Crop Diversification and Banking Resilience: An Entropy-Based Evaluation of Agricultural Lending Performance

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Abstract

Agricultural producers have greatly benefited from the economies of scale in agriculture. By taking advantage of these economies of scale, producers choose to specialize in only a small number of crops. Although specialization has the benefits of higher expected returns, there is a trade-off with increased risk exposure. Consequently, increases in large scale specialization have increased risk for agricultural lenders. This is especially true for regional banks which may only lend to producers in a small number of neighboring counties. I evaluate whether declines in crop diversification have negatively impacted agricultural loan performance and if certain types of diversification have less of an impact than other types. I show that diversification does have an impact on delinquency rates of agricultural loans. Contrary to conventional wisdom, diversification increases delinquency rates for agricultural production loans and real estate loans secured by farmland. A one standard deviation increase in a lender's diversification exposure raises production loan delinquencies by over 13% and real estate loan delinquencies by 11%. The negative impact of diversification on real estate loans is primarily driven by diversification "within similar" crop groups. My results suggest that not all diversification is created equally, and some forms of diversification are actually risk increasing instead of risk mitigating.

I. Introduction

In 2024, over $200 billion of the almost $13 trillion of loans held by U.S. banks was tied to agricultural production and farmland. Even though agricultural lending makes up less than two percent of total lending, over 30% of U.S. commercial banks specialize in agricultural lending. Fifty-five percent of the total agricultural loan volume can be attributed to the nearly 1,500 banks that specialize in agricultural lending (American Bankers Association 2024a). These agricultural lenders can have farm loan concentration levels (the ratio of farm loans to all other loans) above 90% (American Bankers Association 2024b). Although farm loans are relatively safer than other types of bank lending (Kauffman and Kreitman 2023), there is still a high degree of financial instability in agriculture (Kuethe and Hubbs 2020). Additionally, banks with similar asset holdings (Huang and Liu 2021), that are geographically close to each other (Chu, Deng, and Xia 2020), or both (Glass and Kenjegalieva 2023), as is often the case in agricultural lending, exhibit increased levels of systemic risk.

Regulators are aware of the high underlying risk and cyclical nature of agricultural lending. In the *Risk Management Manual of Examination Polices* published by the Federal Deposit Insurance Corporation (FDIC 2023), special underwriting guidelines are outlined for agricultural loans. The FDIC's recommendations to best mitigate the underlying risk revolve around guaranteeing that individual lendees are financially sound investments. Cofer and McGregor (2010) point out that, due to the small geographic footprint of agricultural banks, loan portfolio diversification may not be realistic, and the only feasible risk mitigation strategy is sound oversight of their agricultural portfolios. This means at a minimum, farm operations must have the capacity to endure income shocks to remain solvent and pay off their debts. The capacity for farmers to pay off debt can be directly tied to the delinquency rate of local agricultural lenders.

Agricultural producers have greatly benefited from the gains from specialization present in agriculture (Chambers and Pieralli 2020, Kislev and Peterson 1982). That same specialization which has benefited producers has further increased risk in agricultural lending. Due to the agroclimatic advantages of certain growing regions, farmers tend to specialize in crops that are spatially correlated with their neighbors. This leads to vast swaths of the country growing only a few crops. While specialization has the benefit of higher expected returns, there is a trade-off with increased risk exposure. This is especially true for regional banks which may only lend to producers in a small number of neighboring counties. A bank's entire agricultural loan portfolio could be tied to the performance of only one or two crops. Even though agricultural diversification may not be currently feasible in some areas, diversification is a well-known tool for managing risk. To help combat the systemic risk inherent in agriculture, should policymakers incentivize local diversification? This paper answers that question by first determining whether areas with higher levels of crop diversification have decreased risk to agricultural lenders through lower rates of agricultural loan delinquencies, and then by determining if different types of diversification are better at mitigating said risk.

I analyze two types of agricultural loans: agricultural production loans and real estate loans secured by farmland. I use the information provided by quarterly banking institution level call reports submitted to the FDIC. To measure diversification, I use two primary measures: the Herfindahl-Hirschman Index (HHI) and entropy. The HHI has the benefit of being widely used in the literature. Entropy is better suited for this analysis as it can be decomposed to measure diversification among similar crops (within group) and diversification across dissimilar crops (between group). By decomposing entropy, I differentiate between types of diversification and gain a more nuanced understanding of diversification's impact.

