# Bank performance and general specialization vs agricultural loan specialization: an analysis of US banks



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**Abstract**

**Purpose** – The effects of bank lending specialization are unclear. To explore this issue, we contrast the performance effects of general lending specialization and agricultural specialization. The latter is important given small or community banks account for a significant share of all agricultural lending, while the number of such banks continues to shrink.

**Design/methodology/approach** – This article develops a novel measure of general lending specialization for the percentage of loans that could be shifted across seven categories to mimic market allocations. Using US government data, we analyze small-, medium- and large-sized banks for four performance indicators in random effects regressions for 2011–2019, with four sets of subsidiary analyses.

**Findings** – Results suggest specialized lending reduces risk for small, community banks, and that large-sized banks face a risk-reward trade-off such that general specialization improves returns, but increases risk. Agricultural lending is associated with improved returns and lower risk for small-sized banks, particularly in rural locations, but with poorer performance for large-sized banks. Analyses of bank performance around the global financial crisis and COVID-19 pandemics suggest these were black swan events. Overall results suggest that both general lending specialization and agricultural specialization warrant separate analytical treatment and that small, community banks continue to play a crucial role in the US economy.

**Originality/value** – This is the first article to contrast general and agricultural lending, and across small-, medium- and large-sized banks, finding distinct effects. Future studies of other types of lending specialization are warranted.

**Keywords** Bank lending, Agricultural lending, Loan diversification

**Paper type** Research paper

## Introduction

The effects of banks specializing in particular types of lending continue to attract the interest of researchers (e.g. Blickle *et al.*, 2023). Researchers have also studied the effects of specialization in agricultural loans. The latter diverges from other sectors by involving substantial weather risk, many small producers who have both regular short-term and long-term lending needs and supply-constrained credit markets (Bierlen and Featherstone, 1998; Barry *et al.*, 2000; Briggeman *et al.*, 2009).

Policymakers recognized these market deficiencies over a century ago and established the Farm Credit System (FCS) as part of the Federal Farm Loan Act of 1916.[1] As of 1935, the Farm Services Agency (FSA) began providing additional supports (Farm Services Agency, n. d.a.). Both entities are discussed further below.

The Federal Deposit Insurance Corporation (FDIC) defines “farm banks” (hence “agricultural banks”) as commercial banks with at least 25% of their loan portfolio in lending secured by farms or for agricultural production (Cofer and Anderlik, 2021). As of December 2020, such banks held 44% of all agricultural loans held by commercial banks, and they tend to be small, with almost three-quarters having less than \$250 m in total assets, such that most fit the FDIC definition of a “community bank” (Ibid.). The role of community banks is crucial in what follows because they tend to specialize in the gathering and use of soft information to better identify credit risks relative to large banks (Berger and Udell, 1995). Specifically, banks are placed in one of three asset categories, small or community banks,

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medium-sized banks and large-sized banks, to understand whether the effects of specialization diverge across those categories.

Research on bank specialization and diversification generally is concerned with bank risk and return (Blickle *et al*., 2023; Regmi and Featherstone, 2020). Some research suggests a risk/return trade-off such that more profitable banks also take on higher levels of risk (Liang and Savage, 1990). Other research, discussed below, does not support the trade-off logic. Regardless, two measures of rewards, return on assets (ROA) and return on equity (ROE), are used here along with two measures of risk, nonperforming loans (NPL) and a Z-score to measure bank failure risk.

The research here asks first how bank specialization in general affected bank performance from 2011 to 2019, using those measures of reward and risk. A novel measure of bank specialization, developed from work by Blickle *et al*. (2023), yields the proportion of total loans which would need to be shifted in order to achieve the overall market allocation of loan types. That measure may allow us to shed new light on an ongoing debate regarding the general effects of specialization. Additionally, such effects are compared to those for concentration in agricultural lending. As far as we are aware, such comparisons have not appeared in previous research, so they may help us to understand whether and how agricultural lending diverges from other types of loan specialization and whether the risk/return relationship varies across different size banks for agricultural lending.

For the analyses, random effects regressions are utilized, along with relevant control variables. Three subsidiary analyses are provided. These address the potential effects of rural location, very small bank status related to Basel III capital requirements, and the periods prior to and after the 2011–2019 years – for the global financial crisis (GFC) beginning in 2007, and the COVID-19 pandemic beginning in early 2020.

## Background

### *General effects of lending specialization*

The reason for interest in the general effects of bank lending specialization involves disparate findings. For example, Liang and Savage (1990) analyzed nonbank subsidiaries of bank holding companies and found higher but more variable ROA for specialized lenders. This result fits standard economic logic regarding the trade-off between risk and reward, here as applied to diversified loan portfolios reducing risk, with more specialized portfolios favoring profitability. Further, specialization may simultaneously improve capitalization while nonetheless increasing insolvency risk. Similar results were found by Nash and Sinkey (Sinkey and Nash, 1993; Nash and Sinkey, 1996) for banks specializing in credit card lending.

On the contrary, Eisenbeis and Kwast (1991) found that bank specialization in real estate lending improved profitability and reduced risk, at least in the long run. However, Kimball (1997) noted that even this study found that result related to a mix of low-risk residential and higher-risk commercial and development real estate holdings. In general, Kimball's (1997) study of lenders specializing in small loans (less than $100,000) to small businesses concluded that such specialized lenders should face higher capital requirements than more diversified banks to mitigate insolvency risk.

Among more recent studies, Acharya *et al*. (2006) analyzed 105 Italian banks and found that diversification is not guaranteed to either improve performance or reduce risk. Tabak *et al*. (2011) analyze Brazilian banks and find both enhanced profitability and reduced risk associated with diversification.

