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The relationship between bank mergers and acquisitions and local commercial bank lending to agriculture: a county-level analysis

Rui Ju, Ani L. Katchova and Abdoul G. Sam
Department of Agricultural, Environmental and Development Economics, The Ohio State University, Columbus, Ohio, USA

Abstract

Purpose – This study examines the relationship between mergers and acquisitions (M&As) among U.S. commercial banks and county-level agricultural lending.

Design/methodology/approach – We aggregate bank-level information sourced from the Federal Deposit Insurance Corporation (FDIC) to county-level data and employ the Callaway and Sant'Anna (2021) estimator to explore how bank M&As are related to changes in commercial banks' agricultural loan volume.

Findings – The estimates show that counties experiencing a commercial bank M&A subsequently exhibit statistically and economically significant declines in agricultural loan volumes held by commercial banks, with no evidence of differential pre-trends. These patterns are robust in subsamples focusing on rural counties and on community banks.

Originality/value – Research examining the localized effect of bank M&A activities remains limited. Our study bridges this research gap by incorporating the latest available data to conduct a detailed analysis at the local level.

Keywords Bank consolidation, Mergers and acquisitions, Commercial banks, Agricultural loans, Agricultural lending

Paper type Research article

Introduction

From the 1950s to the early 1970s, stringent regulations placed restrictions on U.S. banks by limiting both interstate expansion and intrastate branching. In the 1970 and 1980s, deregulatory measures eased these restrictions, allowing banks to establish multiple branches and promoting mergers, acquisitions, and diversification. Consolidation increased further after the implementation of the 1997 Riegle-Neal Act, which eliminated the last expansion restrictions. Over the past 2 decades, the trend of mergers and acquisitions (M&As) among banks has intensified, leading to a significant reduction in the number of banking institutions. As depicted in Figure 1, data from the Federal Deposit Insurance Corporation (FDIC) indicate a significant decline in the number of mainland U.S. commercial banks in the United States, ranging from 10,432 in 1994 to 4,027 in 2023. This substantial decline in the number of banks has been largely attributed to the prevalence of M&As within the banking industry. Each year, about 2%–4% of all banks have been involved with M&A events, significantly contributing to the overall consolidation of the banking sector.

The trend of bank consolidation significantly impacts small business lending, primarily because small business borrowers are typically more dependent on loans compared to others.

JEL Classification — Q14, G21, G34

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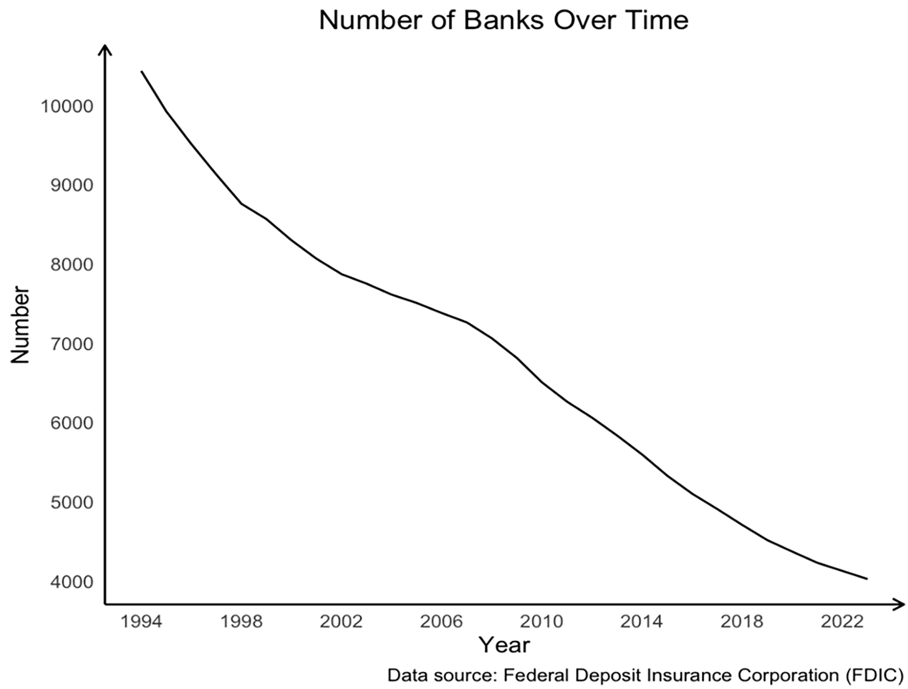


