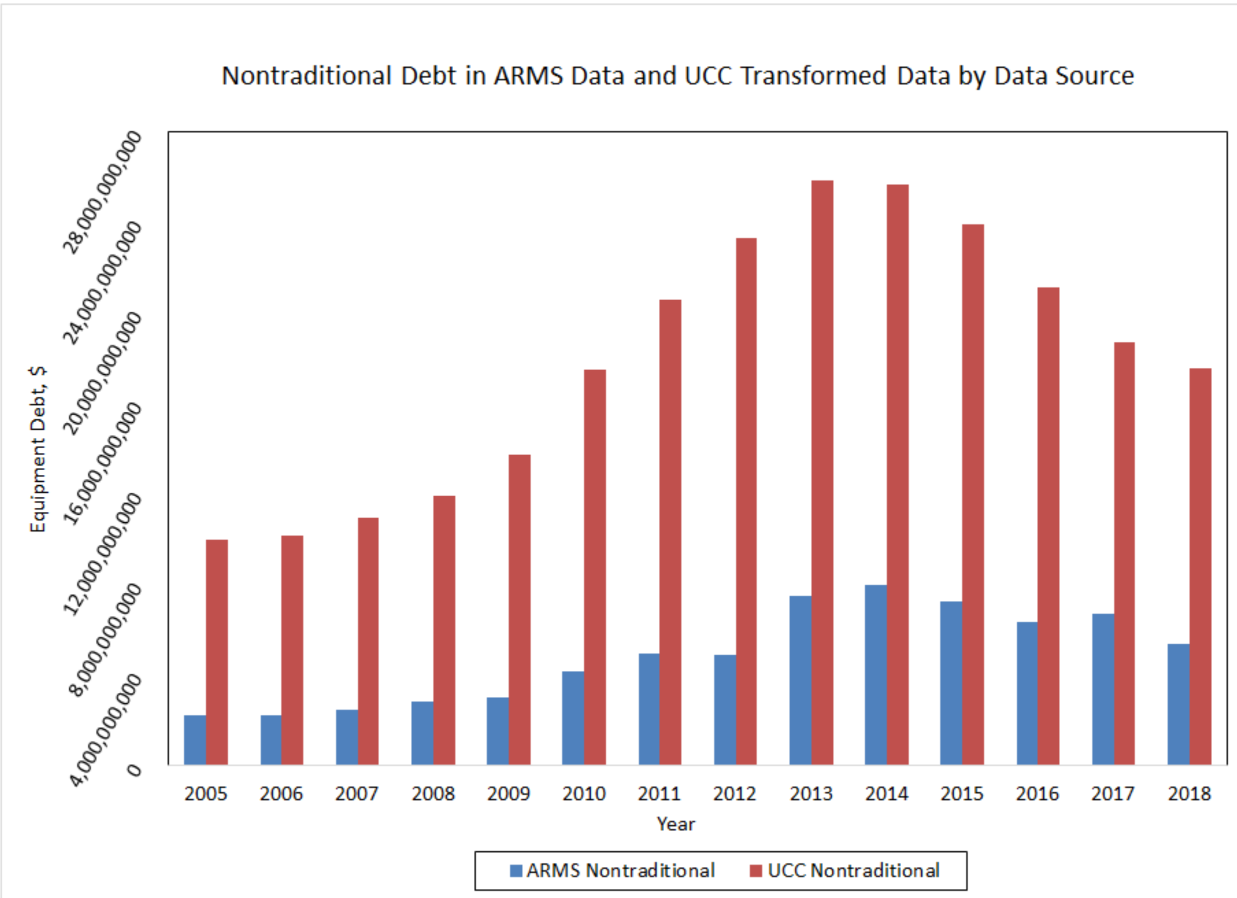
Figure 7-1 Traditionally Sourced Nonreal Estate Equipment Debt in ARMS Data and UCC Transformed Data by Data Source



Sources: USDA, National Agricultural Statistics Service and Economic Research Service, 2005-2018. Agricultural Resource Management Survey, non-real estate long term debt data (equipment use only) from 14 states; Equipment Data Associates data on select equipment for 14 states, 2000-2018.

When 5% interest rates, 5-year loan lengths, and loan-to-value ratios of 0.65 are assumed for traditionally secured liens, transformed UCC lien data and ARMS data follow the same general debt volume pattern. Transformed UCC data for nontraditionally secured liens, whose only calculation difference is a 0.80 loan-to-value ratio, depict a very different story. Coinciding with the empirical results, doubling or even tripling current ARMS estimates of nontraditional nonreal estate equipment debt would bring estimates roughly closer to debt volumes implied by population data.

Figure 7-2 Nontraditionally Sourced Nonreal Estate Equipment Debt in ARMS Data and UCC Transformed Data by Data Source



Sources: USDA, National Agricultural Statistics Service and Economic Research Service, 2005-2018. Agricultural Resource Management Survey, non-real estate long term debt data (equipment use only) from 14 states; Equipment Data Associates data on select equipment for 14 states, 2000-2018.

USDA farm sector debt estimates provide reliable, consistently measured estimates of the majority of farm sector debt sources, but supplemental information on nontraditional lenders is necessary to fully understand the broader agricultural debt landscape. ARMS' role in the formulation of USDA farm sector debt estimates in the “Individuals and Others” lender category is drawn into focus in conjunction with the findings of this study. If ARMS nonreal estate equipment debt data provide sustained, overly conservative depictions of nontraditional lenders’ volume of lending, confusion may arise about the role of “Individuals and Others” as lenders in the agricultural sector. This assessment is aided by the finding that relative underestimation of nontraditionally sourced equipment debt does not significantly vary across time or region.

Revisiting certain elements of the construction and dissemination of ARMS is worth consideration, to address the underestimation of nontraditional lending. Like Briggeman, Koenig, and Moss (2012), these proposed changes focus in large part on the loan table provided in the survey, though they do not need to be confined to there. Whether in the loan table or elsewhere, data collection could be improved by testing questions that more directly elicit nonreal estate equipment loans from nontraditional sources, or loans from nontraditional sources more generally. This may help ensure that nontraditional loans are not omitted from survey responses due to their size or respondents’ perception. For example, respondents may not perceive some types of vendor finance as a loan or as an important type of loan for reporting purposes.

A secondary conclusion of this study is that UCC lien filing data provides a novel basis for future research in agricultural economics. Its unique position as representing the population of a significant source of farm debt data set affords it the opportunity to be used for the corroboration of alternative data sources or for the evaluation of farm investment and equipment lending trends.