As Blickle *et al*. (2023) noted, specialization may allow banks to gain valuable information on industries, sectors, particular market segments and, perhaps most importantly, on potential customers. The latter supports bank engagement in relationship lending (Berger and Udell, 1995), which involves long-term relationships and is largely associated with small, community banks. Specifically, banks which engage in relationship lending focus on the gathering and use of "soft information" via personal interactions over extended time periods with clients, which allows the bank to more accurately gauge default probabilities for informationally opaque borrowers, such as small businesses (DeYoung *et al.*, 2004). As Stein (2002) notes, it is likely that diseconomies of scale are involved in relationship lending, because only small, community banks have local staff engaged with clients and the local community; by way of contrast, larger banks tend to use strict lending rules enforced by loan officers operating at a distance (both informationally and geographically) from clients.

In what is perhaps the most detailed study to date, Blickle *et al.* (2023) used highly granular loan data from banks subjected to stress tests between the third quarter of 2011 and the first quarter of 2021 and had extensive controls available. They found that banks which were more specialized by industry tended to earn slightly lower but more stable returns.

*Agricultural lending specialization*

Before considering banks proper, note there are unique characteristics surrounding agricultural markets. These include the FCS and FSA. The FCS operates through 12 regional federal land banks, and coverage expanded to one-fifth of all farm mortgages under an executive order of President Roosevelt in 1933, in response to large-scale farm foreclosures during the Great Depression. As of September 30, 2023, the FCS was responsible for $385.1 bn in gross loans (Tillman, 2023). The FSA was established to, in part, not only support new and disadvantaged farmers and distressed farms but also to help guarantee agricultural loans from either commercial banks or the FCS (Farm Services Agency, n.d.a). As of 2023, the FSA was responsible for $5.8 bn in agricultural loans, but more than $3 bn of these were in the form of guarantees to banks or FCS lenders (Farm Services Agency, n.d.b).

Another factor which is relatively unique to agricultural markets involves the existence of widespread, federally subsidized crop insurance, which serves to reduce farm default risk (Regmi *et al.*, 2023; Yu and Perry, 2024) and hence the default risk on agricultural loans. Hartarska and Nadolnyak (2013) document the effectiveness of such supports, with NPL at agricultural banks having their lowest levels following severe weather events across El Nino weather cycles. Similarly, Li *et al.* (2013) found lower default rates for agricultural loans during the GFC, presumably due to crop supports.

Turning to agricultural banks, using the FDIC definition of at least 25% of lending in agriculture, these banks accounted for 1,818 out of 8,231 commercial banks as of 2003 (see Table 1 below). By 2022, they accounted for 1,071 out of 4,663 commercial banks in total, so they shrank by a slightly lower percentage (41%) relative to all banks (43%). Nonetheless, agricultural banks remain small, with average assets equaling $276 m as of 2022, compared to $4,528 m for the average commercial bank (see Table 1). Even though these banks are small in

**Table 1.** Patterns of agricultural lending and lenders (# of banks in parentheses)

| Variable | 2003 | 2011 | 2019 | 2022 |
|---|---|---|---|---|
| AgLending % | 13.87 (8,231) | 14.40 (6,766) | 16.13 (5,264) | 14.72 (4,663) |
| AgLending % ≥25% | 46.07 (1,818) | 45.94 (1,542) | 48.62 (1,329) | 47.13 (1,071) |
| AgLending % >0% and ≤25% | 6.40 (4,751) | 6.52 (4,079) | 6.53 (3,104) | 6.45 (2,818) |
| Assets all banks | $1,599 m (9,223) | $2,363 m (7,570) | $4,008 m (5,264) | $4,528 m (4,711) |
| Assets if AgLending≥25% | $113 m (1,818) | $174 m (1,542) | $253 m (1,329) | $276 m (1.071) |
| Assets if AgLending >0 and <25% | $2,206 m (4,751) | $3,302 m (4,079) | $5,656 m (3,104) | $6,041 m (2,818) |
| Total AgLending | $62.2 b (9,223) | $83.7 b (7,570) | $117.8 b (5,264) | $106.5 b (4,765) |
| AgLending if ≥25% | $22.49 b (1,818) | $33.38 b (1,542) | $53.55 b (1,329) | $44.02 b (1,071) |
| AgLending if >0% and <25% | $39.75 b (4,751) | $50.29 b (4,079) | $64.21 b (3,104) | $62.48 b (2,818) |

**Note(s):** All dollar figures in 2022 dollars
**Source(s):** Table created by authors

number and size, they continue to play a substantial role in supporting US agriculture, accounting for approximately two-fifths of all agricultural lending by commercial banks from 2003 to 2022 (see Table 1). Nonetheless, given that three-fifths of agricultural lending is accounted for by non-agricultural banks, they also warrant their coverage in the empirical analysis below.

The soft information advantage accruing generally to small, community banks is likely of greater import in terms of agricultural lending. In addition to building relationships with clients, banks engaged in agricultural lending may benefit from paying close attention to farm income forecasts (U.S.D.A., 2024), local weather patterns, changes in capital and seed and feed costs affecting agricultural producers, the resilience of particular producers in terms of responding to adverse conditions and detailed knowledge of which federal support programs different producers are accessing. Particularly in light of those government supports, which effectively subsidize lending (in part by protecting against default risk), and agricultural bank success with relationship lending, such banks may often be seen as attractive acquisitions for larger banks. Kim and Katchova (2022) find evidence supporting that assertion and find that profitability tends to be enhanced for the first year after a larger bank acquires a smaller, agricultural bank. However, in years further past the acquisition, this advantage fades and disappears, which is precisely what Stein (2002) predicts in terms of diseconomies of scale for soft information.

