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County Level Grain Production Correlation and Implications for Cooperative Mergers

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Abstract

This study analyzes correlations in county-level grain production in Oklahoma and Kansas from 2013 to 2023 to evaluate risk diversification potential in cooperative mergers. Using ordinary least squares, and Bayesian regression, we model how spatial distance, crop composition, adjacency, and production scale affect production correlations. Results show modest county-level heterogeneity, with east–west distance consistently reducing production correlations. Overall, findings suggest that the distance between a cooperative and a potential merger partner is not a reliable predictor of the degree of correlation in grain receipts.

Key Words Cooperatives Mergers; Uncertainty; Spatial Correlation; Bayesian analysis; Risk diversification

Introduction

Agricultural cooperatives play an important role in U.S. grain marketing by providing storage, handling, and marketing services for producers. In recent decades, these cooperatives have gone through structural changes, with consolidation becoming a common feature. According to the most recent (2023) USDA Agricultural Cooperative statistics, there were 489 cooperatives marketing grains and oilseeds in 2023, a decrease of 2.6% from the 502 reported the previous year. That decline is consistent with the overall trend for U.S. agricultural cooperatives, which decreased from 1,671 to 1,647 during that time period. While some of the decline was from cooperatives dissolving, the majority were from mergers and acquisitions (M&A) (Briggeman et al. 2016; Ofori et al. 2025).

Grain marketing and farm supply cooperatives are an important subset of agricultural cooperatives. Additionally, there has been rapid consolidation in that cooperative sector, and several recent consolidations have combined cooperatives in different states and with non-adjacent market territories. Grain marketing cooperatives often merge to achieve economies of size and scope. The recent trend of cross-state mergers suggests that cooperative boards of directors may also hope to increase diversification and thus reduce risk through a merger Fulton et al. (1996), Henehan (2002), and Kenkel et al. (2003) document improvements in financial indicators as a result of merger or consolidation, while others—including Parliament and Taitt (1989), Hoshino (1995), and Meliá-Martí and Martinez-García (2015)—report minimal or negative financial effects. Most recently, Grashuis (2023) finds that cooperatives engaged in M&A tend to exhibit lower profitability, efficiency, and liquidity, particularly among marketing cooperatives. These mixed financial results suggest that boards may seek to minimize coordination costs by consolidating with nearby cooperatives. However, while merger with a nearby grain marketing cooperative might minimize coordination costs it might not diversify grain volume risks. Studies such as Goodwin (2014) show that correlations between county grain production decline with distance, while Goodwin et al. (2024) conclude that north–south distance reduces correlation more than east–west distance. Those studies of county grain production correlation were focused on the corn belt. Mergers of grain cooperatives in the Southern Plains introduce new issues such as how the crop mix and production scale impact the correlation of county grain production. In addition, weather and climate patterns differ between the Southern Plains and corn belt which could impact the effect of distance on county grain production correlation.

As we have suggested, grain cooperative consolidation decisions may involve a trade-off between easier coordination from combining with nearby cooperatives and potential risk reduction from combining with more distant ones. While the reduction of grain volume risk is unlikely to be the primary driver of a cooperative merger, it could be a contributing goal. This study asks three related questions: (1) What is the correlation between county grain production within a region, and how does correlation change with distance between counties? (2) Does merging with a cooperative in a county with lower production affect risk differently than merging with a cooperative located in a major grain producing county? (3) In the Southern Plains, where grain production is divided between winter crops (primarily wheat) and summer crops (primarily corn, soybeans, and sorghum), does the ratio of winter to summer crops influence the correlation of total grain production across counties?

This paper contributes to the cooperative consolidation literature by examining the issue of diversifying grain volume risk. It also provides insights into the recent trend of cross-state mergers of grain marketing cooperatives. Prior studies have concentrated on profitability, efficiency, and coordination costs, while this study explores how spatial distance, crop composition, and production scale shape county-level correlations in grain production. By identifying how these factors influence risk diversification, these results can help cooperative boards to consider whether a merger with a more distant cooperative will decrease grain volume risk relative to merging with a cooperative in an adjacent trade territory.

The paper proceeds as follows: Section 2 develops a theoretical framework linking spatial correlations and merger risk outcomes. Section 3 describes the data from Oklahoma and Kansas counties (2013–2023) and the methodology, including OLS and Bayesian regression for pairwise and baseline analyses. Section 4 presents results, detailing how spatial distance, crop composition, and production scale influence yield correlations. Section 5 discusses implications for cooperative merger strategies, highlighting risk diversification trade-offs. Section 6 concludes with policy recommendations and limitations, suggesting avenues for future research.

Theory

A grain marketing cooperative could decrease grain procurement risk by merging with a similar sized cooperative if the two grain production regions have low correlation. The relevant grain procurement risk would relate to the total grain production in the cooperatives' market area. In the Southern Plains, total production would involve winter wheat as well as corn, grain sorghum and soybeans, with the latter three grains being considered summer crops. Total grain production in a county would vary year-to-year based on the growing conditions for each crop and by the crop mix. Additionally, winter wheat can be grown as a dual-purpose crop for both grazing and grain yield. Changes in the portion of wheat which is harvested relative the portion grazed out can have a substantial impact on harvested bushels.