Using an institution-year fixed effects model, I find that diversification does impact some agricultural loans' performance. Higher levels of diversification exposure lead to increases in the delinquency rate of real estate loans secured by farmland. A one standard deviation increase in diversification exposure results in an 11% increase in the mean real estate delinquency rates. The increase in real estate delinquency rates is driven primarily by increased diversification among crops with similar uses. I find diversification exposure to have a more pronounced effect in agricultural production loan delinquency rates, but, due to the timing of loan repayment and crop year, the lag of diversification exposure is the significant treatment variable. A one standard deviation increase in the lag of diversification exposure results in an 14% increase in the mean production delinquency rate. Unlike real estate delinquency rates, the type of diversification does not play a significant role in production loan delinquency rates.

Even though diversification has a strong theoretical underpinning as a risk-mitigation strategy, the empirical evidence of diversification's effectiveness is mixed. For diversification to be effective, income variance and downside risk must be large enough to offset the reduction in expected income. Katchova (2005) and O'Donoghue et al. (2009) both find modest discounts to diversification: reducing farm values and expected income, respectively. Featherstone and Moss (1990) use certainty equivalence in a mean-variance model to show that, for orange growers in Florida to be better off diversifying than specializing, the growers would need to be unrealistically risk averse. On the other side, Chaves and Di Falco (2011) find a diversification benefit of 17% of expected revenue for Ethiopian farms. They focus on the trade-offs between economies of scale and risk, noting that downside risk management provides a larger incentive to diversify than volatility risk. Even in finance applications, asset diversification is not a guaranteed risk mitigation strategy. Stiroh and Rumble (2006) show that U.S. financial holding companies which diversified into non-interest income introduced more risk exposure into their revenue streams. This is due to non-interest income being more volatile, but not necessarily more profitable, than interest-based income sources.

Complicating matters is the role of the U.S. Federal Crop Insurance Program (FCIP) and other government programs. If downside risk protection is the primary incentive for diversifying, as in Chaves and Di Falco, government programs may be providing a better alternative risk mitigation strategy. Participation in FCIP guarantees an income floor for agricultural producers, nearly eliminating downside risk. Other research suggests that producers are substituting away from diversification to crop insurance participation. O'Donoghue et al. (2009) find that increases in FCIP subsidies caused a decline in enterprise diversification. Spangler et. al. (2020) document how U.S. farm policy from 1933-2018 has incentivized and reinforced agricultural specialization. Lee et al. (2024) focus on how crop insurance participation lowers delinquency rates. In a similar vein to diversification raising the income floor of banks, crop insurance raises the income floor of farmers, increasing their ability of repayment. From a lender's perspective, lending to producers who enroll in crop insurance reduces risk but does not guarantee full loan repayment. Lending institutions may still benefit from diversifying their lending portfolio.

A possible explanation for the contradicting literature on the effectiveness of diversification as a risk mitigation strategy is that, in practice, not all diversification is the same. Gardebroek, Hernandez, and Rogles (2016) find that market volatility spillovers across commodities, especially between wheat and corn, lower the effectiveness of diversification strategies. Stevens and Teal (2024) further show that diversification can have helpful and harmful impacts on firm resilience in the U.S. agri-food supply chain, depending on how a firm decides to diversify. Similarly, Rossi et al. (2020) provide evidence that the type, "where," and "when" of diversification in banking revenue streams are paramount in the effectiveness of diversification. My primary contribution to this literature is to empirically estimate the impact of diversification in agricultural lending. This will also bridge the literature gap between general banking and asset management risk and agricultural production risk.

My other contribution to the literature is quantifying some of the costs associated with increases in local diversification. Agricultural diversification has been promoted as a solution for myriad environmental problems exacerbated by agricultural intensification (Bene et al. 2022, Browne et al. 2013, Tamburini et al. 2020, Rasmussen et al. 2024). However, there is little debate that agricultural intensification has increased farmer profitability. Increasing diversification and maintaining farm profits do not have to be mutually exclusive goals. In fact, the Food and Agricultural Organization of the United Nations notes that supply chain diversification "does not mean producers should not specialize… [it means] they should not *all* specialize in the *same* product" (United Nations 2021, p. 83; emphasis in the original). Other research suggests that increases in agricultural diversification increase crop productivity. Burchfield, Nelson and Spangler (2019) find that highly diversified agricultural systems can increase corn and winter wheat yields by as much as 20%. Although higher yields do not equate to higher producer profits, increases in farm productivity can address concerns about global food security.