Chapter 8 - References

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Appendix A - Supporting Tables

Table A-1 Regression Results for Primary Econometric Models of Year-Over-Year Change in ARMS Nonreal Estate Equipment Debt Estimates for 2005 to 2018[11]

	Dependent Variable ($\Delta \boldsymbol{ARMS_{slt}}$, \$)			
Variable	Baseline Model	Nontraditional Binary Model	Combined Model	Combined Model, State FE
Intercept	2.356 (21.59)	37.96 (31.14)	-1.897 (46.97)	-10.98 (66.59)
Equipment Value	0.05765 (0.04245)	0.1066* (0.04907)	0.2603. (0.1442)	0.4327* (0.1887)
Nontraditional Binary		-51.18. (29.31)	-0.00541 (53.84)	13.39 (57.64)
Time Trend		-4.006 (3.222)	-4.086 (3.222)	-4.942 (3.321)
Equipment Value* Nontrad.			-0.1730 (0.1527)	-0.2877 (0.1781)
RMSE	254.0	253.3	253.2	256.7
Adjusted R^2	0.002154	0.007897	0.008622	-0.01925
Observations	390	390	390	390

Significance codes: '***'→ 0.001, '**'→ 0.01, '*'→ 0.05, '.'→ 0.1

[11] Intercept, nontraditional binary, time trend, regime binary, nontraditional1*region, nontraditional2*region, nontraditional*trend, RMSE in terms of millions

Table A-2 Regression Results for Primary Econometric Models of Year-Over-Year Change in ARMS Nonreal Estate Debt Estimates for 2003 to 2019[12]

	Dependent Variable ($\Delta \boldsymbol{ARMS_{slt}}$, \$)			
Variable	Baseline Model	Nontraditional Binary Model	Combined Model	Combined Model, State FE
Intercept	-39.63 (28.95)	-112.3** (40.91)	-156.6* (60.59)	-171.2* (85.77)
Equipment Value	0.1469* (0.06094)	0.2399*** (0.0677)	0.4222* (0.1961)	0.8376*** (0.2466)
Nontraditional Binary		-152.5*** (38.33)	-95.27 (69.32)	-69.18 (73.05)
Time Trend		11.96*** (3.306)	11.88*** (3.307)	10.39** (3.361)
Equipment Value* Nontrad.			-0.2061 (0.2081)	-0.4721* (0.2362)
RMSE Adjusted R^2 Observations	391.1 0.00948 504	380.2 0.06394 504	380.2 0.0639 504	381.9 0.05594 504

Significance codes: ‘***’→ 0.001, ‘**’→ 0.01, ‘*’→ 0.05, ‘.’→ 0.1

[12] Intercept, nontraditional binary, time trend, RMSE in terms of millions

Table A-3 Regression Results for Primary Econometric Models of ARMS Nonreal Estate Equipment Debt Estimates in States Selected for State-level Data Publication for 2005 to 2018[13]

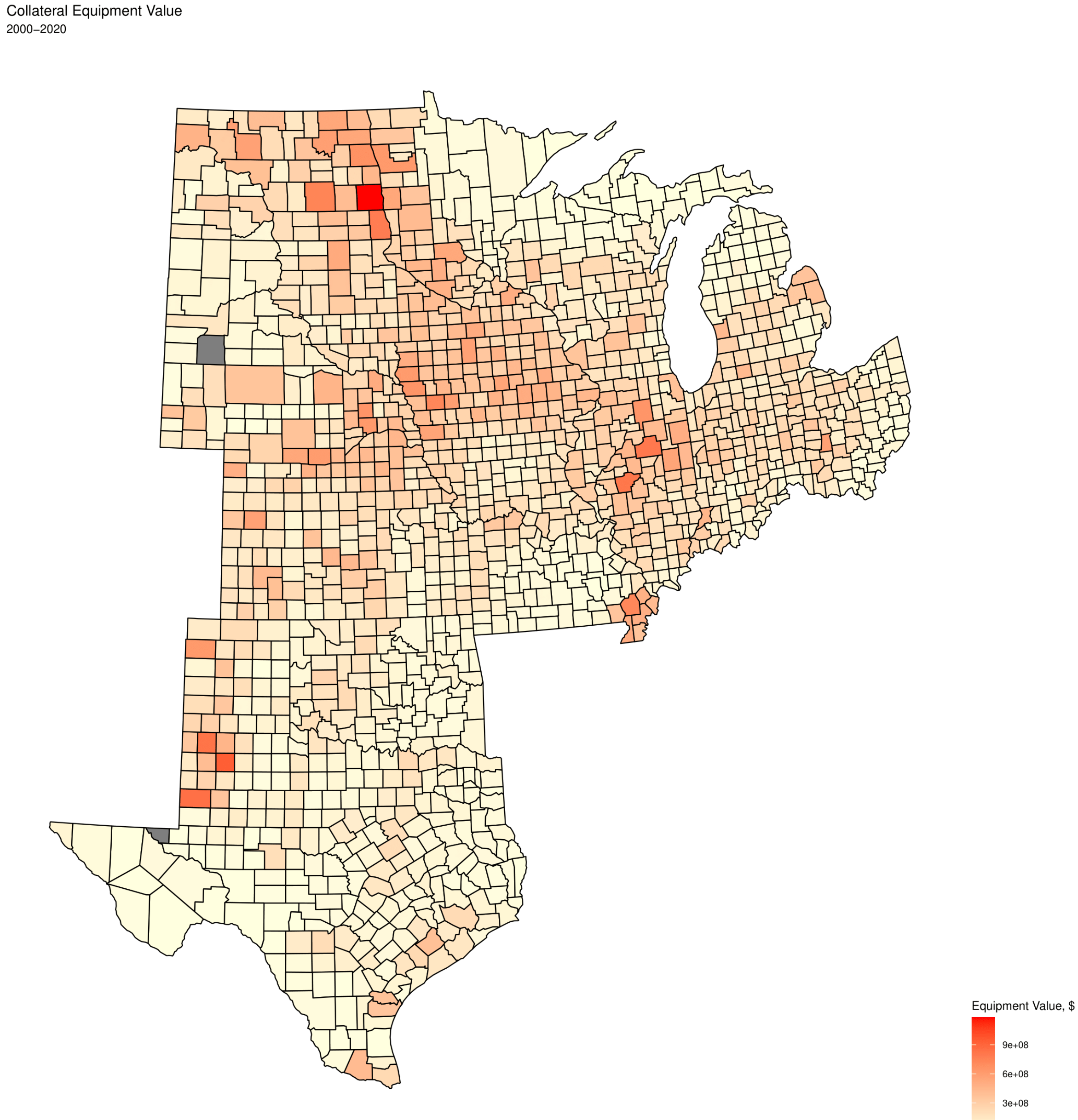
	Dependent Variable ($\boldsymbol{ARMS_{slt}}$, \$)			
Variable	Baseline Model	Nontraditional Binary Model	Combined Model	Combined Model, State FE
Intercept	443.1*** (39.93)	187.2*** (41.47)	178.1** (67.58)	163.7* (68.65)
Equipment Value	0.1277. (0.06773)	0.3250*** (0.06438)	0.3549. (0.1860)	0.07646 (0.1935)
Nontraditional Binary		-316.1*** (41.01)	-304.2*** (80.63)	-192.3* (74.24)
Time Trend		42.20*** (4.227)	42.19*** (4.236)	45.83*** (3.663)
Equipment Value* Nontrad.			-0.03388 (0.1972)	-0.04757 (0.1920)
RMSE	346.7	265.5	266.1	227.3
Adjusted R^2	0.01008	0.4194	0.4171	0.5748
Observations	252	252	252	252

