

Essays on farm debt use and safety net programs

by

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B.A., Economics, University of Ghana, 2012

M.A., Economics, Cleveland State University, 2016

AN ABSTRACT OF A DISSERTATION

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Abstract

Farm debt and safety net programs are critical to effective farm management. While farm debt alleviates credit constraints, safety net programs—such as Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC)—help producers manage income volatility and potential financial losses. In this dissertation, I explore how a combination of these programs can enhance profitability and reduce profit variability. Additionally, I investigate the financial status and local credit market conditions linked to the use of multiple forms of debt in U.S. agriculture. I also examine how cash flow shocks arising from the weather impacts debt types. These underexplored areas are briefly discussed in the remainder of this abstract.

Chapter One evaluates the effectiveness of farm safety net strategies in increasing profitability and reducing profit variability. Using the relative mean of profit and the coefficient of variation, I compare counterfactual safety net strategies across a sample of 28,615 observations from 2,486 farms producing four dryland crops—corn, soybeans, sorghum, and wheat—in Kansas over nine crop years (2014–2022). A “no safety net” scenario serves as the benchmark for each alternative strategy to determine if policy customizations are statistically different. The findings show that safety net program combinations with high profit-enhancing potential also tend to lower profit risk for dryland wheat and sorghum production. However, this relationship is not observed for dryland corn and soybean production, where low-cost strategies that boost profits do not necessarily reduce profit risks.

In Chapter Two, I analyze the issue of multiple borrowing—the practice of using multiple lenders to finance farm operations—which raises concerns for both lenders and policymakers. This chapter aims to improve our understanding of the producers who engage in this practice by developing a precise farm-level measure of multiple borrowing and exploring how financial status and local credit market conditions influence the likelihood of its occurrence. Using an extensive dataset of Kansas farm financial records spanning nearly two decades, we find that

more profitable and leveraged producers are more likely to engage in multiple borrowing, with leverage being the strongest predictor. Additionally, producers in regions with a higher presence of commercial banks are less likely to rely on multiple borrowing.

Chapter Three explores how producers debt and investment respond to weather-induced cash flow shocks. This chapter focuses on U.S. agriculture, specifically Kansas, where climate change has had significant effects on productivity. I reaffirm the negative association between extreme weather and both crop income and yields. I also find that producers exposed to extreme temperature tend to use long-term debts. Additionally, the response of producers to weather-induced cash flow shocks vary depending on farm size, leverage and operator age.

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Dedication

To my parents, Sampson and Faustina Gaku:

I could not have come this far without your unwavering support and countless sacrifices!

Chapter 1

Evaluation of Alternative Farm Safety Net Program Combination Strategies

1.1 Introduction

Agricultural production is fraught with uncertainty, posing significant risks to producers' livelihoods. Recent challenges, like the COVID-19 pandemic ([Baldwin et al., 2023](#)), geopolitical conflicts such as the Russia-Ukraine war and China-US trade disputes ([Morgan et al., 2022](#)), and climate change ([Ortiz-Bobea et al., 2021](#); [Perry et al., 2020a](#); [Shew et al., 2020](#); [Tack et al., 2015](#)), have intensified these threats. Producers utilize various strategies to mitigate these risks, including savings ([Adhikari and Khanal, 2022](#); [Jensen and Pope, 2004](#); [Mishra and Chang, 2009](#); [Mishra et al., 2012](#)), irrigation ([Barham et al., 2011](#); [Dalton et al., 2004](#); [Lin et al., 2008](#); [Vandever et al., 1989](#)), diversification ([Aguilar et al., 2015](#); [Katchova, 2005](#); [MacDonald et al., 2018](#); [Mishra et al., 1999, 2004](#); [Purdy et al., 1997](#)), futures and options hedging ([Coble, 2004](#); [Coffey and Schroeder, 2019](#); [Franken et al., 2012](#); [Maples et al., 2022](#); [Walters and Preston, 2018](#); [Wang et al., 2004](#)), and seeking off-farm employ-

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ment (Chang and Mishra, 2012; Key et al., 2017; Khanal and Mishra, 2014; Kharisma and Abe, 2020; Whitt et al., 2020). Nevertheless, government-backed safety net programs remain essential (Baldwin et al., 2023; Belasco, 2020; Mahul and Stutley, 2010; Smith and Glauber, 2012; Tsiboe and Turner, 2023). In the U.S., the primary framework for these support measures is the Farm Bill, a comprehensive legislative package passed approximately every five years that oversees numerous agricultural and food initiatives.¹ The 2018 Farm Bill (The Agriculture Improvement Act of 2018, Public Law [P.L.] 115-334), projected by the Congressional Budget Office (CBO) to cost \$428 billion from 2019-2023 (McMinimy et al., 2019), aids U.S. farmers and ranchers by compensating for various setbacks, ranging from natural disasters to price volatility.

The Commodity title (Title I) of the 2018 Farm Bill provides farm support programs at no cost to producers, designed to protect against prolonged (i.e., persisting over multiple seasons) and widespread (i.e., national- or county-wide) price and/or farm revenue declines. Several studies have shown that the three main risk management programs under this title, County Agriculture Risk Coverage (ARCCO), Individual Agriculture Risk Coverage (ARCIC), and Price Loss Coverage (PLC), effectively address risks in traditional row crop production (Westbrook et al., 2023). These programs are sometimes called “counter-cyclical” because they counter the cycle of the market: when market conditions worsen (i.e., prices fall), these programs automatically kick in to provide support, and when market conditions improve (i.e., prices rise), the support is automatically reduced. However, because these programs are not tied to current production, there is a potential mismatch between present farm losses and past regional or national ones. Thus, producers might not get payments from ARCCO, ARCIC, and PLC for specific current-year losses. To manage the risk of revenue drops and price fluctuations within the year, the Federal Crop Insurance Program (FCIP), backed by the Farm Bill’s Title XI, is available. With subsidized premiums, FCIP offers diverse insurance options, allowing producers to tailor coverage to their specific risks for the year. These options range from the kind of protection (yield, revenue, margin) to the risk

¹Titles in the most recent farm bill (The Agriculture Improvement Act of 2018, Public Law [P.L.] 115-334) encompassed farm commodity revenue supports, agricultural conservation, trade and foreign food assistance, farm credit, research, rural development, forestry, bioenergy, horticulture, and domestic nutrition assistance.

pooling type, risk aggregation level, coverage extent (from 50% to 95%), and commodity type. For 2022, over two million unique insurance policies were available to cater to diverse producer needs (RMA, 2024). Producers can combine FCIP insurance policies with some restrictions. SCO can be combined with PLC, but not ARCCO or ARCIC.

Theoretical and empirical studies on risk balancing indicate that producers might increase financial risk as business risk declines (Cheng and Gloy, 2008; Featherstone et al., 1988; Gabriel and Baker, 1980; Ifft et al., 2015; Turvey and Kong, 2009). Consequently, farm policy programs like FCIP, PLC, ARCCO, and ARCIC, which offer safety nets against unexpected drops in market prices or yields, can influence agricultural credit and the broader financial landscape. However, a clear understanding of how these programs, and their strategic combinations, differ in risk reduction and profit enhancement is yet to be established. Previous research has focused on evaluating the relative performance of FCIP products, examining various parameters like net payouts and indemnities at different levels (Coble and Dismukes, 2008; Cooper et al., 2012). However, these studies have not fully assessed the risk mitigation and income transfer potential across various policy customizations in the Farm Bill’s Title I and XI. A more in-depth assessment could provide insights into how these programs’ utilization by producers could alter the business risk in the agricultural credit landscape, informing the development of the Farm Bill and broader agricultural policies.

The objective of this paper is to evaluate the efficiency of US farm safety net program combination strategies at enhancing profit levels and reducing inter-crop-year farm profit variability. Our research design involves the calculation of farm profit under all available and allowable strategies which are then used to estimate and rank their profit risk mitigation and profit level enhancement potential. We consider thirteen alternative strategies that span across both Title I and XI for this historical analysis. For the FCIP insurance policies we consider four distinct insurance plans (Revenue Protection [RP], Area Revenue Protection [ARPI], Margin Protection [MP], and Supplemental Coverage Option [SCO] with RP basic policy) all at their most popular coverage level elections for each crop to reflect reality. However, we show that our core findings do remain if coverage levels are optimally selected. The method is applied to a sample of 28,615 observations across 2,486 farms and four dryland

crops (corn, soybean, sorghum, and winter wheat) in Kansas (KS) spanning nine crop years (2014 -2022).

Our analysis reveals that for dryland wheat and sorghum, high-profit enhancement from farm safety net programs often corresponds to significant profit risk reduction. The most effective strategies for wheat involve PLC, particularly AR+PLC, PLC only, RP+PLC, and RP+SCO+PLC, reducing risks by 18-20% and boosting profits by 1.5 to 2.3 folds, versus no safety net. For sorghum the best strategies in descending order are RP+PLC, PLC only, RP+ARCCO, and RP+SCO+PLC, decreasing profit risks by around 13 to 21% and increase profits by 26 to 40%. However, for dryland corn and soybeans, the pattern diverges; high income from safety net strategies does not necessarily translate to reduced profit risks. The top strategies for corn (RP+PLC, RP+ARCCO, RP+ARCIC, and PLC only) slightly decreased risk (6.2-9.8%) with modest profit increases (5.1-7.7%), while strategies such as MP only or MP+PLC actually increase risks. The top strategies for soybean (ARCCO only, ARCIC only, RP+ARCCO, and PLC only) show a similar trend, with the best options offering minimal risk reduction and low profit enhancement, and no benefit from PLC due to it never being triggered. For soybeans, ARCCO and ARCIC are the primary cost-saving programs, leveraging the close correlation between county and on-farm revenue losses, making them more effective than paid FCIP policies.

Our findings have implications for the formulation of the Farm Bill and broader agricultural policies. They highlight the complexity of agricultural risk and the necessity for nuanced policy design. For instance, the effectiveness of PLC in reducing profit risks for wheat and sorghum producers underscores the value of tailored support for different crops, suggesting that a one-size-fits-all approach may not be optimal. These insights can guide policymakers to refine the structure and funding of agricultural support to maximize economic efficiency and target the unique needs of various producers. Moreover, the role of these programs in enhancing creditworthiness can influence the broader rural financial landscape by affecting lending behaviors. Understanding this dynamic is vital for integrating financial health into agricultural policy development. The relationship between program combinations and financial risk also indicates that policies must balance the provision of

safety nets with the potential for encouraging risk-taking behavior among producers. Evidence from our analysis provides a robust foundation for decision-making, promoting an adaptive policy framework that can respond to changing market conditions and risk profiles. It also has broader implications for the financial stability of rural economies and the global competitiveness of U.S. agriculture as stakeholders leverage empirical evidence to support the economic sustainability of the agricultural sector while avoiding incentives for excessive risk-taking.

The remainder of this study is as follows. Section 1.2 provides the background information on crop insurance in the U.S. Section 1.3 discusses our data sets and presents the methodology. Section 1.4 concludes with policy implications.

1.2 Background

In the U.S., the farm bill is a key legislation governing various agricultural and food initiatives, including crop insurance, food access, support for conservative initiatives and rural development. Typically renewed every five years, the farm bill provides the opportunity to lawmakers to thoroughly address issues in both the agricultural and food sectors. Since the 1930s, Congress passed 18 farm bills and supervises its implementation (Johnson and Monke, 2024). The farm bill has 12 titles with titles 1 and titles X1 relevant for risk management. While Title 1 deals with widespread systematic risks, title X1 deals with the specific risks that producers can select for their unique risk profile.

Production uncertainty has led to the adoption of several strategies including crop insurance to deal with adverse outcomes. Congress first authorized crop insurance in 1938 as one of those strategies to deal with the impacts of the Great Depression and the Dust Bowl. By this authorization, the Federal Crop Insurance Corporation was established to administer the Federal Crop Insurance Program (FCIP) such that the federal government provides premium subsidies while the Approved Insurance Providers sell those products. In this public-private framework, several insurance products are available to cover a variety of crops and provide indemnities based on individual and group indices. Individual level plans

include those based on Actual Production History, while group-based insurance plans are based on county yield or group metrics. Individual plans have provided financial support to producers, yet they may be fraught with moral hazard ([Chambers, 1989](#)), adverse selection ([Skees and Reed, 1986](#)) and high delivery cost ([Barnett and Mahul, 2007](#)). On the other hand, group-based plans can deal with these problems by minimizing information asymmetry and reducing program costs to accrue annual savings of about \$4 billion ([Barnett and Mahul, 2007](#); [Belasco, 2020](#)); however, their index could deviate from individual loss experience. Despite those challenges, the Federal crop insurance program has expanded steadily over the years. According to the RMA, insured acreage increased from 206 million acres in 2000 to 444 million in 2021 partly due to the authorization of Pasture, Rangeland and Forage Coverage. Total liabilities have also increased over the years, rising to 31 percent of total value of production in the U.S. agricultural sector. Additionally, premium subsidy cost increased from \$ 94 million in 1981 to \$3 billion in 2020. Producers also rely on countercyclical programs funded by the Commodity Credit Corporation as a strategy to manage farm risks. These programs, including ARC and PLC, were introduced in the 2014 Farm bill with one-time enrollment to make payouts when either price or revenue are low. ARC is free with two varieties: farm (ARC-IC) or county level coverage (ARC-CO). At the county level, ARC-CO makes payments when actual county revenue lies below the county guarantee (86% of a benchmark guarantee that is the five-year Olympic average national price times the five-year Olympic average yield per planted acre). At the individual level, ARC-IC makes a payout when average actual revenue/acre is less than 86% of the farm's average benchmark revenue/acre. Producers can enroll in PLC and receive payments when the commodity's reference price is greater than the market year average price.

Despite reauthorizing these programs, the 2018 Farm Bill made changes applying to both programs. Under the 2014 Farm bill, ARC benchmark revenue was based on the Olympic average from the five most recent years. However, the 2018 Farm Bill established ARC benchmark revenue based on the Olympic average from the five years that immediately precede the past year. Unlike the 2014 Farm bill that prioritized the use of NASS county yields, the 2018 Farm Bill prioritized the use of the RMA yields. Under the 2014 Farm

Bill, producers made one-time enrollment into ARC or PLC for the period 2014-2018, while they (producers) make annual enrollments starting from 2021 under the 2018 Farm Bill. Both ARC and PLC have made significant payouts over the years. According to the USDA Farm Service Agency (FSA) program data, ARC enrollees received \$4.5 billion while PLC enrollees received \$780 million in 2014. For PLC, rice-long grain producers received \$402 million, representing 51% of total payouts in 2014. Corn producers who enrolled in ARC received \$3.8 billion, representing 83% of total payouts in 2014. Corn producers in 2021 are the largest recipients of ARC payouts, taking home 29% of total ARC payouts valued at \$102 million. Meanwhile, peanut producers received 68% of PLC payouts pegged at \$242 million in 2021. Due to high commodity prices, PLC payouts were not triggered for several commodities including corn, sorghum, soybeans, and wheat in 2021. Countercyclical programs allow for additional insurance programs. Producers who enroll in PLC are eligible to purchase the Supplemental Coverage Option (SCO), an insurance program introduced by the Crop Insurance Title of the 2014 Farm Bill. Once a producer enrolls her crop in ARC-CO or ARC-IC, that crop is ineligible for SCO. However, that crop is eligible for other insurance plans such as Area Risk Protection Insurance (ARPI), Revenue Protection (RP) and Yield Protection (YP).

Safety nets are designed to provide a foundational level of income, consumption, or wage security to individuals or groups, particularly in the face of various potential risks such as income loss, restricted access to credit, or the effects of natural disasters ([Gundersen et al., 2000](#)). Specifically, in the realm of U.S. agriculture, the farm bill implements a safety net that functions by transferring funds to agricultural producers, aiming to mitigate these risks and ensure a level of economic stability. While these transfers may indirectly result in higher profits for farmers, it is crucial to understand that the primary intent is risk mitigation. The term “enhancing profit” used in this study is meant to convey this indirect outcome rather than imply it as the main objective of the policy.

Beyond transferring income, participation in farm safety net programs can enhance producers’ creditworthiness in a couple of ways. Firstly, these programs reduce producers’ borrowing risk by providing a safety net against income volatility and potential financial

losses due to factors like adverse weather conditions or market fluctuations. This increased stability and predictability of income make farmers more attractive borrowers to financial institutions, as they are perceived as less likely to default on loans (Pflueger and Barry, 1985). Additionally, participation in farm safety nets can improve producers' ability to repay loans by providing supplementary income or compensation during challenging times, thereby enhancing their debt servicing capacity (DeLay et al., 2022). Moreover, demonstrating participation in risk management programs may signal to lenders that farmers are proactive in managing financial risks, further bolstering their creditworthiness. Overall, participation in farm safety net programs can strengthen the financial position of agricultural producers, making them more reliable and favorable candidates for credit.

1.3 Methodology and Data

In this section, we discuss the methodology of our study. Our data sources for these analyses are also discussed.

1.3.1 Data

The primary data utilized by the study consists of 28,615 historical farm-level observations, from the Kansas Farm Management Association (KFMA), spanning 2,486 Kansas farms from 2014-2022 for dryland production of corn, sorghum, soybeans, and winter wheat. The data set was cleaned by dropping observations from the sample according to previous works using the KFMA (Tsiboe and Tack, 2022; Tsiboe and Turner, 2023). Our final sample consists of Kansas farm-level unbalanced panel and farm counts for corn, sorghum, soybeans, and wheat are 481, 373, 833 and 799 respectively as shown in Table 1.1. The mean [standard deviation] of the final yields in bu/acre is 121 [53] (corn), 79 [32] (sorghum), 38 [16] (soybeans), and 47 [16] (winter wheat). The final yield observations exhibit a great amount of cross-sectional and temporal variation, as shown on Figure A.1 panel A.

Table 1.1: *Summary statistics of selected producers in the Kansas Farm Management Association (KFMA), 2014-2022*

	Corn	Sorghum	Soybeans	Wheat
Enterprise acres	2074 (1855)	2038 (1724)	1684 (1422)	2004 (1758)
Harvested acres	481 (597)	349 (374)	555 (601)	609 (579)
Harvest yield (bu/acre)	121 (53)	79 (32)	38 (16)	47 (16)
Price received (\$/bu)	5 (1)	4 (1)	10 (2)	6 (1)
Enterprise cost (\$/acre)	362 (231)	255 (138)	363 (334)	302 (183)
Enterprise revenue (\$/acre)	421 (296)	292 (179)	424(470)	342 (227)
Enterprise profit (\$/acre)	59 (143)	37 (94)	61 (221)	40 (123)
Approved yield (bu/acre)	115 (40)	77 (20)	36 (11)	41 (10)
Rate yield (bu/acre)	117 (41)	78 (21)	37 (11)	47 (13)
PLC yield (bu/acre)	111(43)	76 (22)	35 (12)	44 (10)
Number of farms	481	373	833	799
Number of observations	8,672	3,396	9,005	7,542

Note: This table presents the summary statistics of variables from 2014-2020. We use datasets from KFMA, ADM, FSA & RMA. There are 28,615 farm-level observations.

Using the farm level reported output price received for sold production, the study calculated representative county level price received for each crop and year as the median acreage weighted average across all the farms with reported information. Cost in the KFMA is reported at the farm level and not at the crop level. Thus, to get cost solely due to production, we subtracted the recorded cost associated with all federal programs (e.g., FCIP) from the recorded total cost for the farm enterprise. We used a similar approach for revenue, where we subtracted the recorded revenue associated with all federal programs from the recorded total revenue. These two quantities are used in assessing the impact of specific crop participation in portfolios of federal risk management programs on the profitability and its variability of the entire farm enterprise. The mean [standard deviation] of the price received in \$/bu is 5 [1] (corn), 4 [1] (sorghum), 10 [2] (soybeans), and 6 [1] (winter wheat); and that of the per acre enterprise cost of production in \$/acre is 362 [231], 255 [138], 363[334] and 302 [183], respectively. Like the end of season yields, the boxplots of the price received, and enterprise profit also exhibit a great amount of cross-sectional and temporal variation, as shown on Figure A.1 panels B and C, respectively.

In addition to the farm level KFMA data, FCIP Policy rating parameters and insurance policy commodity prices (projected and harvest) are retrieved from RMA’s Actuarial Data Master (ADM) and price addendums.^{2,3} Since KFMA data are farm level observations (as opposed to field level observations) they best mimic enterprise units (EU), and thus the corresponding ADM information for EU is used for the analysis. Similarly, PLC and ARC program parameters (payout factors, reference price, effective price) are also retrieved from official program sources.⁴

For the purposes of calculating FCIP liabilities, premiums, subsidies, and indemnities, the rate yield and approved yield for each KFMA farm for each crop year is calculated based on observed yields in ten successive years serving as the basis for an APH database (Tsiboe and Tack, 2022; Tsiboe et al., 2023a). For PLC and ARCIC, we calculate program yields

²ADM files for each insurance year are available at RMA website (Risk Management Agency [RMA], 2023)

³RMA price addendums are available at <https://legacy.rma.usda.gov/tools/>

⁴Payout data are available on FSA website: <https://www.fsa.usda.gov/programs-and-services/arcplc-program/arcplc-program-data/index>

(for the purposes of payment calculations) for 2014-2017 as average end of season yield from 2004-2013 as dictated by legislation via the 2014 Farm Bill. For the periods after 2017, the 2018 Farm Bill allowed producers to update their PLC and ARCIC program yields, thus for 2018-2022, we replaced the initial yields based on the period 2004-2013 with average end of season yield for the period 2008-2017 if the latter was less. The FCIP rate and approved yields and the PLC/ARCIC program yields also exhibit a great amount of cross-sectional and temporal variation, as shown on Figure A.1 panels D, E and F, respectively.

1.3.2 Methodology

To perform our analysis, we utilize the concept of a representative agent (hereafter referred to as an “agent”) which we define as the unique combinations of KFMA farm id, crop, and irrigation practice. For each agent our empirical analysis assesses the historical relationship between FCIP, PLC, ARCCO, and ARCIC combination payments and their associated cost to ascertain the risk reduction potential of each combination in terms of its efficacy at preserving farm profit and its stability from 2014-2022. We achieve this by taking each combination and counterfactually calculating the outcomes that would have occurred if all agents that had access to the constituent programs had utilized it. Depending on the actual availability by crop and county from 2014-2022, we considered thirteen combination strategies which included RP only, AR only, MP only, PLC only, ARCCO only, ARCIC only, RP+PLC, RP+SCO, RP+SCO+PLC, RP+ARCCO, RP+ARCIC, AR+PLC, and MP+PLC. It is worth noting that notwithstanding the availability of YP, AY, AR-HPE, and MP-HPH, over the periods considered we only consider RP, AR, and MP because they are the most popular FCIP plans respectively classified as individual level, group level, and margin protection. All FCIP plans are evaluated at their most patronized coverage level based on RMA summary of business data; as a result, AR, RP, and MP are evaluated at 80%, 75% and 80% respectively.

The liability, premiums ($P_{i,t}$), subsidy ($S_{i,t}$), and indemnities ($I_{i,t}$) for the FCIP policies are calculated as outlined in the FCIP Appendix III/M-13 Handbooks, and the payment

factors and amounts for the PLC, ARCCO, and ARCIC are the same as those established by FSA. Given the calculations for program cost and benefits, the profit ($\pi_{i,t}^a$) associated with a given safety net program combination (a) for agent (i) in crop year t is calculated as $\pi_{i,t}^a = R_{i,t} - c_{i,t} + I_{i,t}^a + S_{i,t}^a - P_{i,t}^a$; where $R_{i,t}$ and $c_{i,t}$ are the total farm (from all production) revenue and cost, respectively. Based on availability, this profit is separately calculated for each of the thirteen specific alternative safety net policy combinations and then compared along two dimensions: (1) direct profit enhancement and (2) profit variability reduction.

We use two key indicators to compare the thirteen specific alternative safety net policy combinations: relative mean profit and profit variability. Relative mean profit is calculated by taking the average profit each agent earns when using a given safety net combination and dividing it by their average profit when not using any safety net. This ratio gives us insight into the effectiveness of the safety net combination in enhancing profit. For profit variability, we assess the fluctuation in each agent's profit over time using the Coefficient of Variation (CV). This is also calculated in a relative sense, comparing scenarios with and without a safety net. We aggregate (by averaging values between the 5th and 95th percentile) the agent level relative metrics across all agents to obtain an overall measure of a given safety net combination's impact on profit levels and its stability. Lastly, standard errors for each metric are computed via the bootstrap method where the measures are repeatedly calculated in 100 repeated samples generated by resampling whole crop years from 2014-2022 in bootstrap.

Our study is based on the empirical approach that farm profits are mainly influenced by uncontrollable factors like weather, rather than farmers' decisions, minimizing the risk of moral hazard and adverse selection. Although subsidies have reduced adverse selection (Coble and Barnett, 2013; Glauber, 2004, 2013; Just et al., 1999; Tsiboe and Turner, 2023), the debate about moral hazard, especially concerning input use, persists (Horowitz and Lichtenberg, 1993; Smith et al., 2017; Yu and Hendricks, 2020). However, the influence of moral hazard on yields according to the literature (Babcock and Hennessy, 1996; Coble et al., 1997; Mieno et al., 2018; Quiggin et al., 1993) seems minimal due to yields mainly being affected by climatic events. In the FCIP, weather-related factors, specifically drought and temperature (42%) and excess moisture (28%) dominated insurance claims since 2000.

Nonetheless, unbiased comparison of the efficacy of safety net combinations to enhance and sustain farm profits is contingent on the agent’s current behavior remaining constant under all alternatives. For a given agent, we ensure this by maintaining the same yields under all safety net combinations.

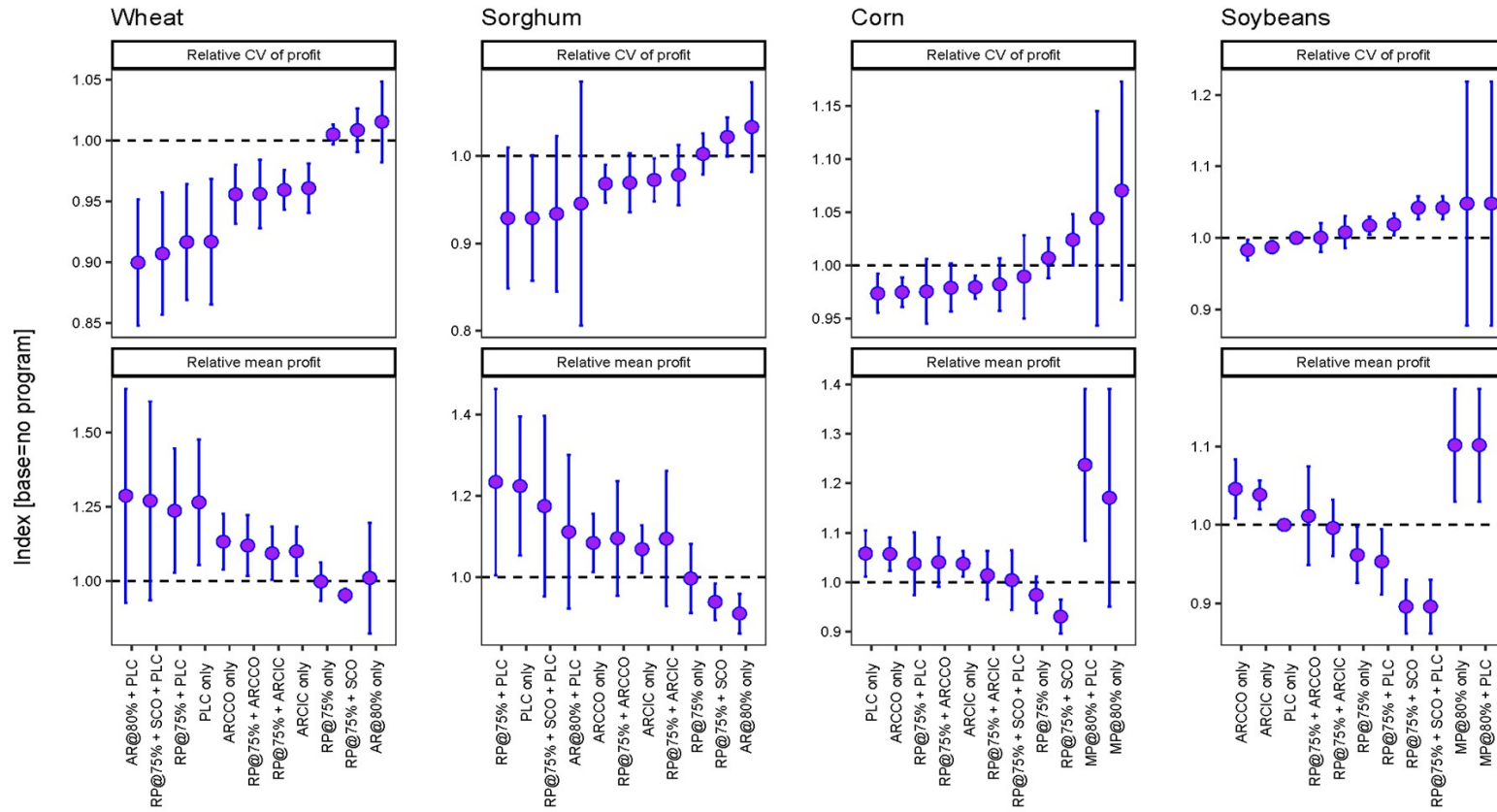
1.4 Results

The results from our analyses pertaining to the direct profit enhancement and profit variability reduction for each crop across the alternative farm safety net program combinations considered for dry land production are shown in Figure 1.1. The general pattern of the results suggests that program combination strategies that have a high- profit enhancement potential necessarily have low profit risk for dryland wheat and sorghum production. On the contrary, such a connection is absent for dryland corn and soybeans production. Low-cost farm safety net strategies that enhance corn and soybeans profits do not necessarily lower profit risks.