By empirically estimating the regional impact of diversification on agriculture delinquencies, I can estimate the policy costs to offset farm solvency issues that could arise from increasing diversification for environmental reasons. Additionally, by identifying the impact of differing types of diversification, I can highlight how to mitigate some costs of diversification and increasing policy efficiency.

The rest of the paper is organized as follows: Section II derives the diversification measures; Section III describes the data and provides summary statistics and time trends; Section IV outlines the estimating model; Section V discusses results and implications; and Section VI concludes.

II. Diversification Measures

I use two different measures of diversification in my analysis: a modified HHI and an entropy-based index. The two indices are highly correlated. The primary distinction between the two is that the entropy index is more sensitive to contributions from small crop shares. The similarities between the two are due to a shared root equation. Outlined in Jacquemin and Berry (1979), diversification can be expressed generally as:

$$D = \sum_{M} s_m w_m$$

where D is the diversification index, M is the set of markets, $m \in M$, s_m is the proportion of m in M, and w_m is the weight assigned to m. For the HHI, $w_m = s_m$, such that $HHI = \sum_M s_m^2$. Entropy sets $w_m = \ln\left({}^{1}/{}_{s_m}\right)$ and $entropy = \sum_M s_m \ln\left({}^{1}/{}_{s_m}\right)$. Entropy in this setting is an inverse measure of diversification. Under complete specialization where there is only one market, such that $s_1 = 1$, entropy is 0. Under perfect diversification where all markets are represented equally, such that $s_m = \frac{1}{M}$, entropy has a maximum value of $\ln(M)$ (Theil 1972).

In the less generalized case of crop diversification, let M be the set of potential crops, $m \in M$, s_{cm} be crop m's share of total acreage planted within a county c, and n be the total number of potential crops, then the HHI and entropy in county c would be, respectively:

$$HHI_c = 100\left(1 - \sum_{I}(s_{ci})^2\right)$$

and

$$E_c = 100\sum_{M}\left\{s_{cm} * \frac{\ln\left(1/s_{cm}\right)}{\ln(M)}\right\}$$

To increase interpretability, I have made a few minor changes to the generalized HHI and entropy. First, since entropy is an inverse measure of diversification, I subtract one from $\sum_M (s_{cm})^2$ in the HHI. In doing so, HHI and entropy are now both inverse measures of diversification. Second, following O'Donoghue, Roberts, and Key (2009), I multiply entropy by $\frac{1}{\ln(M)}$. This rescales entropy such that its new bounds are between 0 and 1, which matches the asymptotic bounds of HHI. I also rescale both measures by 100 for convenience.

Table 1 provides examples of differing levels of crop composition and the corresponding HHI and entropy measures. As more crop types are planted in a county, both indices will increase, representing more diversification. If a county's planted acreage is 50% soybeans and 50% corn, the HHI will be 50. If corn dominates the county and represents 90% of the planted acreage, the HHI will decline to 18. On the other hand, a 50-50 corn-soy county will have an entropy of 100, and the 90-10 corn-soy county will have an entropy of 46.9.

A problem with diversification indices like the HHI is they treat all forms of diversification equally. From a farming perspective, some crop mixes could be more risk mitigating than others. A county which historically grew only wheat but began growing oats would look different than if the same county started growing corn. To grow oats, the country would need very little infrastructure retooling compared to if the county started growing corn. The HHI would not distinguish between these two potential paths. The entropy index can be decomposed into two parts, "within group" diversification and "between group" diversification (Theil 1972). By using the decomposition of entropy to classify differing types of diversification, I can distinguish between the two hypothetical paths overcoming the shortfalls of HHI.

Where G is the set of crop groups, $g \in G$, M is the set of crops, $m \in M$, s_{cg} is group g's share of total planted acreage in county c, s_{cgm} is crop m's share of group g's planted acreage in county c, then within group diversification (W_c) and between group diversification (B_c) are written as:

$$W_c = 100 \sum_G \left[s_{cg} * \sum_M \left\{ s_{cgm} * \frac{\ln \left({}^{1}/_{s_{cgm}} \right)}{\ln (M)} \right\} \right],$$

$$B_c = 100 \sum_G \left\{ s_{cg} * \frac{\ln \left({}^{1}/_{s_{cg}} \right)}{\ln (M)} \right\},$$

and

$$E_c = W_c + B_c$$

The within group diversification and the between group diversification are non-negative and sum to the entropy index. A natural consequence is that the within group and between group diversification are necessarily less than or equal to the entropy index.

