The Boundaries of the Farm and the Death of Small Banks

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Abstract

Using a novel source of exogenous variation in borrowers' structure driven by subsidy-induced consolidation in the agricultural sector, I show that as farms consolidate, large banks capture a greater share of deposits because large borrowers demand large loans, creating a comparative advantage for large banks. In response, large banks expand their branch networks and small bank mergers become more common, creating more concentrated local credit markets. The resulting structure reduces competition and reduces local deposit rates. These findings reveal how consolidation in the real economy can drive structural change within the banking sector and affect credit pricing.

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1 Introduction

How do lenders respond to consolidation in the industries to which they lend? Over the past few decades, firm consolidation has been widespread, with more than 75% of U.S. industries experiencing an increase in concentration (Grullon, Larkin, and Michaely (2019)). Prior research shows that in product markets, consolidation among buyers strengthens their bargaining power, leading suppliers to cut prices, merge, or exit (Galbraith (1952); Fee and Thomas (2004); Becker and Thomas (2009); Bhattacharyya and Nain (2011)). In credit markets, where banks are the suppliers of credit, the implications of borrower consolidation are less clear.

Following from industrial organization (IO) theory, as smaller borrowers are acquired and the remaining firms expand in scale, credit demand may shift toward larger loans, allowing banks with the capacity to supply them to gain market share and increasing concentration in the financial sector (Galbraith (1952); Snyder (1996)). Yet, banking theory shows that incumbent banks have informational advantages, making it costly for borrowers to establish new ties and for new banks to enter (Diamond (1984); Rajan (1992); Boot (2000); Dell'Ariccia (2001)). When small businesses consolidate, they may maintain their existing relationships with the banks that initially financed them, consistent with Brennecke, Jacewitz, and Pogach (2025). In this case, consolidated firms may channel new credit demand toward these incumbent lenders, limiting the extent to which industry consolidation reorganizes the structure of banking markets.

This paper establishes a causal connection between the consolidation of product markets and the structure of financial markets. Using an exogenous shock to an industry's optimal firm size, I show that borrower consolidation reorganizes local banking markets, altering the composition of lenders and the interest rates offered on broader retail financial products. As the average borrower becomes larger, large banks gain more deposits and expand their branch networks relative to small banks, suggesting that lending relationships tied to firm size do not persist once firms expand.

To test whether firm consolidation changes the structure of banking markets, I use a policy shock that accelerated the consolidation of borrowers in U.S. agriculture. The 1996 Federal Agriculture Improvement and Reform (FAIR) Act replaced six decades of price supports, which guaranteed farmers a price floor, with fixed, decoupled payments based on a farm's historical base acres and yields from 1981 to 1985. Unlike earlier subsidy programs that tied payments to planting decisions, the FAIR Act was intended to reduce government intervention and let production decisions follow market demand. The policy applied to major "commodity" crops (wheat, corn, sorghum, barley, oats, rice, upland cotton, and

later oilseeds and peanuts), whose profitability primarily depends on expanding acreage and lowering per-unit costs through scale economies (Duffy (2009); Langemeier (2013); Sumner (2014)). By providing predictable cash transfers to otherwise liquidity-constrained farms (Khanal and Omobitan (2020); Thakor (2023)), the program enabled larger operations to borrow, expand landholdings and equipment investments, and exploit economies of scale, which accelerated consolidation (Becker (2001); Roberts and Key (2008)).

I construct an instrumental variable (IV) using a difference-in-differences model in the first stage that exploits variation in predicted subsidy payments to isolate exogenous shifts in farm consolidation. The instrument assigns estimated county-year subsidy exposure based on historical crop shares that farmers could not have anticipated at the time they made those planting decisions and national, crop-specific subsidy rates that were set uniformly by federal policy from 1996 to 2014. Because the agricultural industry is place-based, local lenders typically play a central role in credit provision to farms, making this an ideal setting to study how borrower-side consolidation affects local banking markets (Akhavein et al. (2004)).

Following the agricultural economics literature, I measure county-level farm concentration using harvested acre-weighted median farm size (the "midpoint") (Roberts and Key (2008)). In the first stage of my IV strategy, I use a continuous difference-in-differences design to estimate whether increased subsidy payments lead to increased farm concentration. Consistent with the findings of Roberts and Key (2008), I first document that subsidy payments contribute to a total increase of 390 acres in county-level farm concentration over 15 years, equivalent to about 52% of the average midpoint farm size. I then use this variation as an instrument for borrower consolidation. A within-county one-standard-deviation increase in predicted farm concentration of about 370 acres leads to an 8% rise in local banking concentration, comparable to one out of seven banks exiting a county. A simple back-of-the-envelope calculation suggests that, by 2014, about 12% of the observed increase in local banking concentration is attributable to subsidy-induced farm consolidation. Importantly, if farm consolidation drives banking consolidation, the effect should be most visible in areas where the policy shock matters. I find that banking consolidation is concentrated in rural counties, where agricultural activity dominates the local economy, and absent in urban counties, where the agriculture-specific shock has little relevance.