In terms of the relative performance of agricultural banks, Kim and Katchova's (2022) study suggests advantages in terms of ROE and Z-scores. Similarly, Li *et al*. (2013) analyzed bank failures around the GFC and found agricultural lending was not correlated with failures, consistent with above-average Z-scores among agricultural banks. Regmi and Miller (2024) analyzed ROA and Z-scores for agricultural and non-agricultural banks covered or not covered by Basel III regulations during the COVID-19 pandemic (discussed below) and found a Z-score advantage for non-covered agricultural banks, while Ellinger (2011) found agricultural banks had higher ROA than other banks in general throughout the GFC and up to Q2 of 2011.

Another relatively unique aspect of agricultural banks is that agricultural lending is largely limited to rural areas, which have distinct types of bank markets compared to urban and suburban areas (e.g. DeYoung *et al.*, 2019). DeYoung *et al.* (2019) found default rates were lower for loans made to rural borrowers by very small, rural community banks (i.e. less than \$250 m in assets using year 2000 dollars), supporting the notion of soft information advantages for rural community banks. Although they do not distinguish agricultural from other types of loans, it would make sense if default risk were generally lower for small, rural banks which specialize in agricultural lending, as opposed to banks with any level of agricultural lending.

According to Kim and Katchova (2020), Basel III had various potential effects on small or agricultural banks. Of greatest import, Basel III imposed stricter capital requirements, issued in 2011 and effective as of 2014–2015. That is, banks were seen as taking on too much risk, so inviting excessive loan defaults or depositor runs on the bank; by tightening capital requirements, banks with a given level of capital need to shrink their loan volume and engage in less risky loans. However, regulatory authorities exempted banks with less than \$500 m in assets from the new capital requirements (Labonte and Perkins, 2021). In sum, Basel III may have impinged upon small, community bank profitability and lending, including agricultural lending, excepting very small banks, which may not only have expanded general and agricultural lending, improving profitability but also increasing risk because they were not subject to Basel III capital requirements.

## Data

Most data are from FDIC Call Reports as of June 30 of each year from 2003 to 2022, including assets, ROA, ROE, NPL, types of loans, etc. as provided by SNL Financial. Additional data are drawn from the annual Summary of Deposits data provided by the FDIC. These are used to calculate the Herfindahl–Hirschman Index (HHI) by defining markets as MSAs or counties outside of MSAs, calculating the share of deposits held at bank offices inside of each market as a proportion of all deposits in the market, and then averaging by using the deposit distribution across markets for each bank as the weight.

Loans are placed in seven categories: agriculture, commercial real estate (CommRE), construction, land development and other land loans (ConLand), one-to-four family residential mortgages (Fam1t4), multifamily residential mortgages (MFam), commercial and industrial loans (CandI) and consumer loans (Consum). There are two agricultural loan items: loans secured by farmland and loans to finance agricultural production. These variables have a correlation coefficient of 0.61, so they are combined. Together, the seven categories account for more than 98% of all reported loans, with some very small categories excluded (e.g. loans to depository institutions and non-depository financial institutions) to prevent outliers from affecting the results.

For an initial glimpse of agricultural lending, various figures are provided in Table 1. The total percentage of agricultural lending in 2003, 2011, 2019 and 2022 can be found in the first numeric row of the table. The years 2011 and 2019 are highlighted because these are later used as the endpoint years for the analysis to avoid contaminating the results with the black swan events of the GFC earlier and the COVID-19 pandemic afterward. Specifically, Li *et al.* (2020) explained the diverse GFC and COVID-19 experiences in terms of shortfalls of bank liquidity during the GFC and excess liquidity during the pandemic. Cofer and Anderlik (2021) found that agricultural banks thrived during the GFC years, while other banks with substantial holdings in residential and commercial real estate did not. The excess liquidity argument around the pandemic makes sense for agricultural lenders given extensive government financial supports for businesses generally, such as the SBA's Paycheck Protection Program, which subsidized wage payments, and the Economic Injury Disaster Program, which provided subsidized loans to small businesses hurt by the pandemic [2], and the USDA's Coronavirus Food Assistance Program, which provided direct assistance to farmers and ranchers [3].

Overall, the percentage of agricultural lending shows minimal change, excepting a slight rise from 2011 to 2019. In terms of agricultural banks, their agricultural loan average is close to 45–49% in all four years, while for banks engaged in agricultural lending but less specialized, the average is between 6 and 7% in all years. Those figures suggest a high degree of stability. That stability is somewhat surprising given the dramatic expansion of online banking practices during the period, which might have given large banks an opportunity to encroach upon the markets of agricultural banks (Waite and Harrison, 2015). It is less surprising given that the fast-growing fintech lending sector mainly services consumer loans (Jagtiani and Lemieux, 2018).

Turning to the relationship between bank size and agricultural lending, relevant figures appear in the next three rows (all in 2022 dollars). The average bank grew dramatically in size over the period, with total assets almost tripling from 2003 to 2022, as the number of banks fell by almost 50%. The banks specializing in agricultural lending (above 25%) shrank in relative terms from around 1/14th the average size in 2003 to less than 1/16th the average size in 2022. The banks with some agricultural lending but 25% or less, however, were almost \$600 m larger than the average in 2003, and with a size advantage approaching \$1.5 bn as of 2022.

Those patterns raise the question of whether most agricultural lending comes from large- or small-sized banks, a question addressed in the last three rows of Table 1. Here the pattern is one of relative constancy: approximately two-fifths of all agricultural lending comes from the banks that are highly specialized in agricultural lending (and small).