To simplify, we assume each grain cooperative's grain procurement is proportional to the total county grain production and that each cooperative has the same average annual grain volume. For every pair of counties, we denote

$$Y_h = r.Y_k,$$

where k is denotation for the other pair, and *r* is the rate of their production. Assuming cooperatives to be representative of their counties, we can convert it to cooperative level

$$y_h^a = r.y_k^b\ ,$$

which we can simplify the cooperative notation and focus only on counties:

$$y_h = r.y_k.$$

Thus, we can conclude

$$Var(y_h) = Var(r.y_k) = r^2 Var(y_k).$$

Let's denote σ_h^2 and σ_k^2 as the grain receive variance by the cooperative in county h, and k respectively, and ρ_{hk} as the correlation of the received grain by cooperatives in counties h and k. Thus we can write the covariance of the cooperative in this format

$$Cov(y_h, y_k) = \rho_{hk}\sigma_h\sigma_k$$

When the cooperatives merge, the total variance is

$$Var(y_h + y_k) = Var(y_k) + Var(y_h) + 2cov(y_h, y_k)$$

Let's simplify it

$$\begin{aligned} Var(y_h + y_k) &= \sigma_h^2 + \sigma_k^2 + 2\rho_{hk}\sigma_h\sigma_k = r^2\sigma_k^2 + \sigma_k^2 + 2r\rho_{hk}\sigma_k^2 \\ &= \sigma_k^2(1 + r^2 + 2r\rho_{hk}) \end{aligned}$$

In the variance of the merged cooperatives, they intend to merge with a cooperative with the same size ($r = 1$), which makes the variance of the merged cooperative $2\sigma_k^2(1 + \rho_{hk})$.

We know that the revenue of the merged cooperatives is a multiply of its received grain in total. The variance in total received grain ($y_h + y_k$) of the merged cooperatives directly creates the variance in revenue, and ultimately the variance in profit.

To reduce the uncertainty from the variance in revenue, cooperatives should look at combining with a cooperative in a county where grain production has a low correlation with the cooperative's current grain procurement region. Geographical factors, such as distance and direction between counties could influence ρ_{ij}, as spatial relationships shape production patterns (Goodwin et al., 2024). In addition, in Oklahoma where wheat can be a dual-purpose crop which is used for both grazing stocker cattle and harvesting grain, there are grain producing counties with relatively low harvested production. Harvested wheat production in a given year can vary due to changes in cattle prices which can incentivize or dis-incentivize producers to graze out wheat rather than removing the cattle in early spring and harvesting a grain crop. These year-to-year shifts between harvested production and grazing are particularly prevalent in counties with lower overall grain production since they tend to encompass more marginally crop land. These production factors suggest that year-to-year variation in harvested yields in lower grain producing counties could follow different patterns relative to typical grain producing counties. For this reason, an indicator for "low production" counties was introduced as a control variable. In addition to spatial relationship, we include the crop mix differences, that is the ratio of winter crops to summer crops, between counties. This framework uses county-level correlations to help cooperative decision makers determine whether merging with a more distant cooperative can lower profit variance.

Data Processing and Methodology

This study examines the correlation in grain productions across counties in Oklahoma and Kansas to assess the potential for risk diversification in cooperative mergers or strategic agreements.

Oklahoma and Kansas were chosen for their dense concentrations of agricultural cooperatives, which often maintain collaborative relationships, making them strong candidates for mergers. More importantly, both states are among the top grain producers in the U.S., and their geographic proximity exposes them to shared economic and environmental factors. While wheat is a major crop in both states, summer grain crops such as corn, soybeans and grain sorghum account for a greater share of total grain production in Kansas as compared to Oklahoma. In addition, there have been several cross-state cooperative mergers within this region in recent years.

The analysis assesses how production correlations are affected by spatial distance, crop composition similarity, county adjacency, and production scale. It employs both global pairwise comparisons (across all county pairs) and county-specific baseline approach. Data on annual harvested production (in bushels) of corn, soybeans, sorghum, and wheat were sourced from the USDA National Agricultural Statistics Service (NASS) for the period 2013–2023. Counties with incomplete data (fewer than two years of records) were filtered out, production a final sample of 171 counties out of 182 counties in total. Total grain production per county-year was calculated by summing the production of the four crops (scaled to millions of bushels), then log-transformed.

Explanatory variables include:

(1) **Absolute** differences in county centroids for longitude ($\boldsymbol{X_{ij}}$) and latitude ($\boldsymbol{Y_{ij}}$), normalized and rescaled to effects per 100 miles using a 69 miles per degree conversion;

(2) Crop-composition similarity ($\boldsymbol{R_{ij}}$), a proxy measure based on the mean crop ratio (averaged over 2013–2023) for each county, computed with $\frac{\min(D_i, D_j)}{\max(D_i, D_j)}$ (ranging from 0 to 1, with higher values indicating more similar crop compositions) averaged across the 11 years, which is calculated using the county's crop diversity ($\boldsymbol{D_i}$), computed with $\frac{\bar{y}_{corn}+\bar{y}_{soybean}+\bar{y}_{sorghum}}{\bar{y}_{corn}+\bar{y}_{soybean}+\bar{y}_{sorghum}+\bar{y}_{wheat}}$,

measuring the proportion of summer crops (corn, soybeans, sorghum) to total production (all four crops) averaged across the 11 years.

(3) Adjacency ($\boldsymbol{A_{ij}}$), a binary dummy for shared borders; and

(4) Low production ($\boldsymbol{S_{ij}}$), a binary variable equal to 1 if at least one county in the pair has small production (bottom 25% of mean total production across 2013–2023), 0 otherwise, capturing the effect of low production scale on production correlations. For the baseline model, $\boldsymbol{S_i}$ is a binary variable equal to 1 if the pairing county has low production (bottom 25% of mean total production across 2013–2023).