Figure 1. Number of banks in the U.S. (1994–2023)

Research by Berger *et al.* (1998) indicates that after consolidation, larger banks often shift their focus and prioritize other more standardized types of loans, which results in a decreased volume for small business lending. On the other hand, Strahan and Weston (1998) argue that consolidated banks will potentially increase their lending to small businesses due to improved efficiency as well as diversification of loan portfolios. Considering that farms are typically classified as small businesses and that commercial banks are the leading providers of farm credit (USDA-ERS, 2016), the trend of bank consolidation is expected to substantially influence agricultural lending.

Debates continue over the impact of bank consolidation on agricultural lending. According to Belongia and Gilbert (1986), small and rural banks often specialize in agricultural lending. However, small commercial banks are frequently targeted for acquisition. Thus, several studies indicate that increased bank consolidation tends to reduce the supply of agricultural credit (Belongia and Gilbert, 1986; Ahrendsen *et al.*, 1999). On the other hand, some research suggests that bank consolidation could increase lending to local businesses and farms, attributing this potential increase to factors such as improved risk distribution, enhanced liquidity, and better resource allocation (Keeton, 1996). Samolyk and Avery (2000) discovered that bank consolidations, especially among smaller banks, generally enhance credit availability for small businesses in local markets. However, Bard *et al.* (2000) reported ambiguous findings on the impact of commercial bank consolidation on agricultural lending, with data not showing a clear direction in the effect. Similarly, Featherstone (1996) demonstrated through a pre-and post-acquisition analysis that banks do not uniformly reduce their agricultural lending, suggesting that the outcomes of bank consolidations can be mixed. Additionally, older studies such as Berger *et al.* (1998) delve into the complex impacts of M&As, revealing that initial negative and static effects may be offset by dynamic effects from other local banks, which can alleviate the disruptions resulting from consolidations.

In this study, we examine the relationship between bank consolidation through M&A events and agricultural lending among U.S. commercial banks. Specifically, we explore how bank M&As are associated with changes in the volume of agricultural loans at the county level in the U.S. There is a body of research that has examined the various effects of bank consolidations. Several prior studies have investigated the impact of bank consolidation on agricultural lending, focusing mainly at the bank level (Kim and Katchova, 2022; Regmi and Featherstone, 2022; Featherstone, 1996). However, due to data constraints, these studies have largely been restricted to examining banks' lending behaviors without fully exploring how consolidations influence credit availability in local geographical markets. As emphasized by Adams (2012) and Avery *et al.* (1999), local and geographical contexts are crucial in shaping the landscape of small business lending.

This study makes two key contributions to the literature. First, this study contributes to the literature by employing a county-level approach to analyze credit availability, which is justified by the highly localized nature of bank lending to farm businesses. By focusing at the county level rather than at an individual bank level, our analysis provides a framework for understanding how bank M&As impact agricultural lending and shape the economic conditions of specific regions through localized financial resources. Becker's (2007) findings are particularly relevant to our study as they demonstrate that the market for bank capital is divided geographically. Similarly, Nguyen (2019) shows that geography remains crucial in banking, particularly for small business lending, by pointing out the localized impact of bank branch closures and the persistence of local credit constraints due to branch closures. Therefore, we focus on the local nature of bank lending to agriculture at the county level. Using county level data also allows us to link the data and use agricultural and economic variables as controls in our study.

The second contribution of our study is the utilization of the most recent data and a robust modeling approach. We employ data spanning from 2016 to 2023, updating the datasets from prior studies to examine whether recent patterns shed additional evidence on how M&As are associated with agricultural lending trends. We implement the Callaway and Sant'Anna (2021) estimator to account for differential treatment timing and check for parallel trends. Our approach aligns with the recommendation of Baker *et al*. (2022) for addressing potential bias in staggered difference-in-differences models in financial applications.