For dryland wheat producers, the most effective strategies for reducing profit risk and enhancing profits are, in descending order of relative CV: ARPI+PLC [0.899 and 1.288], RP+SCO+PLC [0.907 and 1.271], RP+PLC [0.916 and 1.237], and PLC only [0.917 and 1.266]. These strategies decrease profit risks by around 8 to 10% and increase profits by approximately 24 to 29% compared to scenarios without a farm safety net. Contrarily, the least effective strategies are AR only [1.015 and 1.011], RP+SCO [1.008 and 0.953], RP only [1.005 and 0.999], and ARCIC only [0.961 and 1.101]. These strategies increase profit risks by -4 to 2% and only enhance profits by about -5 to 10% more than scenarios lacking a farm safety net. For dryland wheat producers, safety net combinations that include PLC tend to drive risk reduction. This is unsurprising as PLC, which comes with no out-of-pocket costs, has consistently triggered payments for wheat producers from 2014-2022 due to its association with reducing risks at zero additional costs. Moreover, lower-than-average wheat prices over the considered period indirectly suggest higher-than-average yields due to the natural hedge (negative relationship between price and yield). This implies that programs

focused solely on compensating for yield shortfalls are likely to be less effective. Consequently, FCIP plans covering price risks, for which producers pay extra, may not perform better than combinations like ARPI+PLC, where price risk components are fully subsidized, and county yields, determining yield risk components, align closely with on-farm yields.

Like wheat, we also find that safety net combinations that include PLC tend to drive risk reduction for sorghum producers. Particularly, the most effective strategies for reducing profit risk and enhancing profits are, in descending order of relative CV: RP+PLC [0.929 and 1.234], PLC only [0.929 and 1.224], RP+SCO+PLC [0.934 and 1.174], and ARPI+PLC [0.946 and 1.111]. These strategies decrease profit risks by around 5 to 7% and increase profits by 11 to 23% compared to scenarios without a farm safety net. Contrarily, the least effective strategies are ARPI only [1.033 and 0.91], RP+SCO [1.022 and 0.938], RP only [1.002 and 0.996], and RP+ARCIC [0.978 and 1.094]. These strategies increase profit risks by -2 to 3% and only enhance profits by about -9 to 9% more than scenarios lacking a farm safety net. Again, this pattern is consistent with the benefit of zero out-of-pocket costs associated with PLC, the consistent triggering of PLC payments for sorghum producers from 2014-2022, due to low demand and drought conditions.



Programs sorted from best to least risk reduction

Note: This figure presents the relative CV (top) and relative mean (bottom) for wheat, sorghum, corn and soybeans from 2014 to 2022. We use no insurance policy as the baseline for comparison. If relative CV is lower than one, it means the combination strategy reduces profit risk compared to no insurance policy. However, a combination strategy elevates profit risks if its relative CV is above 1. Similarly, a relative mean above one means a combination strategy enhances profits compared to no insurance. A relative mean below one implies that a combination strategy reduces profits compared to a no insurance policy.

Figure 1.1: *Income Transfer Potential and Profit Risk*

While a linear relationship between income transfer and profit risk reduction exists for wheat and sorghum, this isn't the case for dryland corn and soybean production. High-income transfers from low-cost farm safety net strategies do not consistently equate to reduced profit risks. Specifically, the strategies most effective at decreasing profit risk for corn, in descending order of relative CV, are PLC only [0.973], ARCCO only [0.975], RP+PLC [0.975], and RP+ARCCO [0.979], which cut profit risks by only 2.1 to 2.7%. However, with profit enhancement metric respectively estimated at 1.058, 1.057, 1.037, and 1.04, they increase profits by only 4 to 5.8% compared to scenarios without a farm safety net. Conversely, for dryland corn production, strategies like MP only or MP+PLC, despite their high-income transfer scores (1.171 and 1.237), increase profit risks by about 7% and 4.4%, respectively.

The trend is similar for dryland soybean production, where strategies that transfer the most income don't guarantee the greatest risk reduction. The most effective strategies, in descending order of relative CV, are ARCCO only [0.983], ARCIC only [0.987], PLC only [1.000], and RP+ARCCO [1.000], reducing profit risks marginally by up to 1.7%. The profit enhancement for these strategies is also minimal, at 0 to 4.6% compared to having no farm safety net. Notably, strategies like MP only or MP+PLC also increase profit risks by about 4.8% for soybean production. For soybean producers, PLC has not been beneficial as it has never been triggered, offering no advantage from its zero out-of-pocket cost coverage against price risk. Thus, for these producers, cost savings come from ARCCO and ARCIC programs. Given the smaller size of counties, there is an expectation that county and on-farm revenue losses will be closely correlated, which makes these strategies more cost-effective compared to those with paid FCIP policies that cover both yield and price risks. To ensure the validity of our findings, we performed several robustness checks on the ranking of the alternative farm safety net program combination strategies according to their profit risk reduction and enhancement potential. First, countercyclical payments (PLC and ARC payouts) are often delayed a year after they were triggered. As a result, we use a one-year lag of these countercyclical payouts to understand how our results may vary with timing of payments. We also use the two-year lags of these countercyclical payments to assess whether late payments impact the income and profit risk reduction potential of farm safety net strategies. Results

for a year of delayed payouts and two years of delayed payouts are presented in Figure A.2 in the appendix. These findings are consistent with earlier results. The relative rankings of all strategies for each crop remain consistent across lags, indicating that delay in payments does not matter.

Additionally, we present results of our historical analysis by irrigation status in the appendix. Results by the irrigation status in Figure A.3 are consistent with our main results. In our main model we evaluated FCIP insurance policies at their most popular coverage level elections for each crop to reflect reality. To assess the relevance of comparing different coverage levels across policies, we conducted an additional robustness check by comparing outcomes for all plans evaluated at an optimally (most risk minimizing) selected coverage level. The results shown on Figure A.5 indicate that our findings are robust to the coverage level used. Our results are also robust to revenue risk as shown in Figure A.4.

1.5 Conclusion and Policy Implications

Our comprehensive analysis has assessed the efficiency of combinations of safety net programs offered under the Title I (PLC, ARCCO, and ARCIC) and XI (FCIP) of the U.S. Farm Bill in reducing inter-crop-year farm profit level and its variability. By analyzing a sample of 26,615 observations across 2,486 farms and four dryland crops (corn, soybean, sorghum, and wheat) in Kansas (KS) spanning nine crop years (2014 -2022), we have identified key trends and divergences in the effectiveness of these programs. For crops like wheat and sorghum, we have seen a direct correlation between the use of safety net programs and both reduced profit risk and enhanced profitability. However, this correlation does not hold across all crops, with corn and soybean strategies displaying less consistency in risk reduction and profit enhancement. Our findings underscore the importance of considering the impact of safety net programs on agricultural credit and lending practices. As these programs enhance creditworthiness by reducing borrowing risks (Pflueger and Barry, 1985) and paying down earlier debt (DeLay et al., 2022), they consequently shape the financial landscape of rural economies. The relationship between safety net program utilization and financial risk-taking

also calls for a careful policy balance. While these programs are essential, they should be structured in a way that does not unduly incentivize excessive risk-taking by producers. The goal should be to encourage prudent risk management while providing a reliable support system.

Our analysis is not without limitations and caveats. We perform a historical analysis based on prices received for commodities and yield obtained during our study period. These economic and agronomic variables tend to vary over time and the performance of these FCIP policies may be altered. Thus, historic performance of these policies does not guarantee future performance, yet this analysis provides a starting point to evaluate the efficiency of these programs. Additionally, producers may switch from one policy to the other during our study year. We did not account for such changes that may impact the performance of these FCIP policies for the individual producer.

Our study, while focused exclusively on Kansas farms, serves as a foundational analysis for assessing the efficacy of farm safety net programs across the United States. Given the greater variability of dryland crop production in Kansas compared to regions like the U.S. Corn Belt, policies proven effective in Kansas may potentially perform even better in less variable contexts. However, it is crucial to acknowledge that extending these findings to other major agricultural areas remains an empirical question that merits further investigation. Our results establish a baseline for future studies, which should expand this analysis to other critical farming regions to deepen our understanding of these programs' effectiveness. Moreover, investigating the impact of these safety nets on downside risk in agriculture is essential to comprehend fully their influence on reducing the probability of financial loss.

Chapter 2

The Financial Status and Local Credit Market Conditions of U.S. Farms Engaged in Multiple Borrowing

2.1 Introduction

Many U.S. agricultural producers secure debt financing from multiple lenders — a practice known as multiple borrowing ([Chichaibelu and Waibel, 2017](#)). Policymakers, financial regulators, and lending institutions are concerned about multiple borrowing because credit conditions for some lender types are difficult to observe ([Brewer et al., 2022](#)), coordinating a borrower’s multiple lenders can be difficult, and higher levels of debt may contribute to increased default potential ([Chichaibelu and Waibel, 2017](#)). As such, credit scores of firms are often affected by addition of new loans.

Despite its risks, producers may consider multiple borrowing to capture certain benefits, such as using the practice as liquidity insurance ([Ogawa et al., 2007](#)), a tool to facilitate more ambitious farm business growth, or a tactic to avoid relying on a single lender ([Detragiache et al., 2000](#)). Alternatively, multiple borrowing could be a response to conservative agricultural lending practices ([Boehlje, 2019](#)) or more restrictive bank regulation ([Regmi](#)

and Featherstone, 2022). It may also be more common among more leveraged producers (Brewer et al., 2019) or producers facing cash-flow shocks (Fiechter and Ifft, 2023; Prager et al., 2018). Better understanding the financial profile of agricultural producers engaged in multiple borrowing and the credit market environments in which they operate would enhance the ability of policymakers and lenders to assess the risks and opportunities associated with multiple borrowing.

In this study, we analyze the financial status and local credit market characteristics of Kansas farms engaged in multiple borrowing. We use data from the Kansas Farm Management Association (KFMA), which offers detailed information about all loan obligations held by participating Kansas farms, farm financial status, and other producer characteristics. The KFMA dataset has unique advantages for studying multiple borrowing as very few datasets other than the USDA Agricultural Resource Management Survey (ARMS) contain such broad farm-level information. Although ARMS offers important insights on farm lending practices (i.e., Katchova (2005)), it limits the number of loans reported to five in most years and may under-report debt from nontraditional lenders (Briggeman et al., 2024).

We first develop a novel and precise metric for farm-level multiple borrowing. Unlike measures of multiple borrowing used in previous agricultural finance studies, this study quantifies multiple borrowing by developing measures of lender and loan concentration based on the number of lenders and loan volume. Next, we combine local lender data with KFMA data. We are most interested in cross-sectional variation in multiple borrowing, so we employ ordinary least squares (OLS) with and without region and year fixed effects. Further, we use machine learning (random forest) to analyze which financial status and local credit market characteristics have the strongest relationship with multiple borrowing. Our regression model allows us to quantify how these factors are related to the incidence of multiple borrowing, but random forest has enhanced predictive power (Ifft et al., 2018). Unlike previous studies (Brewer et al., 2014; Katchova, 2005), we find more profitable producers are more likely to use multiple borrowing. Likewise, larger and more leveraged farms more likely engage in multiple borrowing. Credit market characteristics also predict multiple borrowing. For example, multiple borrowing is less prevalent for farms in areas with more banks per person

and more banks specialized in agriculture. Of all farm and credit market characteristics studied, we find leverage has the most predictive power.

This study builds on prior general finance studies on multiple borrowing. The previous work focuses on three questions: (1) which firms use multiple loans or lenders, (2) why do firms engage in multiple borrowing; and (3) what are problems associated with maintaining multiple borrowing relationships? Research on the first issue reveals that firms reporting multiple borrowing behavior are typically older, larger, and more leveraged ([Bolton and Scharfstein, 1996](#); [Degryse et al., 2009](#); [Ongena et al., 2012](#)).

To answer the second question, several prior works explore factors that may motivate multiple borrowing. Firms engaged in multiple borrowing seek to diversify their credit profiles and mitigate rent extraction by individual lenders ([Elsas et al., 2004](#); [Farinha and Santos, 2002](#); [Kosenko and Michelson, 2022](#)). As such, multiple borrowing serves as a risk management strategy as it reduces the risk of complete credit withdrawal by a single lender during ongoing projects ([Detragiache et al., 2000](#); [Diamond, 1991](#)). Expanding firms in need of greater financial resources also may turn to multiple borrowing to supplement services from existing lenders ([Van Tassel, 2018](#)). Moreover, firms experiencing financial distress or facing adverse shocks may engage lenders concurrently to access additional credit to repay debt ([Degryse et al., 2009](#); [Tirri, 2007](#)).

Regarding the challenges associated with multiple borrowing, the practice can lead to borrowers incurring high costs ([Degryse and Ongena, 2001](#)), impose default externalities on current creditors, and result in misallocating loans toward less productive projects ([Green and Liu, 2021](#)).

Within an agricultural context, previous studies shared similarities with finance studies that highlight how firms using multiple borrowing tend to be larger and more leveraged ([Detragiache et al., 2000](#)). [Katchova \(2005\)](#) found that higher farm revenue and total farm acreage are associated with more loans — similar to [Brewer et al. \(2014, 2019\)](#), who additionally identified an association with higher leverage. While not directly focused on multiple borrowing, [Nadolnyak and Hartarska \(2022\)](#) found local lender density in some cases correlates with nontraditional lender use by beginning and female-operated farms.

In several ways, our study advances the understanding of multiple borrowing in agriculture. First, we use indicators to measure credit institutions’ physical presence and investigate the degree to which these indicators are associated with multiple borrowing behavior. Most multiple borrowing studies have not accounted for local market characteristics; however, [Tirri \(2007\)](#) use a measure of lender market concentration as a control variable and find it is related to multiple borrowing in Italy. Conceptual models of multiple borrowing assume risk-neutral lenders and perfectly competitive lending ([Detragiache et al., 2000](#)). However, credit markets and banking regulations have changed substantially during the past decade ([Cornelli et al., 2023](#); [Regmi et al., 2021](#)). The ongoing decline in local lender branches ([Mashange, 2024](#)) could influence multiple borrowing. [Barboni and Rossi \(2019\)](#); [Cetorelli and Strahan \(2006\)](#) suggest changes in local credit availability may play a role in financing decisions. Local lenders do typically have lower transaction costs and face less information asymmetry than lenders lacking close proximity to their customers ([Agarwal et al., 2006](#); [Guiso and Minetti, 2010](#)). Farms operators may prefer working face-to-face with their lenders ([GSA, 2018](#)) or supporting local businesses ([Ripoll González et al., 2022](#)). Likewise, demand for multiple borrowing could have positive impacts on the number of local lenders by allowing more branches to remain open.

Second, our approach incorporates loan volume as a means to capture the relative importance of each loan. Previous agricultural finance studies have used loan or lender counts (i.e., [Brewer et al. \(2019\)](#)), but the factors influencing the number of lending relationships may differ from those affecting the degree to which a producer’s loans are spread out or concentrated among multiple lenders. For example, loan counts can be disproportionately influenced by promotional vendor financing for relatively small loans that producers often take to reduce costs. This consideration is crucial for identifying capital structure determinants as highlighted in studies such as [Colla et al. \(2013, 2020\)](#); [Guiso and Minetti \(2010\)](#); [Rauh and Sufi \(2010\)](#). Unlike simply counting the number of loans or lenders, this measure (index) accounts for both the volume of loans and the individual contribution of each loan to a farm’s overall debt profile. Thus, it captures the risk associated with depending on a single lender and coordinating multiple lenders. Our analysis suggests that analyses of

lender or loan counts do not reflect the relationship between local credit market conditions and multiple borrowing.

Finally, we employ machine learning techniques to explore which farm and credit market characteristics best predict multiple borrowing. In doing so, we add to an emerging agricultural finance literature that demonstrates machine learning applications (i.e., [Chen et al. \(2021\)](#)). Previous general finance studies of firm characteristics and multiple borrowing did not consider firm characteristics’ relative predictive power.

The remainder of this study is as follows. Section [2.2](#) presents the methodology, and Section [2.3](#) discusses our data sets. Section [2.4](#) summarizes the empirical results, and Section [2.5](#) concludes with policy implications.

2.2 Methodology

In this section, we detail the construction of multiple borrowing measures, which serve as outcome variables. Specifically, we concentrate on two metrics: lender and loan concentration. We also describe the models used to estimate how farm financial status and local credit market attributes link to multiple borrowing.

Producers often secure multiple loans from lenders in a year. To account for this multiple borrowing behavior, prior studies, including (for example; [Brewer et al., 2014](#)), often have counted the number of lending relationships or loans. Number of loans is a multiple borrowing indicator. However, this approach does not capture the volume of secured loans, and it treats all debt types in a farm’s capital structure uniformly. For example, if a producer obtained a \$1,000 loan from lender A and a \$100,000 loan from lender B during 2002, then counting loans leads to only denoting the producer obtained two loans during 2002. However, the producer’s commitments to these lenders may differ because of the differences in loan volumes. Using loan number does treat all loans equally by giving them the same value and weight. Put differently, loan numbers treat farm debt as equally distributed among lenders. Additionally, a review of farm balance sheets reveals that producers often secure loans of different sizes, and failure to capture this heterogeneity may mask important multiple bor-

rowing behavior (Rauh and Sufi, 2010). Although number of loans may reflect some risks associated with multiple borrowing, such as coordination failures, loan size is likely a key factor in such risks.

We capture this debt heterogeneity by denoting L_{ijt} as the loan volume from lender¹ i to farm j and TL_{jt} as total loan volume secured by farm j in year t . We then construct the loan share, $s_{ijt} = \frac{L_{ijt}}{TL_{jt}}$, for all loans in a year. If a farm secures loans from n lenders in year t , accounting for all n loans and adding their contributions (shares) sums to one, $\sum_i^n (s_{ijt}) = \sum_i^n (\frac{L_{ijt}}{TL_{jt}}) = 1$. There is no variation in this value to empirically identify the financial status and credit market factors linked to multiple borrowing behavior in a regression analysis. We circumvent this problem by first squaring each loan share and then adding them to obtain the Herfindahl-Hirschman Index (HHI). Our index, HHI , is thus defined as $HHI_{jt} = \sum_i^n (s_{ijt})^2 = \sum_i^n (\frac{L_{ijt}}{TL_{jt}})^2 = s_{1jt}^2 + s_{2jt}^2 + \dots + s_{njt}^2$, where s_{ijt} is the loan share from lender i computed by dividing a loan amount from source i by total loan volume received by farm j in year t . We refer to this metric as lender concentration, consistent with prior studies (Guiso and Minetti, 2010; Li et al., 2021; Ongena et al., 2012).

A farm with an HHI of 1² in a year indicates the producer in that particular year took all loans from a single lender, and an index close to 0 signifies borrowing from more than one lender. For instance, an index of 0.5 implies borrowing from two lenders with equal loan volumes, yet an HHI of 0.8 signifies a producer secured loans from two lenders in unequal amounts. Additionally, an index close to 0.25 signifies borrowing from multiple sources with unequal loan amounts.

According to Hannan (1997), HHI_{jt} can be decomposed into two terms: $HHI_{jt} = (V_{jt}^2/N_{jt}) + (1/N_{jt})$, where V_{jt} is the coefficient of variation of total loans secured by farm j at time t , and N_{jt} is the number of lenders. By this decomposition, our metric accounts for the number of lending relationships and the inequality arising from securing different loan volumes from multiple lenders.

Producers also secure multiple loans from the same lender (or lender type) in the same

¹This is obtained by summing loan volumes secured from the same lender types in a year.

²In the data and results sections, we scale this index by 100 for ease of interpretation.

period. In order to unmask factors linked to this borrowing behavior, we use individual loan volumes, instead of loan volumes by lender type, to construct another metric, which we refer to as loan concentration. Thus, we have $HHI_{jt} = \sum_i^n (s_{ijt})^2 = \sum_i^n (\frac{L_{ijt}}{TL_{jt}})^2 = s_{1jt}^2 + s_{2jt}^2 + \dots + s_{njt}^2$, where s_{ijt} is the individual loan share computed by dividing the ith individual loan amount by total loan volume secured by farm j in year t . Considering the above decomposition, we expect loan concentration to be lower than lender concentration because loan numbers are inversely related to our metrics, and loan numbers are either equal or greater than number of lenders in a year.

We use the following model to estimate how local credit market characteristics and farm financial status are related to lender and loan concentration:

$$y_{it} = F'_{it}\beta + M'_{it}\gamma + X'_{it}\alpha + \epsilon_{it} \quad (2.1)$$

where y_{it} is HHI_{it} of farm i in time t for both lenders and loans. F_{it} is the financial status of farm i in time t . It is measured using a debt-to-asset ratio, current ratio and return on assets ratio. M_{it} measures local credit availability, including number of agricultural banks, banks per person and presence of FCS lender locations. X_{it} is farm i 's characteristics in time t including farm size (in acres), number of operators and employees. ϵ_{it} is the error term. We use OLS to estimate our model in eq. (2.1) and estimate heteroskedasticity robust standard errors. We estimate this model with and without year and region fixed effects. This approach balances our interest in cross-sectional variation with the need to test whether our results are robust to (1) general market or economic factors such as crop prices or inflation or (2) fixed locational factors.

Prior studies (e.g., (for example; [Brewer et al., 2014, 2019](#); [Katchova, 2005](#))) have examined how farm attributes such as age, number of operators, leverage, current financial position, land ownership, number of workers, profitability and size are related to number of loans. In view of that, we examine how these variables are associated with multiple borrowing in our model in eq. (2.1) to determine whether those associations still hold over time.

We also include local credit market factors such as physical presence of banks, number of agricultural banks³ and banks per person to capture the proximity of lenders to borrowers, which can significantly impact transaction costs when seeking financing (Brevoort and Wolken, 2009; Elliehausen and Wolken, 1990). Lenders being geographically close to borrowers often reduces transaction costs associated with borrowing (Brevoort and Wolken, 2009). Proximity facilitates easier communication; allows for more frequent and direct interactions between borrowers and lenders; and streamlines the process of loan application, approval, and disbursement (GSA, 2018; Wang et al., 2024). As a result, borrowers may incur lower administrative costs, such as travel expenses or time spent on paperwork, when accessing credit from nearby lenders (Troisi and Alfano, 2023). Moreover, proximity can also reduce information asymmetry between lenders and borrowers and lead to lower monitoring and enforcement costs for lenders (Agarwal et al., 2006; Guiso and Minetti, 2010). Lenders can more easily assess a borrower’s creditworthiness by having direct knowledge of local market conditions, collateral, and other relevant information. This reduces the need for costly and time-consuming due diligence processes and increases lenders’ confidence in extending credit to borrowers.

We estimate our primary model with lagged explanatory variables as a robustness check to account for how lenders and borrowers make decisions. Lenders may not exclusively observe and consider a producer’s present or recent financial status as they review a loan application. Their financing decisions instead may reflect past financial status. Likewise, producers exploring financing options may not accurately gauge local credit market factors that influence their borrowing practices. Instead, they may rely on past information about bank branches and openings.

Although we estimate a predictive model and don’t make causal claims, newly added debt could disproportionately influence our results. For example, a new real estate loan could affect our measures of loan or lender concentration. Additionally, producers taking on a large loan, such as a real estate loan, in the current year would likely have a higher

³A bank is classified as an agricultural bank if at least 25% of its total loans are allocated to agriculture (Regmi and Featherstone, 2022).

debt-to-asset ratio. Similar results with this model would suggest our results are not driven by newly added debt.

We also examine whether financial status and local credit market conditions related to our measure of multiple borrowing are different from results based on number of lending relationships used in prior studies. Consequently, we use the number of lending relationships (lenders) as the dependent variable in equation 2.1 and compare these results to our main findings with lender concentration. Likewise, we use number of loans as our dependent variable in equation 2.1 for comparison.

We supplement this OLS regression of our empirical model in eq. (2.1) with a random forest model. In addition to having higher predictive power, random forest provides feature selection and ranking (Ifft et al., 2018). This allows for an explicit ranking of what financial variables and local credit market attributes best predict multiple borrowing behavior.

To obtain the feature ranking estimate, we follow Schonlau and Zou (2020) and set the model parameters that ensure the best model fit. We randomly select 50% of our dataset for training, which helps prevent the model from relying on the sequence of observations. The remaining 50% is used to test the model after training. We then adjust the hyperparameters to find the model with the highest testing accuracy. The out-of-bag (OOB) prediction accuracy, which depends on the number of iterations and variables, is calculated through multiple iterations starting at 10 and increasing by 10 each time until reaching 500 (Schonlau and Zou, 2020). We use the 50% of data not used for training to compute the OOB error, and the testing data to compute the validation error. This helps us determine the best model. After identifying the number of iterations and variables to randomly consider at each split for the highest accuracy, we estimate the importance of each variable (Biau and Scornet, 2016).

2.3 Data

We use farm-level data collected by the Kansas Farm Management Association (KFMA) from 2002-2020. KFMA provides its members who are Kansas agricultural producers with

financial and accounting services, and in return, it confidentially maintains farm financial and production data made available for research purposes. Several studies have used these data: (Bierlen and Featherstone, 1998; Brewer et al., 2014, 2019; DeLay et al., 2022; Gaku and Tsiboe, 2024; Sajid et al., 2022; Skevas et al., 2023).

Lenders including commercial banks, nontraditional lenders, and Farm Credit System (FCS) lenders provide short- and long-term credit for KFMA producers. Prior studies (Brewer et al., 2014, 2019) categorized the lenders for KFMA farm-level loans from 2002 to 2012. Loans funded by an FCS member institution were categorized as FCS loans. The commercial bank category includes large national banks such as Bank of America. Nontraditional lenders consisted of vendor financiers such as John Deere Credit or Case Credit. Similar categorizations were done to other identified lenders including credit unions, individuals, and AgDirect for that period. Our analyses use these datasets from 2002 to 2012.

We extend the dataset developed in prior studies (Brewer et al., 2014, 2019) by classifying KFMA farm loans from 2013 to 2020 using the following steps.⁴ First, we consulted with KFMA economists who use keywords and abbreviations to describe each farm-level loan observation. Next, we used the keywords and abbreviations to classify loans. For loan observations that were still not classified, research assistants did a loan-by-loan review, and KFMA economists were consulted. These steps resulted in classifying nearly all loans into 12 categories — namely, AgDirect, commercial banks, cooperative finance, credit card, credit union, Farm Credit, government agencies, individuals, insurance, nontraditional, rural banks and others — after adjusting for minor changes in categories from 2002-2012 and 2013-2020. KFMA producers use several debt types, and their associated keywords and abbreviations are in Table B.2. Farms without any loans or loans with negative values were excluded from the analysis.⁵ Additionally, only farms where all loans could be categorized in a year are used in this study’s primary or preferred analyses.