Table 1 provides the descriptive statistics of the data. Figure 1 maps the spatial distribution of production scale, crop diversity ratio, and mean total grain production across the studied counties, highlighting regional variations and areas with zero production, thus elaborating further on the data presented in Table 1.

The analysis employs two estimation methods—ordinary least squares (OLS) regression, and Bayesian regression. Two different levels of analysis a conducted. A global pairwise analysis that considers all possible pairwise combinations. That analysis considers the most general case and could uncover very strong systematic factors impacting correlation. In addition to the pairwise analysis, a more focused baseline analysis is conducted. The baseline analysis focuses on three representative baseline counties and considers correlations with those reference baselines. **Detrending Productions**

To remove temporal trends, per-county ordinary least squares (OLS) regressions are fitted

$$y_{it} = \alpha_i + \gamma_i . t + \epsilon_{it}$$

where y_{it} is the normalized log-production for county *i* in year *t*, α_i is the intercept, γ_i is the slope, and ε_{it} are residuals. The residuals ε_{it} are used for subsequent analysis to isolate correlated variability across counties, ensuring that the focus remains on spatial and covariate-driven correlations rather than temporal trends.

Global Pairwise Approaches

OLS

Empirical Pearson correlations ρ_{ij} are computed from the detrended residuals across all unique pairs ($i < j$), using pairwise-complete available observations. The OLS model directly regresses these correlations on the covariates:

$$\rho_{ij} \ = \ \beta_0 \ + \ \beta_1 \, X_{ij} \ + \ \beta_2 \, Y_{ij} + \beta_3 R_{ij} + \beta_4 A_{ij} + \beta_5 S_{ij} + v_{ij}$$

where ρ_{ij} is the correlation between counties i and j, X_{ij} and Y_{ij} are rescaled directional distances, R_{ij} is crop-composition similarity, A_{ij} is adjacency. S_{ij} is small production, and $v_{ij} \sim N(0, \sigma^2)$. β_0, β_1, β_2, β_3, β_4 and β_5 are coefficients and are estimated via standard OLS. This method, consistent with Goodwin et al. (2024), provides rapid estimates but assumes independence among pairs, potentially underestimating uncertainty.

Bayesian Model

Bayesian versions of the global pairwise model were estimated in Stan via the R package brms (Bürkner, 2017, 2018) using CmdStan as backend.

Weakly informative empirical priors were centered on the corresponding OLS point estimates with standard deviations inflated to allow substantial updating by the data:

- Coefficients: Normal($\hat{\beta}_{OLS}$10 × SE_{OLS})
- Residual standard deviation σ: Student-t(3, 0, 2.5) (default weakly informative prior in brms)

This prior structure anchors the sampler near the frequentist solution while remaining extremely permissive (effective prior standard deviations are 10 times larger than the OLS standard errors).

Four Markov chains were run for 20,000 iterations each (4,000 warmup), yielding ≥ 8,000 effective posterior samples per parameter, trace plots with no divergences, and Gelman-Rubin diagnostics $\hat{R} \leq 1.01$. Posterior means and 95% highest-density credible intervals are reported.

Compared to OLS, the Bayesian model provides comprehensive probabilistic inference on correlations, integrating uncertainty effectively.

Baseline Approaches

The baseline approach fixes a reference county (Garfield, Barton, and Ottawa) and computes correlations with all others. This reduces comparisons to focus on county-specific patterns, making results easier to interpret than a full pairwise correlation map. Unlike the pairwise approach, which is impossible to compare with a visualized correlation map, the results from baseline method results can be illustrated with a correlation map.

The baseline counties were chosen to represent both states and to capture distinct production profiles.

- Garfield County is a high-producing, winter-crop-dominant county in Oklahoma's grain belt, representing Oklahoma cooperatives considering mergers.
- Barton County is a major producer in Kansas, more summer-crop oriented, and recently merged with a cooperative in northwest Oklahoma, representing Kansas merger prospects.
- Ottawa County was included because it hosts the headquarters of a major cooperative with branches in adjacent counties, providing an additional perspective.

For each baseline county, we estimate the regression

$$\rho_i = \alpha_0 + \alpha_1 X_i + \alpha_2 Y_i + \alpha_3 R_i + \alpha_4 A_i + \alpha_5 L_i + e_i$$

where subscript i indexes all counties paired with the fixed baseline, ρ_i is the correlation between the baseline county and county i, X_i and Y_i are rescaled absolute distances between the baseline county and county i, R_i is the crop-composition similarity measure of county i relative to the baseline, A_i is adjacency. S_i here is different from the pairwise model, it is low production and equals 1 if the county i is a low producer, zero otherwise, α_0, α_1, α_2, α_3, α_4 and α_5 are coefficients and are estimated via standard OLS, and Bayesian. $e_i \sim N(0, \sigma^2)$ is the error term for the OLS. Bayesian regression implemented in the same manner as the global pairwise model (Section 3.2.2): empirical priors centered on the baseline-specific OLS coefficients (coefficients ×10 SE_{OLS}), Student-t(3, 0, 2.5) prior on σ, 4 chains × 20,000 iterations via brms/Stan. Posterior means and 95% highest-density intervals from the Bayesian specification are shown alongside OLS point estimates.