My identification strategy isolates the causal effect of farm consolidation on bank consolidation only through the component of farm consolidation that is driven by the subsidy payments. The exogeneity of the instrument rests on two key features. First, historical crop shares were determined before the policy was enacted, and second, national subsidy rates are uniform, predetermined in six-year intervals with each farm bill authorization, and set

independently of local economic conditions. I also include county and year fixed effects and control for banking deregulation using Célerier and Matray (2019)'s state-year-level index. A strong first-stage relationship further supports the interpretation that shifts in borrower structure, rather than changes in banking structure, drive the results.

Borrower consolidation may not only increase local credit market concentration but also change the composition of banks. Because of balance sheet constraints and regulatory rules, small banks may be unable to finance the larger loans demanded by consolidated borrowers. In 2004, banks warned the Office of the Comptroller of the Currency that the single-borrower cap of 15% of risk-based capital reduced community banks' competitiveness, as farm consolidation had "resulted in fewer, but larger, farms with expanded credit needs" (Office of the Comptroller of the Currency (2004)). Even after the cap was raised, lending limits remained binding for many small agricultural banks (Ellinger (2012)), suggesting that small banks may be structurally disadvantaged when serving larger borrowers. In contrast, large banks may be better positioned to expand in consolidating markets.

Moreover, the traditional advantages of small banks, relationship lending and the use of soft information, become less valuable as borrowers grow (Petersen and Rajan (1994)). As borrowers consolidate, their financing needs may shift toward hard-information-intensive credit products, such as larger and more diverse credit lines. Large banks, with broader product offerings and larger internal capital markets, may be better positioned to meet these demands (DeYoung, Hunter, and Udell (2004); Berger et al. (2005)). As a result, borrower consolidation may reallocate market share within local credit markets toward large entrants and away from smaller incumbents (Dell'Ariccia and Marquez (2004)).

I find that borrower consolidation reallocates credit toward banks with the scale and capacity to serve larger borrowers, while smaller banks adapt primarily through consolidation rather than expansion. On the extensive margin, large banks are about 4% more likely to be present in consolidated counties following a within-county one-standard-deviation increase in farm concentration. On the intensive margin, they expand more aggressively once present, adding about 17% more new branches and increasing their deposits per resident by 27% every five years. In contrast, mergers among small banks increase, but those among other banks remain unchanged. These results suggest that small banks, facing lending constraints due to their size, adapt through consolidation, whereas large banks increase their presence and market share.

In counties where farming is more costly and capital-intensive, consolidated farms are likely to require a greater amount of capital to fund their next investment. When small banks are unable to provide the capital that farms require, large banks have greater scope to expand their market share. In high-cost counties, defined as those where the average cost to

farm one acre is above the nationwide median, large banks' deposits per capita increase by about 33%, compared to 7% for small banks. In contrast, in low-cost counties, small banks increase their deposits per capita by about 18%, while large banks show no statistically significant change. These results suggest an IO-driven channel in which large banks expand most in capital-intensive markets where small banks are more likely to be capital constrained.

If large banks enter primarily to serve larger borrowers, their share of agricultural loan growth should increase. Using imputed county-level data (following Key, Burns, and Lyons (2019) and Ifft et al. (2024)), I find that a within-county one-standard-deviation increase in farm concentration increases large banks' share of total agricultural lending growth by about 50%. Agricultural lending by small banks increases by one-seventh of the increase among large banks. Decomposing by loan type, real estate loan growth, collateralized by farmland, increases by about 50% for large banks but remains flat for small banks, consistent with small banks being unable to extend loans that match the collateral value of consolidated farms. For non–real estate loans, which are used to finance agricultural production, both large and small banks contribute to increased lending, but large banks expand their volumes by nearly three times as much, suggesting that borrower consolidation primarily benefits institutions capable of serving larger clients.

The effects are even larger for banks that specialize in agricultural lending. In response to a within-county one-standard-deviation increase in farm concentration, the likelihood that a large agricultural bank is present in a county is more than three times higher than for large banks overall. Their deposits per capita also increase by 74% following a within-county one-standard-deviation increase in farm concentration, compared with a 21% increase among small agricultural banks. The effect of farm concentration on lending is similarly amplified within this subset: agricultural lending volumes increase by 123% for large agricultural banks and by 8% for small agricultural banks. These results suggest that the shift toward large banks is not just market-wide. Large agricultural banks, with the necessary scale and relevant industry expertise, capture a greater share of market growth in the actively consolidating industry.

The results indicate that deposit growth generated by subsidy-induced farm consolidation accrues primarily to large agricultural banks. I then consider a counterfactual in which the subsidy-induced increase in total deposits per capita is allocated based on small and large agricultural banks' local market share. Under this counterfactual, small agricultural banks would have experienced about 24% higher deposit growth, equivalent to about $66 million per county, in markets where large banks operate. By contrast, in the absence of subsidy-induced consolidation, deposit growth at large agricultural banks would have been about 42% lower, compared with a 6% reduction for small agricultural banks. These counterfactuals

show that farm consolidation reallocates deposit growth toward larger, more agriculturally specialized banks rather than generating uniform expansion across institutions.