Table B.3 presents the inflation-adjusted loan statistics for all farms and farms with all

⁴Thus, our study period can be subdivided into 2 periods, with the first period (period 1) starting from 2002 to 2012 and the second period (period 2) starting from 2013 to 2020. We examine whether there are differences across these two time periods and conduct several robustness checks.

⁵Farm loan observations with zero or negative values constitute about 5 percent of the initial 175,270 loan observations.

loans categorized. The average total loan volume for farms with all loans categorized is \$490,796. Mean loan volume for these farms increased about 161 percent from \$277,358 in 2002 to \$723,300 in 2020, consistent with increasing debt volume reported by [Kauffman and Kreitman \(2023\)](#). The average producer has had a larger loan volume over time. This trend implies potential shifts in producers' borrowing behavior or financial needs over time.

The share of farms with all loans categorized is substantially higher in the second period of our study, with at least 66 percent of farms having all loans classified in a single year from 2013 onwards (Table B.3). Further, loan volumes are not statistically different when considering categorized or uncategorized loans from 2013. These differences potentially influence our measures of lender concentration but not loan concentration. We conduct robustness checks to assess how sensitive our results are to (1) including farms with uncategorized loans in models of loan concentration, (2) running separate regression analyses for the two time periods (i.e., 2002-2012 and 2013-2020), and (3) maintaining the original categories for the two time periods without reducing them to 12 (categories).⁶ This approach balances our preference for a longer period of analysis with transparency for the sensitivity of our results to different categorization procedures and rates over two periods.

County-level data on banks and FCS lenders approximate local credit provider availability; USDA estimates that banks and FCS lenders jointly held 81 percent of farm sector debt in 2022. Other lenders are less likely to be locally based ([Fiechter and Ifft, 2020](#)). Federal Deposit Insurance Corporation (FDIC) call data on the count of agricultural banks is aggregated to the county-year level. According to [Monke \(2022\)](#), commercial banks not classified as agricultural banks hold a 36 percent share of farm debt. To capture the presence of banks not specialized in agricultural lending, we use data on number of banks per 1,000 people in a county from 2002-2020 obtained from the Institute for Policy & Social Research (IPSR), University of Kansas. Consistent with [Kim and Katchova \(2022\)](#), the number of banks per person decreased in Kansas by 40 percent from 0.15 in 2002 to 0.09 in 2020 as shown in Tables B.5 and B.6. Approximately 53 percent of Kansas counties experienced a

⁶While there were 13 categories from 2002-2012, our recent categorization for the period 2013-2020 yielded 15 categories. All these were reduced to 12 uniform categories from 2002-2020, affecting a small percent of farms. These changes only affected 3% of the initial 175,270 observations.

decline in banks per capita in our study period, and 44 percent experienced an increase. This change in bank numbers stems from migration of population toward larger urban centers, bank failures, mergers, and acquisitions ([Bhat and Ryan, 2015](#); [Sengupta and Dice, 2019](#); [Siebenmark, 2013](#)).

Both FCS lender branches and outposts offer financial services; however, outposts are typically open less frequently than branches. To identify FCS lender branches, we use publicly available data from the websites of the four Farm Credit associations in Kansas: Frontier Farm Credit, Farm Credit of Western Kansas, High Plains Farm Credit, and American Ag-Credit. We also reached out to each association for information about branch and outpost closures and openings before 2020 because these details were not readily available online. For example, the High Plains outpost in Greensburg opened in 2017, and a branch in Pratt opened in 2002. Also, Frontier Farm Credit closed four outposts and three branches during our study period. Table [B.4](#) presents the details of these FCS lenders serving Kansas counties.

Definitions of all variables are provided in Table [B.1](#), and the summary statistics of our final sample are presented in Table [2.1](#). During the study period, farm size operated by a KFMA member averaged 2,225 acres, and KFMA producers rented about 62 percent of these acres for production. The average age of a KFMA farm operator was 57 years old. KFMA producers are similar to large U.S. farm businesses specializing in crop production ([Kuethe et al., 2014](#)). Larger farms contribute the majority of production and are much more likely to use debt ([Whitt et al., 2020](#)). Therefore, they are more relevant to lenders and financial regulators.

Table 2.1: *Summary Statistics of Variables, 2002-2020*

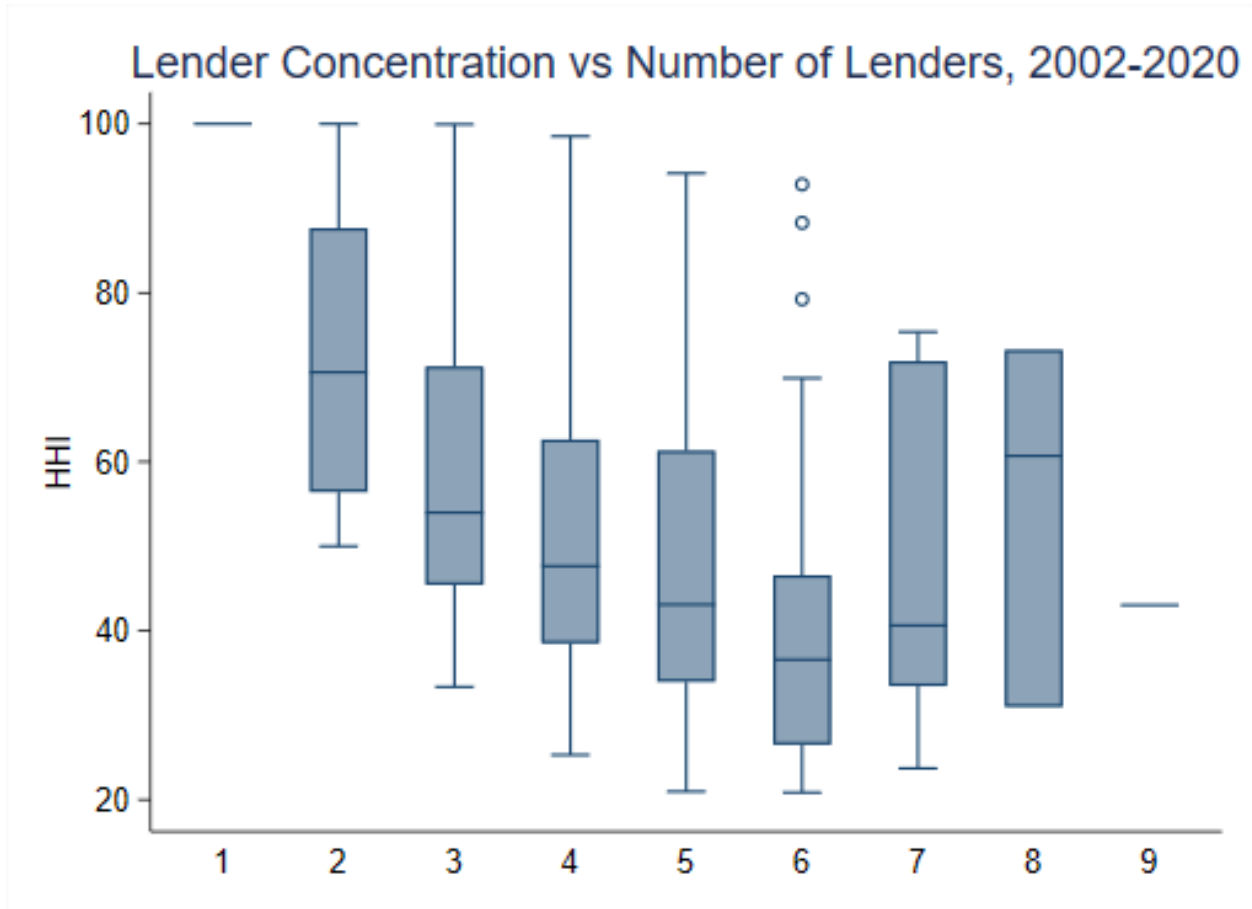
	Obs	Mean	SD	Median
Farm Structure				
Operator's age	9368	56.98	12.74	58.00
Number of workers	9368	1.53	1.48	1.10
Total Operated Acres	9368	2225.17	2146.74	1645.00
Total Operated Acres	9368	7.34	0.92	7.41
Share of Operated Acres owned	9368	0.38	0.32	0.32
Financial Status				
Debt to Asset ratio	9368	0.31	0.35	0.23
Return on Assets (%)	9368	1.19	22.46	1.00
Normalized Current Ratio (%)	9368	0.05	1.50	0.02
Local Credit Market Indicators				
Number of agric. banks	9368	1.21	1.17	1.00
Banks per people	9368	0.57	0.35	0.51
Physical presence of farm credit	9368	0.17	0.38	0.00
Physical presence of farm credit outpost	9368	0.15	0.36	0.00
Outcome Variables				
Loan Concentration, scaled by 100	9368	56.11	29.40	50.04
Lender Concentration, scaled by 100	9368	79.53	22.72	90.06
Others				
Number of Loans	9368	4.39	3.85	3.00
Number of Lenders	9368	1.97	1.08	2.00
Location				
North Central	9368	0.16	0.37	0.00
South Central	9368	0.13	0.34	0.00
Southwest	9368	0.06	0.24	0.00
Northeast	9368	0.17	0.37	0.00
Northwest	9368	0.14	0.35	0.00
Southeast	9368	0.34	0.47	0.00

Note: This table presents the summary statistics of variables from 2002-2020. We use datasets from KFMA, FDIC, FCA & IPSR. There are 2,173 farms in this 19-year period. Lender and Loan concentration are scaled by 100.

In Table 2.1, we observe that only 17 percent of KFMA producers operate in a county that has an FCS lender branch and 15 percent for FCS lender outposts. For all KFMA member operations included in the analysis, we consider three primary farm financial metrics, similar to [Brewer et al. \(2014, 2019\)](#); [Guiso and Minetti \(2010\)](#); [Katchova \(2005\)](#); [Ongena et al. \(2012\)](#). The debt-to-asset ratio measures farm solvency, return on assets measures profitability, and the current ratio measures farm liquidity. The current ratio is normalized to minimize the role of outliers; the inverse current ratio used in previous studies ([Alan Russell et al., 2013](#); [Brewer et al., 2019](#); [Langemeier and Yeager, 2022](#)) precludes estimation with farms with no current debt. The average debt-to-asset ratio of a KFMA farm is 0.31, and return on assets averages 1 percent.

We use KFMA loan data to construct a Herfindahl-Hirschman Index for each producer in a year. Lender concentration best captures multiple borrowing behavior, but loan concentration is a similar measure that allows for (1) the potential that producers could have loans with different lenders of the same type (i.e. different banks) and (2) robustness checks that include non-categorized loans. We scale our indices by 100 and observe in Table 2.1 that producers obtain multiple loans with an average index of 56 compared to 80 for lender concentration, highlighting the earlier results that farmers may take several loans from a particular lender or lender type.

Figure 2.1 presents our preferred measure of multiple borrowing, lender concentration, and number of lenders. Lender concentration is not equivalent to number of lenders, suggesting the factors that drive the number of lending relationships and this measure of multiple borrowing behavior (lender concentration) may be distinct. Lender concentration is 1 when a producer receives loan(s) from a single lender in a year. With two lenders, the lender concentration ranges from 0.50 to 0.99, with a standard deviation of 0.17. Producers with HHI of 0.50 would have received equal loan volumes from two lenders, but those with an HHI of 0.99 received a significant loan volume from one lender and a small amount from another lender. We would be unable to detect this variation if we relied solely on the number of lenders. The motivations to increase the number of loans thus may be different from factors that drive producers to increase the degree to which their credit concentrates among



Note: This figure shows lender concentration and number of lenders for KFMA producers from 2002 to 2020. Lender concentration ranges between 0 and 100 after scaling by 100. A value close to 0 means the producer uses several lenders. A value of 100 means the producer uses a single lender. The number of farm-year observations is 9,368.

Figure 2.1: *Lender Concentration vs Number of Lenders, 2002-2020*

different lenders.

2.4 Results

Table 2.2 presents the results of equation 2.1 with lender concentration as the outcome. Large farms, measured by number of workers and acres operated, tend to spread out debt across multiple lenders. Older farm operators usually rely on fewer lenders — consistent with older operators reporting lower debt use (Ifft et al., 2014). Additionally, as producers own more land, they tend to spread out debt across more lenders, though this result is not consistent across specifications.

The debt-to-asset ratio has a statistically significant and negative association with lender concentration in our study period. More leveraged farms tend to spread out their credit across more lenders. A 10-percentage-point increase in leverage is associated with about a 0.5- to 0.7-unit decrease in lender concentration.⁷ This may be because they are obtaining newer loans from new lenders, which is consistent with [Brewer et al. \(2014\)](#), who find that more leveraged farms tend to keep multiple lending relationships. Return on assets is negatively associated with lender concentration. On average, a 10-percentage-point increase in return on assets is associated with approximately 0.2- to 0.4-unit decrease in lender concentration. The relationship between the normalized current ratio, a measure of liquidity, and lender concentration is not statistically significant.

Although many studies have shown leverage’s association with multiple borrowing ([Detragiache et al., 2000](#); [Ongena et al., 2012](#)), a positive relationship with profitability and multiple borrowing was not found in previous agricultural finance research ([Brewer et al., 2019](#); [Katchova, 2005](#)). In the general finance literature, earlier studies have typically found no significant relationship between profitability and multiple borrowing ([Detragiache et al., 2000](#); [Iturralde et al., 2010](#); [Ongena et al., 2012](#)). However, recent studies find a notable association between these variables and attribute this finding to borrowers, potentially indicating a preference for benefits of not relying on a single lender instead of the benefits of a single lending relationship ([Pasiouras et al., 2021](#); [Refait-Alexandre and Serve, 2020](#)). Specifically, on the demand side, this multiple borrowing behavior may be driven by demand from producers who want to take advantage of growth opportunities ([Farinha and Santos, 2002](#)) and wish to mitigate risks of relying on a single lender ([Elsas et al., 2004](#)). Although we cannot conclude whether profitability or farm characteristics correlated with profitability lead to higher multiple borrowing, the tendency of larger, more leveraged, and more profitable farms to engage in multiple borrowing suggests that growth-oriented farms either prefer multiple borrowing or have limited options to fund more aggressive growth with a primary lender.

Credit market factors are also associated with lender concentration. A new agricultural

⁷This is equivalent to a 6-8 percentage points of average lender concentration.

bank opening generates about a 0.4- to 0.6-unit increase in lender concentration.⁸ Producers in areas with more agricultural banks and more banks per person tend to rely on fewer lenders. This may reflect preference for a local lender and associated benefits related to transaction costs and information asymmetry as well as banks' strategic location decisions. The location of FCS branches and outposts is not related to lender concentration. Several Kansas counties do not have an FCS lender or outpost, but each county averages 1.21 agricultural banks. Therefore, location and community relationships likely play a larger role for banks. These findings are broadly consistent with [Nadolnyak and Hartarska \(2022\)](#), who find that local lender density has a mixed relationship with use of nontraditional lenders by beginning and women-operated farms.

Results for loan concentration (Table 2.3) are largely consistent with lender concentration. The magnitude of coefficients is often larger for loan concentration, which is likely due to a higher variability in loan concentration being explained. This generally suggests that farm characteristics that predict adding credit from an existing lender (or lender type) are similar to those that predict adding credit from an additional lender. Producers with more access to banks hypothetically could engage in more lending relationships. Instead, we observe lower levels of multiple borrowing, measured either by lender or loan concentration. This is consistent with the importance of relationship lending in agricultural and small business in general ([Antwi and Ohene-Yankyira, 2017](#); [Berger and Udell, 1995](#); [Elyasiani and Goldberg, 2004](#); [Petersen and Rajan, 1994](#)). Further, our results suggest that producers don't engage in multiple borrowing simply because they have convenient access to more local banks. When producers do engage in multiple borrowing, additional credit is likely to be provided by a nontraditional lender ([Brewer et al., 2019](#)) as opposed to a nearby bank or FCS lender. Development of lending platforms like AgDirect⁹ by several FCS institutions may be in part a strategy to capture this business.

Our results are consistent under a number of specifications. First, we observe that including all loans in our measure of loan concentration provides consistent results as shown

⁸This is equivalent to a percentage point of average lender concentration.

⁹For more information on AgDirect, see <https://www.agdirect.com/about-us>.

in Table B.8. This provides strong evidence that different lender categorization procedures across our study period do not drive results. Second, our findings are not driven by newly added debt, as shown by the lagged variable regression results in Tables B.9 and B.10. Third, the comparative analyses for the two periods (2002-2012 and 2013-2020) in Tables B.11 and B.12 do not yield conflicting results such as sign changes for statistically significant variables. Four, neither does using all loans in Table B.13 nor maintaining the original lender categories as presented in Tables B.14 and B.15.

Analyzing results from the two time periods does reveal some interesting findings. The relationship between leverage and profitability and lender or loan concentration is stronger in the second period. Banks per capita had a stronger positive relationship with lender concentration during the second period but a stronger relationship with loan concentration in the first period. An FCS lender branch was related to lower lender concentration in the first period but not the second; this association was present but weaker for loan concentration. FCS outposts were related to lower loan concentration in the second period. Jointly, these results may reflect changing credit market dynamics during the study period and the increasing relevance of multiple borrowing behavior.

Our findings confirm that the factors influencing multiple borrowing, as measured by our specific metric, can differ from those affecting the number of lending relationships a producer maintains. In Table 2.2, it is evident that the number of agricultural banks is related to lender concentration. However, this factor does not have the same association with the number of lending relationships as demonstrated in Table B.16. Although the presence of numerous agricultural banks is related to higher lender concentration, it does not necessarily increase the number of different lenders from which a producer borrows money. Different dynamics are at play in lender concentration versus the number of lending relationships.

Table 2.2: *Determinants of Lender Concentration in Kansas, 2002-2020*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Debt to Asset ratio			-5.152*** (1.236)	-6.518*** (1.324)			-5.186*** (1.240)	-6.519*** (1.330)
Return on assets			-2.549** (1.013)	-3.691*** (1.068)			-2.497** (1.019)	-3.720*** (1.069)
Normalized Current ratio			7.668 (13.844)	11.417 (13.995)			5.837 (13.011)	11.498 (13.290)
Number of agric. banks					0.424** (0.206)	0.569*** (0.214)	0.410** (0.205)	0.572*** (0.213)
Banks per people					3.310*** (0.791)	2.606*** (0.844)	3.341*** (0.789)	2.591*** (0.839)
Physical presence of farm credit outpost					0.419 (0.657)	-0.092 (0.657)	0.497 (0.656)	-0.014 (0.655)
Physical presence of farm credit					1.292* (0.730)	-0.762 (1.038)	1.296* (0.727)	-0.832 (1.029)
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9368	9368	9368	9368	9368	9368	9368	9368
R^2	0.035	0.073	0.040	0.081	0.039	0.075	0.045	0.084

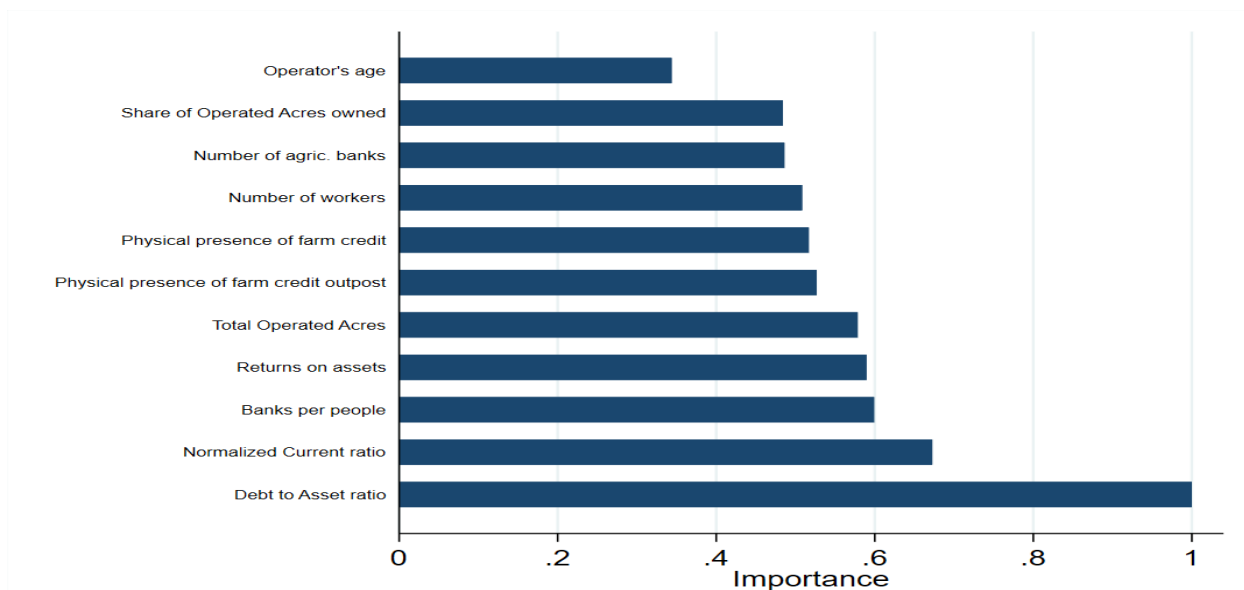
Note: This table presents the results of OLS estimation of equation 1.1. Each column presents a separate regression results for the period 2002-2020: Variables are gradually included in the models, with the last model containing all variables in our analyses. Models 2, 4, 6 and 8 have both year and region fixed effects. Lender concentration is the dependent variable, which is scaled by 100 for easy interpretation. We log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3: *Determinants of Loan Concentration in Kansas, 2002-2020*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Operator's age	0.424*** (0.025)	0.455*** (0.025)	0.312*** (0.034)	0.338*** (0.034)	0.430*** (0.025)	0.454*** (0.025)	0.320*** (0.035)	0.337*** (0.034)
Number of workers	-0.909*** (0.239)	-0.452** (0.224)	-0.946*** (0.227)	-0.446** (0.214)	-0.816*** (0.237)	-0.415* (0.224)	-0.850*** (0.226)	-0.411* (0.214)
Share of Operated Acres owned	2.555** (1.038)	0.626 (1.044)	-2.470** (1.146)	-5.184*** (1.159)	2.184** (1.054)	0.491 (1.051)	-2.876** (1.161)	-5.303*** (1.167)
Total Operated Acres	-6.562*** (0.364)	-6.935*** (0.382)	-7.327*** (0.359)	-7.769*** (0.380)	-6.930*** (0.387)	-7.059*** (0.384)	-7.718*** (0.383)	-7.890*** (0.382)
Debt to Asset ratio			-19.113*** (3.300)	-20.708*** (3.329)			-19.112*** (3.302)	-20.694*** (3.334)
Return on assets			-6.810** (2.802)	-8.103*** (2.750)			-6.774** (2.807)	-8.121*** (2.751)
Normalized Current ratio			32.040 (20.643)	38.474* (21.820)			30.776 (19.872)	38.290* (21.105)
Number of agric. banks					0.422 (0.264)	0.539** (0.273)	0.358 (0.253)	0.529** (0.262)
Banks per people					3.529*** (0.980)	2.996*** (1.051)	3.666*** (0.954)	2.989*** (1.016)
Physical presence of farm credit outpost					-1.289 (0.817)	-1.229 (0.824)	-0.996 (0.792)	-0.972 (0.796)
Physical presence of farm credit					-0.254 (0.920)	-0.625 (1.271)	-0.238 (0.883)	-0.881 (1.213)
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9368	9368	9368	9368	9368	9368	9368	9368
R^2	0.088	0.122	0.131	0.172	0.091	0.124	0.133	0.174

Note: This table presents the results of OLS estimation of equation 1.1. Each column presents a separate regression results for the period 2002-2020: Variables are gradually included in the models, with the last model containing all variables in our analyses. Models 2, 4, 6 and 8 have both year and region fixed effects. Loan concentration is the dependent variable, which is scaled by 100 for easy interpretation. We log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

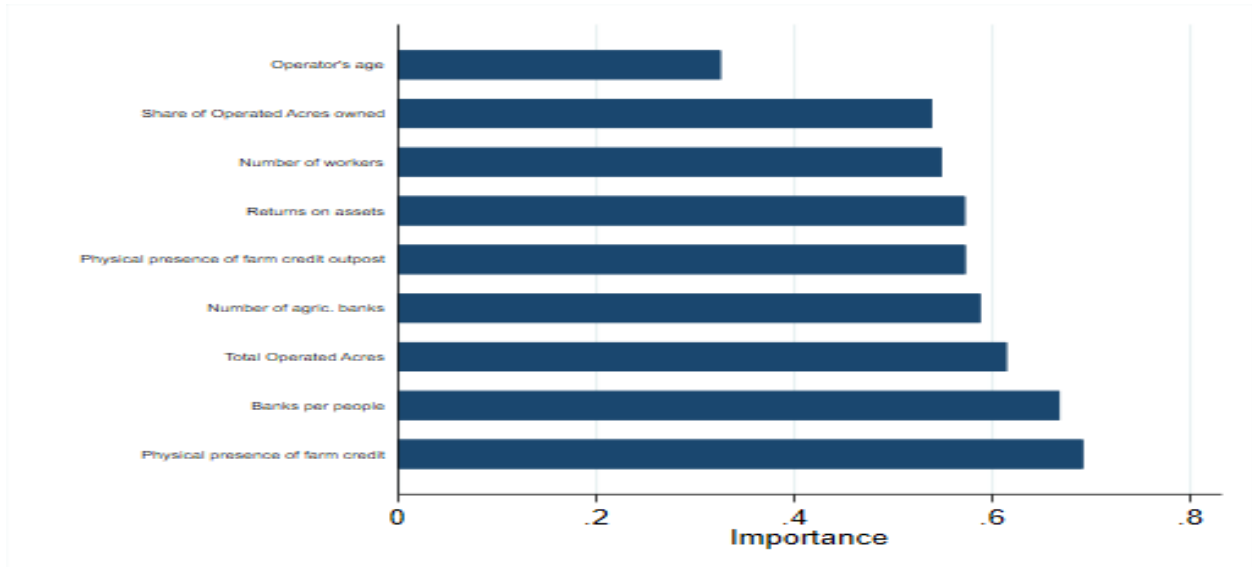
We now use a machine learning technique called random forest — a better predictor than OLS (Malladi, 2023) — to (1) further examine the association between financial status, local credit market conditions, and multiple borrowing and (2) determine the relative importance of financial status and local credit market conditions in explaining multiple borrowing.



Note: This figure displays the importance scores from our random forest model with both financial and local credit market variables. The analysis reflects 2002-2020 data with both region and year fixed effects not reported. Lender concentration is the dependent variable, which is scaled by 100 for easy interpretation. We log-transform farm acres operated by KFMA producer. This figure contains 11 observations, excluding fixed effects. These observations are derived from an initial 9,368 farm-year observations.

Figure 2.2: *Importance Scores for Lender Concentration, 2002-2020*

Figure 2.2 presents results from the random forest specification. Our findings show the debt-to-asset ratio is the strongest predictor of lender concentration. Other farm and credit market characteristics have similar importance scores, though operator age has lower predictive power. The result is similar when the model is estimated with lagged characteristics and thus not driven by newly acquired debt, as displayed in Figure B.7. Figures B.5 and B.6 display similar results for loan concentration. Overall, results of the random forest emphasize that both farm characteristics and local credit market characteristics relate to multiple borrowing, consistent with Tirri (2007). The large importance score for leverage suggests either lenders are less likely to extend additional credit to more leveraged borrowers or more leveraged



Note: This figure displays the importance scores from our random forest model. Lender concentration is the dependent variable, which is scaled by 100 for easy interpretation. We log-transform farm acres operated by KFMA producer. Both year and region fixed effects are included in this random forest model. This figure contains nine observations, excluding fixed effects. These were derived from an initial 9,368 farm-year observations.

Figure 2.3: *Importance Scores for Lender Concentration, Excluding Debt-Related Variables 2002-2020*

borrowers prefer to use a new lender when adding credit. This finding is also consistent with collateral value playing a large role in lending decisions ([Weber and Key, 2015](#)).

Figure 2.3 shows the importance scores from our random forest, excluding debt-related variables. In the absence of debt-related variables in our model, most variables other than operator age have similar importance scores for predicting lender concentration.