For each baseline, visualized correlation analysis includes a map of correlations to illustrate spatial and compositional effects

Results

Pairwise Analysis

The pairwise analysis considers the most general situation of one cooperative randomly located in any grain producing county merging with another cooperative randomly located in any different grain producing county. Table 2 presents estimates of production correlations across 171 counties in Oklahoma and Kansas from 2013 to 2023, derived using two distinct statistical models: OLS and Bayesian regression with weakly informative empirical priors centered on the OLS estimates. These models assess how spatial distance, crop-composition similarity, adjacency, and production scale influence correlations, with implications for agricultural risk diversification.

The intercept (β_0) estimation 0.373 in both models is consistently significant ($p < 0.01$), indicating a positive baseline correlation among county production, suggesting a level of inherent regional production synchronicity.

The X-direction distance coefficient (β_1) is negative and significant with estimates of –0.052 per 100 miles, confirming that east-west spatial separation reduces production correlations. Although it is a robust finding across both methods, the magnitude of the coefficient is small and minor on correlation.

The Y-direction distance coefficient (β_2) is -0.026, which is also significant but half in magnitude compared to X-direction, suggesting a less pronounced north-south impact.

Crop-composition similarity (β_3) is negative, showing that when two counties have similar crop production patterns, they will have smaller correlation by -0.04, which contradicts the expected theory.

The adjacency coefficient (β_4) has a positive sign, suggesting that counties with shared borders have higher correlation by 0.03. But Bayesian does not confirm the significance of adjacency.

Low production (β_5) has a significant negative sign. The negative sign of this coefficient suggests that when at least one of the two counties has low grain production, they have less correlation, and they have less risk for collaboration.

Its magnitude is high suggesting that is important to control for the different patterns in low grain producing counties.

The OLS model has an adjusted R^2 of 0.061, indicating that the covariates explain a small but significant ($p < 2.2e-16$) portion of the variation in pairwise correlations.

Bayesian confirms OLS results only reject the significance of the adjacency. In general, the pairwise approach has low power in predicting the model since counties have different behaviors, and all of those effects are considered simultaneously.

The low explanatory power of the pairwise analysis is not surprising given that the analysis models a very general situation comparing every grain producing county will all other grain producing county. It is likely that many effects are canceled out across the entire universe of combinations.

Baseline Analysis

The baseline analysis is a more focused approach which examines production correlations from the context of three reference counties. Garfield County, Oklahoma, Barton County Kansas and Ottawa County Kansas were used as reference counties. While the selection of the reference counties was somewhat arbitrary, there are one or more grain cooperatives located in each of these counties. Each reference county was paired with the remaining 171 counties to identify county-specific patterns. Building on insights from the pairwise analysis, which demonstrated the Bayesian model's robustness due to its comprehensive uncertainty quantification, only the Bayesian regression with OLS-informed priors is implemented for the baseline approach. Results are summarized in Table 3.

- **Garfield County Oklahoma**
  The OLS model for Garfield County Oklahoma indicated the highest fit ($R^2 = 0.276$) compared to other baseline models. The intercept was positive and significant and the coefficient for east-west distance was negative and significant, The crop diversity effect and low production, were significant while the coefficients for adjacency were not significant.

Bayesian results confirm the significance and the magnitude of the OLS results.

These findings suggest that Garfield's production correlations are primarily driven by east-west distance and crop mix while the low production indicator was a significant control variable.

Table 1 shows that the diversity ratio (D) of Garfield County is 0.29, which indicates a higher percentage of wheat production. The negative and large magnitude of the diversity ratio of the pairing county suggests that when a cooperative in Garfield County merges with a cooperative in another county that has a high diversity ratio (greater percentage of summer grain crops), it significantly reduces the correlation. Two contrasting counties sharply illustrate how the model operates in practice:

- **Noble County, Oklahoma** is not a low production county and adjacent to Garfield County (low x and y distance). Its crop diversity ratio (0.38) is toward winter production. Accordingly one would expect the correlation to be high, and the empirical correlation ($\rho = 0.95$) confirms that effect. A merger of a Garfield-based cooperative with one based in Noble County would do little to reduce the variation in grain receipts.

- **Jackson County, Kansas** is 137 miles east and 210 miles north, with a high crop diversity ratio (0.89). The combination of meaningful east-west separation and opposite crop seasonality results in a negative correlation ($\rho = -0.21$). A Garfield based cooperative could meaningfully reduce their variations in grain receipts by merging with a Jackson County Kansas based cooperative. Figure 2 confirms the horizontal distance and adjacency in the geographical pattern from the baseline estimated models for the county. For the case of a Garfield County based cooperative, grain yields in the adjacent counties are highly correlated. Merging with a cooperative located further west would have some potential to reduce grain receipt variability while the greatest reduction in correlation could be obtained by focusing northeastward into summer-crop territory.

- **Barton County Kansas**
  The baseline model for Barton has moderate explanatory power with a $R^2 = 0.261$ in OLS, with a significant positive intercept, significant negative effects for both east-west and north-sought distances. The coefficients for crop diversity and adjacency are small and non-significant. The coefficient for the low production control variable is significant in OLS, but Bayesian does not confirm the significance of that coefficient. The large magnitude

of the coefficients for both east-west and north-south distances suggest that the correlation of pairing counties with Barton County mainly follows the geographical dispersion. The results in Table 1, indicate that the crop diversity of Barton County is 0.60, implying that it weighted toward summer grain crops (soybean, sorghum, and corn) relative to wheat. The positive sign for the diversity ratio suggests that matching with a county with a high percentage of wheat production might reduce total grain volume correlation. Two counties illustrate the primary effects of distance on grain production correlation.