Significance codes: ‘***’→ 0.001, ‘**’→ 0.01, ‘*’→ 0.05, ‘.’→ 0.1

[13] Intercept, nontraditional binary, time trend, RMSE in terms of millions

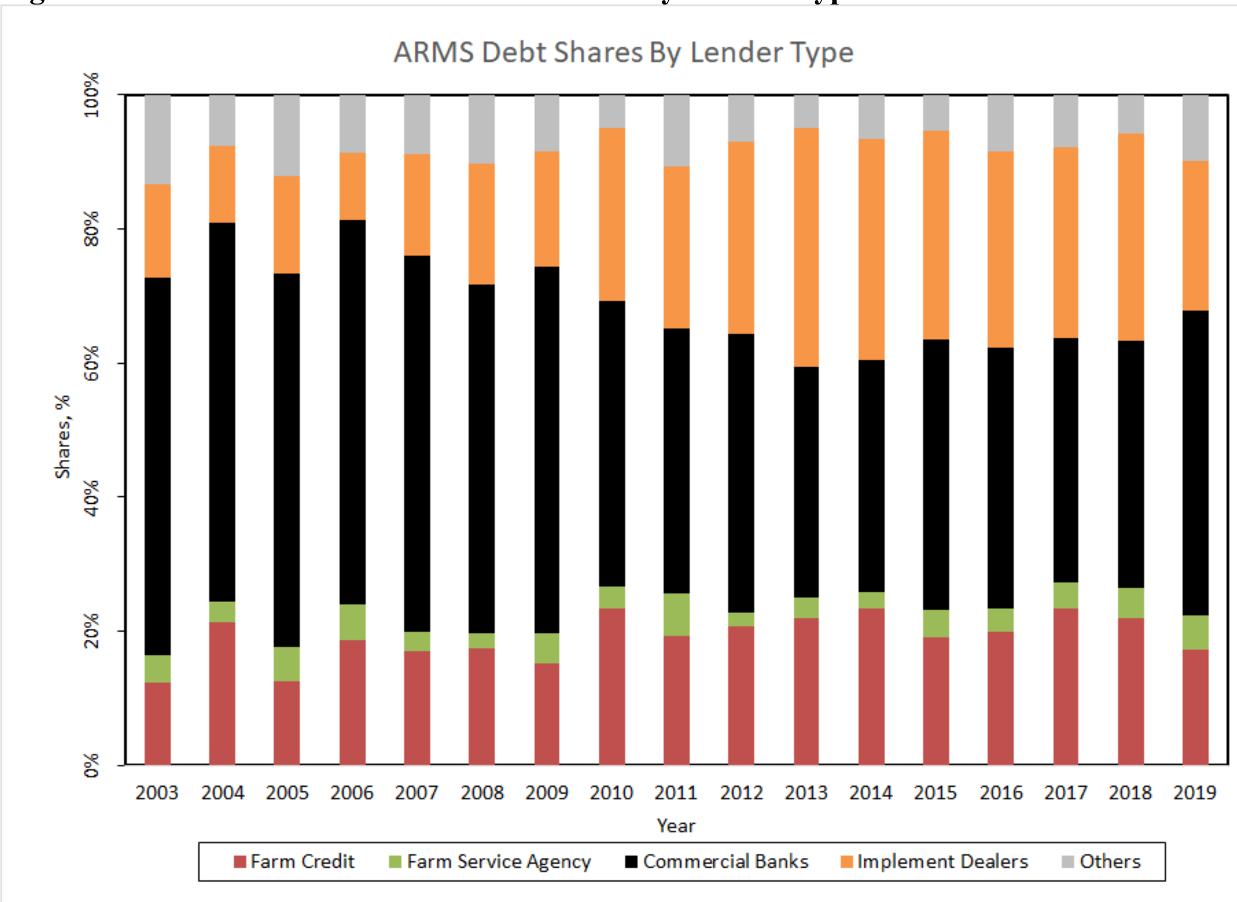
Appendix B - Supporting Figures

Figure B-1 Collateral Equipment Value County-level Regional Distribution



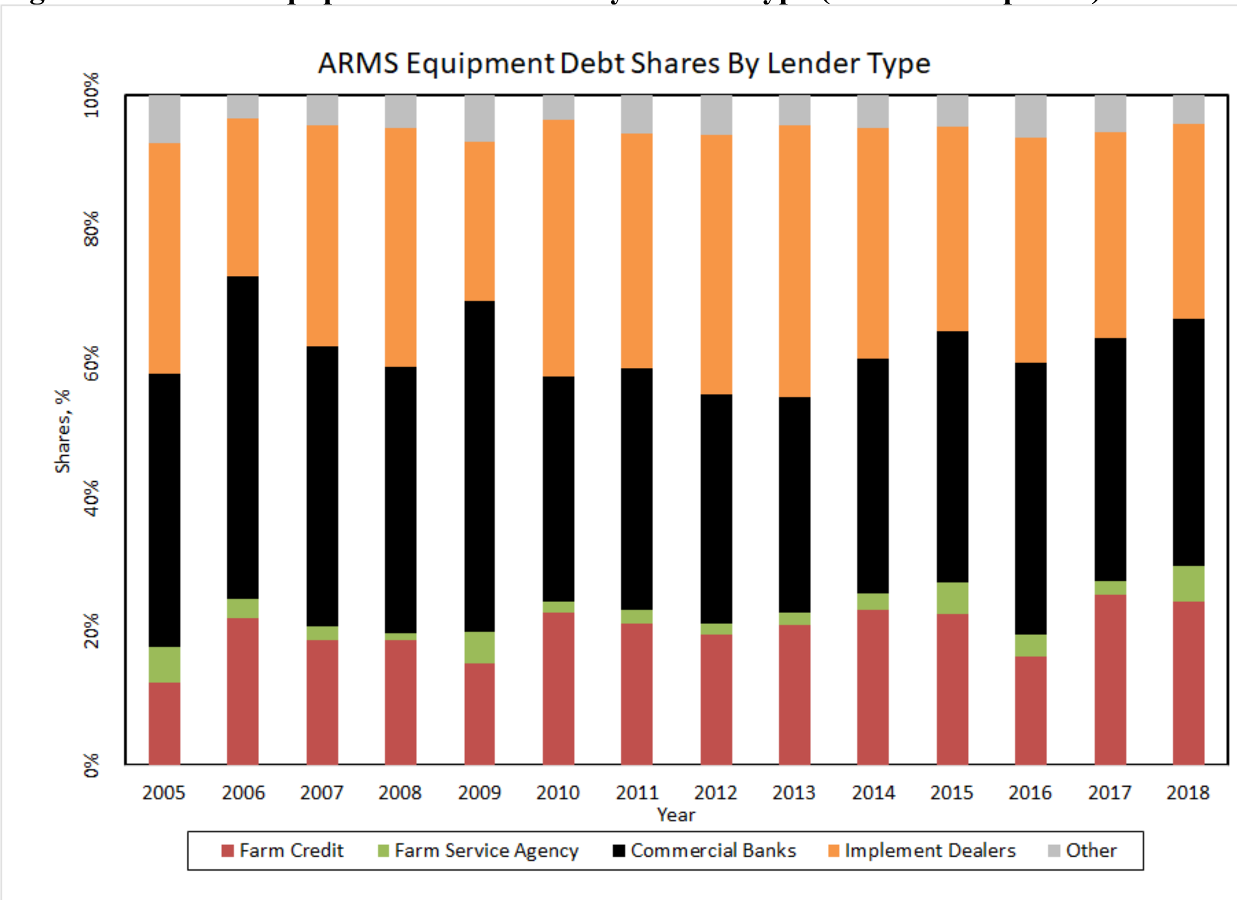
Source: Equipment Data Associates data on select equipment for 14 states, 2000-2020