2.5 Conclusion

This study provides a foundation for understanding the financial status and credit market environment of producers most likely to engage in multiple borrowing. Using a large dataset containing nearly two decades (i.e., 2002-2020) of Kansas farm financial records, we find that higher leverage predicts multiple borrowing. Additionally, we observe higher farm profitability, measured by return on assets, as a factor associated with multiple borrowing behavior. Producers in counties with more agricultural banks and more banks in general —

those of any specialization, including agriculture — per person are less likely to engage in multiple borrowing. This finding could reflect a preference for farms working with a single local lender and provides insight into the strategy lending institutions employ when choosing where to locate branches or outposts. Of all the factors studied for their association with multiple borrowing, leverage has the strongest predictive power. Other farm and credit market characteristics have similar predictive power. These results are not driven by differences in dataset construction, the definition of multiple borrowing, or an operation adding debt or making other operational changes in an observation year.

These results provide several important considerations for future research on multiple borrowing. Our precise measure of lender and loan concentration could be applied to future agricultural finance and multiple borrowing research. While both our study and previous research shows that financial risk plays a role in multiple borrowing, this study shows that future research also needs to account for beneficial aspects of multiple borrowing that may attract larger and more profitable farm businesses to the practice. Although farm financial factors are strongly correlated with multiple borrowing, credit market competition may also drive multiple borrowing behavior. Future research on multiple borrowing or agricultural finance in general should account for relevant credit market characteristics. Further, the degree to which increasing lender regulation or demand factors drive multiple borrowing is an important future research topic.

The KFMA dataset used for this research provides a unique opportunity to study multiple borrowing in agriculture. Such a regional focus is often necessary to yield these detailed insights, but because this paper’s analysis focuses exclusively on Kansas producers, its findings could have limited external validity. That said, Kansas has a diverse agriculture industry similar to the agricultural makeup found in states situated within the Corn Belt and Plains regions, which jointly constitute the largest crop production area in the U.S. Specifically, northeast Kansas farms have Corn Belt-quality soils and use production practices typical of those adopted by Corn Belt operations. The western part of the state uses more irrigation and has more highly variable dryland production. Further, the lending practices observed in the KFMA data are broadly consistent with those of commercial-scale farms reflected in

ARMS, a nationally representative survey ([Katchova, 2005](#); [Kuethe, 2015](#)). Nevertheless, future research could build on the approaches developed in this study to analyze multiple borrowing in other regions or across the nation. Development of novel datasets would enhance such efforts.

This study focused on the financial profile and credit market environment of agricultural producers that have higher levels of multiple borrowing. As such, we are most interested in cross-sectional variation in these characteristics and estimate a predictive model. Although we do not make causal claims, future research that uses causal methods would shed light on how these variables impact producer choices about using multiple lenders. Such studies would likely have to focus on single factors, such as changes in lender availability or liquidity shocks. Causal analysis of debt heterogeneity’s impact on credit quality would further deepen understanding of U.S. agricultural credit markets. Such an analysis could reveal specific factors that influence creditworthiness among different types of debtors. Additionally, it could provide insights into how varying debt structures affect overall financial stability within the agricultural sector.

Our study provides several insights for lenders and policymakers. First, we observe a risk-return trade-off with multiple borrowing. Although farms that use multiple borrowing may be more leveraged, our results suggest expanding and competitively managed farm operations also more likely engage in multiple borrowing. This represents an opportunity for lenders and helps policymakers better assess the implications of increased multiple borrowing. Specifically, increasing or maintaining business with current customers may be an opportunity for lenders. Our analysis shows that local branches likely play a role in maintaining agricultural loan market share for commercial banks, but demand for multiple borrowing is likely met by nontraditional lenders. Tracking credit held by many types of nontraditional lenders is an ongoing challenge for policymakers ([Briggeman et al., 2024](#)). If the trends toward fewer local bank branches ([Mashange, 2024](#)) and more nontraditional lending entities ([Brewer et al., 2022](#)) continue, then tracking and understanding multiple borrowing will be critical for lender strategy and policy.

Chapter 3

The Impact of Cash flow Shock on Credit Market Behavior

3.1 Introduction

Cash flow shocks from unexpected weather conditions can severely impact financial health ([Brown et al., 2021](#); [Xie et al., 2024](#)). Producers stand a high risk of experiencing these shocks that elevate credit risks because both crop and livestock production depend heavily on the weather ([Hess et al., 2002](#); [Keefe and Nguyen, 2023](#)). However, how farms respond to these weather-induced cash flow shocks still remains an empirical question.

Extreme temperatures pose a major risk to the global economy, adding to several threats that impact production ([Cevik and Jalles, 2023](#)). Since the pre-industrial era, the global average temperature has increased by approximately 2 degrees Fahrenheit ([Lindsey and Dahlman, 2020](#)). Additionally, projections suggest that extreme weather events will increase over the next century, with the world's annual temperature rising by roughly 10.2 degrees Fahrenheit compared to the 1901-1960 average ([Lindsey and Dahlman, 2020](#)). Both the demand and supply side of markets will be influenced by extreme temperature and its accompanying events ([Frame et al., 2020](#)). This is thus a concern for stakeholders because of the increase in intensity, duration and frequency of extreme temperatures ([Bell et al., 2024](#)).

A large literature explores the economic impact of rising temperatures ([Lobell et al., 2014](#); [Perry et al., 2020b](#); [Schlenker and Roberts, 2009](#)); however, research on its impact on credit market behavior of agricultural producers remains limited. Prior theoretical and empirical studies suggest that nonagricultural firms respond to cash flow shocks by deviating from their leverage targets ([Chaderina, 2023](#)), altering their short-term finance ([Brown et al., 2021](#)) and changing overall debt levels ([Byun et al., 2019](#); [Gatchev et al., 2010](#)). [Islam and Singh \(2019\)](#) demonstrates that credit access becomes more restricted as temperature extremes intensify. [Brown et al. \(2021\)](#) also shows that firms respond to weather-induced cash flow shocks by adjusting their credit lines.

In this study, our objectives are three-folds. First, we examine the credit market response of producers to weather-induced cash flow shocks. Specifically, we examine how cash flow shocks impact farm debt structure in the short and medium term. In doing so, we examine how farm may react to multiple cash flow shocks over an extended period. Second, we explore how this response may vary for farms that are more likely to face some type of financial constraints. Three, we investigate whether farm investments respond to these weather-induced cash flow shocks. Examining how producers respond to weather-induced cash flow shocks, which can be frequent and varying, is important for stakeholders and the credit market because certain agricultural producers perceive credit access as a significant obstacle for farm start-ups and expansion ([Shute et al., 2011](#)). In the U.S., approximately 5% of sole proprietor farms reported that their credit applications were declined or they refrained from applying for loans for fear of rejection ([Briggeman et al., 2009](#)). Another set of producers are credit-constrained because their demand for credit exceeds the lending capacity available to them ([Petrick, 2005](#)). Some producers who are able to borrow may face borrowing constraints ([Bierlen and Featherstone, 1998](#); [Key, 2020](#)), and extreme weather can further hinder their ability to access credit by adversely impacting their cash flow.

Our study examines whether cash flow shocks from arguably exogenous weather shocks impact farm debt structure and investment. The weather shocks reduce production while increasing costs of production with long-term consequences ([Brown et al., 2021](#)). We focus on these shocks to isolate a pure liquidity shock and deal with confounding factors that impact

credit use. We investigate these relationships to shed more light on farm debt structure that is not well understood and could be a source of concern for lenders. Optimal debt structure balances the risk of relying on a single lender and the risk of lender coordination ([Detragiache et al., 2000](#)), which poses a concern for stakeholders ([Bräuning and Wang, 2020](#)).

We use a panel of farms from the Kansas Farm Management Association (KFMA) members to examine how producers respond to weather-driven cash flow shocks. KFMA provides accounting services to members, and its high-quality data sets have been used in several prior studies (for example, [Brewer et al., 2014, 2019](#); [DeLay et al., 2022](#); [Gaku and Tsiboe, 2024](#); [Kim et al., 2020](#)). This data set has detailed information on loan sizes, lenders, farm and producer characteristics, including assets, production and sales from 2013 to 2020. We also use county-level temperature from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) data to assess producers' responses to these shocks occasioned by the weather. Our final sample, thus, affords us the opportunity to examine producers' debt structure and investment decisions following weather shocks. We measure these weather shocks by constructing growing and extreme degrees with a threshold consistent with prior studies ([Perry et al., 2020b](#); [Sajid et al., 2022](#)).

In this study, we use farm fixed effects model. This approach deals with unobservable county characteristics and year-specific events that may impact our results. In this model, we focus on the relationship between extreme degree days and our outcome variable to capture the total impact that weather-driven cash flow shocks has on debt structure or investment. Additionally, our study also examines producers who are likely to face financial constraints. We also employ an estimation technique that considers potential dependence due to spatial proximity ([Conley, 1999](#)).

We also find that producers respond to weather-driven cash flow shocks by increasing debt volume. Producers are relying on debt to finance their operations when facing weather-induced cash flow shocks. The impact of weather-driven cash flow shocks varies across debt maturity. We also find that producers use long-term debt following cash flow shocks from the weather. The reliance on long-term debt is to minimize rollover risk. Additionally, the impact of weather-induced cash flow shocks varies across farm types. Farms that are more

likely to be financially constrained are tend to vary their use of debt type in response to cash flow shocks. Our results also show that farms exposed to multiple shocks over the years tend to reduce short-term debt and machinery investment. Our results suggest that producers use external finance to deal with weather-induced cash flow shocks, and they tend to use long-term debt to minimize debt rollover.

We make several contributions to the existing literature on liquidity management by further examining the role of credit as a tool for navigating liquidity challenges. Our findings align with prior studies that underscore the significance and efficiency of credit utilization in managing liquidity needs (Brown et al., 2021; Campello et al., 2011; Holmström and Tirole, 1998; Shockley and Thakor, 1997). We also builds on the growing body of literature examining the impact of natural events on farm yields, operational activity and firm decision-making (Brown et al., 2021; Dessaint and Matray, 2017; Schlenker and Roberts, 2009). However, we focus on extreme temperature which may be more frequent than natural disasters Xie et al. (2024). Examining how the extreme temperatures induce cash flow shocks and its impact on agricultural borrowing behavior, and investment provides valuable insights into how climate-related shocks shape both financial and strategic decisions of farms. by doing this, our study extends prior work by offering evidence on how weather variability affects not only farm productivity and income but also broader financial choices, such as the decision to invest and to use short, medium or long-term debt.

The remainder of this paper is as follows. Our data sets are discussed in Section 3.2 while presenting the empirical model in Section 3.3. We discuss the results in Section 3.4 and conclude in Section 3.5.

3.2 Data

Our analyses rely on farm-level data from the Kansas Farm Management Association (KFMA) from 2013 to 2020. KFMA members contribute significantly to the state’s output, and willingly report their annual production and financial management data to the association. Producer characteristics and other demographic information about members of the producer’s

household are also made available to the association. Several crops, including barley, corn, grain sorghum, oats, rye, wheat and millet are grown by KFMA producers who also raise livestock, such as cattle, sheep and pigs.

KFMA producers obtain loans from a variety of sources, including commercial banks, nontraditional lenders, individuals, and the Farm Credit System. We use these loan volumes to construct a precise measure of multiple borrowing that accounts for asymmetry in loan size from each lender type identified in this and prior studies (Brewer et al., 2014, 2019). We compute a Herfindahl-Hirschman Index (HHI) to measure multiple borrowing, defined as $HHI = s_1^2 + s_2^2 + \dots + s_k^2$, where s_k is the loan k scaled by total debt for a producer in a year. We define this as loan concentration and use it for the remainder of our analyses. We multiply our measure of multiple borrowing by 100 for easy interpretation. Loan concentration index of 100 indicates that a producer maintains an exclusive relationship by receiving all debt from a single source, while an index close to 0 signifies the use of a more diversified debt sources. If a producer receive equal loan amounts from two sources, the index will be 50. Additionally, we employ the same approach to construct lender concentration by using the amount of loan from a lender type.

We also use number of loans as an indicator of multiple borrowing. Loan numbers do not use loan volume that measures the extent of exposure to a particular lender; however, it is used to assess the consistency of our results to prior studies, including Brewer et al. (2014). We also use data on current, intermediate and long-term loans to gauge their response to weather-induced cash flow shocks. By this analysis, we identify the differential impacts on short-term liquidity needs, mid-term financial adjustments, and long-term financing decisions. KFMA data on net farm income, crop yields, assets, and investments are also used to evaluate how agricultural productivity and profitability respond to these shocks. With the KFMA dataset, we are able to gauge the short and long-term responses to these shocks, particularly when farm capital structure may be altered.

We rely on a widely used data set—PRISM data set—for annual county level temperature to estimate the impact of weather-driven cash flow shocks on farm debt structure, investment and crop yields. Multiple studies, including Daly et al. (2000), Daly et al. (2002), Bishop

and Beier (2013) and Tsiboe et al. (2023b), use PRISM for analyses. We transform this dataset into Growing Degree-Days (GDD) and Extreme Degree-Days (EDD) by using the following:

$$\text{GDD}_{\text{base,opt}}(EDD) = \sum_{t=1}^N \Delta T_t, \quad \Delta T = \begin{cases} 0 & \text{if } T_t < T_{\text{base}} \\ T_t - T_{\text{base}} & \text{if } T_{\text{base}} \leq T_t \leq T_{\text{opt}} \\ T_{\text{opt}} - T_{\text{base}} & \text{if } T_t > T_{\text{opt}} \end{cases} \quad (3.1)$$

where t is a day in the growing season (April to September), N is the number of days in the growing season, and ΔT represents degree-days. Our base temperature, T_{base} , is 10°C with a maximum temperature, T_{opt} , of 32°C . EDD is obtained by accumulating degree-days over 32°C with $T_{\text{base}} = 32^\circ\text{C}$ and $T_{\text{opt}} = \infty$. Such a transformation yielded the average extreme degree-days in Figure 3.2 with variation across Kansas counties.

We include precipitation in our analyses, consistent with prior studies, including Schlenker and Roberts (2009). Precipitation can lower the effects of extreme temperature and boost production that impacts farm cash flow. We compute our annual measure of precipitation by aggregating monthly precipitation data for each year.

We examine the response to cash flow shocks by farm types that may face financial constraints. To measure financial constraints, we construct binary indicators based on three variables (age, leverage and size), consistent with prior studies that leverage, size and age as correlates of financial constraints (Auer et al., 2021; Hadlock and Pierce, 2010; O'Connor Keefe and Tate, 2013). While producers below age 46 (years) are classified as young producers, those above 45 years are considered as old. If the operated farm size is lower than the overall median farm size in a year, that farm is classified as small, while those above the median are considered as big farms in a year. When debt to asset ratio is above 50%, we consider that farm as a high leverage farm, while those below that cutoff are regarded as low leverage farms.

Our final sample has farm-year observations ranging from 5137 to 8,811 with 1,915 unique farms. Lender concentration and loan numbers have the lowest farm year observations.

Table 3.1 reports the summary statistics of our combined data set. Consistent with prior studies (for example, [Brewer et al., 2014, 2019](#)), our data set reveals that KFMA producers tend to use multiple loans from a variety of sources. On average, KFMA producers obtain a current loan of \$256,000. Average long-term loan is \$254,000, while the average intermediate loan is \$139,000.

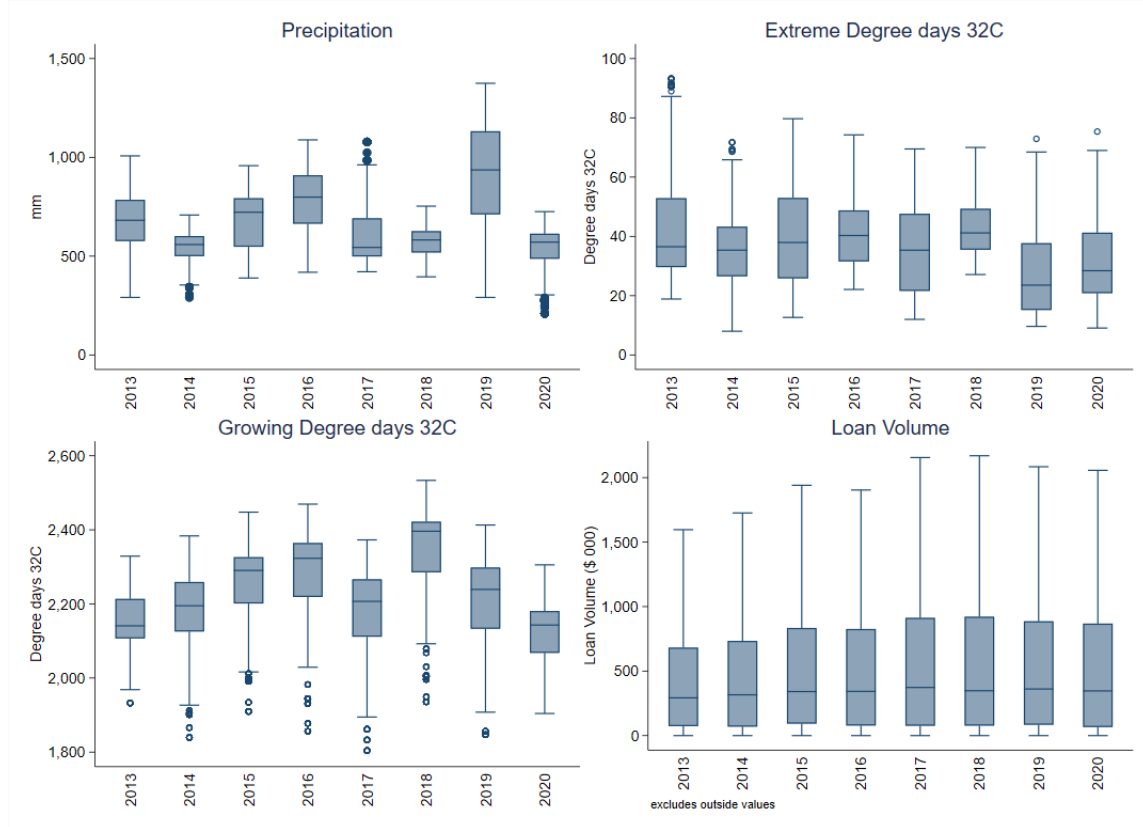
Based on our cutoff, 17% of farms in our final sample are highly leveraged. Old producers constitute 83% of our final sample. Average yields per acre ranges from 33 (sorghum) to 65 (corn). On average, these KFMA farms in our final sample are exposed to 37 Extreme Degree Days (EDD) and 2212 Growing Degree Days (GDD) during the crop growing season from 2013 to 2020. In the same period, the average precipitation stands at 664mm.

Table 3.1: *Summary Statistics of Variables, 2013-2020*

	Obs	Mean	SD	Median
Current Loans	8811	256.02	502.32	88.86
Long-Term Loans	8811	253.76	564.54	58.74
Intermediate Loans	8811	138.56	259.98	46.30
Extreme Degree Days (EDD)	8811	37.30	15.03	36.18
Growing Degree Days (GDD)	8811	2211.81	138.12	2226.38
Precipitation	8811	663.73	192.63	619.18
Lender Concentration	5137	75.64	23.49	79.87
Number of Loans	5137	5.32	4.50	4.00
Machinery Investment	8811	44.50	82.77	13.03
Aggregate Investment	8811	126.00	247.95	45.98
Gross Farm Income	8811	729.95	967.97	483.98
Net Farm Income	8811	99.96	225.82	58.15
Corn Yields	8811	65.24	140.48	0.00
Sorghum Yields	8811	33.12	50.07	0.00
Soybeans Yields	8811	35.09	29.06	35.60
Wheat Yields	8811	36.50	31.03	39.12
High Leverage	8811	0.17	0.37	0.00
Young Producer	8811	0.17	0.37	0.00
Small Farm	8811	0.50	0.50	0.00

Note: Lender Concentration are scaled by 100. All financial variables are adjusted for inflation, and divided by 1000. *Source:* KFMA and PRISM

Figure 3.1 displays the annual variation in our independent variables and loan volume. Loan volume varied over the period. Both extreme and growing degree days also display significant variability over the years; however, we see much variability in growing degree days compared to extreme degree days. Precipitation also varied greatly over the years.

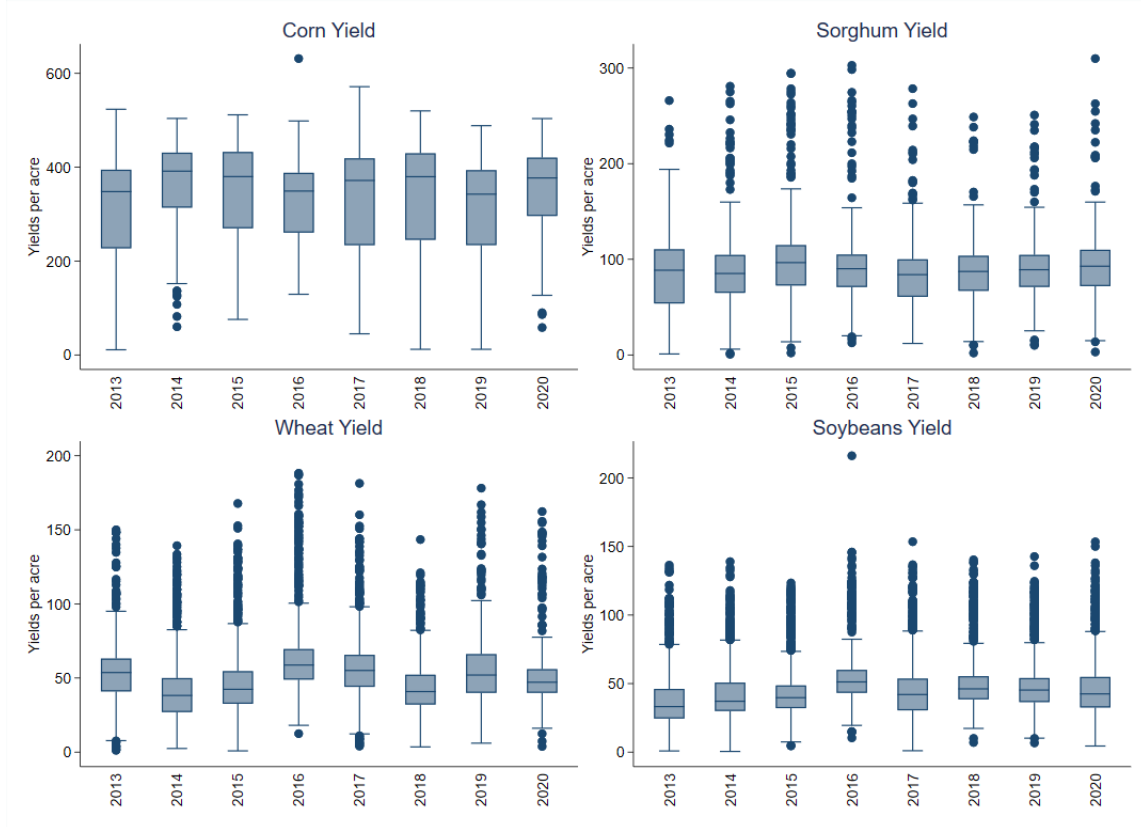


Note: This figure displays the precipitation, loan volume, growing degree days and extreme degree days for Kansas counties from 2013 to 2020.

Figure 3.1: *Annual Variation, 2013-2020*

Figure 3.2 shows the average EDD for each Kansas county from 2013 to 2020. On average, KFMA farms in southwestern counties are exposed to higher temperatures as demonstrated by higher EDD values compared to south east and north eastern counties.

Figure 3.4 shows annual crop yields from 2013 to 2020. All the four major crops (corn, sorghum, soybeans and wheat) displayed significant variability over the years. Crop yield variability within this period can be attributed to factors, such as temperature fluctuations, precipitation levels and the frequency of extreme weather events.



Note: This figure shows major crop yields for KFMA producers from 2013 to 2020. Prior to 2002, these major crops were aggregated with other crops.

Figure 3.4: *Major Crop Yields in Kansas, 2013-2020*

3.3 Empirical Model

We empirically investigate how KFMA producers respond to weather-driven cash shocks by using the following farm fixed effects model:

$$y_{it} = \beta_1 EDD_{ct} + \beta_2 GDD_{ct} + \beta_3 Prec_{ct} + \rho_t + \gamma_i + \epsilon_{it} \quad (3.2)$$

where y_{it} is our outcome variable, which includes loan concentration, crop yields, debt, debt type and investment of firm i at time t . GDD_{ct} and EDD_{ct} are respectively Growing Degree-Days and Extreme Degree-Days for county c in time t . $Prec_{it}$ is precipitation for county c at time t . While γ_i are farm fixed effects that control for time-invariant unobservable cropland factors unique to a farm, τ_t are year fixed effects that deal with time-specific factors that vary across years. ϵ_{it} is the error term.

We use year-to-year fluctuations in temperature and precipitation to identify their impacts. We also focus on the reduced-form results, consistent with prior studies, including [Burke et al. \(2015\)](#) and [Brown et al. \(2021\)](#).

Spatial proximity and potential correlations across time for our measures can impact our results. We thus cluster the standard errors at the county level. Additionally, we use [Conley \(1999\)](#)'s standard errors to account for both spatial and temporal autocorrelation in temperature data. We use a time cutoff of 8 years and distance cutoff of 125 kilometers (approximately 78 miles).

We now set out to confirm cash flow shocks by regressing crop yields and income on our temperature and precipitation measures. In doing so, we also conduct an inverse hyperbolic sine (IHS) conversion of variables and examine their association with extreme degree days (EDD). A negative relationship between EDD and crop yields, as well as farm income, shows that extreme temperatures induce cash flow shocks in our sample.

Certain producers may be exposed to extreme temperature over an extended period. Such exposures could lead to no farming in a number of years or successive crop losses. To gauge how this could impact farm finance, we also explore how producers respond to multiple shocks, which measure multiple shocks with 10 year moving average of EDD for a county. The 10 year moving average of EDD is included as the main covariate of interest to gauge whether consistently higher EDD can impact farm debt structure.

In our next set of regressions, we investigate the empirical relationship between exposure to extreme degree days (EDD) and several debt structure. These debt variables include the number of loans, total loan volume, and lender concentration. We then examine how machinery investment and debt types based on maturity respond to cash flow shocks. We

proceed by examining the response of farms that are more likely to be financially constrained. Following [Dizon and Yu \(2021\)](#), we interact EDD and the 10 year moving average with indicators for young producer, small, and high leveraged farms.

In our final set of empirical investigations, we examine whether weather-induced cash flow shocks influence aggregate investment or other farm investments, including land, building and improvements. We also conduct several robustness checks using the IHS transformed outcome variables and the above-mentioned standard errors by ([Conley, 1999](#)).

3.4 Results

Table [C.2](#) presents the impact of EDD on crop yields. Farms exposed to extreme temperature tend to experience yield losses. Yields for corn, soybeans and sorghum decline with EDD. Despite a negative relationship, the impact of EDD on sorghum yields is not statistically significant. The relationship between wheat yields and EDD is also not statistically significant. Our results, however, affirm findings in prior studies (for example, [Sajid et al., 2022](#); [Schlenker and Roberts, 2009](#); [Tack et al., 2017](#)). Temperatures in excess of 32 EDD are harmful to crop yields. Specifically, exposure to temperatures above that threshold can impose significant stress on crops, which causes a reduction in productivity. This highlights how agricultural production is sensitive to extreme temperatures, especially beyond the 32 EDD level.

Table [C.3](#) presents the effects of extreme degree days on farm income. Exposure to higher temperatures is associated with decreases gross and net farm income, consistent with [Sajid et al. \(2022\)](#). As the number of extreme degree days rises, gross farm income reduces, which reflects the adverse impact of extreme temperature on agricultural output. Similarly, net farm income, which accounts for operating costs and other expenses, also decreases with an increase in EDD. This highlights how agricultural producers are particularly vulnerable to extreme weather conditions since farm profitability declines with more exposure to extreme temperatures.