## Methods

Specialization is measured using Blickle *et al.*'s (2023) indicator of excess specialization as a starting point. For each bank b, loan type l and year t, define specialization in a loan type by the proportion of such loans at bank b to total bank b loans, less the proportion of all such loans out of total loans by all banks or:

$$\text{Spec}_{\text{blt}} = \text{Loans}_{\text{blt}}/\text{Loans}_{\text{bt}} - \text{Loans}_{\text{lt}}/\text{Loans}_{\text{t}}. \tag{1}$$

For a reason discussed shortly, negative values are set to zero with the following constraint:

$$\text{Spec}_{\text{blt}} = \text{Loans}_{\text{blt}}/\text{Loans}_{\text{bt}} - \text{Loans}_{\text{lt}}/\text{Loans}_{\text{t}} \text{ if } > 0, \tag{2}$$

$$\text{Spec}_{\text{blt}} = 0 \text{ otherwise.}$$

A general measure of bank specialization can then be obtained by summing across all loan types or:

$$\text{Spec}_{\text{bt}} = \Sigma \text{Spec}_{\text{blt}} \tag{3}$$

This measure has several desirable characteristics. First, it captures specialization across all types of loans. Second, it is strictly bounded upward by "1," with a lower bound of "0." Third, it has the intuitive interpretation of yielding the overall percentage of loans which would need to be switched to yield perfect diversification, where that term is used to mean the average distribution of loan types across all banks in a given year. Note that if negative values of the specialization term had been retained (i.e. ignoring (2)), this measure would reduce to 0% in all cases, which is not useful.

Alternative specialization measures include Stiroh's (2004) and Archarya *et al.*'s (2006) application of the HHI to loan types, which assumes that equal distribution across each loan type is associated with perfect diversification. Given some categories of loan types are empirically much larger than others, it seems more reasonable to assume markets set ideal diversification levels. Additionally, Blickle *et al.* (2023) developed a relative measure of specialization, which uses the ratio of a bank's loan type to the mean value for all banks. So, for example, a bank with 10% of its portfolio in a type of loan which represents 1% of all bank loans would yield a value of 10 (or 1,000%), while a bank with 40% of its portfolio in a loan type representing 30% of all bank loans would yield a value of 1.3 (or 130%). Aggregation of this measure would have no intuitive interpretation.

Using $\text{Spec}_{\text{bt}}$ as an independent variable in various performance regressions may shed new light on the general effects of specialization. Specifically, if specialization is associated with a risk-reward trade-off, then it will positively influence ROA and ROE while leading to higher NPL and lower Z-scores. However, the key question here is whether specialization in agricultural loans has different effects than general specialization. Because agricultural lending is relatively rare – with 25% of all banks making no agricultural loans, and with half of all banks having 6% or less of their loan portfolio in agricultural loans – we use the percentage of agricultural loans (AgLending) for the analysis, rather than a version of the general specialization measure. Note further that, by construction, $\text{Spec}_{\text{bt}}$ and AgLending are collinear ($r = 0.248$), so the variables are entered in separate analyses.

Four dependent variables are used for the analysis. Standard measures of profitability or rewards include ROA and ROE (Archarya *et al.*, 2006; DeYoung *et al.*, 2004; Regmi and Featherstone, 2020). One common indicator of risk used here is NPL (Blickle *et al.*, 2023). It is also standard to estimate a Z-score to capture insolvency risk (e.g. Berger *et al.*, 2014). In analyzing a variety of Z-scores for panel data on a large sample of banks, Lepetit and Strobel (2013) applied a minimum root mean square error analysis to each and found the minimum associated with the measure:

$$\text{Z} = (CAR_{bt} + ROA_b)/(\sigma_{roab}), \tag{4}$$

where $CAR_{bt}$ is the risk-weighted capital asset ratio for bank b at time t, $ROA_b$ is the mean ROA for bank b over the entire period and $\sigma_{roab}$ is the variance of ROA for bank b over the entire period. This measure has the additional desirable characteristic of not excluding initial years used to calculate rolling variance estimates. In further research, Lepetit and Strobel (2015) found that the natural log of the Z-score can be interpreted as negatively proportional to the odds of insolvency. That measure is applied here.

Using ROA as an example, the bank performance regressions take the following form:

$$\mathrm{ROA_{bt}} = \alpha + \beta_1(\mathrm{Spec_{bt}}) + \boldsymbol{\beta}\mathbf{Xb_t} + \nu_\mathrm{b} + \varepsilon_\mathrm{bt}, \quad (1)$$

where $\beta_1$ is the coefficient for the effects of specialization, $\mathbf{X}_\mathrm{bt}$ is a matrix of independent variables with coefficient vector $\boldsymbol{\beta}$, $\nu_\mathrm{b}$ captures panel-level random errors and $\varepsilon_\mathrm{bt}$ individual observation errors. Independent variables include the log of real assets (measured in 2022 dollars; Stiroh, 2004), HHI for deposit market concentration, a standard measure of monopoly power (Pilloff and Rhoades, 2002) and a related measure of the percentage of deposits in urban areas (Urban), given the variable reflects constraints on agricultural lending specialization and differences across urban and rural banking markets (DeYoung *et al.*, 2019). Additionally, the non-interest income share (NonInt) is included to capture relative specialization in lending as opposed to other services (Stiroh, 2004), along with the ratio of the number of bank depository offices to real assets to capture any economies of scale for bank branching (Archarya *et al.*, 2006). To capture macroeconomic effects, such as changes in inflation or the federal funds rate, year dummy variables are included. Note that this is a random effects specification; fixed effects were considered and rejected (see Appendix 1).