The remainder of the paper is organized as follows. We continue with the Data section, which provides an overview of the dataset's sources and characteristics, explains the approximation of the outcome variables, defines the main variables, and outlines the pre-processing steps that were taken. Next, we outline our Methodology, describing the statistical methods and models applied to assess how bank M&As are related to agricultural lending. Following this, our Results section presents the empirical findings. In the Conclusions section, we summarize the key insights from our study and discuss their implications for policymaking.

Data

To evaluate the impact of bank M&A on agricultural loans in the U.S., we obtained agricultural loan data from the Federal Deposit Insurance Corporation (FDIC) Call Reports. According to the FDIC data structure, there exists a variable labeled as "loans to finance agricultural production and other loans to farmers." In our study, due to data availability, we focus on these loans, which are intended to finance agricultural production to farmers, excluding those for agricultural real estate. Importantly, our study considers all commercial banks, in contrast to previous studies that focused solely on agricultural banks (Kim and Katchova, 2022). Due to the unavailability of branch-level agricultural loan data, we utilized a two-step approximation process similar to a methodology used by Morris *et al.* (2015) using multiple data sources. First, we estimate branch-level agricultural loans by multiplying the total loans for banks by the branch's deposit share. Next, we aggregate these estimated loans across all branches within a county.

The geographical location of bank branches and total branch deposit data were sourced from the FDIC's Summary of Deposits (SOD) data. Information on M&As was obtained from the Federal Deposit Insurance Corporation (FDIC), focusing specifically on those bank M&As that occurred without government assistance. Additionally, crop acreage data were sourced from the Farm Service Agency, USDA. Population data came from the U.S. Bureau of Labor Statistics. Unemployment rates were provided by the U.S. Department of Labor, Bureau of Labor Statistics.

Our comprehensive dataset spans from 2016 to 2023 and includes panel data from the continental United States, excluding Alaska, Hawaii, and the District of Columbia [1]. The primary independent variable in our study is an "M&A dummy," which is defined as a binary indicator that signals the occurrence of bank M&A within a county in a given year. The dependent variable is the total amount of agricultural loans held by commercial banks in that county in a given year. We also incorporate demographic factors, including population size and unemployment rate, along with agricultural variables such as farm acres and farm count per county, that may impact agricultural lending. Table 1 reports descriptive statistics for the full sample and separates averages for counties that ever experienced a bank M&A ("ever-treated") and those that are never experienced ("never-treated"). Spanning from 2016 to 2023, our dataset includes 23,808 county-year observations. The average annual agricultural loan volume is $24.84 million across all counties, and a county has about 26 bank branches on average. The M&A dummy indicates that roughly 10% of all observations (county-years) experience an M&A event. When counties are separated by treatment status, we find that ever-treated counties have higher agricultural loan volumes, substantially larger population, and more bank branches. In contrast, unemployment rates and farm characteristics are comparable across the two groups. Among counties that have ever experienced an M&A, the mean for the M&A dummy rises to 0.21 because these observations include both merger and many non-merger years for these counties; approximately 21% of their county-year observations correspond to the actual merger year. The final row of the table reports the number of county-year observations in each group.

Empirical methodology

Given that treatment (M&A) occurs across counties in different years, we employ the staggered difference-in-differences estimator proposed by Callaway and Sant'Anna (2021)—henceforth CS estimator. Following their framework, counties are grouped according to the year they first experience an M&A, denoted by cohort g. Our treatment variable is a binary indicator equal to one if county i experiences an M&A in year t. For each cohort-year pair (g, t), the group-time average treatment effect on treated counties is defined as:

Table 1. Summary statistics

Variable	All counties Mean	SD	Ever-treated counties Mean	SD	Never-treated counties Mean	SD
Agricultural loans (millions)	24.84	75.28	31.84	98.94	18.20	40.90
M&A dummy	0.10	0.30	0.21	0.41	0	0
Population (thousands)	99.19	324.19	173.49	450.66	28.78	45.36
Unemployment rate (%)	4.51	1.86	4.54	1.83	4.49	1.88
Planted acres (thousands)	223.35	358.16	187.02	319.97	257.78	387.80
Farm count	841	742	887	801	797	679
Branch count	26	65	42	90	10	13
Observations (county-years)	23,808		11,584		12,224	