Table 3.2: *Effect of Extreme Degree Days (EDD) on Debt Structure, 2013-2020*

VARIABLES	(1) Number of Loans	(2) Lender C.	(3) Loan Volume	(4) Number of Loans	(5) Lender C.	(6) Loan Volume
EDD	-0.004 (0.013)	0.000 (0.001)	1.768** (0.848)			
10yrs MA				0.025 (0.080)	-0.002 (0.003)	-2.132 (4.249)
Observations	5,137	5,137	8,811	5,137	5,137	8,811
R-squared	0.016	0.019	0.012	0.016	0.019	0.011
Number of farms	1,466	1,466	1,915	1,466	1,466	1,915
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
GDD	YES	YES	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with debt structure as the outcome. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. While FE stands for Fixed Effects, MA and C. represent Moving Average and concentration respectively. Fixed Effects, GDD and precipitation are included in this regression. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.2 reports the results of equation 3.2 with debt structure as the outcome. More exposure to extreme temperature above 32 EDD level is associated with increased borrowing. Producers experiencing cash flow shocks may increase their debt to meet operational expenses. We also find that our measure of multiple shocks, 10 year moving average, has no effect on debt structure.

Table 3.3 reports the estimates of EDD's impact on different debt types and investment. Farms exposed more to extreme temperature tend to use long-term loans, inconsistent with the theoretical predictions of Chaderina (2023). However, this credit market behavior is consistent with producers avoiding the risk associated with lenders' unwillingness to extend the maturing debts or grant new loan.

Producers exposed to multiple shocks tend to lower their current loans, consistent with earlier findings. They also increase intermediate loans following weather-induced cash flow shocks. We also find that farms exposed to multiple cash flow shocks reduce their investment in machinery. However, this relationship is not statistically significant. Producers facing such multiple shocks may be facing financial uncertainties that forces them to reduce long-term investments.

Table 3.3: *Debt Type and Investment, 2013-2020*

VARIABLES	(1) Current Loans	(2) Intermediate Loans	(3) Long-Term Loans	(4) Machinery Investment	(5) Current Loans	(6) Intermediate Loans	(7) Long-Term Loans	(8) Machinery Investment
EDD	0.563 (0.595)	0.133 (0.368)	1.071* (0.596)	0.181 (0.172)				
10yrs MA					-3.946* (2.225)	6.382*** (2.050)	-4.569 (3.094)	-0.800 (0.945)
Observations	8,811	8,811	8,811	8,811	8,811	8,811	8,811	8,811
R-squared	0.018	0.022	0.014	0.027	0.018	0.024	0.014	0.027
Number of farms	1,915	1,915	1,915	1,915	1,915	1,915	1,915	1,915
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
GDD	YES	YES	YES	YES	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with debt type and investment as outcome variables. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. While FE stands for Fixed Effects, MA represents Moving Average. Fixed Effects, GDD and precipitation are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Tables 3.4 and 3.5 report the relationship between EDD, multiple shocks and debt types for farms that more likely to experience financial constraints. This analysis also allows us to gauge which farm types are driving our results. We find that farms exposed to temperature above 32 EDD level tend to more long-term loans, consistent with our earlier findings. The results further reveal that farm size, leverage and operator age matter in the choice of debt type and how the farm responds to weather-induced cash flow shocks. Financially constrained farms exposed to more extreme temperature respond differently to their use of debt types.

Table 3.4: *Debt Type and Investment (Heterogeneity : Part 1)*

VARIABLES	Current Loans	Intermediate Loans	Long-Term Loans	Machinery Investment
EDD	1.178* (0.655)	0.010 (0.391)	1.218* (0.614)	0.073 (0.214)
EDD x SF	0.175 (0.498)	-0.466 (0.345)	-0.080 (0.456)	0.267 (0.163)
EDD x HL	-0.817* (0.417)	0.588* (0.333)	-0.159 (0.435)	-0.022 (0.163)
EDD x Yp	-1.325* (0.708)	-0.033 (0.447)	-0.096 (0.701)	-0.018 (0.182)
Observations	8,811	8,811	8,811	8,811
R-squared	0.020	0.022	0.014	0.027
Number of farm	1,915	1,915	1,915	1,915
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
GDD	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with debt type and investment as outcome variables. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. While FE stands for Fixed Effects, MA represents Moving Average. While SF is an indicator for small farms, Yp and HL are indicators for young producers and high leveraged farms respectively. Fixed Effects, GDD and precipitation are included in this regression. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5: *Debt Type and Investment (Heterogeneity: Part 2)*

VARIABLES	(1) Current Loans	(2) Intermediate Loans	(3) Long-Term Loans	(4) Machinery Investment
10yr MA	-0.443 (2.370)	6.315** (2.888)	-0.115 (4.187)	-0.840 (1.379)
10yrMA x SF	-6.006** (2.974)	-6.066** (2.484)	-0.095 (3.372)	-0.081 (1.023)
10yrMA x HL	-0.727 (3.260)	5.380** (2.216)	-7.536** (3.397)	0.140 (0.824)
10yrMA x Yp	-1.209* (0.683)	-0.043 (0.367)	-0.046 (0.613)	-0.022 (0.146)
Observations	8,811	8,811	8,811	8,811
R-squared	0.021	0.028	0.016	0.027
Number of farm	1,915	1,915	1,915	1,915
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
GDD	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with debt type and investment as outcome variables. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. While FE stands for Fixed Effects, MA represents Moving Average. 10yrMA stands for 10 year moving average of EDD. While SF is an indicator for small farms, Yp and HL are indicators for young producers and high leveraged farms respectively. Fixed Effects, GDD and precipitation are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.4.1 Robustness Checks

Table 3.6 reports the relationship between our measures of exposure to extreme temperature and different debt types using the standard errors that account for spatial proximity and temporal autocorrelation. We observe that our results are consistent with earlier findings. These estimates reaffirm earlier suggestions in Table 3.3 that machinery investment does not respond to cash flow shocks.

Tables C.4 and C.5 present the impact of EDD and 10 year moving average on IHS transformed debt type and investment for plausibly financially constrained farms. Our results are consistent with those in Tables 3.4 and 3.5.

Tables C.6 and C.7 reports the impact of EDD on aggregate and other farm investments. Our results reveal that weather-induced cash flow shocks have no effect on aggregate investments. However, we observe that response of investment type may depend on farm size, leverage or operator age. We include a squared term of precipitation in Table C.8, and find that the results are consistent with earlier findings. We further examine the impact of EDD or 10 year moving average on loan concentration and number of lenders in Table C.9 and find no statistically significant association.

Table 3.6: *Debt Type and Investment, 2013-2020*

VARIABLES	(1) Current Loans	(2) Intermediate Loans	(3) Long-Term Loans	(4) Machinery Investment	(5) Current Loans	(6) Intermediate Loans	(7) Long-Term Loans	(8) Machinery Investment
EDD	0.563 (0.491)	0.133 (0.402)	1.071*** (0.415)	0.181 (0.214)				
10yr MA					-3.946 (2.565)	6.382*** (2.150)	-4.569* (2.374)	-0.800 (1.077)
Observations	8,498	8,498	8,498	8,498	8,498	8,498	8,498	8,498
R-squared	0.000	0.001	0.001	0.001	0.001	0.003	0.001	0.001
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
GDD	YES	YES	YES	YES	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES	YES	YES	YES	YES
Conley SE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with debt type and investment as outcome variables. Each column presents a separate regression result for the period 2013-2020. We report County Conley Standard Errors in parentheses. While FE stands for Fixed Effects, MA and SE. represent Moving Average and Standard Error respectively. Fixed Effects, GDD and precipitation are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.5 Conclusion

We examine how debt structure and investment respond to weather-induced cash flow shocks in the agricultural sector. Our results show that more exposure to extreme temperatures reduces crop yield and farm income. Our results also reveal that farm borrowing behavior is impacted by weather-induced cash flow shocks. Producers increase their loan volume and increase the use of long-term debt to reduce the risk associated with debt rollover.

Our analyses show that farm machinery investment is not statistically associated with extreme degree days. While producers balance long-term financial considerations with short financial needs after experiencing cash flow shocks, farm machinery and aggregate investments do not significantly change.

Producers' response to weather-driven cash flow shocks is policy relevant, yet this study focuses on Kansas. Future research can explore this relationship in other major agricultural areas in the U.S. and other parts of the world. This will be important in assessing how responses to cash flow shocks from the weather vary across different regions. Additionally, future studies examine the long-term impact of these shocks using long differences approach. By doing this, we can identify the long-term financial adaptation strategies used by producers as temperatures are expected to increase.

Overall, the results show that farm household income is vulnerable to the vagaries of the weather, which raises the need for further adaptive strategies to enhance resilience as the climate changes.

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Appendix A

Evaluation of Alternative Farm Safety Net Program Combination Strategies

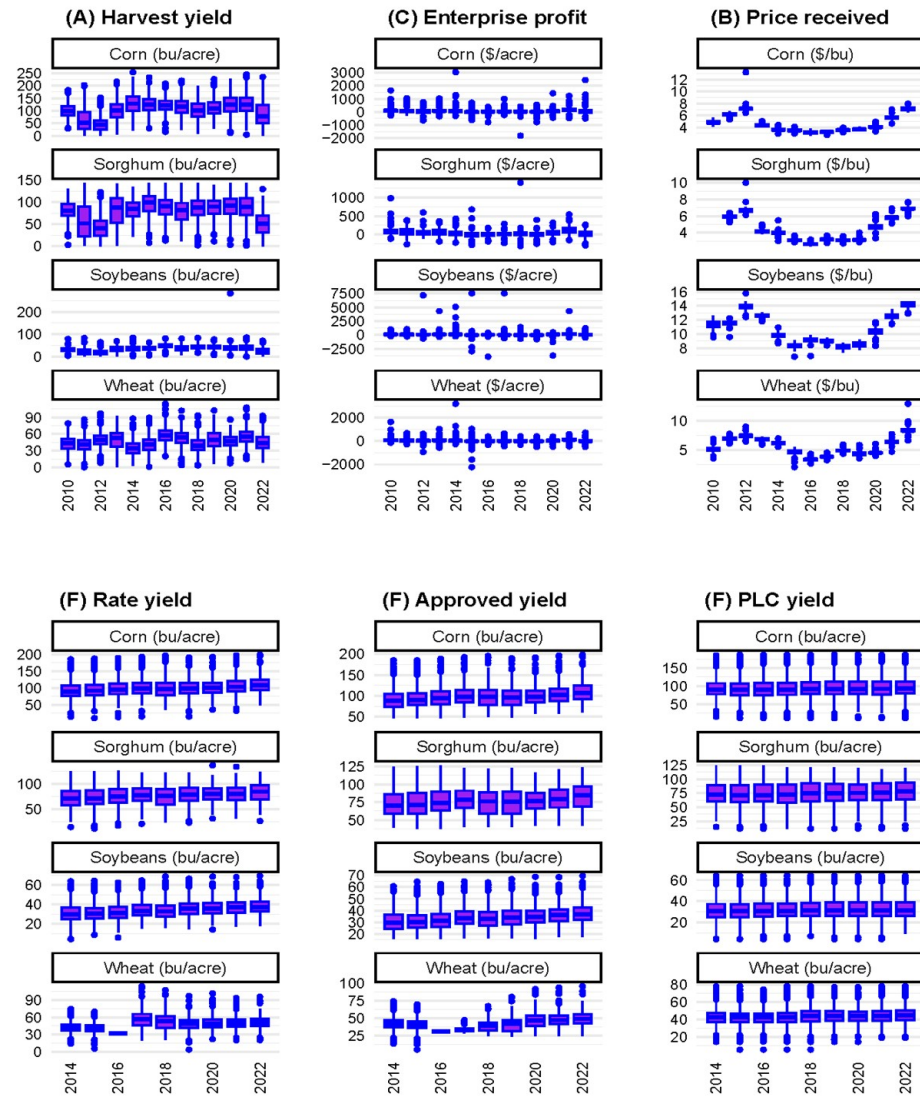
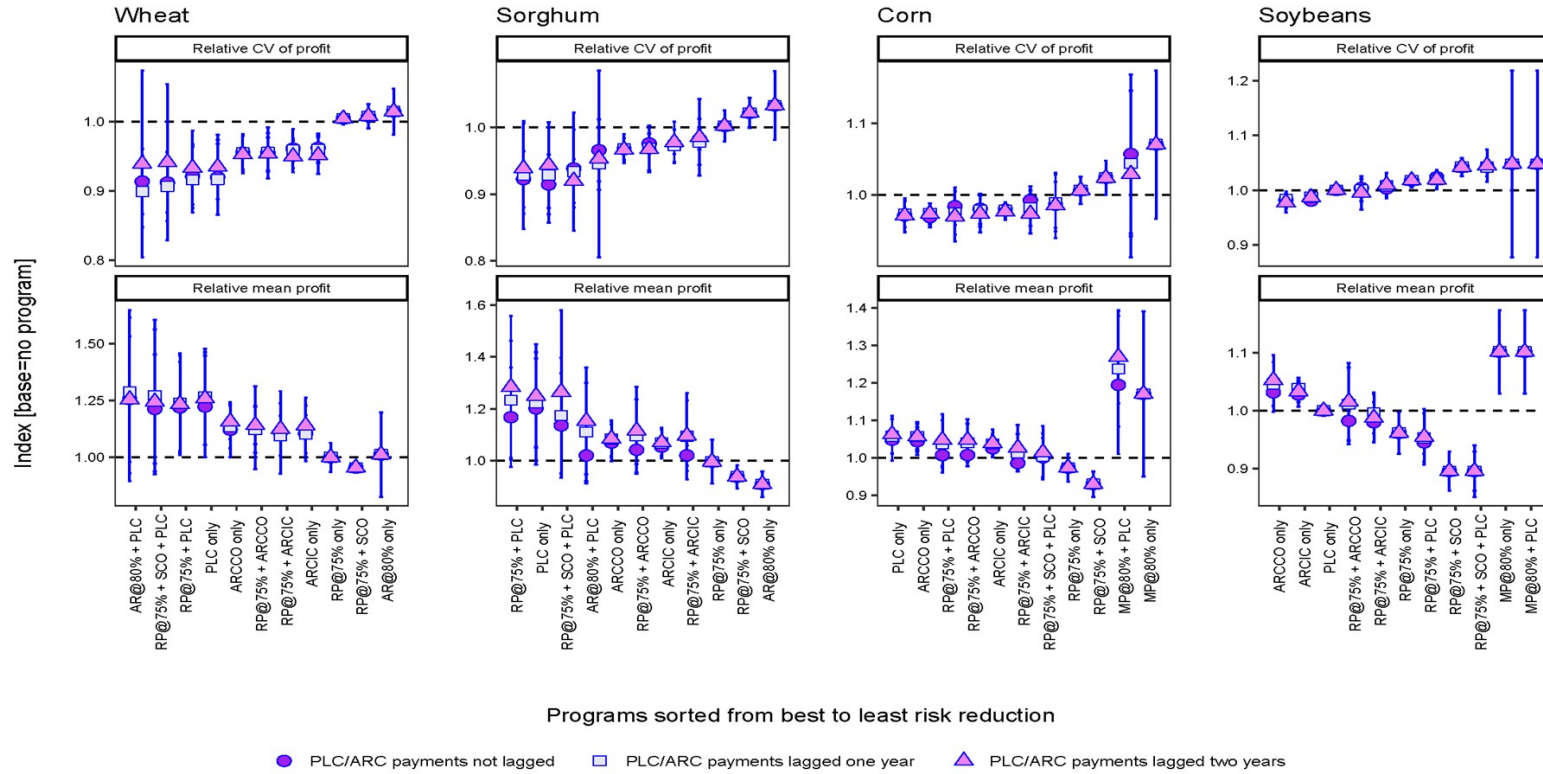
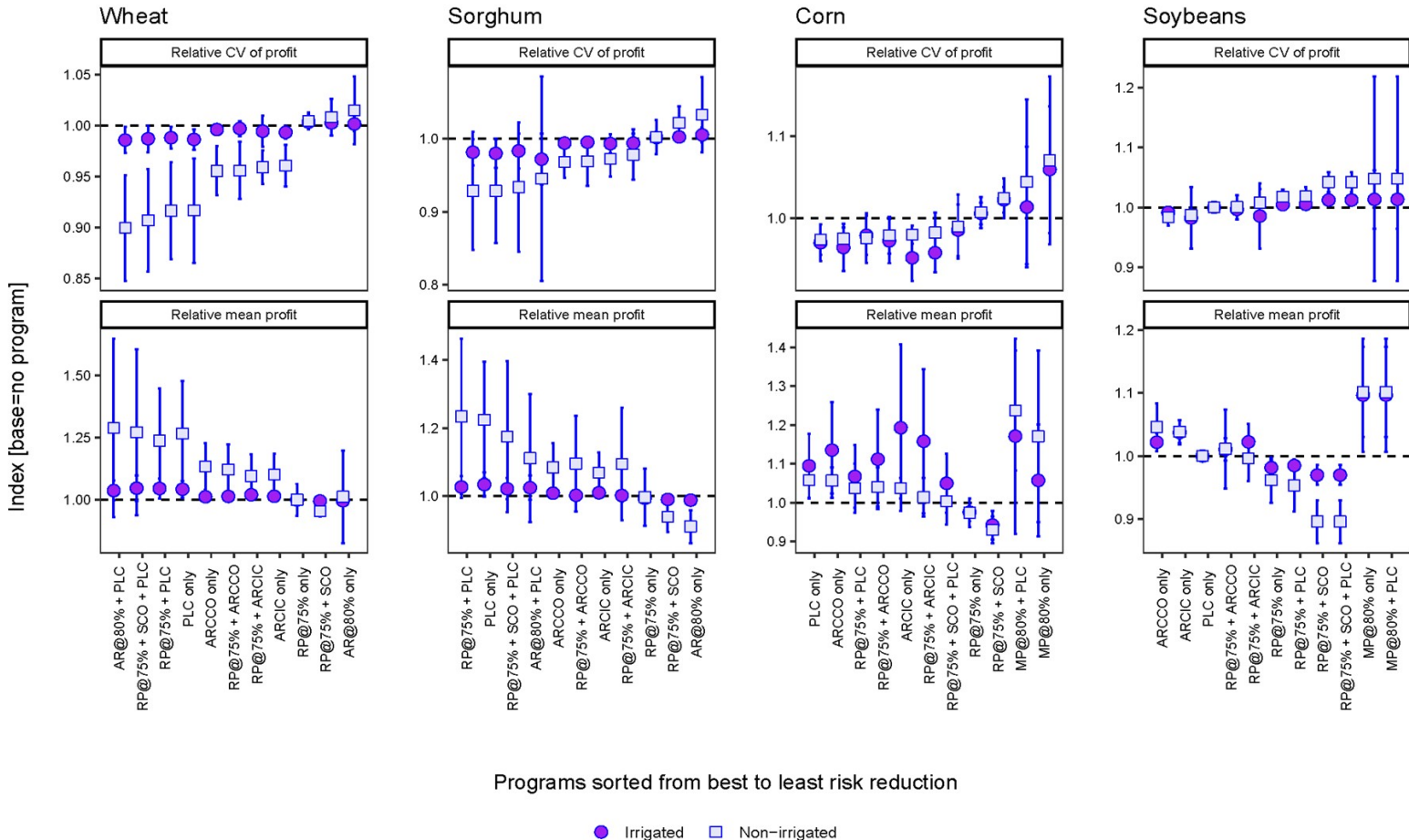


Figure A.1: *The Distribution of Yield, Profit, and Price*



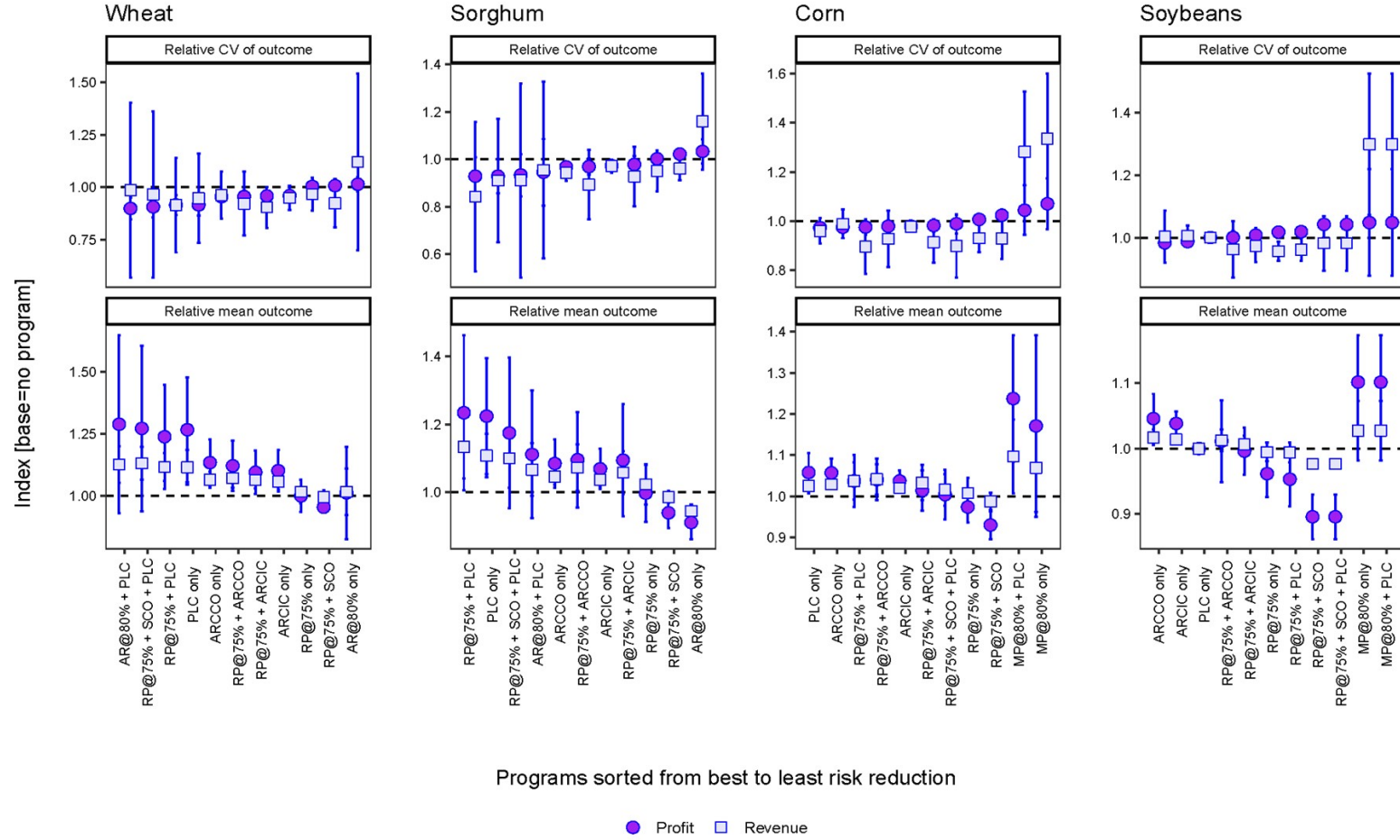
Note: This figure presents the relative CV (top) and relative mean (bottom) for wheat, sorghum, corn and soybeans when there is delay in PLC/ARC payments. We use no insurance policy as the baseline for comparison. If relative CV is lower than one, it means the combination strategy reduces profit risk compared to no insurance policy. However, a combination strategy elevates profit risks if its relative CV is above 1. Similarly, a relative mean above one means a combination strategy enhances profits compared to no insurance. A relative mean below one implies that a combination strategy reduces profits compared to a no insurance policy.

Figure A.2: *Profit Risk and Income Transfer Potential with Year Lags*



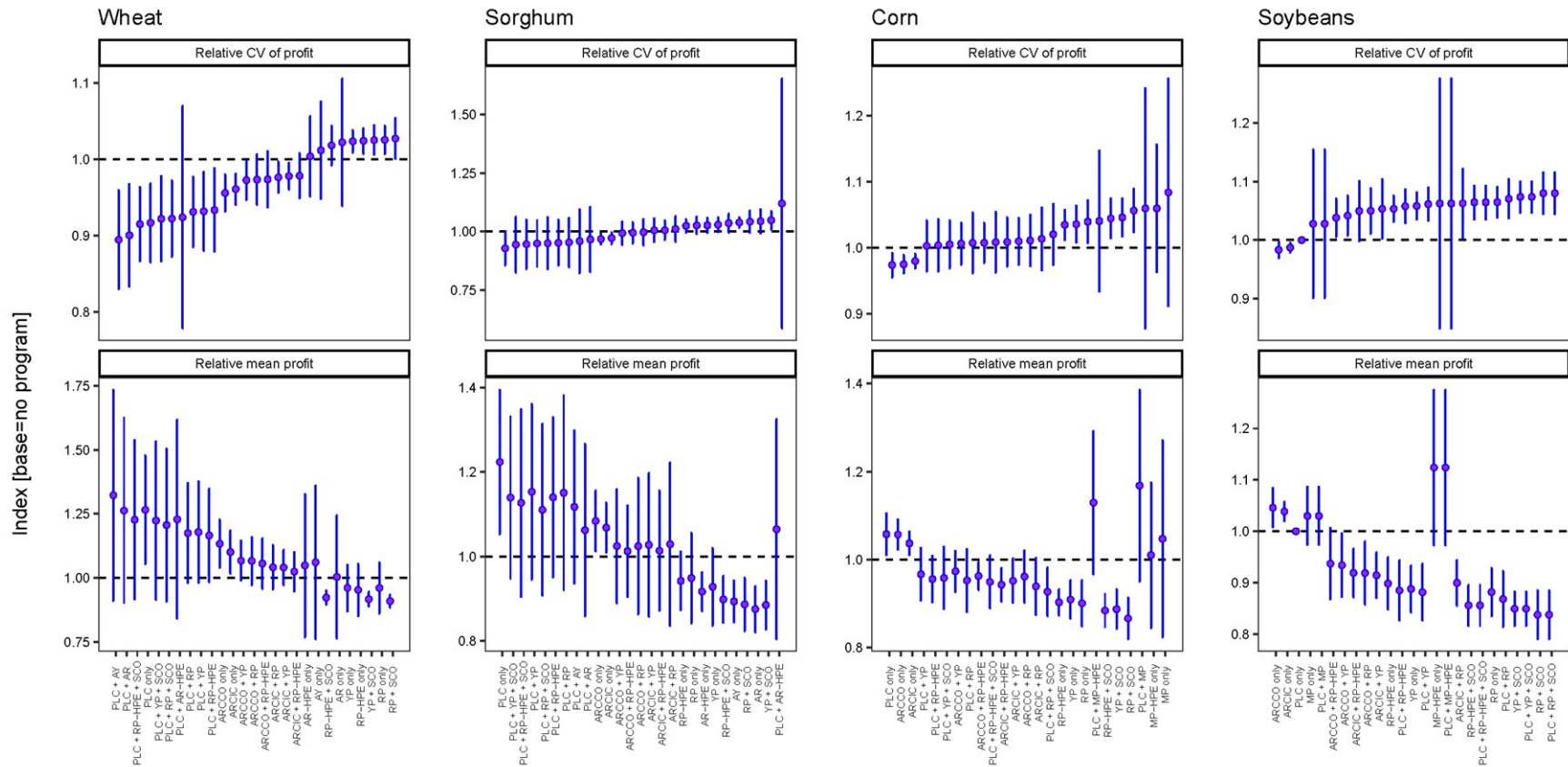
Note: This figure presents the relative CV (top) and relative mean (bottom) for wheat, sorghum, corn and soybeans based on irrigation status. We use no insurance policy as the baseline for comparison. If relative CV is lower than one, it means the combination strategy reduces profit risk compared to no insurance policy. However, a combination strategy elevates profit risks if its relative CV is above 1. Similarly, a relative mean above one means a combination strategy enhances profits compared to no insurance. A relative mean below one implies that a combination strategy reduces profits compared to a no insurance policy.

Figure A.3: *Profit Risk and Income Transfer Potential by Irrigation Status*



Note: This figure presents the relative CV (top) and relative mean (bottom) for wheat, sorghum, corn and soybeans using revenue. We use no insurance policy as the baseline for comparison. If relative CV is lower than one, it means the combination strategy reduces revenue risk compared to no insurance policy. However, a combination strategy elevates revenue risks if its relative CV is above 1. Similarly, a relative mean above one means a combination strategy enhances revenue compared to no insurance. A relative mean below one implies that a combination strategy reduces revenue compared to a no insurance policy.