Figure B-2 ARMS Nonreal Estate Debt Shares by Lender Type



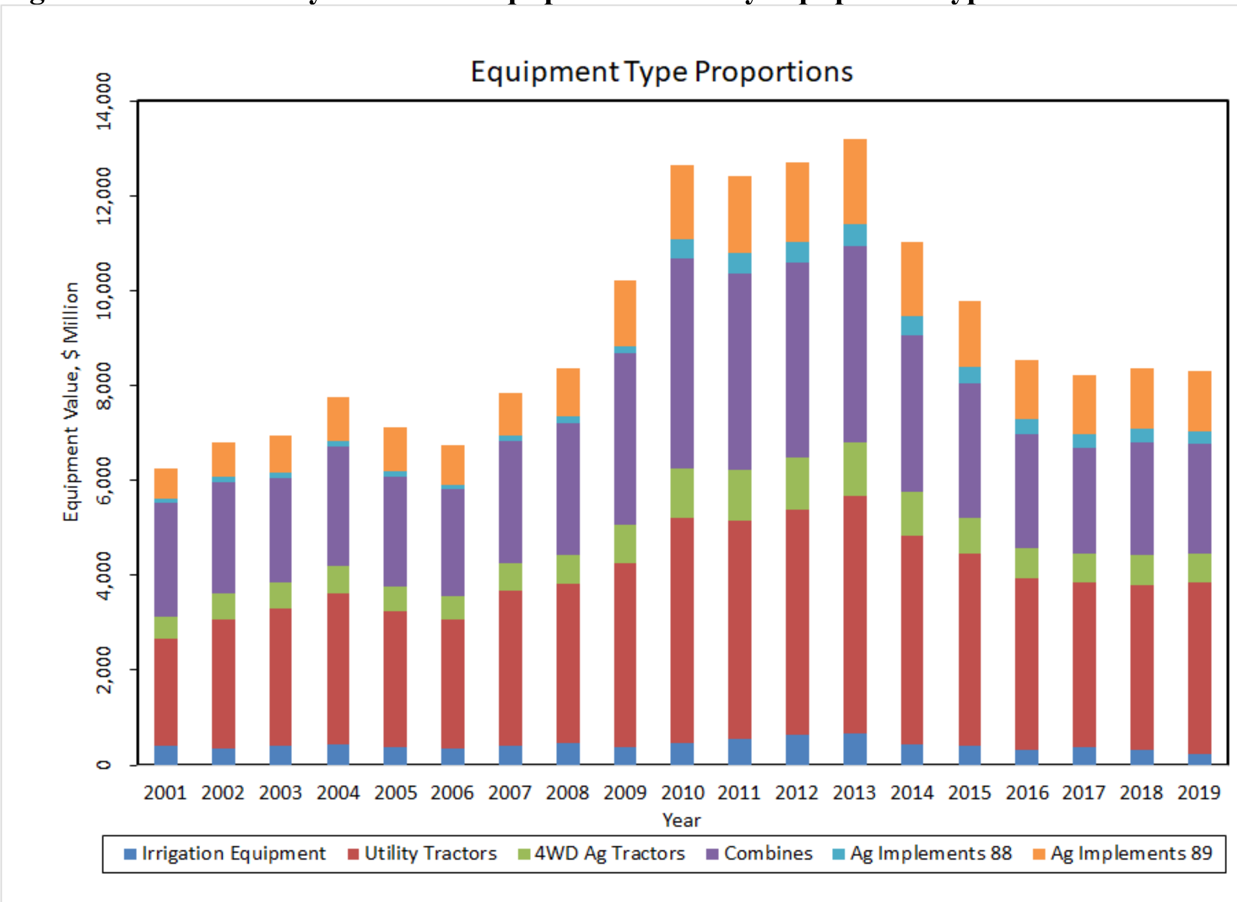
Source: USDA, National Agricultural Statistics Service and Economic Research Service, 2003-2019. Agricultural Resource Management Survey, non-real estate long term debt data from 14 states.

Figure B-3 ARMS Equipment Debt Shares by Lender Type (Not Sector-Specific)