Given specialization or diversification can have nonlinear effects (e.g. Ali *et al.*, 2016), the coefficients for a quadratic specification are tested for joint significance and, where significance is found, those results are reported. Following the initial specification, the agricultural loan variable (AgLending), is used and, as with the general specialization variable, the joint significance of a quadratic is reported as relevant.

Historically, community banks were defined as those with less than \$1 bn in assets (DeYoung *et al.*, 2004). Correcting for inflation using the June CPI-U figure from the BLS, \$1 bn in 2004 translates to \$1.56 bn in 2022 dollars, so that cut-off is applied here, and accounts for 87% of all banks in the sample (9,211 of 10,601). However, the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010, categorized banks as community banks with less than \$10 bn in assets, among other conditions (Gilbert *et al.*, 2013). Again applying the CPI-U figure, \$10 bn in 2010 is the equivalent of \$13.6 bn in 2022 dollars, so that cut-off is used to capture a set of 1,141 medium-sized banks (10.8% of the sample). There are then 239 large banks, and regressions are applied separately to the three groups.

Note as an empirical matter that bank size is negatively correlated with agricultural loans (see Table 1 or Regmi and Featherstone, 2020). Given that fact, where coefficients on the agricultural loan variable(s) are significant, simulations will use values of 0, 25 and 50% to understand size effects for small- and medium-sized banks, but lower figures of 0, 15 and 30% for large-sized banks.

Four subsidiary analyses are performed. First, DeYoung *et al*. (2019) suggested there is a performance advantage for rural receipt of loans (including agricultural loans) by small community banks located in rural areas. Therefore, for the small-sized banks, the inverse of the urban percentage is used to represent the rural percentage, and the term is interacted with the agricultural lending variable to test for any relevant performance effects and with the general specialization variable to see if any agricultural effects are unique.

Second, given banks with less than \$500 m in assets were exempted from Basel III capital requirements, the small-sized bank sample is divided into those with less than \$500 m in nominal assets and those with greater assets. The main regressions are then replicated to isolate any potential effects of this exemption on bank specialization effects.

Third, as mentioned earlier, the main regressions are limited to the years 2011–2019, avoiding the black swan events of the GFC and the COVID-19 pandemic. These events are addressed in a subsidiary analysis utilizing one- and two-year first-difference variables for the initial years of 2007 and 2019 and the final years of 2008 or 2009 and 2020 or 2021, respectively, effectively removing fixed or between effects. For those years, dependent variables are limited to ROA, ROE and NPL, given a lengthier time period is required for calculating the Z-score. For each dependent variable and bank size category, simple correlation coefficients for both the general specialization and agricultural loan variables are estimated to understand relevant effects.

For the period 2011–2019, variables are described in Table 2. The larger-sized banks not only tend to have higher ROA, ROE and slightly lower NPL but also lower Z-scores. Overall loan specialization is similar across the three size groups, but agricultural specialization is much more common for the small-sized banks. The non-interest component of income is much higher at the large-sized banks, while the HHI is highest for the small-sized banks, suggesting they face less competition for deposits. The small-sized banks also tend to operate in non-urban markets, while the large-sized banks are concentrated in urban locations, and with fewer branches per (2022) dollar of assets.

## Results

For the effects of general specialization, note that with four dependent variables and three bank size subsamples, a total of 12 regressions are required. Therefore, the regressions are relegated to Appendix Tables I–III, for small-, medium- and large-sized banks, respectively.

Table 3 follows from those general loan specialization regressions, with simulations for various values of $Spec_{bt}$ in cases where the single $Spec_{bt}$ coefficient is significant or the quadratic terms are jointly significant. Beginning with the results for small-sized banks, these suggest that NPL is significantly lower for small-sized banks that are more highly specialized, and the odds of insolvency are also lower (slightly higher Z-score). For the medium-sized banks, the ROA and ROE effects are curvilinear and contradictory, with ROA falling and then rising along with general specialization, but ROE falling and then rising; NPL uniformly rises with specialization. For the large-sized banks, the results point toward a risk-reward trade-off, with not only greater loan specialization increasing both ROA and ROE but also increasing NPL and increasing the odds of insolvency.

Next the general specialization variable is replaced by the agricultural lending term(s). Again, the regression results are relegated to Appendices (Appendix Tables IV–VI), with significant agricultural loan effects simulated as above in Table 4 below, although it should be recalled that the maximum simulated agricultural loan value is 50% for small- and medium-sized banks, but only 30% for large-sized banks.

**Table 2.** Descriptive statistics, 2011–2019

| Variables | Small-sized banks | Medium-sized banks | Large-sized banks |
|---|---|---|---|
| *ROA %* | 1.078 | 1.190 | 1.251 |
| *ROE %* | 9.289 | 10.555 | 10.758 |
| *NPL %* | 1.974 | 1.907 | 1.907 |
| *Log-Z score* | 1.595 | 1.546 | 1.283 |
| $Spec_{bt}$ *%* | 32.28 | 32.31 | 35.77 |
| *AgLending %* | 9.246 | 0.769 | 0.291 |
| *Assets* | $323 m | $4,004 m | $13,290 m |
| *Non-interest inc. %* | 0.13.63 | 18.45 | 24.49 |
| *HHI* | 0.212 | 0.171 | 0.175 |
| *Urban %* | 49.15 | 84.30 | 94.86 |
| *Branches/Assets* | 0.000018 | 0.0000097 | 0.0000045 |