- **Sumner County, Kansas** lies only 88 miles east and 86 miles south of Barton, the small separation in both directions with a medium crop diversity ratio (0.43), is expected to have a high correlation according to the estimated model, and the empirical correlation confirms that hypothesis ($\rho = 0.73$.)
- **Muskogee County, Oklahoma** is 233 miles east and 198 miles south of Barton. The large combined east-west and north-south separation pushes it into the humid subtropical influence zone of eastern Oklahoma, where summer-crop dominance (ratio of 0.80) and different storm tracks produce negative correlation and meaningful risk reduction ($\rho = -0.23$).

For Barton-centered cooperatives, crop diversity and adjacency are not the dominant drivers. Risk diversification is almost entirely a function of distance in any direction. Merging within roughly 150 miles guarantees high positive correlation and delivers fairly insignificant variance reduction. Figure 2 shows the map of the correlation of other counties with Barton County.

- **Ottawa County Oklahoma.** Ottawa exhibits weaker explanatory power ($R^2 = 0.114$) in OLS, with a significant intercept, *north-south*, east-west , and crop **diversity** effects. The Bayesian does not confirm the significance of the north-south distance. While not significant, the adjacency coefficient was negative. suggesting that adjacent counties are not highly correlated. (Figure 4). From Table 1, the diversity ratio of Ottawa County is 0.47, which positions it in the mid-range, meaning that it is half wheat and half summer grain crops producer. The magnitude of the diversity ratio coefficient shows that a cooperative in this county has better opportunity to reduce uncertainty by merging with a county that has high diversity ratio (greater percentage of summer grain crops).

A clear illustration of the model's drivers is the stark contrast between two non-adjacent counties of comparable production scale:

- **Caddo County, Oklahoma** lies only 50 miles east but large north south separation, 273 miles south of Ottawa, with a low crop diversity ratio (0.17 – heavy wheat-producer), it is expected to have high correlation with Ottawa county in Kansas. In fact, their empirical correlation ($\rho = 0.7$) confirms the expectation. This implies almost no risk-reduction benefit from a hypothetical merger with this county.

- **Grant County, Kansas** is 252 miles west and 108 miles north of Ottawa. The strong east-west separation combined with Grant's high crop diversity ratio (0.74) produces strongly negative correlation, confirmed by empirical correlation ($\rho = -0.5$These two examples demonstrate that, for Ottawa-based cooperatives, east-west geographical separation and—more importantly—merging with counties that have markedly different crop diversity ratio dominates the risk-reduction potential.

Discussion

The global pairwise analysis demonstrated very low explanatory power. That results was not surprising since many effects likely cancelled out across the large universe of possible combinations. Those results were in contrast to previous studies in the corn belt and reflect the great diversity of grain production and in precipitation in the Southern Plains. The baseline models had higher explanatory power, but the drivers of correlation were not consistent across all of the baseline cases. The correlation between Garfield county and other counties were primarily driven by east-west distance and crop mix. Barton County's correlations were driven by both east-west and north-south distances while crop mix and the small production effect were insignificant. The baseline model using Ottawa County exhibited weaker explanatory power but east-west distance, north-south distance and crop mix were all significant. The adjacency variable was only significant for the Garfield County baseline. This suggests that while the grain production patterns in adjacent counties can be highly correlated, the effect is not universal.

The results expose critical limitations in predicting how distance, crop mix and adjacency impact the correlation of grain production. Our pairwise analysis lacks explanatory power because they averaged across highly heterogeneous counties, causing local patterns to cancel out. Baseline pairwise analysis obviously depends on the choice of baseline counties. Our three choices illustrated the fact that production drivers vary sharply by location. East-west distance appears to have a greater impact on correlation relative to north-south distance. That conclusion is logical since precipitation in the Southern Plains exhibits more variability along the east-west dimension. The mix of summer and winter crops had a significant impact on correlations in two of the baseline counties while adjacency was only significant in one county. These differences underscore the fact that, in the Southern Plains, generic conclusions on grain production correlation are problematic.

These findings add insight to the correlation effects found by Goodwin et al. (2024), who used only a global pairwise approaches and concluded that, in the corn belt, north-south distance had more impact on production correlation relative to east-west distances. Our similarly constructed pairwise model results yielded east-west coefficients twice as large as north-south coefficients, but the effects of distance were relatively small. The low overall fit of the general pairwise model suggested that many of the effects were cancelling out. Our baseline models provided more insights. Those results illustrated that while distance, crop mix and adjacency impact grain production correlation, the effects are not consistent across counties.

Historically, cooperative boards have appeared to prioritize merging with near-by cooperatives because of lower coordination costs and managerial convenience. The emergence of cross-state mergers suggests that some boards may also be considering the potential to reduce grain volume risk as an additional merger benefit. The trade-offs in pursuing that merger benefit are clear. Merging with an adjacent cooperative minimizes coordination costs but does little to reduce grain volume risks. Merging with a more distant cooperative, and one with a different crop mix, increases coordination costs but can materially lower profit variance. Our analysis suggests that the potential to reduce grain procurement risks are dependent on the cooperative's location. Cooperative boards need to evaluate the effect of a proposed merger on grain procurement risk on a case-by-case basis since the effect of distance, adjacency and crop mix on production correlation are not universal.