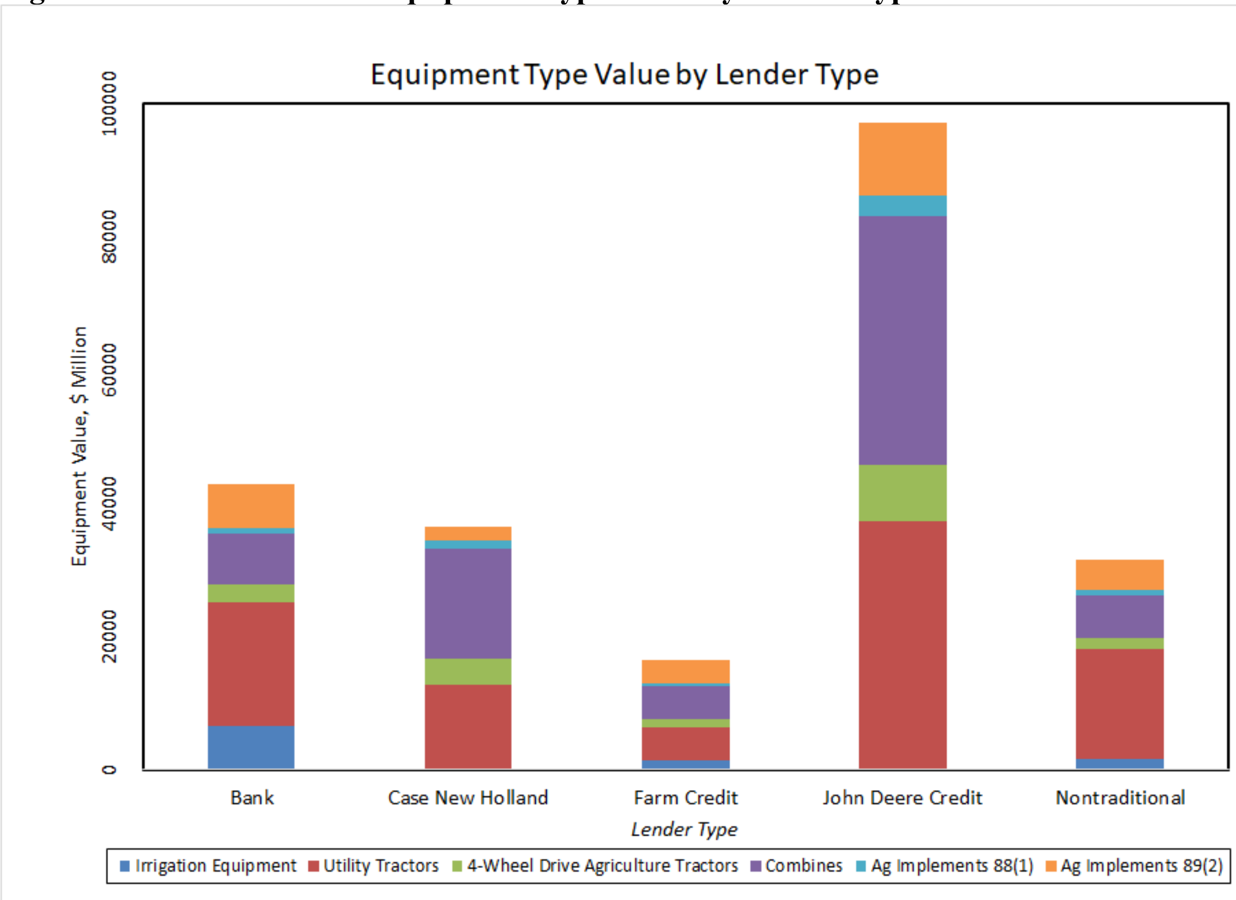
Source: USDA, National Agricultural Statistics Service and Economic Research Service, 2005-2018. Agricultural Resource Management Survey, debt data (equipment use only) from 14 states.

Figure B-4 UCC Yearly Collateral Equipment Value by Equipment Type



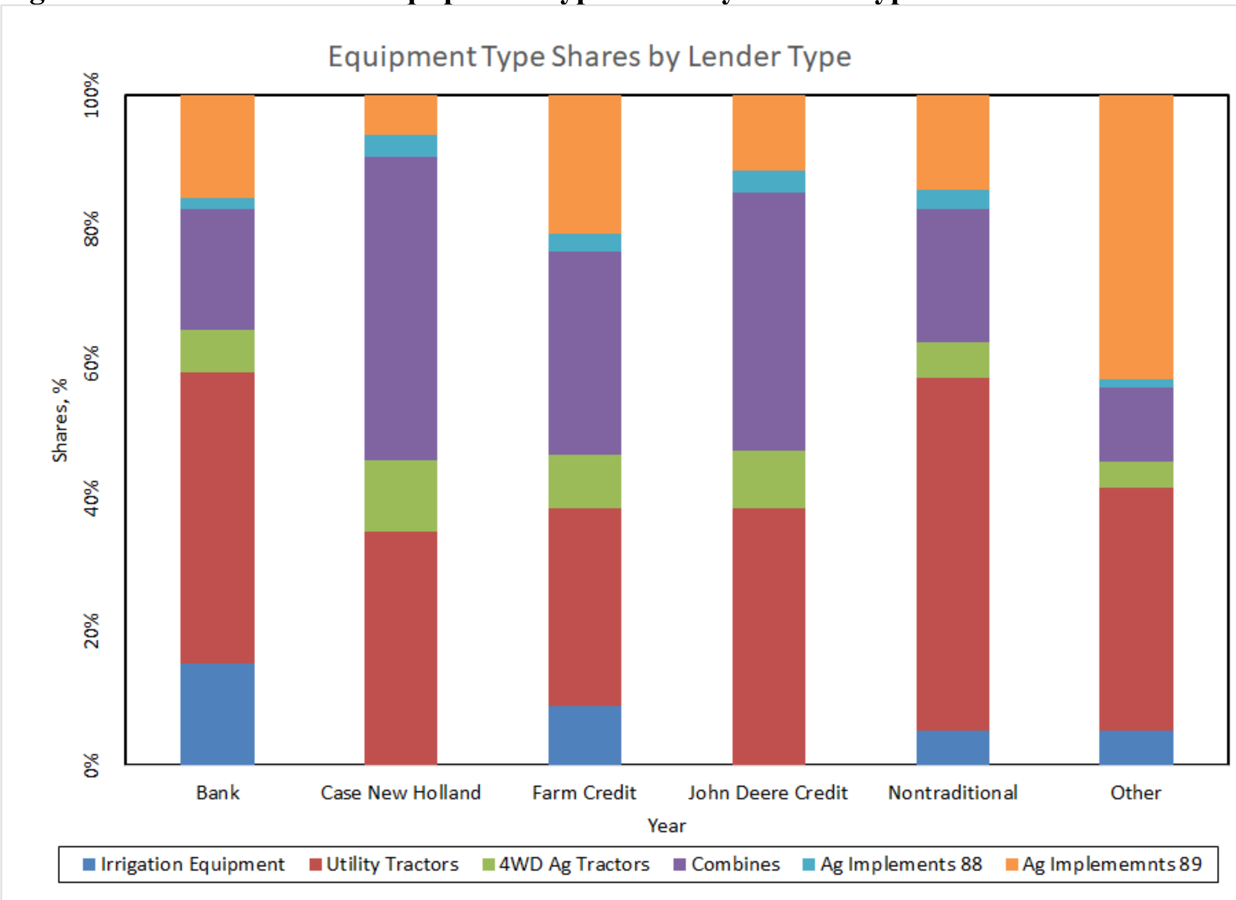
Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019, inflation-adjusted 2019$