Having shown that borrower consolidation influences the structure of local banking markets, I next study its effects on the prices offered by commercial banks for broader consumer financial products. Existing IO theory shows that the effect of buyer consolidation on supplier prices depends on the competitiveness of the supplier market (Galbraith (1952); Snyder (1996); Chipty and Snyder (1999)). On the one hand, if suppliers have market power, buyer consolidation weakens competition among buyers for suppliers and leads suppliers to lower prices for all buyers in the market (Galbraith (1952); Snyder (1996)). On the other hand, if suppliers are able to price discriminate, buyer consolidation may lead them to lower prices for large buyers while raising prices for smaller ones (Inderst and Valletti (2011)). Within my setting, Kropp and Whitaker (2011) document that farms with a greater share of base acres, and therefore larger relative cash payments under the FAIR Act, receive lower interest rates on their operating loans, potentially because these subsidies provide a risk-free source of income. However, it remains unclear whether or how changes in borrower structure spill over into broader consumer financial markets. In more consolidated local markets, banks could raise prices by exercising market power or lower them to attract deposits and retail customers.

To test the spillover effects, I examine interest rates on consumer financial products offered by banks, focusing on deposit accounts and auto loans. Following Drechsler, Savov, and Schnabl (2017), I study the inflation-adjusted interest rates offered on three deposit products: savings deposits ($10,000 money market accounts), checking deposits (interest-bearing checking accounts), and time deposits (12-month $10,000 certificates of deposit, or CDs). I find that interest rates on savings and checking deposits fall by 24 and 13 basis points, respectively. The magnitudes are large: real interest rates decline by 20% and 8% relative to their unconditional means, respectively.

On the lending side, I analyze the offered interest rates on auto loans, which are standardized, broadly held products unrelated to farm lending, making them a useful test of spillovers into consumer credit markets. I find that auto loan interest rates increase by about 88 basis points, on average. These results show that borrower consolidation changes the structure of local banking markets, with important follow-on effects on consumer credit prices.

2 Literature Contributions

This paper contributes to five strands of literature by introducing borrower consolidation as a structural shift in credit demand that alters the supply and composition of financial

intermediation.

First, it contributes to the literature on the connection between product and credit markets. Prior work shows that credit markets affect product market outcomes, as leverage can commit firms to more aggressive output, and banks can influence competition among firms in product markets by limiting entry and softening price competition (Brander and Lewis (1986); Cetorelli and Strahan (2006); Saidi and Streitz (2021)). Other works show that banking concentration affects deposit pricing, loan spreads, and firm dynamics (Berger and Hannan (1989); Drechsler, Savov, and Schnabl (2017); Nguyen (2019)). However, it is difficult to view this as the only source of connection between lender and borrower concentration, because as borrowers grow in scale and complexity, their financing needs evolve, changing not only how much they borrow but also, possibly, from whom. I establish a causal connection between the structure of product market industries and financial industries that adds an additional dimension to what prior studies show. Recent empirical work finds that declines in small firm growth reduce deposit growth at small banks, indicating that the decline of one customer base affects the growth of the banks that serve them (Brennecke, Jacewitz, and Pogach (2025)). I show that when small businesses grow and consolidate, the additional credit demand does not increase deposit growth at small banks. Instead, borrower consolidation reorganizes local banking markets, with large banks entering affected markets, expanding their deposit base and branch networks, and changing the composition of local banking.

Second, this paper contributes to the literature on the determinants of firm boundaries. Coase (1937) focuses on vertical integration, and subsequent work emphasizes how organizational scale shapes the set of activities firms can efficiently undertake (Berger et al. (2005)). In my setting, fixed subsidy payments relax financing constraints and facilitate land acquisition, expanding the scale and boundaries of the farm through consolidation. As the average farm grows larger, the changes in the boundaries of the farm lead to changes in local banking market structure.

Third, it contributes to research on the determinants of banking market structure. Prior work emphasizes supply-side drivers of consolidation such as deregulation, technology, and economies of scale (Jayaratne and Strahan (1998); Berger, Demsetz, and Strahan (1999); Calomiris (2000)). I highlight a complementary demand-side channel, which follows from IO theory and empirical work showing that buyer concentration can cause supplier concentration (Galbraith (1952); Fee and Thomas (2004); Becker and Thomas (2009)). Becker and Thomas (2009) find that, across industries, increases in buyer concentration lead to supplier consolidation. However, in credit markets, banks of different sizes tend to have different comparative advantages. Small banks rely on soft information and local ties (Petersen and

Rajan (1994); Berger and Udell (1995); DeYoung, Hunter, and Udell (2004)), while large banks specialize in standardized and scale-intensive lending (Boot and Thakor (2000); Berger et al. (2005); Alessandrini, Presbitero, and Zazzaro (2009)). I find evidence suggesting that borrowers switch lenders despite established relationships, indicating that growth in borrower scale may alter the loan amount and type of credit services they demand. Moreover, building on Brickley, Linck, and Smith (2003), who show that large banks concentrate in urban areas where borrower scale supports centralized operations, I demonstrate that industry consolidation can change the composition of borrowers and induce entry by large banks into markets they previously avoided.