Table 1 additionally shows examples of counties with various crop compositions and the associated within and between group diversifications. For the within and between group diversifications, corn and soy are in the same crop group, and wheat is considered a separate crop group. If all crops were considered to be in separate groups, the within group entropy would be

0, while the between group entropy would be equal to the total entropy. When corn, soy, and wheat are planted in equal proportions, the county's entropy describes the county as perfectly diversified. The within and between group entropies provides the additional context that nearly 58% of the total entropy is associated with the diversification of the corn-soy (66%) group and the wheat group (33%). When the corn-soy and wheat groups are split 50-50 in the 25-25-50 corn-soy-wheat county, overall diversification falls, but the between group diversification is associated with nearly 67% of the total diversification. As the crop group shares become closer to equal, the between group entropy will become a higher proportion of the total entropy.

The added value of the within and between groups is clearly seen in the differences between the 45-45-10 and 45-10-45 corn-soy-wheat composition. In each of these compositions, the HHI and entropy are both the same at 58.50 and 86.37, respectively. A model would fail to attribute any differences between these two counties when using either the HHI or entropy. The within and between group entropies accurately portray the differences in the two counties. The 45-45-10 county has a within group entropy of 56.78 and a between group entropy of 29.59. The difference in the within and between group entropy provides context that the majority of the planted acreage is in the corn-soy group. Meanwhile, the 45-10-45 county has a within group entropy of 23.74 and a between group entropy of 62.64. This difference provides the opposite context that the planted acreage is more evenly split between the corn-soy group and the wheat group.

When calculating entropy for each county, I use a constant M of 436. I do this because I am interested in a national analysis. Although not agriculturally feasible, a perfectly diversified county would have equally planted acres for each of the crops. If I instead set M to be the number of crops planted in a county, I would be ignoring the possibility a county could be more diversified. Consider again the 50-50-0 corn-soy-wheat mix in Table 1. In this case, $M = 3$, as wheat could be planted but is not. The county's entropy is 63.09. If, as in row 3, I set $M = 2$, the number of crops observed to have been planted, the entropy would be a perfectly diversified value of 100. In this case, the county would be incorrectly categorized.

III. Data

For my empirical analysis, I use data from a variety of administrative sources, namely the Federal Depository Insurance Agency (FDIC), Farm Service Agency (FSA), and the U.S. Bureau of Labor Statistics (BLS). Data from FSA and BLS are at the county level, while FDIC data are at the lending institution level. All three data sources are available at different time scales; BLS data series is monthly, FDIC is quarterly, and FSA is yearly. The analysis is conducted from 2009 to 2024. The following subsections further describe the data cleaning process, provide summary statistics, and are organized as follows: Subsection A describes agricultural delinquency rates, Subsection B diversification indices, Subsection C additional controls, and Subsection D aggregation to the lending institution level.

A. Delinquency Rates

Loan default rate data come from FDIC call reports. Banks insured by the FDIC must submit information on their holdings and business practices quarterly to the FDIC. This information includes the dollar value of all agricultural production loans and real estate loans secured by farmland and the dollar value of these loan types which are delinquent or in default.

A loan is considered delinquent when a loan payment is late. The call reports break down loan delinquencies by loans which are 30-89 days delinquent and accruing interest, loans which are greater than 90 days delinquent and accruing interest, and loans which are delinquent and not accruing interest. I calculate the total value of delinquent loans as the sum of the value of all three delinquency types. The delinquency rate is then the total delinquency value divided by the total value of all loans of that type. I further take the quarterly rates and average them by year. In this paper, I focus on two types of delinquency rates: agricultural production loans and real estate loans secured by farmland.

Agricultural production loans are typically loans for capital investments and operating expenses. Real estate loans are larger purchases in both value and term length. Real estate loans are also associated with more risk, as shown in Table 2. Over the sample period, the median real estate delinquency rate is 2.46%, whereas the median production delinquency rate is 0.93%.

B. Diversification Indices

To calculate a county's level of agricultural diversification, I use the FSA's crop acreage reports. The FSA data consists of annual reports submitted by producers regarding all annual cropland use on their farms. Any producer participating in several government programs, including Agriculture Risk Coverage, Price Loss Coverage, marketing assistance loans, and loan deficiency payments, are required to submit the report. FSA then aggregates the reports to the county level for public dissemination. My sample period begins with the first year of data availability in 2009.