Figure A.4: *Revenue Risk and Income Transfer Potential*



Programs sorted from best to least risk reduction

Note: This figure presents the relative CV (top) and relative mean (bottom) for wheat, sorghum, corn and soybeans using optimal coverage level. We use no insurance policy as the baseline for comparison. If relative CV is lower than one, it means the combination strategy reduces profit risk compared to no insurance policy. However, a combination strategy elevates profit risks if its relative CV is above 1. Similarly, a relative mean above one means a combination strategy enhances profits compared to no insurance. A relative mean below one implies that a combination strategy reduces profits compared to a no insurance policy.

Figure A.5: Profit Risk and Income Transfer Potential by Optimal Coverage Level Selection

Appendix B

The Financial Status and Local Credit Market Conditions of U.S. Farms Engaged in Multiple Borrowing

Table B.1: *Definitions of variables, 2002-2020*

Variable name	Description
Operator's age	Age of the farm operator
Number of Operators and employees	Number of Workers including operator, family and hired labor
Total Operated Acres	Total Farmland Operated (in Acres)
Share of Operated Land Owned	Proportion of total operated farmland owned
Debt to Asset ratio	Total liabilities divided by total assets
Rate of Return to Asset	Net farm income divided by average total assets
Normalized Current Ratio	Current assets divided by current liabilities
Number of Agricultural Banks	Number of agricultural Banks in a county
Banks per people	Number of banks per 1000 people
Physical presence of farm credit	Farm Credit Branch exists in that county
Physical presence of farm credit outpost	Farm Credit outpost exists in that county
Loan concentration	Herfindahl-Hirschman Index for loans
Lender concentration	Herfindahl-Hirschman Index for lender
North Central	Counties in North Central Kansas
South Central	Counties in South Central Kansas
Northeast	Counties in Northeast Kansas
Northwest	Counties in Northwest Kansas
Southeast	Counties in Southeast Kansas

Table B.2: Lender Identification, 2002-2020

Lender Type	Keywords \ Abbreviations
Ag Direct	"ag d", "agdirect", "ag direct", "ag direct"
Commercial Bank	"central", "bank of am", "umb", "pnc", "wells", "wls frgo", "frmr nb", "frmr nb", "frmr nat", "frmr nat", "td finance", "frmr nb", "frmr nb", "frmr nat", "frmr nat", "td finance", "edward jones", "ed jones", "cnb", "cent nat", "boa", "gmac", "bank one", "us bank", "u s bank", "ally", "synchony", "synchony", "merrill", "merrill", "commerce bank", "bank o am", "td auto", "td avta", "bk of am", "american nat", "5th 3rd", "fifth third", "gd bank", "first merit", "intrust", "commercial bank", "commercaill bank", "harris bank", "harris bk"
Cooperative Finance	"coop finance", "cfa", "cf"
Credit Card	"credit card", "credit card", "discover", "visa", "amer exp", "american exp", "home depot card", "gold delta", "citi", "mastercard", "chase", "capital one"
Credit Union	"gpc", "c.r", "security service", "credit union", "hcu", "meritrust", "unwfcu", "unscfu", "nwruc", "panhandle", "pcu", "great plains", "hutch credit", "mid kansas", "mid america cu", "mkc", "gpfc", "mid america credit", "kcu", "golden plains", "envista", "cessna", "ecu", "golden plains", "colden plains", "aa credit", "mid am cred", "mid-american credit", "grt plains", "gr pl", "fd credit", "element fi"
Farm Credit	"farm cred", "fc", "fc", "fc", "frontier", "high plains", "pca", "ag cred", "am ag", "american ag", "hpfc", "wksfc", "ag country", "wks fc", "fc land", "ag choice", "hpc", "fcla", "wkfsc", "fsc", "hi plains", "production credit association", "ffc", "fcs", "fcwk", "aac", "flb", "federal land bank", "fcla", "wskfc", "fcc", "fr farm cr", "farm credit"
Government Agency	"fha", "fca", "usda", "ccc", "khrc", "sba", "farm service agency", "udsa", "fmha"
Individual	"A HOOVER" "A HUMMEL" "A WAHL CONTRACT" "Aaron Krehbiel" "AARON KREHBIEL" "Aaron Wagner" "Abe Enszt" "Adelgren land" "ALBERTA STOCKEBRAND" "Alice Tholen" "ALICE/WHEAT" "ALLEN HAMMER-SCHMIDT" "ALLISON LAND" "AM EXP - BILL'S" "AM EXP - SUSIE'S" "Amex/Nancy cc" "Andrew" "ANDREW" "ANITA" "Anja Miller Estate" "ANN KENT" "Ann Kent" "ANNA BEEGHLEY" "ANNA BEEGHLEY-RE" "ANNETTE VOTH" "ARLENE GRIMM" "Art & Helen" "ART CHAPMAN - LAND" "ASCHER" "AUDREY NOTE" "audreys note" "AUSTIN" "BACH-KRAUSE RE" "BAILEY BOHN" "BAILY BOHN" "BARB" "BARKMAN LAND" "BARNES LAND" "Benadette" "benadette" "BETTIE BOBBITT ESCROW" "BETTY HOWARD" "BET-TYS" "BETTY'S" "BILL BALDOCK" "BILL MARSTON" "BILL MARSTON" "BOB MEDLIN" "Bobs Contract for Deed" "BOBS LAND" "BOB'S LAND" "BODENHAUSEN FARM" "BOLINE LAND"
Insurance	"mass mutual", "state farm", "northwestern mutual", "bcbs", "ozark nat", "nw mutual"
Nontraditional	"t-l", "j d", "j deere", "john deere", "jd credit", "new holland", "john der", "john deere", "cb real estate", "phi", "pioneer", "agco", "komatsa", "rabo", "ag co", "jd f", "metlife", "met life", "cps", "pacific financial", "vermeer cr", "toyota", "prudential", "vemeer", "veermeer", "vc", "cnh cap", "ford credit", "ford mo credit", "ford motor credit", "ge capital", "ge money bank", "kansota", "agsun", "chs", "jdf", "jd f", "gehl", "chrysler capital", "chrysler financial", "deere and co", "sheffield", "case credit", "deere cred", "ford credit", "gm credit", "agricred", "kabota credit", "northland capital", "prudential", "agri fi", "deerre fin", "cnh america", "deere fi", "deer fi", "class fi", "chrysler fi", "cnh cap", "deerre fi", "vermeer", "naeda fi", "morton building", "hyundai fi", "greyhawk fi", "ford credit", "for credit", "diversified fi", "div fi", "dfs", "agri cred", "cnh industrial capital", "cn capital", "nortland capital", "deerre fin", "deere fin", "chrysler fi", "catipaller fin", "claus fin", "jp fin", "jd - fin", "deere fin", "agoc fin", "case ih fin", "closs fin", "lexus fin", "nissan fin", "scheffield fin", "shelfield fin"
Others	"farm bureau", "fsa", "tax liab", "tax", "payroll", "payoll", "janis moore trust", "sbi trust", "100 trust", "delmar green trust", "joe trust", "ray trust", "bryant trust", "germann trust", "milleret trust", "friesen - trust", "bwp trust", "cooper trust", "dlabal trust", "dunbar trust", "sergeant trust", "popp", "german trust", "hubbell trust", "mueller trust", "pondera trust", "jrp trust", "dorothy trust", "luckert trust", "sprauka trust", "miller trust", "friesen trust", "maxine trust", "ponderosa trust", "marilyn's trust", "oestmann trust", "strahm trust", "schuetz trust", "lenhart trust"
Rural Bank	"fb", "first bank", "security state", "csb", "citizen", "ubt", "cbok", "hnb", "cvb", "bsb", "pb", "bennington", "nbeodesha", "neodeshya", "bank of the west", "bankwest", "bank of west", "bank of w", "fkb", "first kansas bank", "dcb", "douglas", "kvb", "ub&t", "ub & t", "united bank", "1st bank", "fsb", "farmers b", "swnb", "tescott", "enb", "gnb", "land mark", "neodesha", "1st kansas", "1st ks", "1st state", "first st", "neodesha", "neodesha", "1st option", "first option", "1st security", "1st st", "wsb", "psb", "fcb", "girard national", "ycbb", "people", "marian bank", "sw bank", "farmers & drovers", "cub", "metz", "landmark national", "hiawatha national", "holyrood", "bern", "bank of atchison", "bank of mcclouth", "ub of ks", "almena state", "valley b&t", "am first", "fmb", "first national bank", "1st nat", "1st", "mid american", "mid america bank", "university", "centera", "bk of osage", "bk of comme", "tsb", "ssb", "shbk", "sbb", "rsb", "msb equip", "msb oper", "msb seed", "lsb", "lrsb", "2012 state bank", "the bank", "pin bank", "stockgrowers", "state bank", "sbd", "lankmark", "swb", "mnb", "f&m", "fmb", "western stat", "banwest", "bankwest", "woodbine state", "valley st", "walnut bank", "union st", "unb", "ubk", "u-bank", "u/b", "u bk", "tpb", "verus", "veras", "towanda", "tampa", "sunflower bank", "stockton", "axtell", "spring hill", "hoxie", "state bank", "southeast national bank", "southwest national bank", "solomon", "snb", "slb", "sjn", "silver lake", "st bk", "st bk", "smb", "sb cow", "sb equip", "sb loc", "st bank", "pony exp", "peabody", "s.l.b", "rcb", "peb", "astra", "hometown bank", "home bank", "fmsb", "pinn bank", "pinnacle", "patriots", "ksb", "kvsb", "labette", "fbb", "labette", "labette", "labette bank", "labette bank", "landmark", "lb", "lb", "lb 6", "lb 7", "lb bank", "lb home", "legacy bank", "lmb", "lnb", "pin bk", "mid mo", "empire bk", "mjb", "nebraska bk", "nebraska st", "nickerson st", "offerle", "u-bk", "pb&t", "pbt", "peopel", "exchange bk", "ecb", "labete", "cbank", "cornerbank", "b of vw", "asb", "grt so", "gsb", "hawthorn", "hb&t", "hb & t", "hbt", "corner bank", "holton", "hsb", "horton nat", "hometown bank", "home town", "state bank", "state bank", "pinn", "nakoma", "nekoma", "lyons", "exchange nat", "walton", "vintage", "gardner bank", "heritage b", "bank of col", "cb&t", "cb", "cbk", "cvt", "bank of com", "bank of b'game", "bank of denton", "bank of greeley", "bank of hays", "holyrood", "bank of minden", "bank of osage", "bank of palmer", "burlingame", "banner capiital", "bk of at", "bk of greeley", "bk osage", "chetopa", "chetpa", "cimarron", "bailleyville", "bank of minden", "bank at west", "bank of tescot", "holrood", "bank of cunningham", "bbok", "bank of minden", "bank of commerce", "eastman nat", "eastman bank", "mccook nat", "arvest", "av bank", "avsb", "baldwin bank", "bank of minden", "bank of at", "c b & t", "conway bank", "empire bank", "dickinson county bank", "dubuque b&t", "f. s. bank", "farmer & merch", "farmers merchant", "farmers st", "esb", "dsb", "f&d", "f & d", "f&s", "f & s", "farmer bank", "first natioanl", "first nat", "m & j", "first commerce", "first kansas", "first natl", "first nat'l", "m&j", "first needy", "first oaks", "flinthills", "comm nat", "emprise", "m+j", "first nat", "first n bank", "first oak", "fo bk", "fob", "emppise", "impact bank", "kanza bank", "sw nat", "st bank", "osb", "frms nat"

Table B.3: *Annual Farm Numbers and Average Farm-Level Total Loan Volume*

Year	All Farms		Cat. Farms		Difference in	
	#	\$	#	\$	%	\$
2002	1759	455003	321	277358	18	177645***
2003	1726	458136	327	288409	19	169727***
2004	1649	454376	409	288778	25	165598***
2005	1499	465224	428	295691	29	169533***
2006	1424	478356	399	322668	28	155688***
2007	1354	492254	401	314379	30	177875***
2008	1348	489282	392	302344	29	186938***
2009	1357	534977	403	327533	30	207445***
2010	1197	570483	426	333888	36	236595***
2011	1150	395665	391	256903	34	138763***
2012	993	399945	320	258964	32	140981***
2013	1018	574014	688	549572	68	24442
2014	1006	620707	708	607459	70	13248
2015	902	649173	635	644394	70	4779
2016	885	633959	688	640197	78	-6238
2017	876	677353	660	657677	75	19676
2018	854	696227	681	671228	80	24999
2019	871	781254	574	724630	66	56623
2020	747	724098	517	723300	69	798

This table presents the number of farms and loan data used in this study. #, % and \$ represent the number of farms, the share of farms with all loans categorized and the average loan respectively. Cat. farms stand for categorized farms. These loan values are inflation-adjusted using Consumer Price Index (CPI) from the U.S. Bureau of Labor Statistics. This study estimates the average loan values for each year by first computing farm-level total loan volume in a year and then finding the average using all farms in that year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: *Kansas Farm Credit Branches and Outputs, 2002-2020*

Branches	County	Period	Outposts	County	Period
HighPlains			HighPlains		
Pratt	Pratt	2002-2020	Wakeeney	Trego	2002-2020
Phillipsburg	Phillips	2002-2020	Stockton	Rooks	2002-2020
Ness City	Ness	2002-2020	Smith Center	Smith	2002-2020
Larned	Pawnee	2002-2020	Russell	Russell	2002-2020
Hays	Ellis	2002-2020	Quinter	Gove	2002-2020
Dodge City	Ford	2002-2020	Osborne	Osborne	2002-2020
			Norton	Norton	2002-2020
			Jetmore	Hodgeman	2002-2020
			Hoxie	Sheridan	2002-2020
			Hill City	Graham	2002-2020
			Greensburg	Kiowa	2017-2020
			Dighton	Lane	2002-2020
FCWKS			FCWKS		
Colby	Thomas	2002-2020		Wallace	2002-2020
				Thomas	2002-2020
				Sherman	2002-2020
				Sheridan	2002-2020
				Rawlins	2002-2020
				Logan	2002-2020
				Gove	2002-2020
				Decatur	2002-2020
				Cheyenne	2002-2020
FFC			FFC		
Baldwin	Douglas	2002-2020	Abilene	Dickinson	2002
Emporia	Lyon	2002-2020	Clay Center	Clay	2002-2014
Hiawatha	Brown	2002-2020	Council Grove	Morris	2002
Manhattan	Riley	2002-2020	Columbus	Cherokee	2002-2008
Marysville	Marshall	2002-2020			
Parsons	Labette	2002-2020			
Chanute	Neosho	2002-2010			
Eureka	Greenwood	2002-2012			
Ottawa	Franklin	2002-2006			
Lawrence	Douglas	2002-2006			

Note: FCWKS and FFC stand for Farm Credit of Western KS and Frontier Farm Credit respectively.

Table B.5: *Banks per People in Kansas (Part 1), 2002-2020*

Area	Year		Change	Area	Year		Change
	2002	2020			2002	2020	
Allen	0.5	0.4	D	Linn	0.62	0.63	I
Anderson	0.74	0.64	D	Logan	0.67	1.09	I
Atchison	0.36	0.31	D	Lyon	0.31	0.28	D
Barber	0.79	0.71	D	McPherson	0.44	0.36	D
Barton	0.36	0.39	I	Marion	0.75	0.76	I
Bourbon	0.39	0.42	I	Marshall	0.94	0.8	D
Brown	0.67	0.63	D	Meade	0.64	0.74	I
Butler	0.26	0.21	D	Miami	0.24	0.23	D
Chase	0.66	0.78	I	Mitchell	1.04	0.86	D
Chautauqua	0.48	0.59	I	Montgomery	0.31	0.22	D
Cherokee	0.36	0.41	I	Morris	0.67	0.93	I
Cheyenne	0.66	1.53	I	Morton	0.89	0.74	D
Clark	1.26	1.51	I	Nemaha	0.95	0.68	D
Clay	0.58	0.62	I	Neosho	0.54	0.44	D
Cloud	0.7	0.89	I	Ness	0.9	1.49	I
Coffey	0.8	0.48	D	Norton	0.68	0.73	I
Comanche	1.53	1.18	D	Osage	0.48	0.44	D
Cowley	0.22	0.2	D	Osborne	1.17	1.14	D

Source: Institute for Policy & Social Research (IPSR). I, D, N stand for Increase, Decrease and No change.

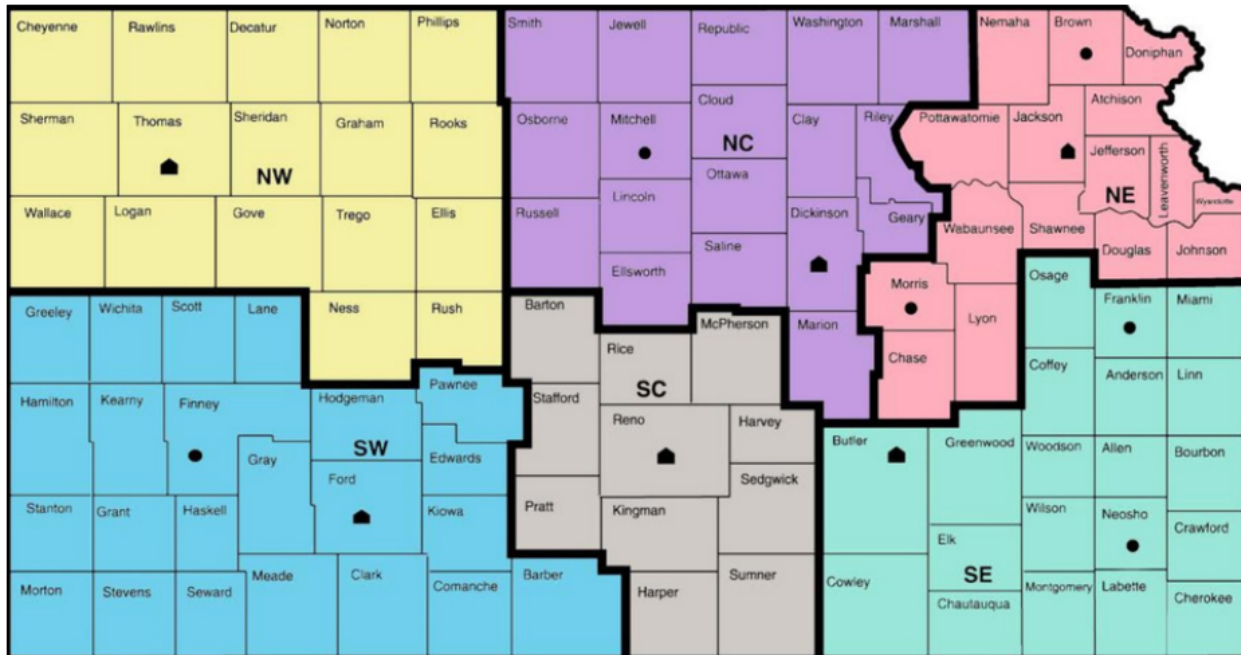
Table B.6: *Banks per People in Kansas (Part 2), 2002-2020*

Area	Year			Area	Year		
	2002	2020	Change		2002	2020	Change
Crawford	0.39	0.28	D	Ottawa	0.48	0.52	I
Decatur	0.89	1.09	I	Pawnee	0.71	0.96	I
Dickinson	0.47	0.49	I	Phillips	0.69	0.6	D
Doniphan	1.1	0.67	D	Pottawatomie	0.43	0.36	D
Douglas	0.22	0.19	D	Pratt	0.31	0.33	I
Edwards	1.21	1.03	D	Rawlins	1.38	1.56	I
Elk	0.95	0.81	D	Reno	0.17	0.18	I
Ellis	0.25	0.35	I	Republic	1.09	1.07	D
Ellsworth	0.93	0.94	I	Rice	0.57	0.42	D
Finney	0.29	0.23	D	Riley	0.21	0.21	N
Ford	0.31	0.29	D	Rooks	0.91	0.81	D
Franklin	0.36	0.35	D	Rush	1.45	1.69	I
Geary	0.22	0.19	D	Russell	0.85	1.05	I
Gove	0.99	1.1	I	Saline	0.18	0.22	I
Graham	1.04	1.24	I	Scott	0.6	0.58	D
Grant	0.38	0.41	I	Sedgwick	0.08	0.07	D
Gray	0.33	0.53	I	Seward	0.22	0.18	D
Greeley	0.7	1.56	I	Shawnee	0.11	0.11	N
Greenwood	0.79	1	I	Sheridan	1.87	1.63	D
Hamilton	0.75	0.79	I	Sherman	0.47	0.67	I
Harper	0.79	0.73	D	Smith	0.93	1.12	I
Harvey	0.3	0.29	D	Stafford	1.29	0.74	D
Haskell	0.24	0.26	I	Stanton	0.83	0.96	I
Hodgeman	0.94	0.58	D	Stevens	0.55	0.38	D
Jackson	0.39	0.3	D	Sumner	0.51	0.45	D
Jefferson	0.32	0.27	D	Thomas	0.86	1.01	I
Jewell	1.43	1.02	D	Trego	0.96	0.71	D
Johnson	0.12	0.1	D	Wabaunsee	0.74	0.73	D
Kearny	0.69	0.5	D	Wallace	0.6	0.66	I
Kingman	0.59	0.54	D	Washington	1.13	1.09	D
Kiowa	1.27	1.63	I	Wichita	0.82	0.93	I
Labette	0.27	0.25	D	Wilson	0.49	0.58	I
Lane	1.01	1.27	I	Woodson	0.83	0.64	D
Leavenworth	0.14	0.11	D	Wyandotte	0.11	0.11	N
Lincoln	1.14	1.36	I	Kansas	0.15	0.09	D

Source: Institute for Policy & Social Research (IPSR). I, D, N stand for Increase, Decrease and No change.

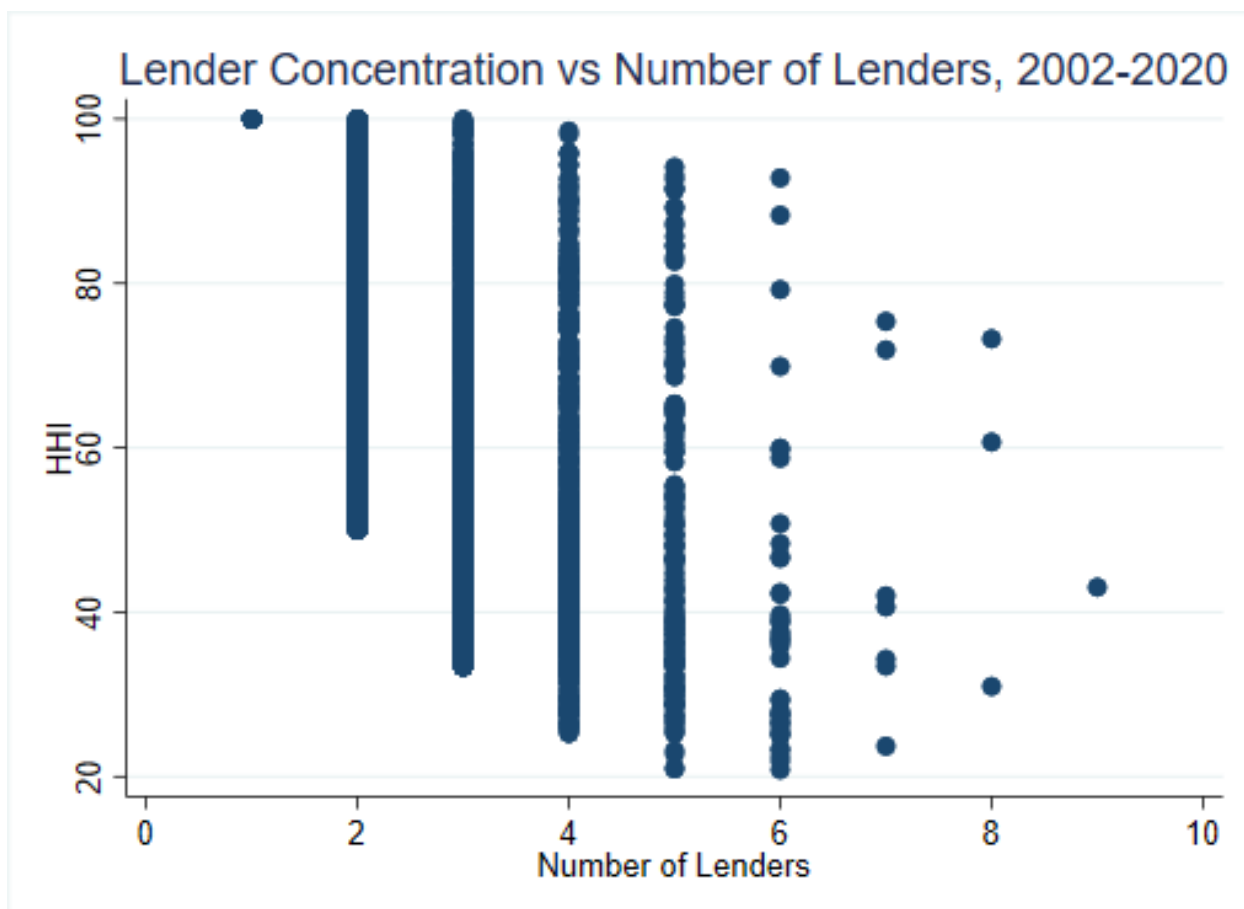
Table B.7: *KFMA Regions, 2020*

Northwest	North Central	Northeast	Southwest	South Central	Southeast
Cheyenne	Clay	Atchison	Barber	Barton	Allen
Decatur	Cloud	Brown	Clark	Harper	Anderson
Ellis	Dickinson	Chase	Comanche	Harvey	Bourbon
Gove	Ellsworth	Doniphan	Edwards	Kingman	Butler
Graham	Geary	Douglas	Finney	McPherson	Chautauqua
Logan	Jewell	Jackson	Ford	Pratt	Cherokee
Ness	Lincoln	Jefferson	Grant	Reno	Coffey
Norton	Marion	Leavenworth	Gray	Rice	Cowley
Phillips	Marshall	Lyon	Greeley	Sedgwick	Crawford
Rawlins	Mitchell	Morris	Hamilton	Stafford	Elk
Rooks	Osborne	Nemaha	Haskell	Sumner	Franklin
Rush	Ottawa	Pottawatomie	Hodgeman		Greenwood
Sheridan	Republic	Shawnee	Kearny		Labette
Sherman	Riley	Wabaunsee	Kiowa		Linn
Thomas	Russell	Johnson	Lane		Miami
Trego	Saline	Wyndotte	Meade		Montgomery
Wallace	Smith		Morton		Neosho
	Washington		Pawnee		Osage
			Scott		Wilson
			Seward		Woodson
			Stanton		
			Stevens		
			Wichita		



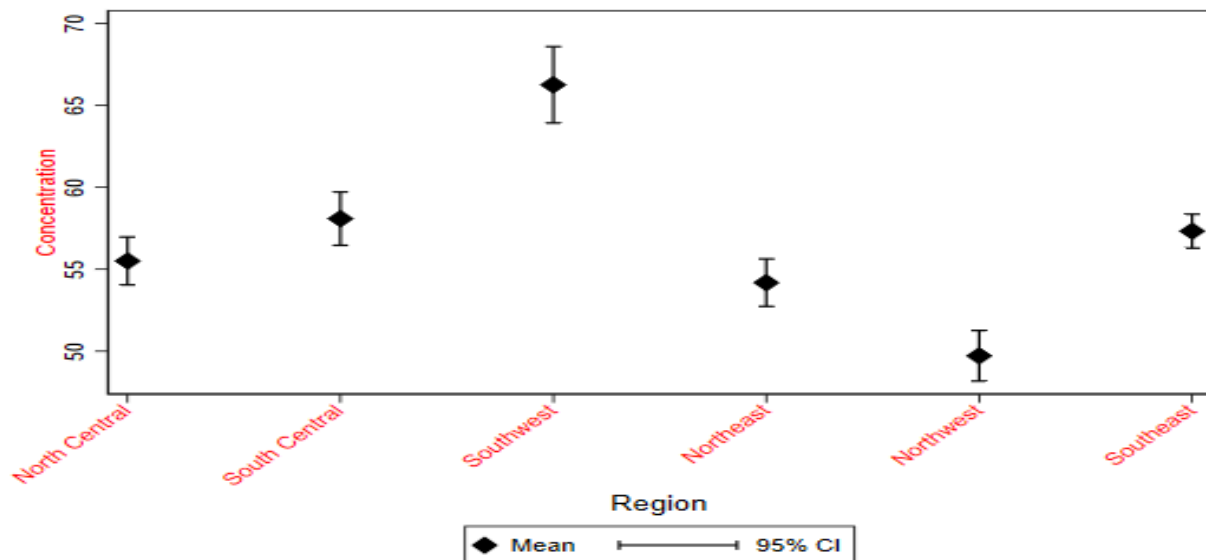
Source: KFMA. This figure displays the current six KFMA regional groupings of all 105 Kansas counties. NW, NC, NE, SW, SC and SE stand for North west, North Central, Northeastern, Southwestern, South Central and Southeastern regions respectively.