Fourth, it relates to research on banking structure and real economic outcomes. Prior studies show that bank market power affects firm entry, competition, and community development (Strahan and Weston (1998); Cetorelli and Strahan (2006); Garmaise and Moskowitz (2006); Nguyen (2019); Saidi and Streitz (2021)). Higher banking concentration is associated with lower deposit rates, higher loan spreads, and higher markups (Berger and Hannan (1989); Neumark and Sharpe (1992); Drechsler, Savov, and Schnabl (2017); Bord (2017); Buchak and Jørring (2021)). My findings add a borrower-driven mechanism to this literature by showing how shifts in industry structure spill over into retail financial products. Kropp and Whitaker (2011) find that farms with a greater share of base acres, and thus higher fixed subsidies relative to farms with fewer base acres, receive lower interest rates on operating loans. I complement this result by showing how the changing structure of borrowers and lenders widens retail interest margins by increasing loan rates and decreasing deposit rates. Thus, this paper also adds to the literature using agriculture as a setting to study wider financial markets (Butler and Cornaggia (2011); Rajan and Ramcharan (2015); Carlin and Mann (2017)).

Lastly, I contribute to research on agricultural finance and the role of federal policy in structuring rural credit markets. Existing work documents how decoupled subsidy programs influence land allocation, farm consolidation, and credit access (Burfisher and Hopkins (2003); Roberts and Key (2008); Coble et al. (2008); Bhaskar and Beghin (2010); Gardner, Hardie, and Parks (2010); Bekkerman, Belasco, and Watson (2015); Ifft, Kuethe, and Morehart (2015)). I show that these policy-induced shifts in farm structure trigger broader changes in local financial intermediation as borrower consolidation pushes credit demand toward larger institutions.

3 Institutional Background

The 1996 FAIR Act marked a sharp break from 60 years of price-contingent farm support. Since the New Deal, federal policy had stabilized farm income through a combination of price floors, nonrecourse loans, and countercyclical deficiency payments (Effland (2001)). In exchange for these supports, farms had to maintain base acreage allocations, meaning that program payments were tied to the production of designated crops on enrolled land.

The FAIR Act replaced this system with seven years of fixed annual payments determined solely by a farm's historical acres and yields, regardless of current production or prices (Coble et al. (2008)). The key innovation was to decouple support from planting decisions, current yields, and market prices, allowing farmers to respond to market signals rather than government incentives.[1] Payments were determined by the number of base acres, defined as the average number of acres planted of program crops (wheat, corn, sorghum, barley, oats, rice, and upland cotton) between 1981 and 1985. The move toward decoupled payments aimed to reduce production distortions, phase down subsidies, and comply with World Trade Organization (WTO) rules.

The FAIR Act removed planting restrictions, so farms with more base acres automatically received higher payments, regardless of what they planted or produced. Although the federal government limited payments to $180,000 annually per person classified as actively engaged in farming, many large farms bypassed these limits by subdividing operations into multiple entities or assigning ownership shares to passive investors (United States General Accounting Office (2004)).

Between 1996 and 2014, the federal government disbursed about $89 billion, or about $4-6 billion per year, in direct payments. At the time of implementation, the program represented the bulk of all federal support for farmers: by 1998, about 79% of all subsidies under the FAIR Act were distributed as direct payments (Williams-Derry and Cook (2000)). The payments were not only important for farms' financial health (Ifft et al. (2012)) but also predictable and likely capitalized into land values and rents (Kropp and Katchova (2011); Paulson (2011)). According to the Government Accountability Office (GAO), the top 25% of recipients collected 73% of all direct payments in 2011 (United States Government Accountability Office (2012)). To illustrate the magnitude of these payments, in 1998, the average direct payment for large farms of about $30,000 would have covered the annual interest payments on a 500-acre farm in Texas at prevailing market rates, an operation about double

[1] See Statement on Signing the Federal Agriculture Improvement and Reform Act of 1996 (https://www.presidency.ucsb.edu/documents/statement-signing-the-federal-agriculture-improvement-and-reform-act-1996).

the size of Rice University or the size of about 380 football fields.[2]

Congress renewed the program in 2002 under the Farm Security and Rural Investment (FSRI) Act, which expanded eligibility to include oilseeds, such as soybeans and peanuts, and allowed base acres to be updated based on average plantings between 1998 and 2001. In 2008, the federal government renewed the program again but without adding new crops or updating base acres. Figure 1 shows a timeline outlining the policy changes.