I make use of the FSA Use Codes found in the data to assign each crop to one of 5 groups. The groups can be found in Table 3 and are human consumption, animal consumption, oil, non-consumption, and other. Human consumption contains the FSA Use Codes edible, fresh, grain, juice, processed, etc. and contains 211 crops. Animal consumption contains the FSA Use Codes forage, grazing, silage, hogged peanuts, and non-table honey and contains 39 crops. Oil contains the FSA Use Code oil and contains 4 crops. Non-consumption contains the FSA Use Codes cover only, green manure, and left standing, and contains 37 crops. The last group, other contains the Use Codes of fiber, seed, sets, and sod and contains 139 crops.

By using acres planted for my diversification indices, I am insulating my model from endogeneity problems associated with yield and price risk. If I were to instead use a revenue or yield measure, my diversification index would be calculated based off information at harvest time. In the event of a large crop failure, an end of season diversification index would measure a county as more specialized than a pre-harvest index. If delinquency rates failed to rise, diversification would have succeeded as a risk mitigation strategy. Empirically, a pre-harvest diversification index would correctly attribute the lack of higher delinquency rates to a diversified crop composition. On the other hand, a post-harvest diversification index would say the opposite, that delinquency rates failed to rise due to specialization.

FSA planted acreage data is not the only agricultural land use data source available to calculate agricultural diversification. O'Donoghue, Roberts, and Key (2008) and Katchova (2005) use the United States Department of Agriculture (USDA) Agricultural Resource Management Survey (ARMS) to calculate farm level enterprise diversification, while Socolar et. al. (2021) and Burchfield, Nelson, Spangler (2019) use the USDA Cropland Data Layer (CDL) to calculate agricultural diversification of the contiguous US. The CDL data is the most appropriate publicly available substitute for FSA planted acreage. Teal (2025) provides an in-depth analysis comparing agricultural diversification measured by FSA planted acreage and CDL. Teal's analysis states that, on average, the two sources are highly similar, but there is a degree of spatial heterogeneity between them. For my analysis, FSA has two primary advantages over CDL. The first is that FSA planted acreage has a higher likelihood of being a production crop, and as such is more likely to need a production loan. The second advantage is the FSA use codes, which allow me to create stable crop groups.

C. Additional Controls

As an additional control, I include a county's unemployment rate. The unemployment rate improves my model in two ways. First, it serves as a proxy variable for off-far income. In times of high unemployment, outside work may be limited, leading to declines in the total household income. On farm income does not need to completely cover the fixed costs of production for an operation to stay solvent. This is especially true for real estate loans which can be used to purchase homes which are not directly tied to production decisions. Second, it serves as an indicator of the health of the local economy.

The unemployment rate data comes from the BLS Local Area Unemployment Statistics series. The unemployment statistic used is a monthly non-survey-based measure of the total non-seasonally adjusted unemployment rate.[1] For my analysis, I take an arithmetic mean to convert the monthly rate to a yearly rate.

D. Institution Level Aggregation

The FDIC call report and the FSA crop acreage report are available at different spatial resolutions. The FDIC data is available at the bank institution level. The FSA crop acreage report is available at the county level. To harmonize these two sources, for each bank I take an average of the diversification index in each county where that bank has a branch weighted by the total crop acreage for each county. Branch location data is available yearly in the FDIC summary of deposits. The new diversification index is a measure of the total level of diversification exposure

[1] https://www.bls.gov/lau/laumthd.htm

for each bank. I use the same method to aggregate the county level unemployment rate to the bank level.

IV. **Estimation**

To estimate the effect of diversification on loan performance, I use a fixed effects model where Div_{it} is the level of agricultural diversification exposure at institution i in year t, R_{ct} is the delinquency rate, $Unemployment_{it}$ is the unemployment rate, α_i are institution fixed effects, τ_t are year fixed effects, and u_{it} is the error term, my primary estimating equation is:

$$R_{it} = \beta_1 D_{it} + \beta_2 Unemployment_{it} + \alpha_i + \tau_t \ .$$

R_{it} is either the real estate loan delinquency rate or the agricultural production loan delinquency rate. I estimate within and between group entropy separately, thus D_{it} is either the HHI or total entropy. To estimate the disaggregated effects, I transform the estimating equation above, leveraging the fact that $Entropy = Within + Between$.

$$R_{it} = \gamma_1 Within_{it} + \gamma_2 Between_{it} + \gamma_3 Unemployment_{it} + \alpha_i + \tau_t + u_{it}$$

is the estimating equation for the disaggregated entropy.