**Note(s):** All dollar figures in 2022 dollars
**Source(s):** Table created by authors

**Table 3.** Simulations for significant loan specialization coefficients, 2011–2019

| | ROA | ROE | NPL | Log (Z score) |
|---|---|---|---|---|
| Small-sized banks | | | | |
| $Spec_{bt}$ 22 | | | 2.047 | 2.652 |
| $Spec_{bt}$ 32 | | | 2.029 | 2.653 |
| $Spec_{bt}$ 42 | | | 1.979 | 2.657 |
| Medium-sized banks | | | | |
| $Spec_{bt}$ 22 | 1.075 | 10.03 | 1.705 | |
| $Spec_{bt}$ 32 | 1.038 | 9.541 | 1.967 | |
| $Spec_{bt}$ 42 | 1.132 | 9.929 | 2.229 | |
| Large-sized banks | | | | |
| $Spec_{bt}$ 22 | 1.026 | 9.175 | 1.384 | 2.755 |
| $Spec_{bt}$ 32 | 1.044 | 9.929 | 1.803 | 2.739 |
| $Spec_{bt}$ 42 | 1.136 | 10.79 | 2.192 | 2.705 |

**Source(s):** Table created by authors

**Table 4.** Simulations for significant agricultural lending coefficients, 2011–2019

| | ROA | ROE | NPL | Log (Z score) |
|---|---|---|---|---|
| Small-sized banks | | | | |
| *AgLending* 0 | 1.097 | 8.786 | 2.325 | |
| *AgLending* 25 | 1.114 | 9.567 | 1.664 | |
| *AgLending* 50 | 1.062 | 10.349 | 1.487 | |
| Medium-sized banks | | | | |
| *AgLending* 0 | 1.172 | 10.197 | | |
| *AgLending* 25 | 1.415 | 13.173 | | |
| *AgLending* 50 | 1.700 | 14.053 | | |
| Large-sized banks | | | | |
| *AgLending* 0 | 1.271 | 10.744 | | |
| *AgLending* 15 | 1.103 | 8.117 | | |
| *AgLending* 30 | 0.936 | 7.304 | | |

**Source(s):** Table created by authors

For the small-sized banks, ROA rises with agricultural lending up to 25%, then falls up to 50%. ROE, however, simply rises with agricultural lending, while NPL falls. For medium-sized banks, both ROA and ROE rise with agricultural lending, while those variables decline with agricultural lending for the large-sized banks.

Note further that most of these findings are economically meaningful. For example, the simulated decline in NPL for small-sized banks switching from 0 to 50% agricultural lending is above one-third. For that the same projected switch, ROE rises by above 17% at the small-sized banks, with similarly large beneficial effects for medium banks and negative effects for large banks.

Turning to the subsidiary analyses, the first involves interacting a rural term with the general specialization or agricultural loan variables, noting that agricultural loans and the rural terms are not interacted for large-sized banks since those characteristics represent outliers. Interactions with the prior yield three significant relationships (all negative): for medium-sized banks, ROA and ROE and for small-sized banks, NPL (results in Appendix Table VII). To understand the simulated effects, we contrast low and high values of the general specialization term (22 and 42%) with low and high values of the rural variable (25 and 75%). For low values of both for medium-sized banks, ROA (ROE) is projected to be 1.056 (10.007), for high on specialization but low on rural, ROA (ROE) is 1.071 (9.662), for high on rural but low on specialization, ROA (ROE) is simulated to be 1.041 (10.355) and for high on both, ROA (ROE) figures are 0.862 (8.926). Therefore, medium-sized banks can experience slight gains in ROA, if not ROE, from general specialization, but not in highly rural markets. For small-sized banks, NPL for low specialization and low rural presence is simulated to be 2.157, falling to 2.146 for high specialization and low rural presence, falling to 1.938 for low specialization and high rural presence, with the lowest figure, 1.823, projected for high specialization in rural markets.

Replicating that exercise for agricultural specialization and excluding large-sized banks yields one significant interaction with the rural term: for small-sized bank NPL (results in Appendix Table VII). For those banks, simulated effects are for 25% as opposed to 75% rural and for 0 and 50% agricultural lending, which projects to NPL of 2.405 for both low, 1.455 for high on agricultural lending but low on rural, 2.222 for low on agricultural lending but high on rural, and 1.413 for high on both characteristics, consistent with an advantage for agricultural lending by small rural banks, as suggested by DeYoung *et al*. (2019). Note that the interaction term itself is positive, but the direct effects of both agricultural lending and rural location are negative (see Appendix Table VII).

Simulations for significant general loan specialization and agricultural specialization for the very small banks exempt from risk-based capital requirements (<$500 m in nominal assets) are relegated to Appendix Table VIII, with relevant regression results in Appendix Tables IX and X. The reason for giving short shrift to this analysis is that the effects are very similar to those for all small-sized banks.

The final subsidiary analysis involves the correlation coefficients for the one- and two-year first-differenced performance variables and the general specialization or agricultural lending variables for the GFC period (2007 to either 2008 or 2009) and the COVID-19 period (2019 to either 2020 or 2021). Starting with the GFC and small-sized banks (Table 5), general specialization has significant adverse effects on five of six measures (negative ROA, ROE and positive NPL), but agricultural specialization has significant beneficial effects across all six measures, consistent with Cofer and Anderlik's (2021) findings. For medium-sized banks (Table 6), the adverse significant effects of general specialization are stronger, and with weaker beneficial effects for agricultural specialization, while for large-sized banks (Table 7), only one of the 12 correlations is significant, a beneficial, negative, significant NPL effect for a one-year lead, suggesting the large banks were either extremely well run or received favorable governmental treatment during the GFC.