Figure B.1: *Kansas Counties and their respective KFMA Regions*



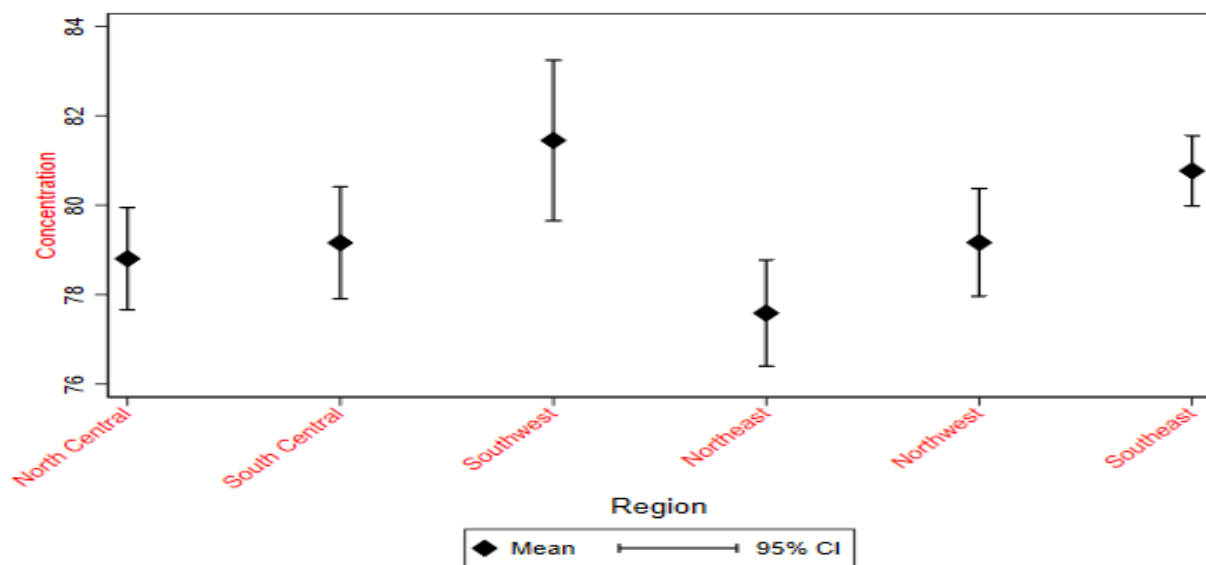
Note: This figure shows lender concentration and number of lenders for KFMA producers from 2002 to 2020. Lender concentration ranges between 0 and 100 after scaling by 100. A value close to 0 means the producer uses several lenders. A value of 100 means the producer uses a single lender. The number of farm-year observations is 9,368.

Figure B.2: *HHI and Number of Lenders, 2002-2020*



Note: This figure shows the average loan concentration of producers across the six KFMA regions. The KFMA dataset spans from 2002 to 2020. Producer concentration indices range between 0 and 100 after scaling by 100. A loan concentration value close to 0 means the producer is using several loans, and a value of 100 means the producer uses a single loan in that period. This figure contains six observations computed using 9,368 farm-year observations.

Figure B.3: *Average Loan Concentration across KFMA Regions, 2002-2020*



Note: This figure shows the average lender concentration of producers across the six KFMA regions. The KFMA dataset spans from 2002 to 2020. Producer lender concentration indices range between 0 and 100 after scaling by 100. A lender concentration value close to 0 means the producer is using several lenders, and a value of 100 means the producer uses a single lender in that period. This figure contains six observations computed using 9,368 farm-year observations.

Figure B.4: *Average Lender Concentration across KFMA Regions, 2002-2020*

Table B.8: *Determinants of Loan Concentration based on all loan data, 2002-2020*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Operator's age	0.408*** (0.015)	0.399*** (0.016)	0.267*** (0.021)	0.270*** (0.021)	0.414*** (0.016)	0.400*** (0.015)	0.274*** (0.021)	0.271*** (0.021)
Number of workers	-1.081*** (0.145)	-1.038*** (0.142)	-1.009*** (0.134)	-0.934*** (0.131)	-0.993*** (0.144)	-1.014*** (0.141)	-0.914*** (0.133)	-0.907*** (0.132)
Share of operated Acres owned	2.275*** (0.699)	1.467** (0.657)	-2.190*** (0.613)	-3.234*** (0.648)	1.928*** (0.689)	1.236* (0.648)	-2.593*** (0.633)	-3.468*** (0.664)
Total Operated Acres	-5.857*** (0.237)	-6.498*** (0.247)	-6.514*** (0.233)	-7.172*** (0.247)	-6.212*** (0.246)	-6.613*** (0.248)	-6.903*** (0.243)	-7.289*** (0.248)
Debt to asset ratio			-20.918*** (1.822)	-20.978*** (1.809)			-20.965*** (1.827)	-20.963*** (1.814)
Returns on assets			-10.453*** (2.220)	-10.094*** (2.174)			-10.422*** (2.222)	-10.175*** (2.181)
Normalized Current ratio			41.509* (22.560)	42.067* (23.340)			39.909* (21.989)	41.737* (22.757)
Number of agric. banks					0.265* (0.151)	0.671*** (0.155)	0.250* (0.145)	0.651*** (0.149)
Banks per people					3.283*** (0.594)	2.036*** (0.644)	3.548*** (0.574)	2.221*** (0.624)
Physical presence of farm credit outpost					-0.856* (0.508)	-1.225** (0.516)	-0.549 (0.489)	-0.838* (0.498)
Physical presence of farm credit					0.296 (0.551)	0.812 (0.714)	0.321 (0.527)	0.537 (0.687)
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	22575	22575	22575	22575	22575	22575	22575	22575
R^2	0.083	0.101	0.142	0.158	0.085	0.103	0.144	0.160

Note: This table presents the results of OLS estimation of equation 1.1. Each column presents a separate regression results for the period 2002-2020: Variables are gradually included in the models, with the last model containing all variables in our analyses. Models 2, 4, 6 and 8 have both year and region fixed effects. Loan concentration based on all loans is the dependent variable, which is scaled by 100 for easy interpretation. We constructed this loan concentration using all farm loan observations. All variables are defined in Appendix. Additionally, we log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: *Lagged Variables and Lender Concentration in Kansas, 2003-2020*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Debt-to-Asset ratio $_{it-1}$			-5.850*** (1.237)	-7.594*** (1.332)			-5.844*** (1.246)	-7.588*** (1.345)
Rate of Return to Asset $_{it-1}$			-4.103*** (0.863)	-4.779*** (0.944)			-4.032*** (0.849)	-4.809*** (0.948)
Normalized Current ratio $_{it-1}$			4.624 (9.335)	8.194 (11.554)			4.682 (9.765)	9.882 (11.504)
Number of agric. banks $_{it-1}$					0.397* (0.236)	0.539** (0.247)	0.402* (0.235)	0.563** (0.246)
Banks per people $_{it-1}$					4.078*** (0.907)	3.520*** (0.976)	4.034*** (0.904)	3.440*** (0.969)
Physical presence of farm credit outpost $_{it-1}$					0.604 (0.749)	-0.017 (0.749)	0.669 (0.748)	0.041 (0.748)
Physical presence of farm credit $_{it-1}$					1.220 (0.835)	-1.477 (1.153)	1.232 (0.833)	-1.481 (1.143)
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	7195	7195	7195	7195	7195	7195	7195	7195
R^2	0.037	0.079	0.043	0.089	0.042	0.083	0.049	0.093

Note: This table presents the results of OLS estimation of equation 1.1. Each column presents a separate regression results for the period 2003-2020: Variables are gradually included in the models, with the last model containing all variables in our analyses. All variables, except region and year fixed effects, are lagged a year. Models 2, 4, 6 and 8 have both year and region fixed effects. Lender concentration is the dependent variable, which is scaled by 100 for easy interpretation. We constructed this loan concentration using all farm loan observations. All variables are defined in Appendix. Additionally, we log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.10: *Lagged Variables and Loan Concentration in Kansas, 2003-2020*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Operator's age _{it-1}	0.498*** (0.029)	0.521*** (0.029)	0.375*** (0.036)	0.389*** (0.036)	0.505*** (0.029)	0.521*** (0.029)	0.382*** (0.036)	0.389*** (0.036)
Number of operators and employees _{it-1}	-0.688** (0.278)	-0.191 (0.255)	-0.761*** (0.264)	-0.212 (0.243)	-0.588** (0.274)	-0.136 (0.254)	-0.665** (0.261)	-0.164 (0.242)
Share of operated Acres owned _{it-1}	3.738*** (1.220)	1.755 (1.228)	-1.361 (1.330)	-4.204*** (1.342)	3.277*** (1.241)	1.580 (1.240)	-1.820 (1.349)	-4.372*** (1.359)
Total Operated Acres _{it-1}	-6.379*** (0.432)	-6.683*** (0.450)	-7.047*** (0.422)	-7.387*** (0.438)	-6.780*** (0.460)	-6.853*** (0.453)	-7.445*** (0.450)	-7.547*** (0.441)
Debt-to-Asset ratio _{it-1}			-20.489*** (3.559)	-22.360*** (3.621)			-20.451*** (3.563)	-22.337*** (3.628)
Rate of Return to Asset _{it-1}			-10.158*** (2.216)	-11.385*** (2.290)			-10.119*** (2.216)	-11.404*** (2.295)
Normalized Current ratio _{it-1}			-1.774 (20.322)	4.239 (22.520)			-1.218 (20.421)	5.582 (22.316)
Number of agric. banks _{it-1}					0.414 (0.301)	0.491 (0.313)	0.409 (0.291)	0.548* (0.301)
Banks per people _{it-1}					3.869*** (1.121)	3.817*** (1.205)	3.755*** (1.091)	3.591*** (1.169)
Physical presence of farm credit outpost _{it-1}					-1.326 (0.915)	-1.395 (0.925)	-1.106 (0.878)	-1.230 (0.885)
Physical presence of farm credit _{it-1}					-0.525 (1.053)	-1.456 (1.427)	-0.447 (1.017)	-1.485 (1.369)
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	7195	7195	7195	7195	7195	7195	7195	7195
R ²	0.093	0.132	0.137	0.183	0.096	0.134	0.139	0.185

Note: This table presents the results of OLS estimation of equation 1.1. Each column presents a separate regression results for the period 2003-2020: Variables are gradually included in the models, with the last model containing all variables in our analyses. All variables, except region and year fixed effects, are lagged a year. Models 2, 4, 6 and 8 have both year and region fixed effects. Loan concentration is the dependent variable, which is scaled by 100 for easy interpretation. We constructed this loan concentration using all farm loan observations. All variables are defined in Appendix. Additionally, we log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: *Determinants of Lender Concentration for Period 1 (2002-2012) and Period 2 (2013-2020)*

	Period 1 Model 1	Period 2 Model 2	Period 1 Model 3	Period 2 Model 4	Period 1 Model 5	Period 2 Model 6	Period 1 Model 7	Period 2 Model 8
Operator's age	0.213*** (0.026)	0.249*** (0.028)	0.184*** (0.028)	0.182*** (0.030)	0.210*** (0.026)	0.255*** (0.028)	0.180*** (0.028)	0.188*** (0.030)
Number of workers	-0.417 (0.362)	-0.302 (0.199)	-0.428 (0.363)	-0.295 (0.194)	-0.376 (0.363)	-0.237 (0.199)	-0.388 (0.365)	-0.233 (0.195)
Share of Operated Acres owned	-0.717 (1.067)	-0.020 (1.222)	-2.332** (1.106)	-2.208* (1.269)	-0.514 (1.074)	-0.499 (1.228)	-2.122* (1.112)	-2.635** (1.273)
Total Operated Acres	-2.947*** (0.388)	-3.605*** (0.397)	-3.156*** (0.399)	-3.802*** (0.394)	-2.961*** (0.394)	-3.803*** (0.397)	-3.154*** (0.407)	-3.989*** (0.394)
Debt to Asset ratio			-4.788*** (1.439)	-10.319*** (1.865)			-4.752*** (1.426)	-10.204*** (1.880)
Returns on assets			-4.338 (2.757)	-4.652*** (0.936)			-4.624* (2.746)	-4.665*** (0.938)
Normalized Current ratio			-86.966 (195.947)	9.933 (14.257)			-99.598 (202.565)	9.528 (12.929)
Number of agric. banks					0.771** (0.302)	0.547* (0.303)	0.811*** (0.301)	0.516* (0.302)
Banks per people					-0.964 (1.201)	4.806*** (1.188)	-1.058 (1.197)	4.874*** (1.180)
Physical presence of farm credit outpost					-0.608 (0.876)	0.127 (0.987)	-0.647 (0.872)	0.417 (0.988)
Physical presence of farm credit					-3.874*** (1.350)	3.160* (1.615)	-3.759*** (1.342)	2.665* (1.600)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4217	5151	4217	5151	4217	5151	4217	5151
R^2	0.043	0.040	0.052	0.052	0.048	0.046	0.057	0.057

Note: This table presents the results of OLS estimation of equation 1.1. Each column presents a separate regression results: Variables are gradually included in the models, with the last model containing all variables in our analyses. All variables, except region and year fixed effects, are lagged a year. Even numbered models are for period 2013-2020, while odd numbered models are for the period 2002-2012. Lender concentration is the dependent variable, which is scaled by 100 for easy interpretation. We constructed this loan concentration using all farm loan observations. All variables are defined in Appendix. Additionally, we log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.12: *Determinants of Loan Concentration for Period 1 (2002-2012) and Period 2 (2013-2020)*

	Period 1 Model 1	Period 2 Model 2	Period 1 Model 3	Period 2 Model 4	Period 1 Model 5	Period 2 Model 6	Period 1 Model 7	Period 2 Model 8
Operator's age	0.500*** (0.036)	0.421*** (0.034)	0.421*** (0.046)	0.226*** (0.037)	0.498*** (0.036)	0.419*** (0.034)	0.420*** (0.046)	0.225*** (0.037)
Number of workers	0.063 (0.528)	-0.479* (0.249)	-0.051 (0.521)	-0.460* (0.236)	0.169 (0.531)	-0.456* (0.250)	0.054 (0.525)	-0.447* (0.238)
Share of Operated Acres owned	1.412 (1.472)	-0.445 (1.519)	-4.193*** (1.590)	-6.993*** (1.574)	1.534 (1.486)	-0.809 (1.525)	-4.092** (1.605)	-7.234*** (1.582)
Total Operated Acres	-6.233*** (0.552)	-7.576*** (0.530)	-7.296*** (0.587)	-8.213*** (0.513)	-6.427*** (0.560)	-7.673*** (0.533)	-7.511*** (0.602)	-8.284*** (0.516)
Debt to Asset ratio			-16.259*** (3.700)	-30.369*** (3.298)			-16.268*** (3.695)	-30.139*** (3.306)
Returns on assets			-4.968 (6.986)	-12.302*** (1.892)			-4.501 (6.993)	-12.291*** (1.884)
Normalized Current ratio			131.981 (208.005)	34.833 (21.631)			134.889 (204.417)	34.642* (20.818)
Number of agric. banks					-0.437 (0.402)	1.550*** (0.366)	-0.448 (0.392)	1.458*** (0.352)
Banks per people					3.365** (1.599)	2.134 (1.419)	3.440** (1.570)	2.321* (1.362)
Physical presence of farm credit outpost					0.315 (1.223)	-3.291*** (1.121)	0.157 (1.184)	-2.422** (1.085)
Physical presence of farm credit					-3.850** (1.689)	3.252* (1.936)	-3.672** (1.645)	1.787 (1.806)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4217	5151	4217	5151	4217	5151	4217	5151
R^2	0.096	0.099	0.143	0.163	0.098	0.105	0.144	0.167

Note: This table presents the results of OLS estimation of equation 1.1. Each column presents a separate regression results: Variables are gradually included in the models, with the last model containing all variables in our analyses. All variables, except region and year fixed effects, are lagged a year. Even numbered models are for the period 2013-2020 (Period 2), while odd numbered models are for the period 2002-2012 (Period 1). Loan concentration is the dependent variable, which is scaled by 100 for easy interpretation. We constructed this loan concentration using all farm loan observations. All variables are defined in Appendix. Additionally, we log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.13: *Determinants of Loan Concentration (All Loans) for Period 1 (2002-2012) and Period 2 (2013-2020)*

	Period 1 Model 1	Period 2 Model 2	Period 1 Model 3	Period 2 Model 4	Period 1 Model 5	Period 2 Model 6	Period 1 Model 7	Period 2 Model 8
Operator's age	0.423*** (0.019)	0.358*** (0.027)	0.308*** (0.025)	0.180*** (0.030)	0.423*** (0.019)	0.356*** (0.027)	0.309*** (0.025)	0.180*** (0.030)
Number of workers	-1.421*** (0.182)	-0.467** (0.209)	-1.270*** (0.171)	-0.459** (0.199)	-1.390*** (0.182)	-0.452** (0.209)	-1.236*** (0.171)	-0.441** (0.199)
Share of operated Acres owned	1.554** (0.769)	0.795 (1.278)	-2.840*** (0.716)	-5.043*** (1.313)	1.388* (0.760)	0.424 (1.284)	-3.011*** (0.732)	-5.358*** (1.320)
Total Operated Acres	-6.379*** (0.289)	-6.847*** (0.451)	-7.090*** (0.312)	-7.438*** (0.442)	-6.491*** (0.292)	-6.954*** (0.453)	-7.207*** (0.315)	-7.542*** (0.445)
Debt to asset ratio			-19.571*** (2.055)	-26.192*** (2.396)			-19.578*** (2.060)	-25.999*** (2.400)
Return on assets			-9.417** (4.520)	-12.119*** (1.433)			-9.438** (4.545)	-12.144*** (1.432)
Normalized Current ratio			212.785 (150.512)	38.894* (22.661)			212.636 (153.542)	38.274* (21.723)
Number of agric. banks					0.286 (0.181)	1.670*** (0.291)	0.282 (0.175)	1.581*** (0.280)
Banks per people					2.001*** (0.771)	2.138* (1.206)	2.092*** (0.750)	2.681** (1.162)
Physical presence of farm credit outpost					-0.211 (0.631)	-4.138*** (0.915)	0.049 (0.607)	-3.450*** (0.886)
Physical presence of farm credit					0.097 (0.805)	3.594** (1.574)	-0.151 (0.780)	2.860* (1.499)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15416	7159	15416	7159	15416	7159	15416	7159
R^2	0.114	0.085	0.173	0.140	0.115	0.093	0.174	0.147

Note: This table presents the results of OLS estimation of equation 1.1. Each column presents a separate regression results for the period 2002-2020: Variables are gradually included in the models, with the last model containing all variables in our analyses. Even numbered models are for period 2013-2020 (period 2), while odd numbered models are for the period 2002-2012 (period 1). Loan concentration is the dependent variable, which is scaled by 100 for easy interpretation. We constructed this loan concentration using all farm loan observations. Additionally, we log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.14: *Lender Concentration with original Lender Categories, 2002-2020*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Operator's age	0.117*** (0.013)	0.159*** (0.013)	0.087*** (0.014)	0.119*** (0.015)	0.119*** (0.014)	0.159*** (0.014)	0.090*** (0.015)	0.119*** (0.015)
Number of workers	-0.530*** (0.117)	-0.382*** (0.115)	-0.522*** (0.116)	-0.359*** (0.114)	-0.482*** (0.116)	-0.376*** (0.115)	-0.473*** (0.116)	-0.353*** (0.114)
Share of operated Acres owned	1.397*** (0.461)	0.314 (0.478)	0.574 (0.487)	-0.976* (0.562)	1.196** (0.468)	0.252 (0.484)	0.370 (0.500)	-1.026* (0.571)
Total Operated Acres	-2.509*** (0.191)	-2.726*** (0.202)	-2.611*** (0.194)	-2.860*** (0.205)	-2.724*** (0.199)	-2.795*** (0.203)	-2.829*** (0.201)	-2.924*** (0.207)
Debt to asset ratio			-3.864*** (0.656)	-5.748*** (0.769)			-3.842*** (0.656)	-5.697*** (0.768)
Returns on assets			-2.954*** (0.791)	-4.879*** (0.976)			-2.976*** (0.788)	-4.945*** (0.984)
Normalized Current ratio			5.615 (14.008)	12.880 (14.341)			4.799 (13.424)	12.853 (13.926)
Number of agric. banks					0.489*** (0.138)	0.650*** (0.145)	0.483*** (0.138)	0.642*** (0.145)
Banks per people					1.984*** (0.547)	1.226** (0.590)	1.991*** (0.546)	1.225** (0.587)
Physical presence of farm credit outpost					-1.169** (0.469)	-1.422*** (0.470)	-1.117** (0.468)	-1.331*** (0.469)
Physical presence of farm credit					0.131 (0.499)	-1.269* (0.690)	0.163 (0.498)	-1.265* (0.686)
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	18923	18923	18923	18923	18923	18923	18923	18923
R^2	0.019	0.048	0.022	0.055	0.021	0.050	0.025	0.057

Note: This table presents the results of OLS estimation of equation 1.1. This sample maintains the original lender categories and includes all categorized loans. Variables are gradually included in the models, with the last model containing all variables in our analyses. The dependent variable is scaled by 100 for easy interpretation. Robust standard errors in parenthesis. The regression covers the period 2002-2020. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.15: *Lender Concentration for Period 1 (2002-2012) and Period 2 (2013-2020) with Original Lender Categories, 2002-2020*

	Period 1 Model 1	Period 2 Model 2	Period 1 Model 3	Period 2 Model 4	Period 1 Model 5	Period 2 Model 6	Period 1 Model 7	Period 2 Model 8
Operator's age	0.128*** (0.016)	0.220*** (0.024)	0.090*** (0.018)	0.169*** (0.026)	0.126*** (0.016)	0.224*** (0.024)	0.088*** (0.018)	0.174*** (0.026)
Number of workers	-0.447*** (0.147)	-0.280 (0.174)	-0.403*** (0.148)	-0.281 (0.172)	-0.458*** (0.146)	-0.230 (0.175)	-0.415*** (0.148)	-0.230 (0.172)
Share of operated Acres owned	0.365 (0.522)	-0.281 (1.081)	-0.842 (0.640)	-1.869* (1.116)	0.450 (0.520)	-0.737 (1.087)	-0.751 (0.632)	-2.307** (1.121)
Total Operated Acres	-2.398*** (0.240)	-3.482*** (0.359)	-2.496*** (0.251)	-3.617*** (0.359)	-2.438*** (0.243)	-3.668*** (0.359)	-2.527*** (0.254)	-3.801*** (0.359)
Debt to asset ratio			-5.225*** (0.892)	-7.098*** (1.357)			-5.182*** (0.886)	-7.050*** (1.364)
Returns on assets			-6.384*** (2.049)	-4.331*** (0.817)			-6.466*** (2.037)	-4.364*** (0.820)
Normalized Current ratio			-39.564 (164.891)	11.768 (14.641)			-51.105 (169.205)	11.152 (13.441)
Number of agric. banks					0.710*** (0.174)	0.736*** (0.257)	0.722*** (0.174)	0.708*** (0.257)
Banks per people					-0.694 (0.718)	3.936*** (1.048)	-0.779 (0.714)	4.089*** (1.045)
Physical presence of farm credit outpost					-2.005*** (0.558)	-0.789 (0.873)	-1.960*** (0.555)	-0.588 (0.875)
Physical presence of farm credit					-3.217*** (0.803)	3.203** (1.376)	-3.124*** (0.799)	3.001** (1.370)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12118	6805	12118	6805	12118	6805	12118	6805
R^2	0.023	0.036	0.031	0.042	0.027	0.041	0.035	0.047

This table presents the results of OLS estimation of equation 1.1. This sample maintains the original lender categories and includes all categorized loans. Variables are gradually included in the models, with the last model containing all variables in our analyses. Models 2, 4, 6 and 8 have both year and region fixed effects. Lender concentration is the dependent variable, which is scaled by 100 for easy interpretation. We constructed this lender concentration using all farm loans categorized. Additionally, we log-transform the farm acres operated by KFMA producer, and report robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.16: *Determinants of Lending Relationships in Kansas, 2002-2020*

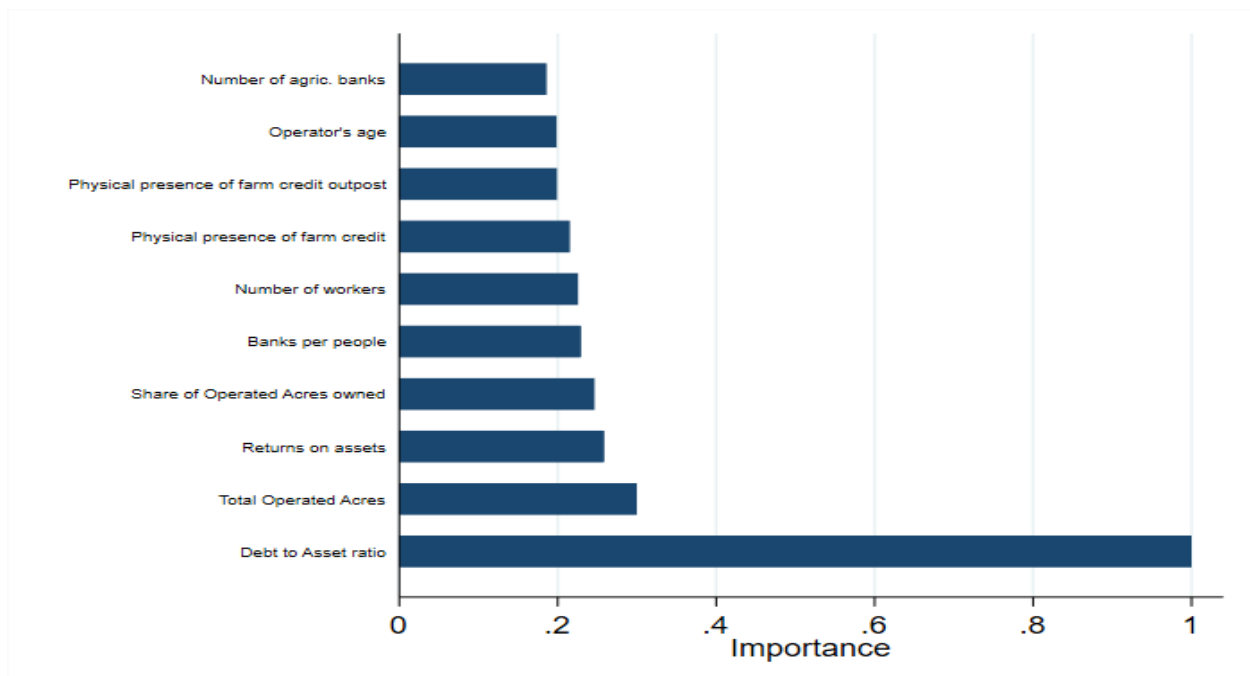
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Operator's age	-0.012*** (0.001)	-0.012*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.011*** (0.001)	-0.012*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)
Number of workers	0.105*** (0.013)	0.087*** (0.012)	0.106*** (0.012)	0.086*** (0.011)	0.107*** (0.013)	0.086*** (0.012)	0.107*** (0.012)	0.086*** (0.011)
Share of Operated Acres owned	-0.027 (0.035)	0.030 (0.034)	0.102*** (0.037)	0.185*** (0.037)	-0.052 (0.035)	0.033 (0.035)	0.077** (0.037)	0.188*** (0.038)
Total Operated Acres	0.231*** (0.013)	0.198*** (0.013)	0.253*** (0.013)	0.222*** (0.013)	0.217*** (0.014)	0.201*** (0.013)	0.239*** (0.014)	0.225*** (0.013)
Debt to Asset ratio			0.477*** (0.083)	0.548*** (0.088)			0.475*** (0.083)	0.548*** (0.088)
Returns on assets			0.083 (0.076)	0.172** (0.074)			0.087 (0.076)	0.172** (0.074)
Normalized Current ratio			-0.308 (0.689)	-0.802 (0.682)			-0.386 (0.673)	-0.804 (0.664)
Number of agric. banks					-0.009 (0.009)	-0.012 (0.010)	-0.007 (0.009)	-0.011 (0.010)
Banks per people					-0.048 (0.038)	-0.072* (0.039)	-0.053 (0.038)	-0.073* (0.039)
Physical presence of farm credit outpost					0.025 (0.030)	0.010 (0.030)	0.017 (0.030)	0.003 (0.029)
Physical presence of farm credit					0.150*** (0.035)	0.031 (0.047)	0.149*** (0.035)	0.038 (0.046)
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9368	9368	9368	9368	9368	9368	9368	9368
R^2	0.099	0.163	0.118	0.188	0.101	0.163	0.121	0.189