For proper casual identification I assume strict exogeneity. I am working with an unbalanced panel of observations. Not every banking institution reports delinquency rates for every year. This complicates the standard strict exogeneity assumption. Let D_{it} equal zero if the itth observation is missing from the panel and one otherwise and $\boldsymbol{X}_{it}$ be the vector of covariates then the strict exogeneity assumption is

$$E[\, u_{it} | \alpha_i, \tau_1, \dots, \tau_T, \boldsymbol{X}_{i1}, \dots, \boldsymbol{X}_{iT}, D_{i1}, \dots, D_{iT}] = 0.$$

First this assumption states any unobservable institutional characteristics are time-invariant, and that any unobserved time-variant characteristics affect all institutions equally. Second, the reason an institution does not report a delinquency is uncorrelated with the error term, conditional on other cofactors. If there are institutions with unusually high delinquency rates, all else equal, that leave the sample then this violates strict exogeneity. This survivorship bias is the largest threat to identification. As the worse performing institutions with the highest delinquency rates exit the market the population pool will on average be better performing. Removing the worst performing institutions will remove high delinquency variation from the sample and bias the estimated effect of diversification towards zero. Although survivorship bias likely exists in my empirical estimation, I am still able to provide a lower bound on the effects of diversification.

V. Results and Implications

Estimation results can be found in Tables 4 and 5. Table 4 shows the regression results for the delinquency rates of real estate loans secured by farmland. All three models have year and institution fixed effects, and standard errors are clustered at the institution level. Model 1 uses HHI as the treatment variable, model 2 uses total entropy as the treatment variable, and model 3 uses within group and between group entropy as treatment variable. In models 1 and 2, the treatment variable is significant at the 1% level, and in model 3, only within group entropy is significant at the 5% level. In all three models, the unemployment rate index is significant at the 1% level.

The most important finding here is that all three statistically significant treatment variables are positive. This is counter to the initial hypothesis that diversification exposure is risk mitigating and is instead risk inducing. For example, model 2 states that a one-point increase in diversification increases real estate delinquency rates by 3.6 basis points. Model 3 provides additional insight: if the one-point increase in total entropy is from an increase in within group entropy, then delinquency rates will increase by 4 basis points. If instead, the one-point increase in total entropy is from an increase in between group entropy, then delinquency rates will be unaffected.

For real estate delinquency rates, the risks of diversification exposure are highly dependent on context. The more specialized the diversification exposure is, the higher the risk. If a banking institution's diversification exposure is more diversified between differing crop groups, then there is no added risk of increased delinquency rates. The most likely explanation is the highly correlated downstream demand within each group. If there is a major decline in the demand for pork, all upstream feed crops will be affected by the decline in the price of pork. In other words, since each crop group has highly correlated uses, there is no risk mitigation for economic shocks in downstream markets.

Table 5 is organized the same as Table 4 except the outcome variable is production loan delinquency rates. Unlike for real estate delinquency rates, none of the treatment variables are statistically significant. Only the unemployment rate index is significant at the 5% level. A major difference between production loans and real estate loans is when payments are due. Production loans are usually due after the end of the production cycle, which makes loan due dates more cyclical than real estate loans. This creates modeling difficulties when comparing the crop year in the FSA acreage data and the calendar year used in the FDIC Call reports. Another contributing factor is that delinquency rates are a lagging indicator for farm stress (Cowley 2018). A poor end of year harvest may not impact a banking institution's balance sheet until the following calendar year. This is less of a concern in real estate loans which have a monthly payment independent of crop cycle.

To address this problem, I include a one-year lag term for each treatment variable. The results are in Table 6. The lag of HHI and total entropy coefficients are both positive and statistically significant at the 1 and 5 percent levels, respectively. The significance of the lagged HHI and total entropy provides evidence there is a timing mismatch between diversification and production loan delinquencies. The positive coefficients mean that as lagged diversification exposure increases, so do the delinquency rates of production loans. These results match those in the real estate delinquency rate model. The magnitude of the coefficients in the production rate model are around a third of those in the real estate model. This is in line with the mean production loan delinquency rate being approximately a third of the mean real estate loan delinquency rate. A one standard deviation increase in diversification exposure would raise production loan delinquencies by over 13% and real estate loan delinquencies by 11%.