[Insert Figure 1 Here]

There was substantial consolidation in farming during the period I study. Although the number of farms nationwide remained relatively stable, their size distribution changed. From 1992 to 2012, the number of large and very-low-sales farms nearly doubled, while small commercial and midsized farms declined (Burns and Kuhns (2016)). In my sample, the average number of farms per county remains within a narrow range, between 650 and 750 from 1992 to 2012, but the average midpoint farm size nearly doubles. Thus, during the observed time period, the primary structural change is a redistribution across farm sizes.

4 Hypothesis Development

This section outlines the mechanisms through which borrower consolidation influences the structure of rural credit markets. The argument proceeds in three steps. First, fixed-cash subsidies relax farms' financial constraints, enabling investment and expansion, particularly among large farms. These investments increase midpoint farm size and accelerate consolidation. Second, as farms grow, credit demand shifts toward larger loans and more sophisticated financial products. Third, banks respond to this evolving borrower landscape: institutions equipped to meet these financing needs expand their footprint, while others exit, merge, or scale back. These changes in the composition of borrowers and lenders may ultimately affect the pricing of consumer financial products in rural communities.

Commodity crop producers have strong incentives to expand. Advances in mechanization, chemical inputs, and crop management practices lower the marginal cost of managing additional acres, making expansion more efficient (Paul and Nehring (2005); Duffy (2009)). Due to high costs and increasing returns to scale, larger farms enjoy lower average costs than smaller farms and account for a growing share of production (Hoppe and Banker (2006); Khanal and Omobitan (2020)). In competitive commodity markets where farms are price

[2]Based on Texas average cropland values in 1998 of $701 per acre and the average interest rate on farm loans in Texas of 8%. See Agricultural Land Values (https://downloads.usda.library.cornell.edu/usda-esmis/files).

takers (Stiers (2022)), expansion becomes the primary strategy to improve margins and cost efficiency (Langemeier (2013); Hoppe (2014)).

Yet expansion requires capital. Land acquisition, machinery purchases, and seasonal operating inputs require substantial upfront investment. Many farms operate with limited internal liquidity or collateral, making them reliant on external finance to fund growth (Hubbard and Kashyap (1992); Barry, Bierlen, and Sotomayor (2000)). Interviews with farmers further confirm that cash constraints remain a central obstacle to investment (Thakor (2023)).

Cash subsidies may help relax these constraints. The fixed direct payments introduced by the 1996 FAIR Act provided farms with predictable annual transfers tied to historical base acres. Because base acres were correlated with farm size, larger farms systematically received larger total payments (Young and Westcott (2000); Roberts and Key (2008)). These payments increased liquidity, particularly for large operations. Anecdotally, reports from the time suggest that large farms used these subsidies to go out "trolling for land".[3] Thus, these subsidies may have incentivized larger farms to actively pursue land acquisitions, accelerating the pace of consolidation.

Debt can scale farm expansion. Between 1994 and 2017, total farm sector debt rose by 69% in real terms, reaching $348 billion in 2017 dollars (U.S. Department of Agriculture Economic Research Service (2025)). Most of this increase came from real estate borrowing, supported by rising farmland values and stronger collateral positions, which may themselves have been influenced by the capitalization of fixed payments (Ciaian and Swinnen (2009); Ifft et al. (2012); Kuethe (2015)). Credit use also differs sharply by farm size. Between 1996 and 2014, 73% of farms with under $100,000 in sales carried no debt, compared to only 33% of farms with over $1 million in sales, on average (U.S. Department of Agriculture, Economic Research Service and National Agricultural Statistics Service (1996)). These facts suggest that debt markets play an important role in financing agricultural investments, particularly among large farms.

As farms grow larger, the nature of credit demand shifts. Larger borrowers require more diverse, multi-purpose credit, spanning land, equipment, working capital, and operating lines. Predictable cash subsidies facilitate this transition by both financing expansion and enhancing borrower balance sheets, improving repayment capacity, and reducing perceived credit risk (Kropp and Katchova (2011)). Theoretically, higher net worth mitigates moral hazard by improving borrower incentives and reducing monitoring costs (Holmstrom and Tirole (1997)). Empirically, farms with more base acres receive lower interest rates on operating loans (Kropp and Whitaker (2011)), and farms with higher net worth obtain more

[3]See Federal Subsidies Turn Farms Into Big Business (https://www.washingtonpost.com/archive/politics/2006/12/21).

favorable lending terms (Hubbard and Kashyap (1992); Roberts and Key (2008)). Lastly, when credit conditions ease, such as when the average borrower's liquidity increases, banks expand lending (Jiménez et al. (2014)). Together, these factors suggest that a more liquid borrower pool may change how credit is allocated. These mechanisms are illustrated in a model in the Internet Appendix.