$$ATT(g,t) = E\left[(Y_t(g) - Y_t(0)) \middle| G_g = 1 \right] t \geq g \tag{1}$$

where G_g is a cohort indicator, i.e. $G_g = 1$ if a county first experiences an M&A in year g. In practice, Eq. (1) is estimated following Callaway and Sant'Anna (2021) using never-treated counties as the comparison group [2]. $Y_t(g)$ denotes the outcome (agricultural lending volume) [3] for a treated county in the cohort group g in year t while $Y_t(0)$ indicates the untreated potential outcome (counterfactual loan volume) in year t. The collection of group–time effects can be summarized using the generic aggregation scheme:

$$\theta = \sum_{g} \sum_{t=2}^{T} w(g,t) \cdot ATT(g,t) \tag{2}$$

where $w(g,t)$ are pre-specified weights (Callaway and Sant'Anna, 2021).

For the event-study results, we re-index time in terms of event time $e = t - g$, which measures the number of years before or after the M&A. The event-time effect at horizon e is defined as

$$\theta(e) = \sum_{g} 1\{g + e \leq T\} P(G = g | G + e \leq T) ATT(g, g + e) \tag{3}$$

where $P(G = g|G + e \leq T)$ is the probability that a treated county belongs to cohort g among those that are observed at exposure length e. In practice, this probability is estimated by the share of treated counties in cohort g that we observe at event time e. Thus, $\theta(e)$ is a cohort-size-weighted average of the effects e years before or after an M&A.

To assess covariate balance between treated and control counties (not yet treated or never treated) in the pre-treatment period, we examine horizons from 1 to 4 years prior to M&As and report standardized mean differences [4] (SMDs) along with p-values for t-tests of equality of means for key baseline controls in Table 2. This follows previous applied work that uses propensity scores, where SMDs are the primary diagnostic for balance under matching or weighting (Caliendo and Kopeinig, 2008; Long *et al*., 2021). As emphasized by Austin and Stuart (2015), SMDs are particularly appropriate in inverse probability weighting because they do not depend on sample size and directly summarize the magnitude of imbalance, whereas t-tests will flag even very small differences as statistically significant in large samples. A common rule of thumb in this literature is that absolute SMD below about 0.10 indicates negligible imbalance. In our data, unemployment rates, planted acres, and farm counts exhibit relatively small pre-treatment differences across treated and comparison counties (|SMD| typically around 0.1), while log population displays a larger standardized difference. These covariates are all included as controls in our doubly robust CS estimation, which combines regression adjustment and inverse probability weighting (IPW) to account for covariate imbalance. In other words, our estimates compare treated counties to control counties that look similar in terms of observed characteristics.

Next, we plot the average agricultural loan volume in a county over time (Figure 2). The points represent the mean agricultural loan volume for each year, while the black bars indicate the range of one standard error above and below the mean for each year. Our analysis uncovers significant heterogeneity in agricultural loan volumes over the years, with a marked decline starting in 2020, likely due to the COVID-19 pandemic, as illustrated in the figure. This observed fluctuation underscores the necessity of integrating year-fixed effects into our model to accurately incorporate the evolving economic conditions.

We anticipate that M&As will have a negative impact on agricultural loan volumes within counties. One possible explanation is that post-consolidation, decision-making shifts away from the local level. This could lead to stricter lending criteria and fewer loan approvals, as

Table 2. Balance tests between treated and not-yet/never-treated groups

Covariate	Treated Mean	Not-yet/ never-treated Mean	SMD	*p*-value (difference in means)
Horizon: 1 year before M&A				
Population(log)	10.739	9.800	0.747	4.90e−89
Unemployment rate	4.886	4.654	0.119	3.21e−04
Planted acres	204.074	258.169	−0.144	1.91e−06
Farm count	873.539	808.599	0.087	1.11e−02
Horizon: 2 years before M&A				
Population(log)	10.711	9.781	0.747	4.83e−155
Unemployment rate	4.807	4.725	0.043	7.88e−02
Planted acres	210.773	260.248	−0.129	1.86e−08
Farm count	874.064	804.582	0.094	2.56e−04
Horizon: 3 years before M&A				
Population(log)	10.685	9.763	0.747	1.03e−206
Unemployment rate	4.812	4.762	0.026	2.08e−01
Planted acres	219.584	262.079	−0.103	8.02e−07
Farm count	869.970	801.520	0.094	2.61e−05
Horizon: 4 years before M&A				
Population(log)	10.645	9.752	0.727	1.39e−225
Unemployment rate	4.779	4.721	0.031	1.10e−01
Planted acres	228.665	263.366	−0.082	3.34e−05
Farm count	881.868	798.083	0.115	3.85e−08