The inclusion of a lag term for within and between group entropy does not provide any improvements to model fit or statistical significance. Unlike in the real estate loan delinquency model, the type of diversification does not impact the risks of production loans, and only total diversification matters. Recall that total entropy is the sum of within and between group entropies. The point estimates for total, within, and between are 0.018, 0.018, and 0.017, respectively. The marginal effects for an increase in any of the three indices are effectively the same. When total entropy is split apart, there is no longer enough good variation in either within or between group entropy to provide enough power for statistical significance.

VI. Conclusion

Agricultural lenders exhibit characteristics that make them highly susceptible to systemic risk (Huang and Liu 2021; Chu, Deng, and Xia 2020; and Glass and Kenjegalieva 2023). One of these characteristics is small geographical footprints, which make asset diversification difficult

(Cofer and McGregor 2010). While asset diversification may be difficult, not all agricultural lenders suffer these limitations. I use variation in the level of agricultural diversification exposure of agricultural lenders to determine if agricultural diversification is a suitable tool to minimize systemic risk in agricultural lending. Using a decomposed measure of diversification, entropy, I am able to test if agricultural diversification exposure between different crop groups or within the same crop groups have a differential impact on risk.

Contrary to my initial hypothesis, I find that agricultural diversification exposure is risk inducing for lending institutions. I find as diversification increases, so do the delinquency rates of agricultural production loans and real estate loans secured by farmland. A one standard deviation increase in diversification exposure would increase mean production delinquency rates by over 13% and real estate delinquency rates by over 11%. In 2024, the average total loan volume for real estate loans secured by farmland was more than 114 billion dollars, and production loans were more than 78 billion dollars. A one standard deviation increase in entropy would increase total agricultural delinquency by 383 million dollars, or 18% of the 2024 delinquent volume. A more modest 10% increase in entropy would still raise delinquency volumes by over 100 million dollars, or 5% of the 2024 volume.

I also find that, in some cases, the type of diversification matters. Increases in diversification of crops with similar uses have a larger impact on real estate delinquency rates than total diversification. On the other hand, increases in diversification between dissimilar crops have no statistically significant impact on real estate delinquencies. Neither increased diversification between similar crops nor dissimilar crops have an impact on the delinquency rates of production loans.

Although I am unable to discern the exact mechanism through which agricultural diversification exposure increases risk, I suggest three potential mechanisms for further study. First, as diversification exposure increases, the number of crops lenders are exposed to is also likely to increase. As the number of crops lenders are exposed to increases, the likelihood each crop has a high-quality insurance product available decreases. Crop insurance serves as a revenue floor for producers and provides a minimum threshold of repayment for lenders. As the quality of insurance diminishes, so does the likelihood of repayment after a price or yield shock, ultimately increasing the risk for lenders. Over time, the increase in uptake of insurance programs like whole farm revenue protection will likely minimize these risks for lenders.

Second, as the number of crops lenders are exposed to increases, the difficulty in underwriting also increases. FDIC underwriting recommendations revolve around guaranteeing individual lendees are financially sound investments. The more crops for which an underwriter needs to determine the quality of the investment, the harder that determination becomes. It is far easier for an underwriter to understand one or two crop markets than it is to understand five or six.

Last, there could be correlated risks between crops which minimize the benefits of diversification. If there is a price shock which lowers the price of corn, the same price shock could be affecting other sources of animal feed. Similarly, agricultural diversification may increase the number of risk vectors lenders are exposed to. When lenders have less agricultural diversification exposure, there are only a few risks that could harm repayment: price, weather, or pest shocks to one of a few crops. As agricultural diversification exposure increases, the lender is exposed to more potential shocks by lending to more crops.

This study is limited in scope to only represent commercial banks insured by the FDIC and does not account for loans from the Farm Credit system, vendor financing, the Farm Service Agency, or credit unions insured by the National Credit Union Association. FDIC insured commercial banks account for a major share of total agricultural loans. From 2012 to 2021, commercial banks' share of farm real estate debt was between 30% and 40% while non-real estate debt was between 40% and 50% (Subedi and Giri 2024). Commercial banks and the Farm Credit system account for nearly all agricultural lending. Commercial banks operate under different legal and fiduciary requirements than Farm Credit system banks. The Farm Credit Association, which oversees the Farm Credit system banks, is a government-sponsored enterprise which grants them certain administrative advantages. Even though Farm Credit lenders are competing for the same clients as commercial institutions, each type of institution has a different objective function, constraints, risk appetites, and asset portfolios. As such it is not appropriate to use all lenders in this analysis or to extrapolate how agricultural diversification might affect other lenders.