Small banks have traditionally maintained a comparative advantage in lending to small, opaque farms through relationship lending and local information advantages. But as farms consolidate and become more creditworthy and transparent, these informational advantages diminish. Moreover, the financing needs of large farms often exceed the lending capacity of small institutions (LaDue and Duncan (1996); DeYoung, Hunter, and Udell (2004)). In contrast, large banks are better positioned to serve these borrowers due to their deeper balance sheets, geographic diversification, and specialized lending teams. It follows that borrower consolidation may induce shifts in the structure of rural banking markets. Large banks may be more likely to enter or expand in areas where borrower scale increases, whereas small banks may lose market share, merge, or exit.

5 Data Sources and Sample Construction

To examine how borrower consolidation influences rural banking markets and financial outcomes, I construct a panel dataset linking county-level farm structure with bank-, branch-, and product-level financial data from 1992 to 2014. This section outlines the measurement of key dependent variables, instrumental variables, and controls. Technical details, such as variable construction, are provided in Appendix B.

5.1 Dependent Variables

The core banking market outcomes include measures of local concentration, bank composition, and consolidation activity. I measure banking concentration using the Herfindahl-Hirschman Index (HHI), calculated from the FDIC's Summary of Deposits (SOD). For each county-year, I compute the deposit share of each bank, square the shares, and sum them to obtain a concentration index ranging from 0 to 10,000, where 10,000 indicates a monopoly and lower values reflect greater competition. To capture changes in the composition of banks, I merge SOD data with the Federal Financial Institutions Examination Council's (FFIEC) Consolidated Reports of Condition and Income (Call Reports) to classify each branch as belonging to a small or large bank based on a $10 billion, inflation-adjusted asset threshold. This threshold follows the Federal Reserve's definition of community banks as institutions

with under $10 billion in assets.[4] I then construct the number of branches and total deposits per capita in each county separately by bank size. I use county-year population estimates from the Bureau of Economic Analysis (BEA).

To track consolidation activity, I use the Chicago Federal Reserve's Bank Merger database to construct three county-level outcomes aggregated over five-year intervals. The first, *Large Acquires Small*, measures the total number of mergers or acquisitions in which a large bank acquires or merges with a small bank. The second and third, *Small Acquires Small* and *Large Acquires Large*, capture the total number of mergers or acquisitions between two small banks and between two large banks, respectively.

I also measure each bank's exposure to agriculture using data on farm real estate loans and loans for agricultural production and farm-related activities from Call Report Schedule RC-C. I classify a bank as an agricultural lender if the share of agricultural loans in the bank's total portfolio exceeds 5% in any of the last five years. To estimate county-level farm loan volumes, I allocate each bank's agricultural lending across the counties in which it operates, using a weighted average based on each county's share of total interest expenses on farm real estate and non-real estate loans, as reported in the most recent Census of Agriculture. For example, if a bank operates in three counties with equal farm interest expenses, I allocate one-third of its total agricultural lending to each county. I repeat this process for each bank and aggregate separately for small and large banks. This approach follows similar allocation strategies used in Key et al. (2019) and Ifft et al. (2024). I then construct three variables by bank size: *Total Agricultural Loan Growth*, *Real Estate Loan Growth*, and *Non-Real Estate Loan Growth*. For each loan type, I define agricultural loan growth as the loan volume of small or large banks relative to the prior period's total agricultural loan volume. This ratio captures how much each group contributes to the overall expansion in agricultural lending across counties and years.

Although this method serves as a proxy for county-level farm loan volumes, it has limitations. First, banks may lend outside their branch networks, which is not captured. Second, the weighted average assumes that banks lend proportionally to historical local demand, proxied by interest expenses, which may not reflect current lending behavior. Nonetheless, the method provides evidence on the geographic distribution of agricultural lending.

To examine how borrower consolidation and subsequent bank responses affect pricing in consumer financial markets, I use deposit and loan interest rate data from RateWatch. I focus on time deposits (12-month $10,000 CDs), savings deposits ($10,000 money market accounts), checking deposits (interest-bearing checking accounts), and auto loans. I convert the interest rates to real terms using the annual inflation rates from the Bureau of Labor

[4]See Community & Regional Financial Institutions (https://www.federalreserve.gov/supervisionreg).

Statistics (BLS). Because the FDIC collects the SOD data in June, I average interest rates over a 12-month window from July of the previous year through June of the current year to align the rate data with the SOD reporting period.

To assess the effect of market-driven consolidation on loans to small farms, I also use data on direct loans issued by the USDA's Farm Service Agency (FSA). These loans are targeted to small, new, or socially disadvantaged farmers who cannot access commercial credit. I aggregate the number and volume of direct ownership and operating loans at the county-year level from 1994 to 2014.