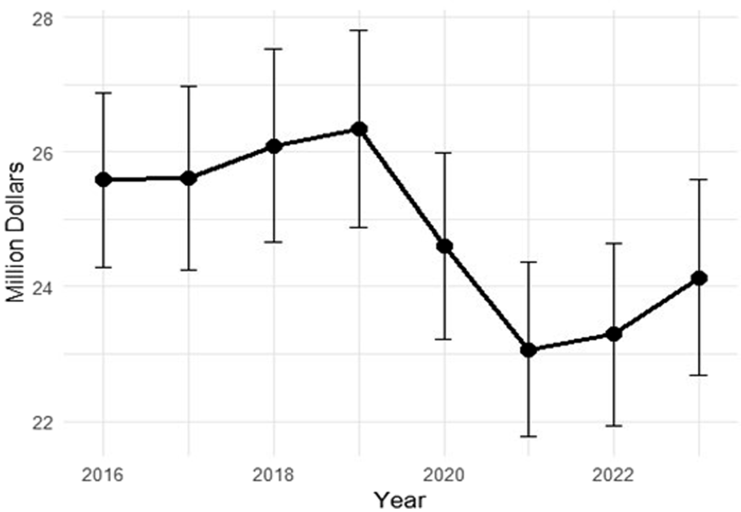


Figure 2. Average agricultural loan volume in a county. Notes: 1. The points represent the mean agricultural loan volume for each year. 2. The error bars indicate the range of one standard error above and below the mean for each year

decisions are made with less familiarity and direct knowledge of local agricultural needs and conditions. We expect that the lagged effects of M&As may also exhibit a significant relationship with agricultural loan volumes, although it is unclear whether this impact will be positive or negative. This uncertainty stems from the potential for delayed responses in the bank structure or local economy, which could either enhance or further restrict access to credit depending on evolving market conditions and regulatory adjustments following consolidation.

Results

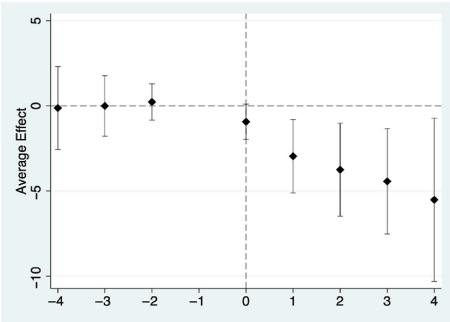
We estimate the relationship between commercial bank M&A activity and agricultural lending at the county level using the CS estimator given the staggered nature of the M&A decisions. Although the M&A timing is likely not exogenous, our identification strategy follows the conditional difference-in-differences framework, which requires a conditional parallel trends assumption rather than strict exogeneity of treatment timing. We present evidence that this assumption is plausible in our setting. Pre-treatment event-study coefficients (Table 3 and Figure 3) show no differential trends in agricultural lending between counties that subsequently experience M&As and those that remain untreated at the same time. This reduces concerns that counties undergoing M&As were already on systematically different trajectories due to unobserved factors. Furthermore, the CS estimator employs inverse probability weighting to balance observable county characteristics related to both M&A activity and lending behavior, which mitigates endogeneity concerns stemming from differences in observable characteristics. Finally, the inclusion of county fixed effects absorbs all time-invariant local conditions and structural features of county banking markets, while year fixed effects account for nationwide economic and regulatory shocks. Together, these design features mitigate endogeneity concerns associated with our observational policy environment. Nonetheless, in recognition of remaining limitations, we adopt cautious language and interpret our estimates as associations that are consistent with a plausible causal interpretation under the maintained conditional parallel trends assumption.