Conclusion

This study adds to the cooperative merger literature by considering the potential to reduce one type of operating risks, i.e. grain procurement risks. The results revealed that, unlike results from the corn belt, spatial distance alone is a poor predictor of diversification potential in the Southern Plains. Those findings have immediate strategic implications for Southern Plains cooperatives. It would be interesting to expand this research into other grain producing areas such as the Northern Plains. There is also the potential for similar research focused on farm supply activities. While we discussed the concept, our research did not investigate the coordination cost of combining the activities of merged cooperatives. Given the advances in information technology and remote meetings, it would be interesting to investigate coordination costs in non-adjacent mergers. Finally, it has long been recognized that cooperative members can value non-economic factors including social cohesion and group benefit. In light of that dimension of the cooperative value package, it would be interesting to investigate how mergers in general, and cross-state mergers in particular, impact the perception of group identity in an agricultural cooperative.

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Table 1: Descriptive Statistics and Values for Baseline Counties across 171 counties after filtering.

	Production (million bushels) (y)	Diversity Ratio (D)	Small Production (S)
Min	0.01	0.00	0
Median	5.76	0.57	0
Mean	7.13	0.52	0.25
Max	27.82	1.00	1
Garfield (OK)	12.88	0.29	0
Barton (KS)	16.94	0.60	0
Ottawa (KS)	8.12	0.47	0

Table 2: Estimation Results for Correlation of Crop Production for the Pairwise Analysis Using OLS and Bayesian.

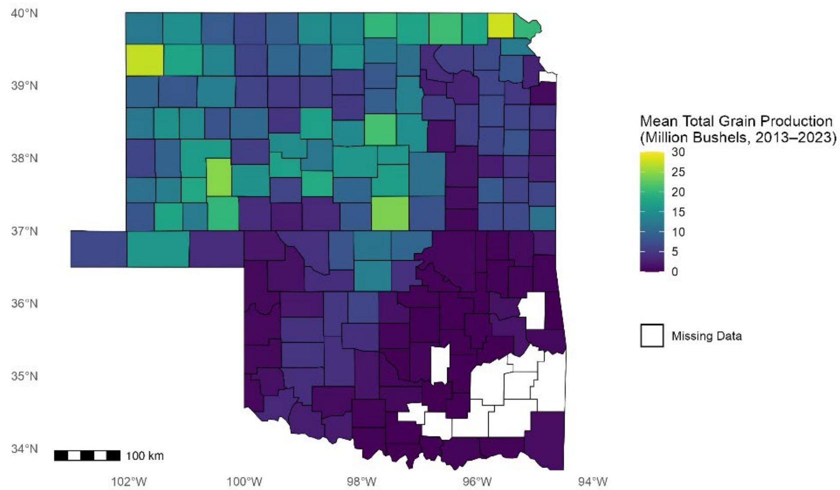
Parameter	OLS (Std. Error)	Bayesian [95% CI]
β_0 (Intercept)	0.373 (0.011)***	0.373 [0.352 – 0.394]**
β_1 (X)	–0.052 (0.003)***	–0.052 [-0.058 – -0.046]**
β_2 (Y)	–0.026 (0.004)***	–0.026 [-0.034 – -0.018]**
β_3 (R)	–0.040 (0.010)***	–0.040 [-0.060 – -0.018]**
β_4 (A)	0.036 (0.020)*	0.037 [-0.003 – 0.076]
β_5 (S)	–0.149 (0.007)***	–0.149 [-0.163 – -0.135]**
Model Fit	Adj. $R^2 = 0.061$ ($p < 2.2e-16$)***	-

Note: Significance codes in OLS: ***p < 0.01, **p < 0.05, *p < 0.1. Significance codes in Bayesian: **p < 0.05

Table 3: Estimation Results for Correlation of Crop Production with Baseline Counties

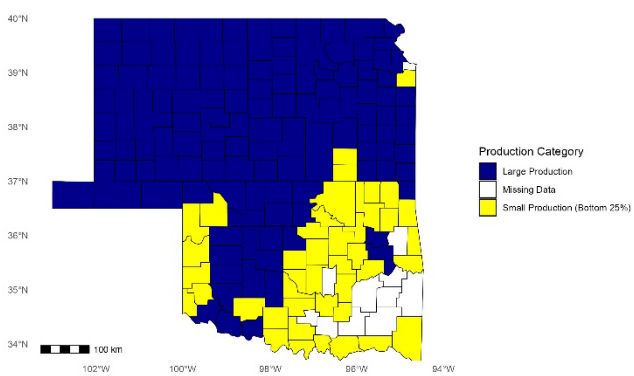
Coefficient	Garfield OLS (Std. Error)	Garfield Bayesian [95% CI]	Barton OLS (Std. Error)	Barton Bayesian [95% CI]	Ottawa OLS (Std. Error)	Ottawa Bayesian [95% CI]
β_0 (Intercept)	0.758 (0.113)***	0.759 [0.853 – 0.934]**	0.655 (0.097)***	0.655 [0.465– 0.844]**	0.749 (0.103)***	0.749 [0.546 – 0.950]**
β_1 (X)	-0.135 (0.040)***	-0. 135 [-0.213 – -0.057]**	-0.191 (0.045)***	-0. 191 [-0.280– -0.103]**	-0.108 (0.035)***	-0. 108 [-0.177 – -0.039]**
β_2 (Y)	-0.045 (0.046)	-0. 045 [-0.135 – 0.044]	-0.110 (0.047)**	-0. 111 [-0.203– -0.017]**	-0.076 (0.039)*	-0.076 [-0.153 – 0.002]
β_3 (D)	-0.364 (0.113)***	-0. 363 [-0.584 – -0.144]**	0.045 (0.142)	0. 40 [-0.238 – 0.323]	-0.329 (0.115)***	-0.329 [-0.554 – -0.100]**
β_4 (A)	0.224 (0.146)	0. 224 [-0.064 – 0.510]	-0.041 (0.147)	-0.040 [-0.329 – 0.249]	-0.117 (0.139)	-0.118 [-0.392 – 0.157]
β_5 (S)	-0.324 (0.068)***	-0.324 [-0.459 – -0.190]**	-0.152 (0.0.82)**	-0.152 [-0.312– 0.008]	-0.062 (0.074)	-0.063 [-0.208 – 0.083]
Adj. R^2	0.276	-	0.261	-	0.114	-

Note: Significance codes in OLS: ***p < 0.01, **p < 0.05, *p < 0.1. Significance codes in Bayesian: **p < 0.05.