The COVID-19 experience was very different and less clear-cut. The small-sized banks experienced mixed ROA and ROE effects for general specialization, while the medium- and large-sized banks experienced significant adverse effects for general specialization, but only for one year. Agricultural specialization only altered one of the six measures for each of the three bank sizes, suggesting that agricultural lending was not counter-cyclical during the

**Table 5.** Correlation coefficients for general specialization, agricultural loan share and bank performance effects of GFC and COVID-19, small-sized banks

| Variables | 2007 $Spec_{bt}$ | *AgLending* | 2019 $Spec_{bt}$ | *AgLending* |
|---|---|---|---|---|
| ROA 1-yr lead | −0.056*** | 0.038*** | 0.013 | −0.014 |
| ROA 2-yr lead | −0.047*** | 0.070*** | 0.045*** | −0.022 |
| ROE 1-yr lead | −0.045*** | 0.103*** | −0.062*** | −0.006 |
| ROE 2-yr lead | −0.020 | 0.116*** | −0.036** | 0.010 |
| NPL 1-yr lead | 0.042*** | −0.150*** | 0.018 | 0.027* |
| NPL 2-h lead | 0.039*** | −0.217*** | 0.020 | 0.007 |

**Note(s):** *$p < 0.10$, **$p < 0.05$ and ***$p < 0.01$
**Source(s):** Table created by authors

**Table 6.** Correlation coefficients for general specialization, agricultural loan share and bank performance effects of GFC and COVID-19, medium-sized banks

| Variables | 2007 $Spec_{bt}$ | *AgLending* | 2019 $Spec_{bt}$ | *AgLending* |
|---|---|---|---|---|
| ROA 1-yr lead | −0.224*** | 0.080 | −0.093* | 0.037 |
| ROA 2-yr lead | −0.242*** | 0.126** | 0.020 | 0.049 |
| ROE 1-yr lead | −0.198*** | 0.070 | −0.123** | 0.045 |
| ROE 2-yr lead | −0.175*** | 0.097* | 0.006 | 0.014 |
| NPL 1-yr lead | 0.096* | −0.069 | 0.144*** | −0.020 |
| NPL 2-h lead | 0.205*** | −0.142*** | 0.078 | −0.087* |

**Note(s):** *$p < 0.10$, **$p < 0.05$ and ***$p < 0.01$
**Source(s):** Table created by authors

**Table 7.** Correlation coefficients for general specialization, agricultural loan share and bank performance effects of GFC and COVID-19, large-sized banks

| Variables | 2007 $Spec_{bt}$ | *AgLending* | 2019 $Spec_{bt}$ | *AgLending* |
|---|---|---|---|---|
| ROA 1-yr lead | 0.056 | −0.051 | −0.282*** | 0.095 |
| ROA 2-yr lead | −0.157 | 0.072 | 0.149 | 0.116 |
| ROE 1-yr lead | 0.089 | −0.054 | −0.321*** | 0.095 |
| ROE 2-yr lead | 0.011 | 0.043 | −0.038 | 0.296** |
| NPL 1-yr lead | −0.205* | 0.134 | 0.246** | −0.003 |
| NPL 2-h lead | −0.198 | 0.093 | 0.048 | 0.047 |

**Note(s):** *$p < 0.10$, **$p < 0.05$ and ***$p < 0.01$
**Source(s):** Table created by authors

pandemic in the way it was during the GFC. This is consistent with Li *et al*.'s (2020) understanding of the GFC as involving a shortage of bank liquidity and the pandemic as involving excess liquidity. That, along with very different government policy responses, may help to explain these patterns.

## Discussion

This study sought to understand the general effects of US bank lending specialization and asked whether concentration in agricultural lending produced distinct effects from general specialization. Considering general effects, a novel measure of specialization followed from the work of Blickle *et al*. (2023) for the percentage of loans across seven broad categories which would need to be switched to equal the overall market distribution in any given year. Dividing the banks into those which are small, community banks (less than \$1.56 bn in assets, 2022 dollars), those of medium-sized banks (between \$1.56 bn and \$13.6 bn in assets, 2022 dollars), it is somewhat surprising to find that the average degree of specialization is just above 32% for small- and medium-sized banks and only slightly higher (35.8%) for large-sized banks (see Table 2).

Random effects regression results for four measures of performance and the relatively stable period of 2011–2019 suggest that small bank specialization is associated with lower NPL and insolvency odds (higher Z-score). This finding is consistent with Berger and Udell's (1995) notion that community banks have soft information advantages not available to larger banks, so can more accurately identify risks from lending, here by virtue of specializing in one or another type of loan (although see Kimball, 1997). There are mixed ROA and ROE effects but adverse NPL effects for medium-sized bank specialization. Large banks yield a traditional risk-reward trade-off such that general specialization is associated with higher performance levels but with greater risk, as found by Liang and Savage (1990), Sinkey and Nash (1993) and Nash and Sinkey (1996), but in contrast to Blickle *et al.* (2023).