Table 3, column (a) presents the CS results by year for several years before and after M&As, while Figure 3, panel A displays the corresponding results graphically. By design, the coefficient for the time period preceding an M&A is normalized to zero for identification. The results indicate that M&A is, on average, associated with a 3.955 million dollars reduction in agricultural lending (post-treatment average coefficient). This represents a 16% reduction in the average agricultural lending volume of 24.8 million dollars (as reported in Table 1). Table 3, column (a) further illustrates the dynamic associations between M&As and agricultural loan volumes for the main model. The coefficients prior to event time 0 are all

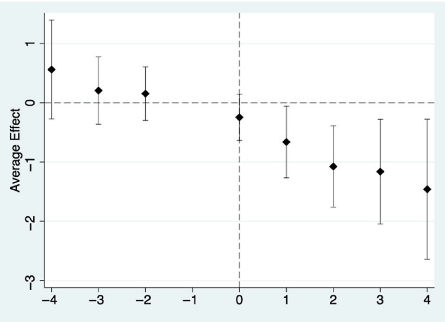
Table 3. CS treatment effects

	(a) Main results	(b) Banks in rural counties	(c) Banks with assets <10 billion
Pre-Treatment	0.375 (0.800)	0.171 (0.468)	−2.630 (2.726)
Post-Treatment	-3.955^{**} (1.797)	-1.092^{**} (0.453)	-1.239^{**} (0.433)
Pre4	−0.128 (1.243)	0.561 (0.426)	−0.190 (0.619)
Pre3	−0.007 (0.906)	0.206 (0.290)	−0.164 (0.394)
Pre2	0.229 (0.542)	0.154 (0.231)	−0.379 (0.430)
Post0	-0.939^{*} (0.527)	−0.245 (0.200)	−0.131 (0.275)
Post1	-2.961^{***} (1.099)	-0.662^{**} (0.309)	-1.163^{**} (0.375)
Post2	-3.752^{***} (1.390)	-1.075^{***} (0.350)	-1.551^{***} (0.468)
Post3	-4.435^{***} (1.578)	-1.162^{**} (0.450)	-1.851^{***} (0.566)
Post4	-5.519^{**} (2.443)	-1.460^{**} (0.603)	-1.618^{**} (0.581)

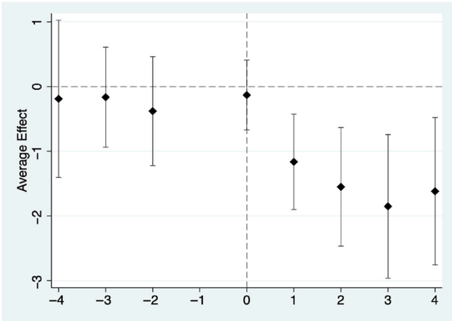
Note(s): *, **, ***$p < 0.01$; 1. Dependent variable: county-level agricultural loans by commercial banks (millions of dollars); 2. Column (a): full sample; Column (b): rural counties; Column (c): community banks (banks with assets < \$10 billion); 3. “Pre4-Pre2”:4, 3, and 2 years before treatment; “Post0-Post4”: treatment year and 1–4 years after



Panel (A): main results



Panel (B): banks in rural counties



Panel (C): banks with assets < 10 billion

Figure 3. CS treatment effects

statistically insignificant, providing support for parallel trends in agricultural lending between treated and control counties prior to M&As. The estimated coefficient is not significant in the first year of the M&A. However, the negative associations become gradually more pronounced and statistically significant over time, culminating in a coefficient of −5.5 million dollars by year four post-M&A.

Overall, our findings align with Berger *et al.* (1998), showing that consolidated banks often deprioritize small business lending. This contradicts the results of Strahan and Weston (1998), who suggest that consolidation might increase small business lending. Additionally, our results support Belongia and Gilbert (1986) and Ahrendsen *et al.* (1999), showing a decline in agricultural lending post-consolidation. However, they are inconsistent with Samolyk and Avery (2000), who found an increase in small business credit availability following consolidation among smaller banks. Our findings contradict the bank-level research by Featherstone (1996), which suggests that agricultural banks increased their lending to agriculture both in terms of the volume and the intensity after the acquisition. Furthermore, in contrast to earlier studies such as Bard *et al.* (2000), which found no effect, our study utilizes the most recent data to provide clearer evidence that bank consolidation is typically associated with reduced credit availability for agricultural lending.