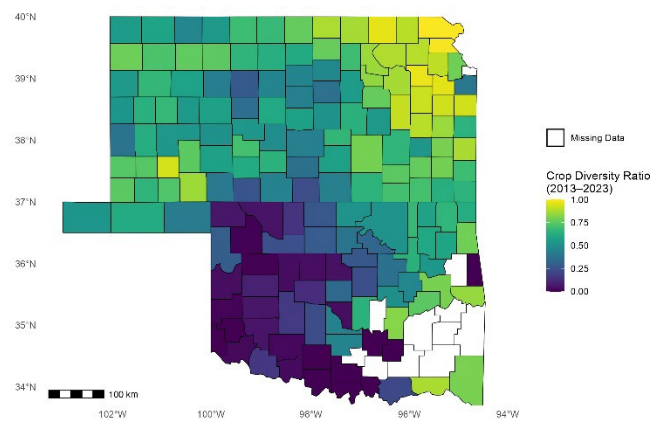
i. Mean total grain production (million bushels)

Note*: Darker shades representing lower production and lighter shades higher production; missing data counties (white).*



ii. Production scale

Note*: Counties are classified as non-small production (dark blue), small production (bottom 25%, yellow), and missing data counties (white).*



iii. Crop diversity ratio (proportion of summer crops to total production)

Note*: Darker shades indicating producing more winter crop (wheat); missing data counties (white).*

Figure 1: Spatial Distribution of Key Variables across Counties in Oklahoma and Kansas (2013–2023).

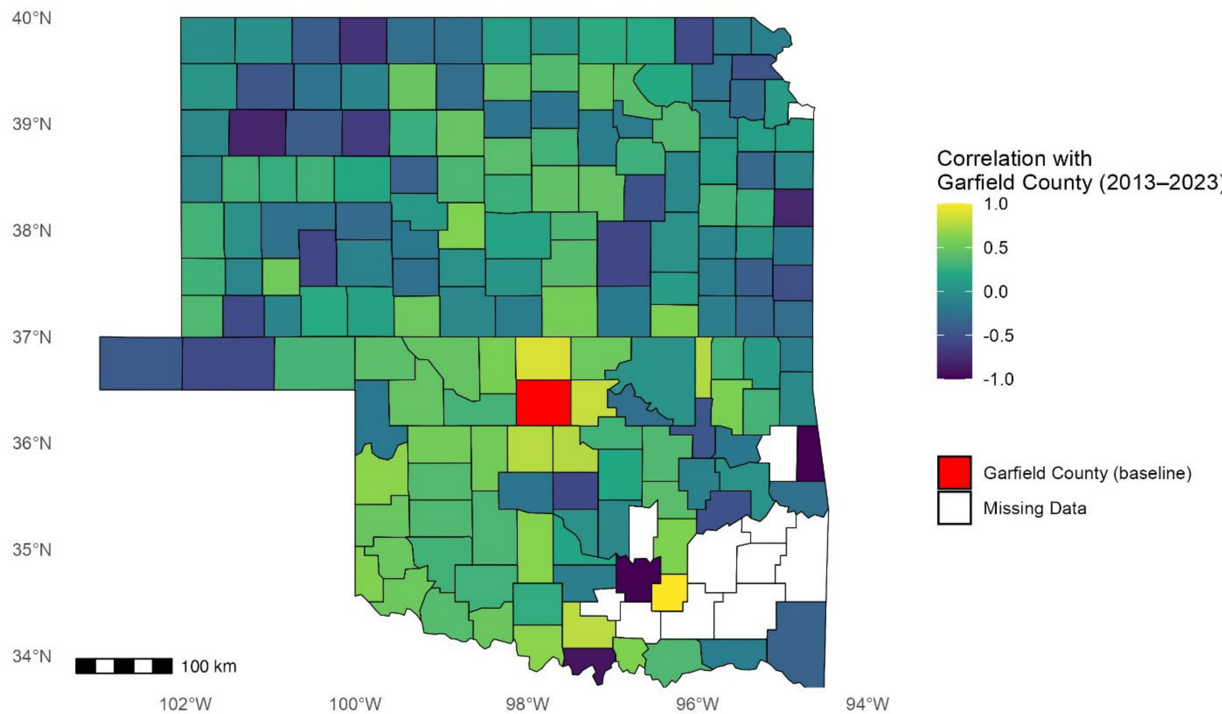


Figure 2: Spatial Correlation of Grain Productions with Garfield County, Oklahoma (2013–2023)