Figure B-5 UCC Collateral Equipment Type Value by Lender Type



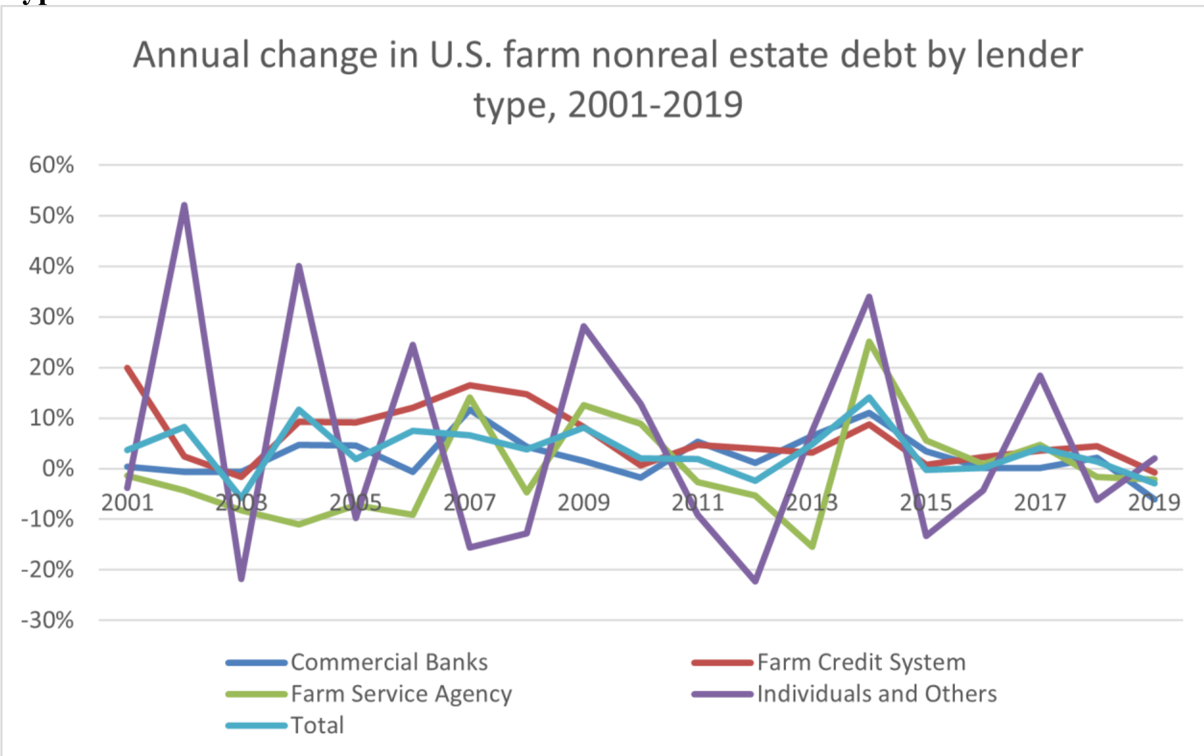
Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019, inflation-adjusted 2019$

Figure B-6 UCC Collateral Equipment Type Share by Lender Type



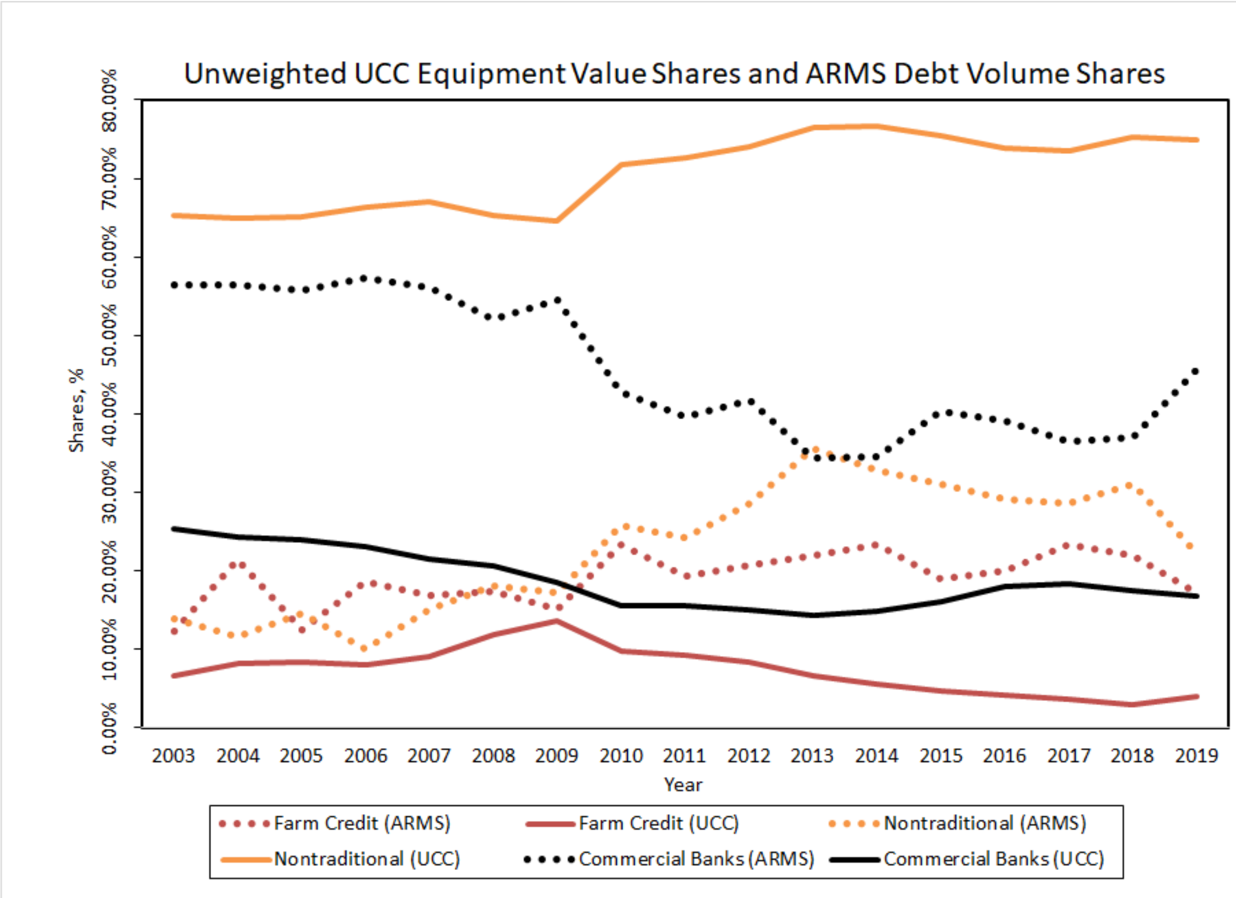
Source: Equipment Data Associates data on select equipment for 14 states, 2001-2019, inflation-adjusted 2019$

Figure B-7 U.S. Farm Sector Nonreal Estate Debt Estimate Annual Changes by Lender Type