5.2 Instrumental Variable: Borrower Consolidation

The public Census of Agriculture reports only the number of farms within acreage categories (e.g., 1–9, 10–49, 50–69, 70–99, ..., 1000–1999, and 2000+ acres), so individual farm sizes are not observed. To compute traditional concentration measures such as the HHI, each farm in a bin would be assigned the same average acreage. For example, a 2,500-acre farm and a 25,000-acre farm in the "2000+ acres" bin would contribute equally to the HHI calculation. Because the upper bins span very wide acreage ranges, this method effectively treats all large farms as the same size. Doing so would tend to introduce bias by Jensen's inequality, since the sum of squared average farm sizes is exceeded by the sum of squared farm sizes. This bias would be largest in the larger farm size buckets, making HHI an unreliable measure of farm concentration.

Given the structure of the data, I follow standard practice in agricultural economics and measure borrower consolidation using the harvested acre-weighted median farm size (the "midpoint") from the USDA's Census of Agriculture (Key and Roberts (2006)). The midpoint is defined as the acreage at which half of a county's harvested cropland lies on larger farms and half on smaller farms. For example, if a county has 2,800 total harvested acres and the eight smallest farms account for 1,400 acres, then the ninth-smallest farm marks the midpoint. If that farm operates 700 acres, then the midpoint farm size is 700 acres. This approach is standard in the literature for two reasons. First, individual farm sizes are not publicly reported. Second, the production distribution is highly skewed: a small number of very large farms harvest most cropland, while the majority of farms remain small. The midpoint therefore more accurately captures shifts in the scale of production than the simple median.

To address endogeneity concerns, I instrument for farm concentration using county-level exposure to fixed-cash subsidies under the 1996 FAIR Act and subsequent updates in 2002 and 2008. I use the total number of county-level base acres per crop and the nationally allocated annual subsidy amount per crop to determine estimated annual subsidy amounts. The

farm concentration measure is lagged by two years to allow time for borrower consolidation to influence downstream banking outcomes.

5.3 Controls

To account for local land-use patterns, I include several county-level farmland controls from the Census of Agriculture: idle cropland, pastureland, and unharvested cropland (Weber and Key (2012)). I also include economic controls from the BEA, including per capita income and the employment rate. For additional analyses, I use measures of the lagged log number of total branches and the log of total interest expenses on farm loans. To study the effect of crop insurance on my results, I include the number of crop insurance policies on the relevant commodity crops from the Risk Management Agency (RMA) under the USDA. To account for the effects of the Farm Credit System (FCS) on commercial banks' consolidation, I incorporate historical FCS branch locations provided by the Farm Credit Administration.

To examine heterogeneous effects in rural areas, I use county classifications from the National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme from 2000 and 2010. I define urban counties as those designated as large central metropolitan areas, metro counties as those designated as broader metropolitan or micropolitan areas, and rural counties as non-core counties. In similar analyses, I use the 2010 Terrain Ruggedness Index (TRI) from the USDA Economic Research Service (ERS) to assess whether the effects of subsidy-induced consolidation differ in areas where large-scale farming is less likely. Counties with an average TRI in the top quartile of the national distribution are classified as rugged terrain areas, while all others are classified as flat-terrain areas. Figure A.1 shows the distribution of U.S. counties by average terrain ruggedness across quartiles.

Lastly, I estimate each major commodity crop's (barley, corn, oats, peanuts, soybeans, sorghum, upland cotton, and wheat) five-year average per-acre economic cost using data from the Farm Costs and Returns Survey (FCRS) from 1990 to 1995, compiled by the U.S. Department of Agriculture's Economic Research Service (ERS), to reflect conditions prior to the start of the subsidy program. I then compute a time-invariant, county-level weighted average of these costs based on each crop's share of harvested acres from the 1992 Census of Agriculture. Counties with weighted average per-acre economic costs above the nationwide median are classified as high-cost, while those below the median are classified as low-cost. Figure A.2 shows the distribution of high- and low-cost agricultural counties across the U.S.

5.4 Sample Construction and Summary Statistics

My primary analysis uses a county-level panel observed in five-year intervals between 1994 and 2014. The USDA Census of Agriculture provides farm structure data every five

years, which I merge with banking data from the FFIEC's Call Reports and FDIC's SOD for the corresponding periods between 1994 and 2014. Farm variables are lagged by two years to allow sufficient time for structural changes in agriculture to influence banking outcomes. I exclude 57 large central metropolitan counties from the main sample to focus on counties where agriculture may be a dominant industry. To avoid overstating economic magnitudes, the measure of farm concentration is standardized within counties across time (Liu and Winegar (2025)).

For the analysis of interest rate outcomes, I construct a separate annual panel from 2002 to 2014, merging branch-level data from RateWatch with bank- and county-level information from the SOD and Call Reports. I estimate fitted farm concentration using the Census of Agriculture, which is available every five years. In interim years, I use the most recently available fitted value of farm concentration. This method preserves the structural variation identified at the census years while allowing annual fluctuations in local economic conditions to enter through time-varying controls in the second-stage regressions. The approach reflects the gradual nature of farm consolidation and assumes slow-moving structural change between census years. This assumption is supported by the data in that farm concentration, measured by midpoint acreage, increases by about 2.5% per year on average. All results are robust to using linearly interpolated farm concentration values as well. I align interest rates with SOD data timing by averaging weekly observations over a July-to-June window.