In terms of general specialization and subsidiary results, medium-sized banks can experience slight gains in ROA, if not ROE, from general specialization, but not in rural areas. However, for small-sized banks, NPL declines with both specialization and rural location. That finding is consistent with DeYoung *et al.*'s (2019) findings and suggests that rural locations facilitate the gathering of soft information for specialized, small-sized banks. Recalling that very small banks, with less than \$500 m in nominal assets, are exempted from Basel III risk-based capital requirements (Labonte and Perkins, 2021), we tested whether the effects of specialization diverged for these very small banks as opposed to all small-sized banks. Differences were minimal, suggesting the Basel III exemption did not lead to excessive levels of risk-taking among small, specialized banks. For market competition (HHI) and general specialization, positive effects of high HHI (i.e. monopoly power) in medium-sized banks are muted by general specialization, while high HHI tends to increase small-sized bank NPL, but specialization tends to mitigate these effects, with high HHI and specialization tending to improve Z-Scores at small-sized banks. For large-sized banks, a high HHI improves the Z-Score, but this effect is countered by the (higher-risk) effects of specialization. For the GFC and COVID-19 two-year performance analysis, the GFC was uniformly associated with adverse performance effects for general specialization, while the COVID-19 pandemic yielded few significant effects, likely because the pandemic led to excess liquidity (Li *et al.*, 2020).

The major purpose of the analysis of general loan specialization was to provide a way to compare and contrast loan specialization of one type: agricultural lending. As found here, general specialization is not linked to any particular size of bank, but agricultural specialization is concentrated in small-sized banks (see Table 1). Further, agricultural banks (with more than 25% agricultural lending) tend to be tiny, with an average of less than \$300 m in assets as of 2022, compared to \$4.5 bn for all banks, yet they account for approximately two-fifths of all agricultural lending from 2003 to 2022.

Ignoring small-sized banks for a moment, consider agricultural specialization for medium- and large-sized banks. For medium-sized banks, general specialization had mixed effects in terms of ROA and ROE while increasing NPL, but agricultural specialization only had positive effects on ROA and ROE; those effects, however, disappear for medium-sized banks in rural markets, with stronger positive ROA effects in less competitive markets (high HHI). For large banks, general specialization yielded the risk-reward trade-off discussed above, but those banks experience significantly lower ROA and ROE for agricultural lending. In general, the effects of agricultural specialization and general specialization diverge for medium- and large-sized banks and suggest that large banks tend to be disadvantaged when engaging in agricultural lending.

Turning to small-sized banks, general specialization tends to reduce risk (see Table 3), but agricultural specialization both reduces risk and improves profitability (see Table 4). That divergence suggests that soft information advantages for small, community banks engaging in specialization are magnified by agricultural lending. That pattern extends to small-sized banks in rural locations. Note that urban locations are associated with significant performance disadvantages for small-sized banks (see Appendix Tables 1 and 4), with the flip side being performance advantages for rural locations. For small-sized banks switching from low to high on rural location and general specialization, NPL is projected to decline from 2.157 to 1.823, but for small-sized banks switching from low to high on rural location and agricultural lending, the ratio declines from 2.405 to a projected 1.413. Together, these effects suggest that it is small, rural banks specializing in agricultural loans which enjoy some of the strongest performance benefits for specialization. The analysis of very small banks exempt from the risk-based capital requirements of Basel III did not alter any of these conclusions.

The GFC and COVID-19 periods were treated as black swan events, warranting separate treatment with first-differenced ROA, ROE and NPL variables for 2007–2008 or 2009 and

2019–2020 or 2021. For the small-sized banks, the earlier GFC period yielded adverse effects for general specialization but beneficial effects for agricultural specialization. Those effects were stronger for general specialization and medium-sized banks but weaker for agricultural specialization and the medium-sized banks, with minimal effects for large-sized banks, consistent with government policies favoring too big to fail banks during the GFC. For the COVID-19 pandemic, the medium and large banks experienced short-term performance losses for general specialization, with minimal effects on small-sized banks and for all banks in terms of agricultural specialization.

In large measure, the rationale for this study was the potential for agricultural lending specialization to have distinct effects relative to general specialization. The results clearly support that possibility, given general specialization only benefits small-sized banks in terms of risk reduction but fits a traditional risk-reward trade-off for large bank specialization. For agricultural lending, small-sized banks have both a risk and a reward advantage, and large-sized bank performance is poorer in terms of ROA and ROE for agricultural specialization.

Given our overall finding that concentration in agricultural lending has distinct effects from general specialization, future research might hone in on other specific types of specialization. That such research might also yield diverse findings by sector is consistent with differences across the findings of earlier studies, such as Eisenbeis and Kwast’s (1991) study of real estate specialization as compared to Kimball’s (1997) study of small business lending.

Future research might also address the period from 2020 to 2024, which witnessed the pandemic period with excess liquidity, followed by very high interest rates which might have adversely affected agricultural lending. This is part of a broader limitation of this study: it is specific to the 2011–2019 period and, particularly given ongoing technological progress around banks and finance, might not reflect future performance. For example, we found no major differences across community banks which fell or did not fall under Basel III capital requirements, but Regmi and Miller (2024) found such differences around the COVID-19 pandemic. Another limitation is due to the absence of detailed returns for different loan types in the FDIC Call Reports; with such data, the specific returns to agricultural lending could be pinpointed more precisely.

Regardless of future research, it is reasonable to conclude that general specialization has effects on bank performance, particularly in terms of risk-reward trade-offs for large banks. However, the particular type of specialization matters, and the findings here suggest small-sized banks, specializing in agricultural lending and located in rural areas, have a significant competitive advantage. While the results might be interpreted as supportive of allowing private sector banks to take on the lending currently occurring under the FCS and FSA, we do not share that interpretation. Indeed, it seems likely that those entities, along with crop insurance programs, help to explain why small-sized banks are so successful in terms of agricultural specialization in rural locations.

## Notes

1. See https://www.fca.gov/about/history-of-fca
2. See https://sbgfunding.com/ppp-vs-eidl-a-side-by-side-comparison/
3. See https://www.farmers.gov/archived/cfap2

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## Further reading

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**Supplementary material**
The supplementary material for this article can be found online.

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