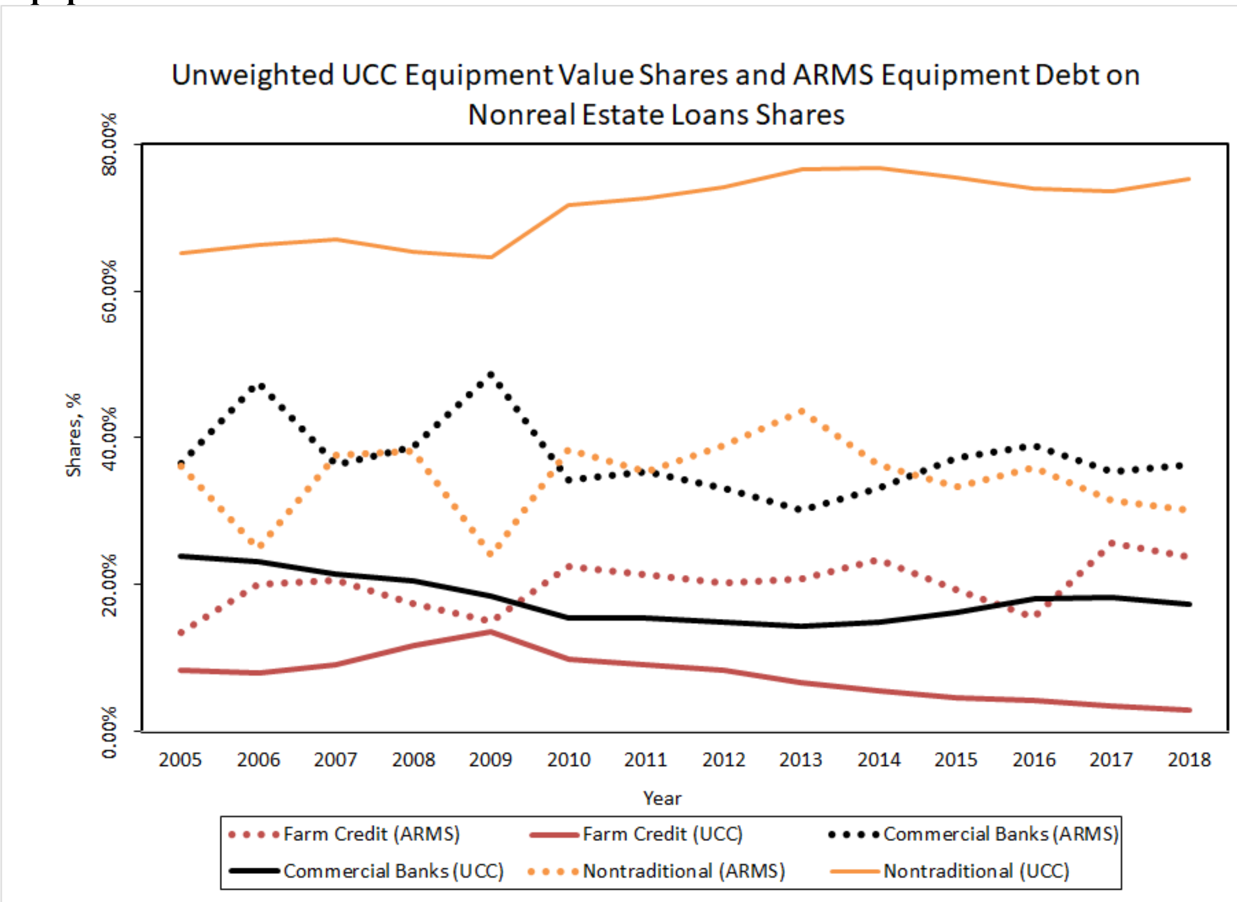
Source: USDA, National Agricultural Statistics Service and Economic Research Service, 2000-2019. Farm Income and Wealth Statistics Balance Sheets

Figure B-8 UCC Equipment Value Lender Type Shares and ARMS Nonreal Estate Debt Lender Shares



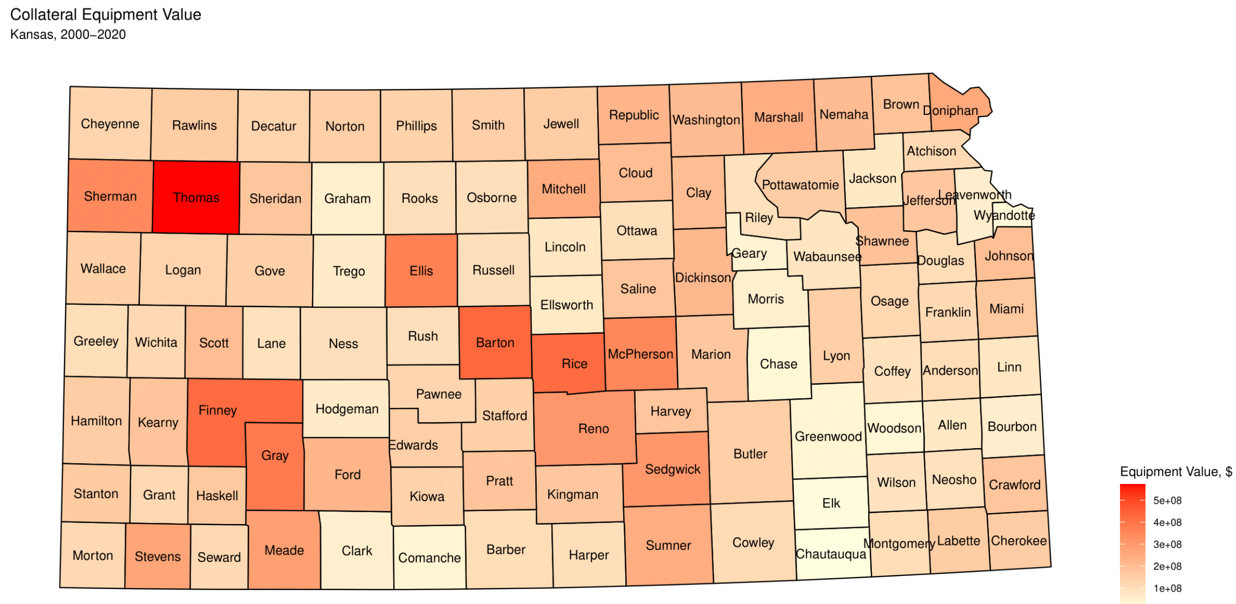
Source: Equipment Data Associates data and USDA, National Agricultural Statistics Service and Economic Research Service, 2003-2019. Agricultural Resource Management Survey, data from 14 states.

Figure B-9 UCC Equipment Value Lender Type Shares and ARMS Nonreal Estate Equipment Debt Lender Shares