Note: This table presents the results of OLS estimation of equation 1.1 with the dependent variable, number of lenders. Each column presents a separate regression results for the period 2002-2020: Variables are gradually included in the models, with the last model containing all variables in our analyses. Models 2, 4, 6 and 8 have both year and region fixed effects. We log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.17: *Determinants of Loan Numbers in Kansas, 2002-2020*

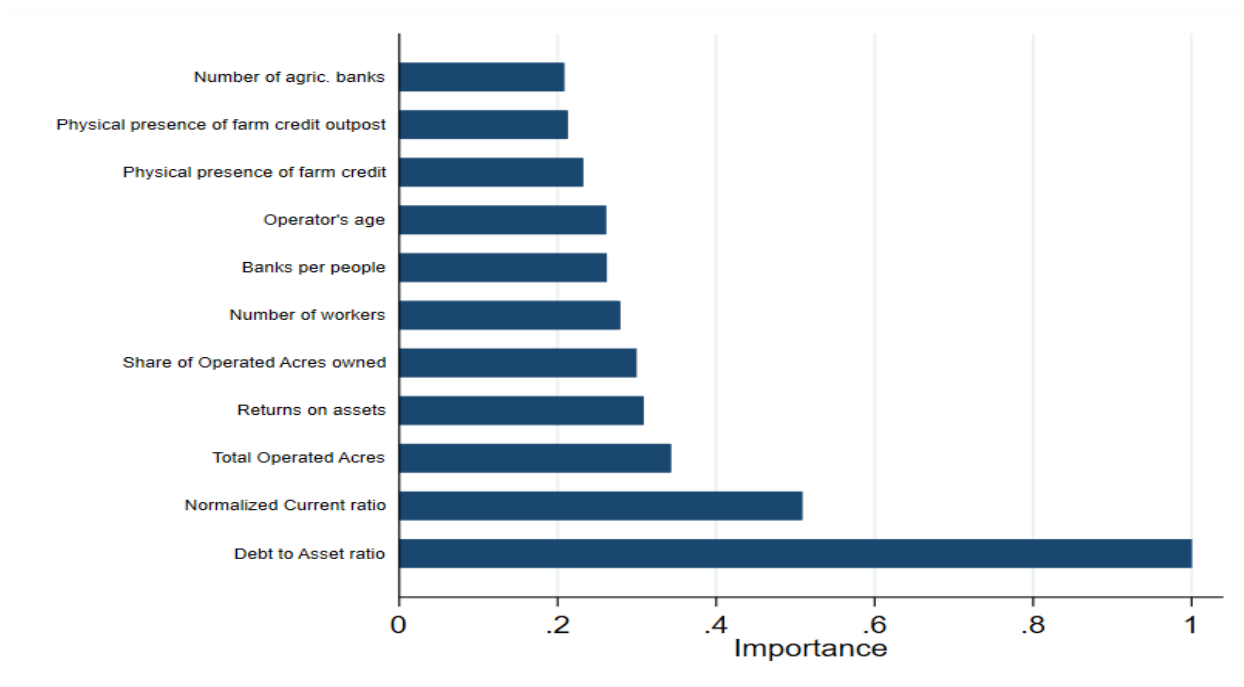
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Operator's age	-0.053*** (0.003)	-0.054*** (0.003)	-0.039*** (0.004)	-0.039*** (0.004)	-0.051*** (0.003)	-0.054*** (0.003)	-0.037*** (0.004)	-0.039*** (0.004)
Number of workers	0.446*** (0.069)	0.380*** (0.068)	0.450*** (0.067)	0.380*** (0.064)	0.452*** (0.071)	0.376*** (0.067)	0.456*** (0.068)	0.376*** (0.064)
Share of Operated Acres owned	0.054 (0.116)	0.195* (0.112)	0.734*** (0.134)	0.985*** (0.131)	-0.049 (0.116)	0.226** (0.114)	0.634*** (0.134)	1.014*** (0.134)
Total Operated Acres	1.069*** (0.058)	0.941*** (0.057)	1.185*** (0.057)	1.066*** (0.055)	1.013*** (0.060)	0.956*** (0.057)	1.132*** (0.059)	1.082*** (0.055)
Debt to Asset ratio			2.530*** (0.399)	2.763*** (0.407)			2.521*** (0.399)	2.761*** (0.408)
Returns on assets			0.454 (0.345)	0.716** (0.333)			0.472 (0.344)	0.718** (0.334)
Normalized Current ratio			-3.828** (1.732)	-5.668*** (1.872)			-4.121** (1.684)	-5.633*** (1.823)
Number of agric. banks					-0.063** (0.030)	-0.052 (0.032)	-0.053* (0.029)	-0.049 (0.030)
Banks per people					-0.160 (0.128)	-0.332** (0.138)	-0.183 (0.124)	-0.335** (0.132)
Physical presence of farm credit outpost					0.209** (0.102)	0.067 (0.099)	0.170* (0.100)	0.031 (0.096)
Physical presence of farm credit					0.560*** (0.118)	-0.123 (0.160)	0.556*** (0.113)	-0.085 (0.152)
Region FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9368	9368	9368	9368	9368	9368	9368	9368
R^2	0.152	0.221	0.196	0.273	0.155	0.222	0.199	0.274

Note: This table presents the results of OLS estimation of equation 1.1 with the dependent variable, number of lenders. Each column presents a separate regression results for the period 2002-2020: Variables are gradually included in the models, with the last model containing all variables in our analyses. Models 2, 4, 6 and 8 have both year and region fixed effects. We log-transform the farm acres operated by KFMA producer, and report Heteroskedasticity-robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



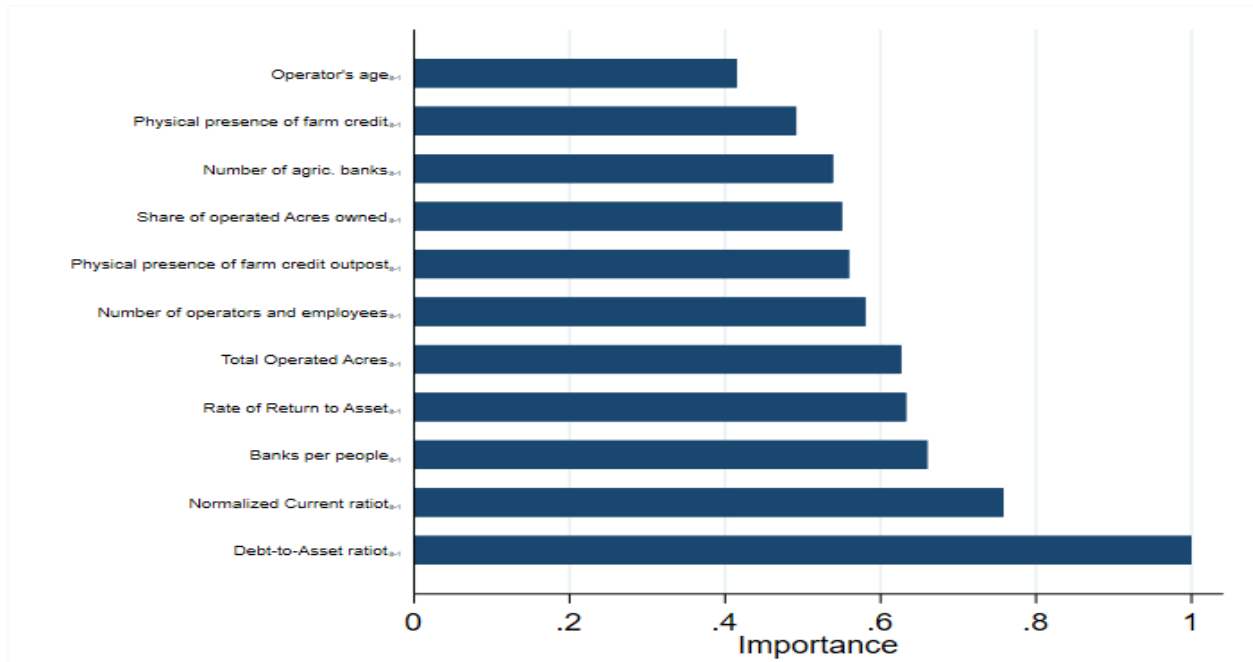
Note: This figure presents the importance scores from our random forest model. This analysis covers the period 2002-2020 and includes year and region fixed effects. However, the year and region fixed effects are not reported. Loan concentration is the dependent variable, which is scaled by 100 for easy interpretation. We log-transform the farm acres operated by KFMA producers. This figure contains 10 observations, excluding the fixed effects. These observations are derived from an initial 9,368 farm-year observations.

Figure B.5: *The Importance Scores of Variables for Loan concentration, 2002-2020*



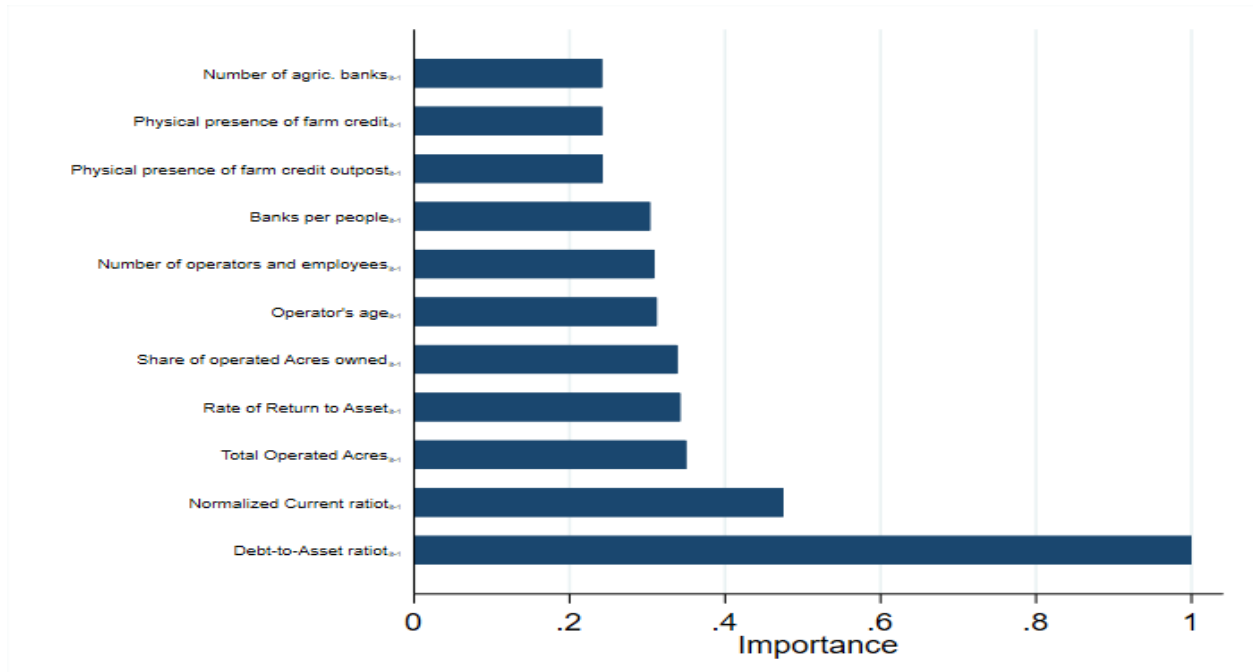
Note: This figure presents the importance scores from our random forest model with both financial and local credit market variables. This analysis covers the period 2002-2020 with both region and year fixed effects. However, the importance scores of these fixed effects are not reported. Loan concentration is the dependent variable, which is scaled by 100 for easy interpretation. We log-transform the farm acres operated by KFMA producer. This figure contains 11 observations, excluding the fixed effects. These observations are derived from an initial 9368 farm-year observations.

Figure B.6: *The Importance Scores of Financial and Local Credit Market variables, 2002-2020*



Note: This figure presents the importance scores from our random forest model with lagged financial and local credit market variables. This analysis covers the period 2003-2020 with both region and year fixed effects. Year 2002 drops out of the analyses. However, the importance scores of these fixed effects are not reported. Lender concentration is the dependent variable, which is scaled by 100 for easy interpretation. We log-transform the farm acres operated by KFMA producer. This figure contains 11 observations, excluding the fixed effects. These observations are derived from an initial 7195.

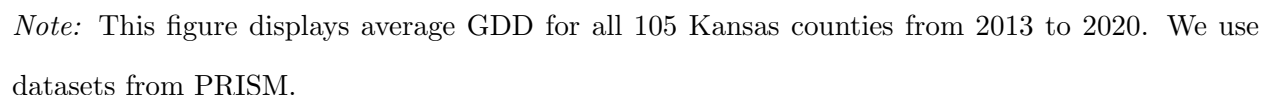
Figure B.7: *The Importance Scores of Lagged Financial and Local Credit Market variables for Lender Concentration, 2003-2020*



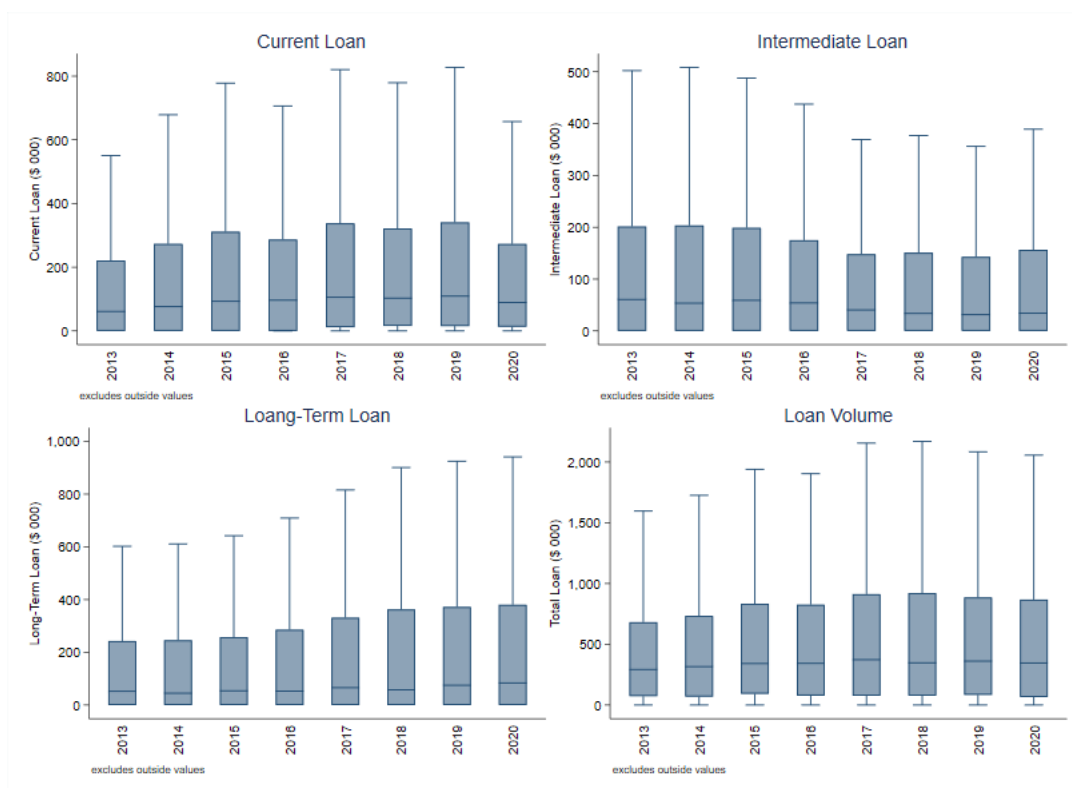
Note: This figure presents the importance scores from our random forest model with lagged financial and local credit market variables. This analysis covers the period 2003-2020 with both region and year fixed effects. Year 2002 drops out of the analyses. However, the importance scores of these fixed effects are not reported. Loan concentration is the dependent variable, which is scaled by 100 for easy interpretation. We log-transform the farm acres operated by KFMA producer. This figure contains 11 observations, excluding the fixed effects. These observations are derived from an initial 7195.

Figure B.8: *The Importance Scores of Lagged Financial and Local Credit Market variables for Loan Concentration, 2003-2020*

The Impact of Cash flow Shock on Credit Market Behavior

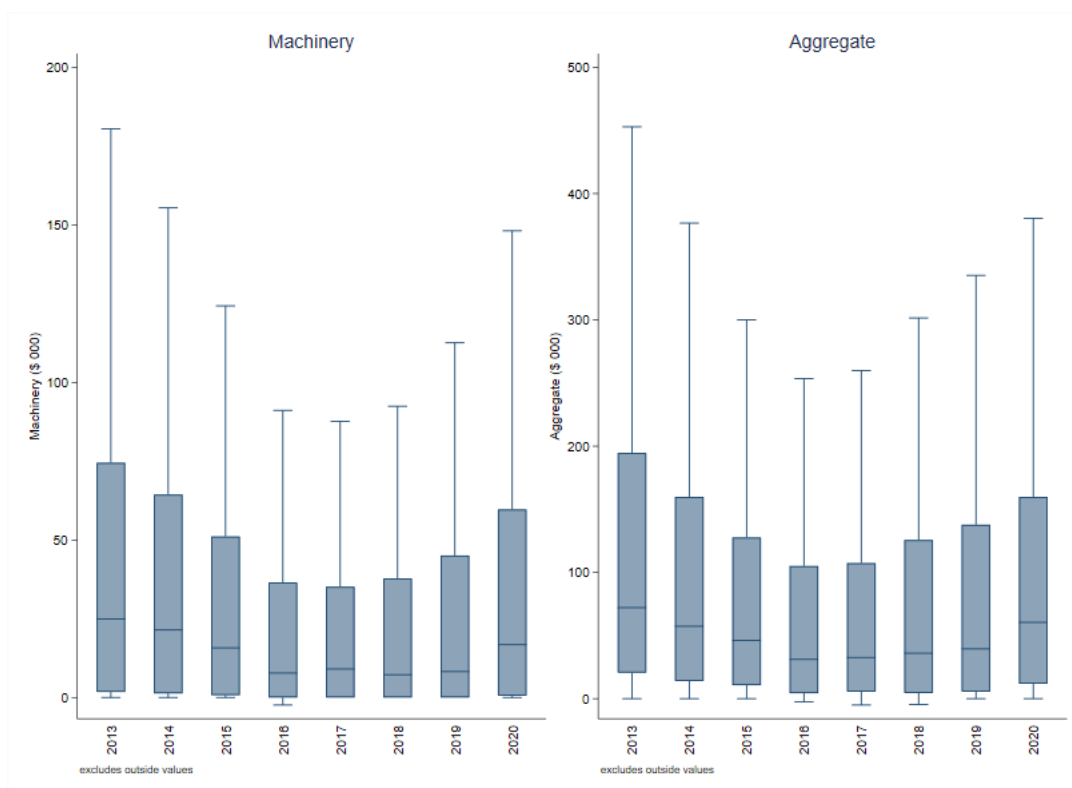


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Note: This figure displays the variations in current, intermediate, long-term and total loan volume from 2013 to 2020. We use datasets from KFMA.

Figure C.2: *Debt Types, 2013-2020*



Note: This figure shows the variation in machinery and aggregate investment of producers from 2013 to 2020. We use datasets from KFMA.

Figure C.3: *Investment, 2013-2020*

Table C.1: *Supplementary Summary Statistics, 2013-2020*

	Obs	Mean	SD	Median
Number of Lenders	5137	2.24	1.19	2.00
Loan Concentration	5137	51.46	28.95	43.53
Buildings and Improvement	8811	10.78	55.28	0.00
Land	8811	33.33	160.37	0.00
Motorized Equipment	8811	35.43	89.17	0.00
Property	8811	1.96	23.08	0.00
Current Loans+	8811	4.29	2.72	5.18
Long-Term Loans+	8811	3.51	3.17	4.77
Intermediate Loans+	8811	3.54	2.74	4.53
Gross Farm Income+	8811	6.82	0.99	6.88
Net Farm Income+	8811	2.80	4.24	4.76
Machinery Investment+	8811	2.86	2.14	3.26
Aggregate Investment+	8811	4.04	2.18	4.52
Total Loan Volume+	8811	11.33	6.77	11.96

Source: KFMA & PRISM. Loan Concentration are scaled by 100. All financial variables are adjusted for inflation, and + indicates that they are IHS transformed.

Table C.2: *The Effect of Extreme Degree Days on Crop Yields, 2013-2020*

VARIABLES	(1) Corn Yields	(2) Soybeans Yields	(3) Sorghum Yields	(4) Wheat Yields
EDD	-0.571*** (0.194)	-0.391*** (0.078)	-0.014 (0.100)	0.163 (0.114)
Observations	8,811	8,811	8,811	8,811
R-squared	0.006	0.084	0.052	0.179
Number of farms	1,915	1,915	1,915	1,915
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
GDD	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with crop yields as the outcome. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. Fixed Effects (FE), GDD and precipitation are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.3: *Effect of EDD on Farm Income, 2013-2020*

VARIABLES	(1) Net Farm Income	(2) Gross Farm Income
Extreme Degree Days (EDD)	-1.506** (0.742)	-1.093 (0.916)
Observations	8,811	8,811
R-squared	0.100	0.081
Number of farms	1,915	1,915
Individual Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Growing Degree Days	YES	YES
Precipitation	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with farm income as the outcome. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. Fixed Effects, GDD and precipitation are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.4: *Heterogeneous Impact on Debt Type and Investment, 2013-2020*

VARIABLES	(1) Current Loans+	(2) Intermediate Loans+	(3) Long-Term Loans+	(4) Machinery Investment+
10yr MA	-0.023 (0.032)	0.027 (0.031)	-0.014 (0.039)	-0.062** (0.026)
10yrMA x SF	-0.064** (0.026)	0.001 (0.030)	0.018 (0.024)	-0.011 (0.025)
10yrMA x HL	-0.004 (0.019)	0.010 (0.024)	-0.028 (0.029)	0.019 (0.019)
10yrMA x Yp	-0.003 (0.002)	-0.006** (0.003)	-0.006* (0.003)	-0.003 (0.002)
Observations	8,811	8,811	8,811	8,811
R-squared	0.027	0.042	0.003	0.050
Number of farms	1,915	1,915	1,915	1,915
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
GDD	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with debt type and investment as outcome variables. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. While FE stands for Fixed Effects, MA represents Moving Average. While SF is an indicator for small farms, Yp and HL are indicators for young producers and high leveraged farms respectively. Fixed Effects, GDD and precipitation are included in this regression. *** p<0.01, ** p<0.05, * p<0.1.

Table C.5: *Heterogeneous Effect of EDD on Debt Structure and Investment, 2013-2020*

VARIABLES	(1) Current + Loans+	(2) Intermediate Loans+	(3) Long-Term Loans+	(4) Machinery Investment+
EDD	0.006 (0.005)	-0.005 (0.005)	0.004 (0.005)	-0.006 (0.006)
EDD x SF	0.001 (0.003)	0.001 (0.004)	-0.001 (0.003)	0.002 (0.004)
EDD x HL	-0.002 (0.003)	0.001 (0.004)	0.005 (0.004)	0.004 (0.004)
EDD x Yp	-0.005** (0.002)	-0.007** (0.003)	-0.007** (0.003)	-0.004* (0.003)
Observations	8,811	8,811	8,811	8,811
R-squared	0.024	0.042	0.002	0.050
Number of farms	1,915	1,915	1,915	1,915
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
GDD	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with transformed debt type and investment as outcome variables. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. While FE stands for Fixed Effects, MA represents Moving Average. While SF is an indicator for small farms, Yp and HL are indicators for young producers and high leveraged farms respectively. Fixed Effects, GDD and precipitation are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.6: *Effect of Extreme Degree Days (EDD) on Investment Type, 2013-2020*

VARIABLES	(1) Aggregate Investment	(2) Buildings & Improvement	(3) Property	(4) Land	(5) Motorized Equipment
EDD	0.198 (0.642)	-0.044 (0.144)	0.008 (0.035)	-0.023 (0.507)	0.076 (0.229)
Observations	8,811	8,811	8,811	8,811	8,811
R-squared	0.012	0.003	0.002	0.002	0.017
Number of farms	1,915	1,915	1,915	1,915	1,915
Individual FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
GDD	YES	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with investment type as outcome variables. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. FE stands for Fixed Effects. Fixed Effects, GDD and precipitation are included in this regression. *** p<0.01, ** p<0.05, * p<0.1.

Table C.7: *Heterogeneous Effect of EDD on Investment Type, 2013-2020*

VARIABLES	(1) Aggregate Investment	(2) Buildings & Improvement	(3) Land	(4) Motorized Equipment	(5) Property
EDD	0.266 (0.760)	0.013 (0.195)	0.197 (0.590)	0.029 (0.272)	-0.047 (0.034)
EDD x SF	0.098 (0.643)	-0.137 (0.165)	-0.195 (0.495)	0.093 (0.188)	0.070** (0.032)
EDD x HL	-0.379 (0.479)	-0.063 (0.175)	-0.350 (0.456)	0.025 (0.199)	0.031 (0.039)
EDD x Yp	0.662 (0.656)	0.264 (0.168)	0.462 (0.481)	-0.071 (0.169)	0.025 (0.032)
Observations	8,811	8,811	8,811	8,811	8,811
R-squared	0.013	0.004	0.003	0.017	0.002
Number of farms	1,915	1,915	1,915	1,915	1,915
Individual FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
GDD	YES	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with investment type as the outcome. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. FE stands for Fixed Effects. While SF is an indicator for small farms, Yp and HL are indicators for young producers and high leveraged farms respectively. Fixed Effects, GDD and precipitation are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.8: *The Effect of EDD on Debt Structure with Additional Control, 2013-2020*

VARIABLES	(1) Number of Loans	(2) Lender Concentration	(3) Loan Volume Volume	(4) Number of Loans	(5) Lender Concentration	(6) Loan Volume
EDD	-0.002 (0.012)	0.000 (0.001)	1.755** (0.824)			
10yr MA				0.020 (0.079)	-0.002 (0.003)	-1.979 (4.148)
Observations	5,137	5,137	8,811	5,137	5,137	8,811
R-squared	0.017	0.019	0.012	0.017	0.019	0.011
Number of farms	1,466	1,466	1,915	1,466	1,466	1,915
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
GDD	YES	YES	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES	YES	YES
Precipitation Squared	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with debt structure as the outcome. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. While FE stands for Fixed Effects, MA stands for moving average. Fixed Effects, GDD, precipitation and precipitation squared are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.9: *The Effect of EDD on Other Measures of Debt Structure, 2013-2020*

VARIABLES	(1) Number of Lenders	(2) Loan Concentration	(3) Number of Lenders	(4) Loan Concentration
EDD	-0.002 (0.003)	-0.000 (0.001)		
10yr MA			-0.015 (0.017)	-0.002 (0.005)
Observations	5,137	5,137	5,137	5,137
R-squared	0.018	0.006	0.018	0.006
Number of farms	1,466	1,466	1,466	1,466
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
GDD	YES	YES	YES	YES
Precipitation	YES	YES	YES	YES

Note: This table presents the results of the estimation of equation 3.2 with other measures of debt structure as the outcome. Each column presents a separate regression result for the period 2013-2020. We report County Cluster Standard Errors in parentheses. While FE stands for Fixed Effects, MA stands for moving average. Fixed Effects, GDD and precipitation are included in this regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.