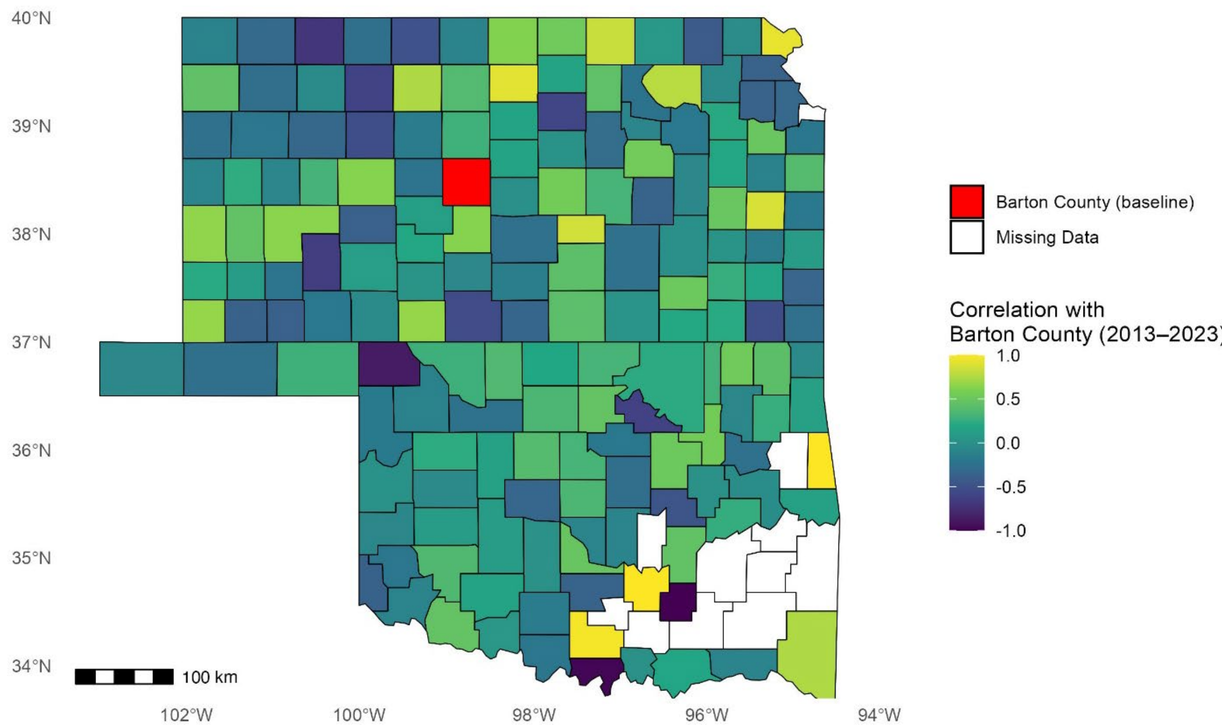


Figure 3: Spatial Correlation of Grain Productions with Barton County, Kansas (2013–2023)

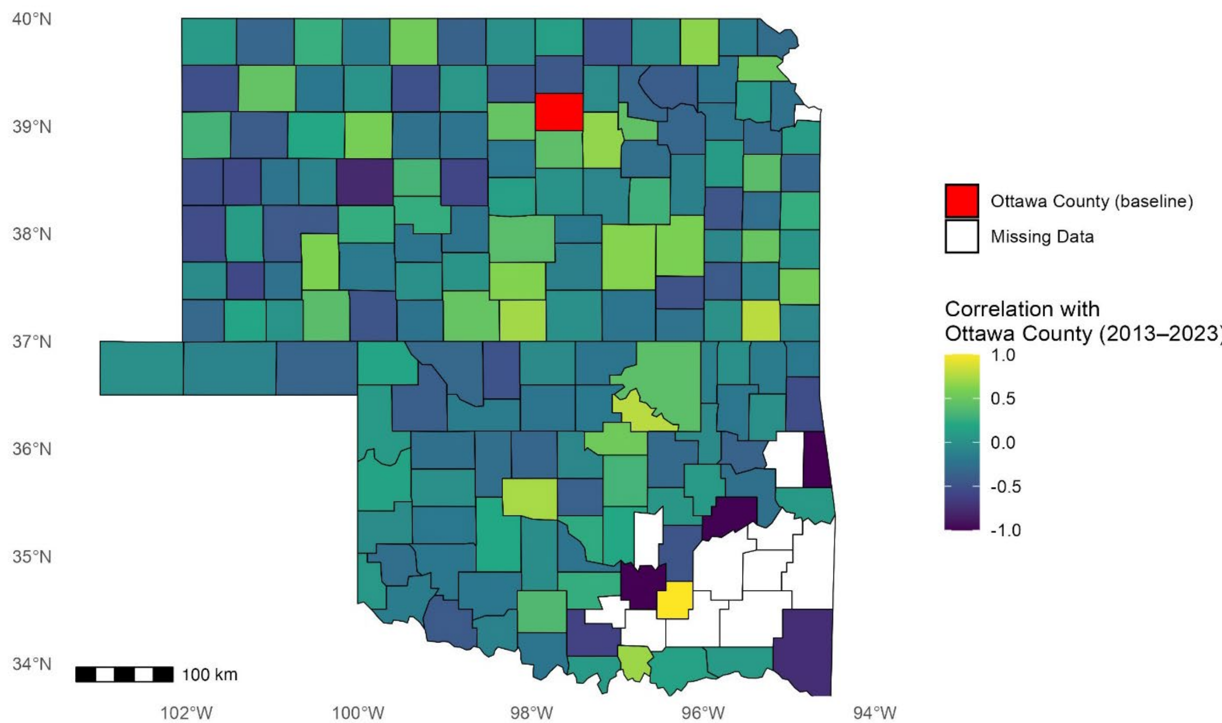


Figure 4: Spatial Correlation of Grain Productions with Ottawa County, Kansas (2013–2023)