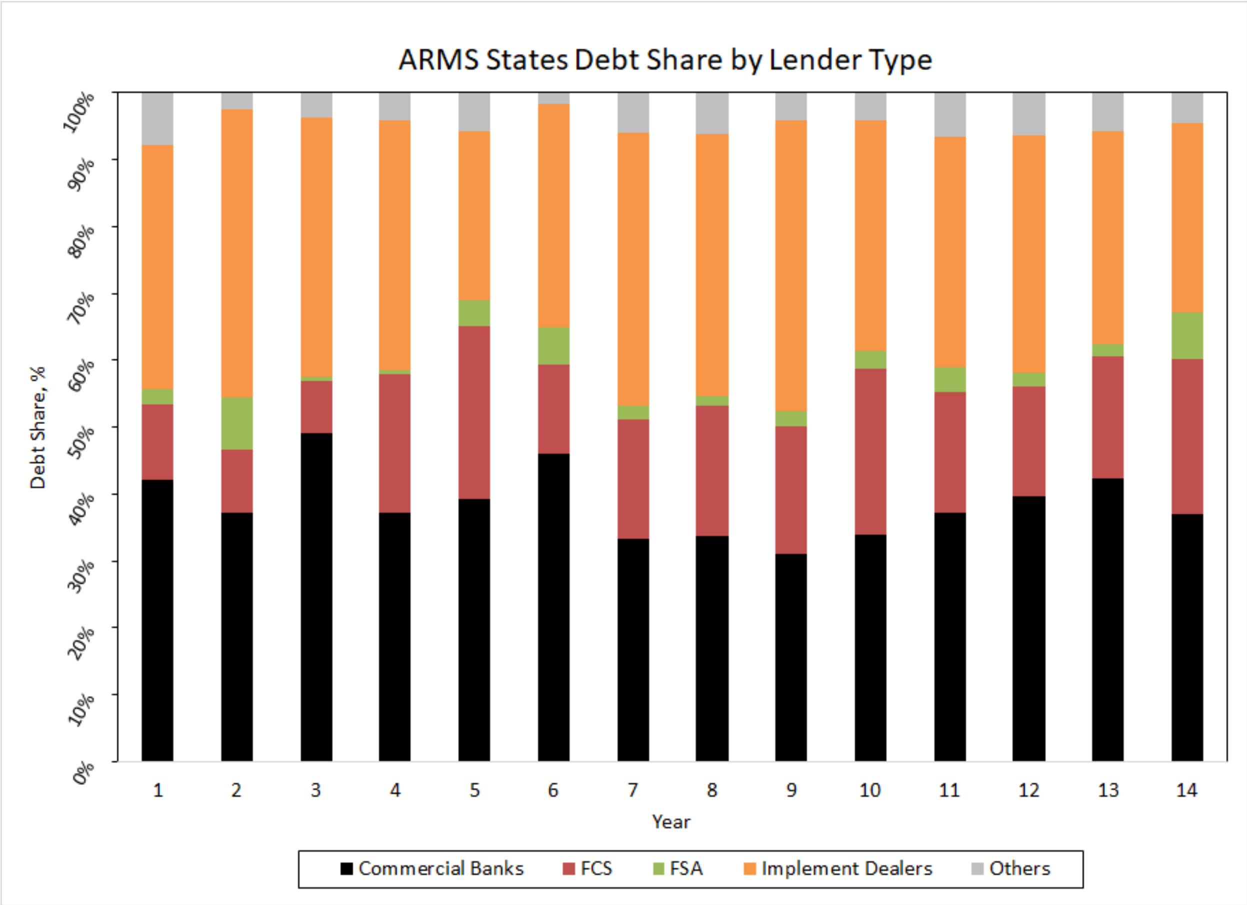
Source: Equipment Data Associates data and USDA, National Agricultural Statistics Service and Economic Research Service, 2003-2019. Agricultural Resource Management Survey, data from 14 states.

Figure B-10 Kansas Collateral Equipment Value County-level Distribution



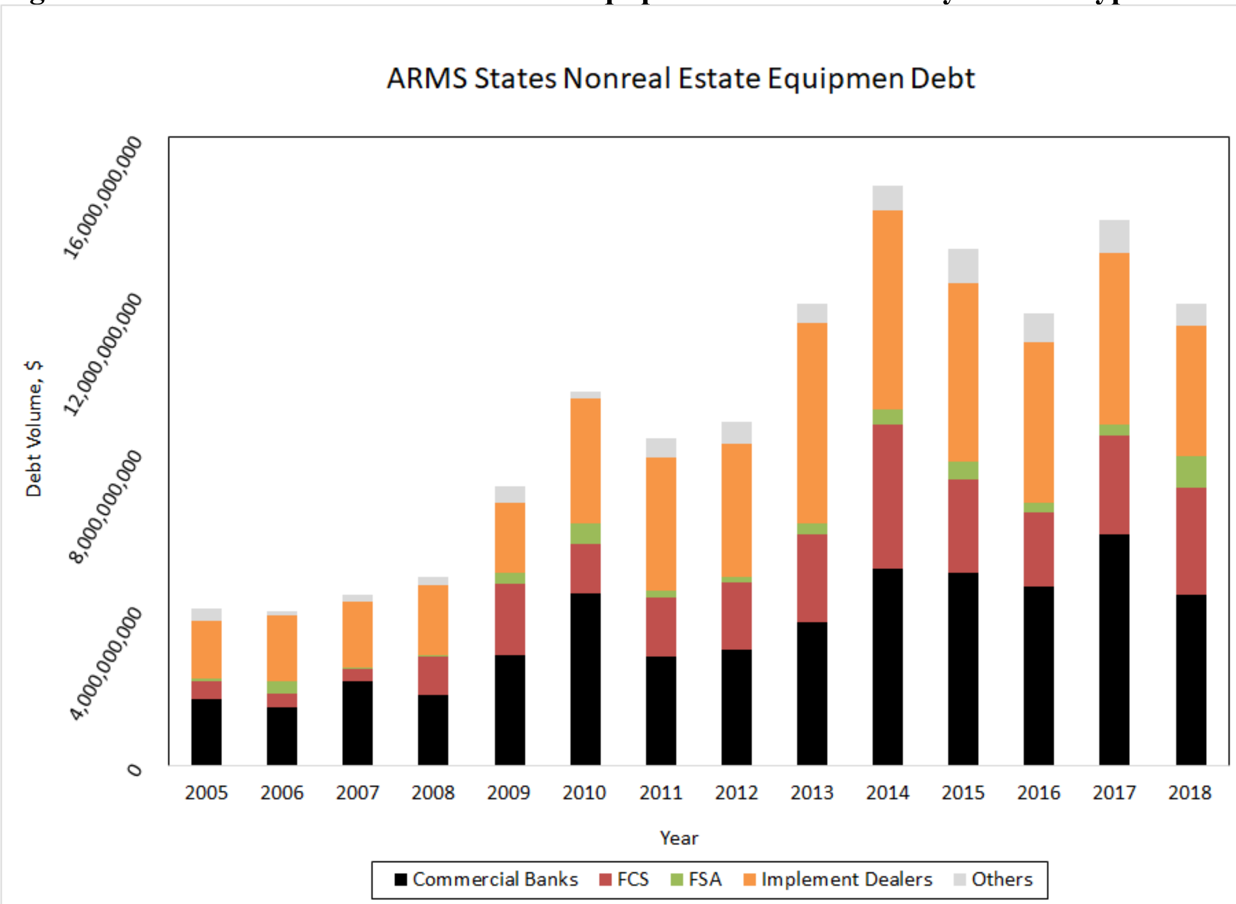
Source: Equipment Data Associates data on select equipment for 14 states, 2000-2020

Figure B-11 ARMS States Nonreal Estate Equipment Debt Share by Lender Type



Source: Equipment Data Associates data and USDA, National Agricultural Statistics Service and Economic Research Service, 2005-2018. Agricultural Resource Management Survey, data from 9 states.

Figure B-12 ARMS States Nonreal Estate Equipment Debt Volume by Lender Type



Source: Equipment Data Associates data and USDA, National Agricultural Statistics Service and Economic Research Service, 2005-2018. Agricultural Resource Management Survey, data from 9 states.