Due to the unavailability of branch-level agricultural loan data, we approximate the dependent variable using a two-step process. To reduce the potential measurement error introduced by this assumption, we undertake robustness checks in the empirical analysis by limiting the data to sub-samples that are more likely to exhibit this proportionality. Specifically, we restrict the sample to (1) bank branches located in rural counties, where agricultural activity is more prevalent and (2) banks with less than $10 billion in assets. The latter cutoff aligns with the common regulatory definition of community banks (Federal Reserve, 2025). In (2), we apply these restrictions at the bank-year level before aggregating loan volumes to the county level. These bank-level restrictions still leave us with an economically meaningful sample. Over the 2016–2023 period, banks with assets below $10 billion account for a larger share which is around 75% percent of total agricultural lending throughout the period.

The corresponding CS results are presented in Columns (b) and (c) of Table 3 and Panels (B) and (C) of Figure 3. In all the three cases, we find evidence in support of parallel trends assumption embedded in a difference-in-difference model with insignificant coefficients prior to event time 0. The results show that our main finding (CS results in Table 3, column (a)) based on the full dataset pertaining to M&As holds up to the various sub-settings of the dataset. Specifically, we find support for the parallel trends assumption in all cases. We also find evidence of negative and significant association between M&As and agricultural lending in all three cases.

Another possible issue with the assumption that bank loans are assumed to be proportional to bank deposits by branch is that when a large bank acquires a small bank, this assumption may lead to breaks in the data when the analysis is conducted at the county level. Again, the robustness checks of restricting the data to smaller banks should alleviate this problem to some degree.

Conclusion and implications

This study examines how bank M&As among U.S. commercial banks are associated with agricultural lending at the county level. Using Call Report data and staggered difference-in-differences estimator of Callaway and Sant'Anna (2021), we estimate group-time average treatment effects of M&As on county-level agricultural loan volume held by commercial banks. From both the main specification and robustness checks, we find that counties experiencing M&As have a persistent decline in agricultural loan volumes held by commercial banks relative to similar counties without M&As. Event-study estimates show no evidence of pre-trends and indicate that these negative effects emerge around the time of the merger and continue for several years afterward.

Our outcome measures agricultural loans reported by commercial banks in the Call Reports, not the total agricultural loan volume in a county. In our study, we do not account for lending by other lenders such as the Farm Credit System. Thus, our estimates provide some evidence that commercial banks reduce their agricultural loan exposures in counties affected by M&As. Other lenders may partially or fully offset the reduction in commercial bank lending, but this is beyond the scope of the current study.

From a policy perspective, our findings suggest that bank consolidation can reduce the agricultural credit provided by commercial banks, especially in rural areas and among smaller banking institutions. Whether this finding warrants policy intervention depends on whether other lenders are able to compensate and whether farm investment and resilience are adversely affected, which are questions that require additional data and analysis which is beyond the scope of this study. Our contribution is to provide evidence of a robust, negative association between bank M&As and commercial bank agricultural lending at the county level, and to highlight the need for future work that traces how consolidation affects the broader agricultural credit market and farm-level outcomes.

Notes

1. The dataset begins immediately after the Federal Reserve ended its near zero-interest rate policy in December 2015, which was implemented to stimulate economic recovery following the Great Recession.
2. See Callaway and Sant'Anna (2021), Equations (4.1) and (4.2), for the formal group–time ATT estimators.

3. FDIC Call Reports are released quarterly and provide the volume of agricultural loans for each quarter. Hence, the dependent variable is obtained by averaging the quarterly volume of agricultural loans over the year for each bank.
4. The standardized mean difference is defined as the difference of sample means in the treated and control subgroups as a percentage of the square root of the average of sample variances in both groups (Caliendo and Kopeinig, 2008).

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Corresponding author
Ani L. Katchova can be contacted at: katchova.1@osu.edu