VII. References

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Tables and Figures

Tables:

Table 1: Diversification Calculations

Corn	Soy	Wheat	HHI	Entropy	Within Group	Between Group
1.0	0.0	-	0.00	0.00	0.00	-
0.9	0.1	-	18.00	46.90	46.90	-
0.5	0.5	-	50.00	100.00	100.00	-
0.5	0.5	0.0	50.00	63.09	63.09	0.00
0.33	0.33	0.33	66.67	100.00	42.06	57.94
0.25	0.25	0.50	62.50	94.64	31.55	63.09
0.45	0.45	0.10	58.50	86.37	56.78	29.59
0.45	0.10	0.45	58.50	86.37	23.74	62.64

Corn and soy are considered in the same group, and wheat is in a second group

Table 2: Summary Statistics

	Mean	SD	Min	Median	Max	N
Delinquency Variables						
Real Estate Delinquency Rate (%)	2.46	7.63	0	0.18	100	71,006
Production Delinquency Rate (%)	0.93	3.26	0	0	99.52	45,310
Diversification Variables						
HHI	56.49	19.15	0	60.36	93.25	71,593
Entropy	19.89	7.57	0	20.12	50.18	71,593
Between Group Entropy	7.98	4.27	0	8.16	22.73	71,593
Within Group Entropy	11.9	5.24	0	12.07	42.49	71,593
Control Variables						
Unemployment Rate	5.79	2.65	1.1	5.12	27.4	71,593

Table 3: Crop Diversification Groups

Group	Use Codes	Number of Crops
Human Consumption	Edible, Fresh, Grain, Juice, Processed, etc.	211
Animal Consumption	Forage, Grazing, Silage, Hogged Peanuts, Non-table Honey	39
Oil	Oil	4
Non-Consumption	Cover Only, Green Manure, Left Standing	37
Other	Fiber, Seed, Sets, Sod	139

Table 4: Real Estate Delinquency Rate

	(1)	(2)	(3)
HHI	0.014***		
	(0.005)		
Entropy		0.036***	
		(0.014)	
Within Group Entropy			0.04***
			(0.018)
Between Group Entropy			0.03
			(0.019)
Unemployment Rate	0.189***	0.187***	0.185***
	(0.036)	(0.036)	(0.036)
N	71,006	71,006	71,006
Mean of Dep Var	2.46	2.46	2.46
Mean of Treatment	56.54	19.9	
Adj. R2	0.39	0.39	0.39
Institution FE	X	X	X
Year FE	X	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;
Standard errors are clustered at the institution level

Table 5: Production Delinquency Rates			
	(1)	(2)	(3)
HHI	0.003		
	(0.002)		
Entropy		0.004	
		(0.006)	
Within Group Entropy			0.008
			(0.010)
Between Group Entropy			0
			(0.014)
Unemployment Rate	0.05**	0.05**	0.048**
	(0.021)	(0.021)	(0.022)
N	45310	45310	45310
Mean of Dep Var	0.931	0.931	0.931
Mean of Treatment	57.51	20.1	
Adj. R2	0.34	0.34	0.34
Institution FE	X	X	X
Year FE	X	X	X

* p < 0.1, ** p < 0.05, *** p < 0.01;
Standard errors are clustered at the institution level

Table 6: Production Delinquency Rates and Lagged Treatment			
	(1)	(2)	(3)
HHI	-0.002		
	(0.002)		
Lag of HHI	0.008***		
	(0.003)		
Entropy		-0.006	
		(0.006)	
Lag of Entropy		0.018**	
		(0.008)	
Within Group			-0.004
			(0.010)
Lag of Within Group			0.018
			(0.011)
Between Group			-0.009
			(0.013)
Lag of Between Group			0.017
			(0.012)
Unemployment Rate	0.081***	0.081***	0.079***
	(0.022)	(0.022)	(0.022)
N	41882	41882	41882
Mean of Dependent Variable	0.931	0.931	0.931
Mean of Treatment	57.51	20.1	
Adj. R2	0.33	0.33	0.33
Institution FE	X	X	X
Year FE	X	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;
Standard errors are clustered at the institution level