Table 1 presents summary statistics. Agricultural subsidies are widespread and highly skewed. On average, counties receive $1.35 million in subsidies per year, with a standard deviation of $1.84 million between counties and $1.18 million within counties over time. These summary statistics suggest that there is substantial cross-sectional and time-series variation in subsidy exposure.

[Insert Table 1]

6 Identification Strategy

There are two main challenges with studying the effect of borrower consolidation on the structure of local credit markets. First, borrower consolidation and bank consolidation may be jointly driven by local characteristics. For example, rural areas with limited economic activity may have fewer banks and fewer, but larger, farms simply due to low population density or substantial land availability. The second is due to reverse causality. Banking consolidation may itself induce borrower consolidation. In areas with more concentrated banking markets, limited competition can restrict capital access for smaller farms. These farms may be forced to exit or sell to larger operators, accelerating consolidation. Alternatively, a larger, more

consolidated banking sector, less suited to lend to informationally opaque borrowers, may have a preference for lending to larger farms (Berger and Udell (2002)). In both scenarios, the structure of the local banking market could itself cause borrower consolidation.

To address these concerns, I use a shift-share-like IV strategy that isolates variation in the optimal size of farms that is unlikely to reflect local credit market conditions. The instrument measures county-level exposure to fixed subsidy payments introduced under the 1996 FAIR Act and extended through the 2002 FSRI Act and the 2008 Food, Conservation, and Energy Act. These programs replaced price-contingent support with fixed payments based on historical planting patterns, fully decoupled from current production or market conditions (see Section 2 for institutional background). Historical planting patterns were determined by base acres and yields, initially based on 1981–1985 averages and later updated in 2002 using 1998–2001 patterns.

The instrument is defined as the inner product of (a) each county's fixed crop-level base acre shares and (b) the national crop-level subsidy amounts in a given year from 1996 to 2014, when the program ended. For example, if a county holds 1% of the nation's corn base acres and the national allocation for corn is \$2 billion in a given year, that county would be assigned an exposure of 1% $\times$ \$2 billion. Base acres are fixed in advance, determined by planted acres from 1981 to 1985 or, for farms that updated in 2002, from 1998 to 2001. The national allocations vary over time and apply uniformly across all counties. Thus, the identifying variation comes from changes over time in national payment levels for each crop interacted with county-level crop shares, as measured by their crop-level base acres. Because both components are determined outside the local banking environment, one by historical planting decisions and the other by national policy, the resulting variation in exposure is plausibly exogenous with respect to local credit conditions.

This identification strategy addresses concerns of reverse causality. For reverse causality to invalidate the instrument, banking consolidation would need to be systematically correlated with subsidy exposure in a way unrelated to expansion, since the instrument extracts the component of farm consolidation that is due to federal subsidies. Reverse causality would be a concern if, for instance, banks consolidated in anticipation of the policy or if historical crop shares predicted future credit market conditions. This is unlikely. The 1996 FAIR Act marked a sharp and largely unexpected break with six decades of price-contingent support, facing considerable political uncertainty and multiple filibusters prior to passage (Orden et al. (1999)). As a result, the policy was not easily anticipated by banks, and planting decisions made more than a decade earlier are unlikely to reflect expectations about future credit conditions. Finally, I lag farm concentration by two years in all baseline specifications to study the subsequent effect on banking consolidation. The results remain robust to alternative lag

structures, including three- and four-year lags (Table A.1).

I construct a difference-in-differences-style instrument that captures county-level exposure to policy allocated pre-announced national subsidies. The specification is:

$$\textit{Farm Concentration}_{i,t} = \beta_1 \sum_c \left(\frac{\textit{Base Acres}_{c,i,t}}{\textit{Base Acres}_{c,t}} \times \textit{Natl Allocation}_{c,t} \right) + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}, \quad (1)$$

where c represents the crop type, i represents the county, t represents the year, and d represents state-level banking deregulation. $\textit{Base Acres}_{c,i,t}$ is the number of historical base acres of crop c in county i and year t, and $\textit{Natl Allocation}_{c,t}$ is the total federal subsidy amount allocated for a given crop and year. $\textit{Base Acres}_{c,t}$ is the total number of historical base acres in the U.S. of crop c in year t. $\mathbf{X_{i,t}}$ is a vector of control variables, including county-level economic characteristics and farm characteristics to control for land availability. These controls include employment rate, log income per capita, and lagged measures of idle cropland, pastureland, and cropland left fallow, lost to crop failure, or otherwise unharvested. I include a fixed effect for state-level branching deregulation using the index from Célerier and Matray (2019), which captures the staggered implementation of interstate branching reforms between 1994 and 2005. County and year fixed effects absorb time-invariant county characteristics and national shocks. Identification therefore comes from changes in national subsidy amounts and base acre allocations within a county.

The dependent variable, $\textit{Farm Concentration}_{i,t}$, is measured as the midpoint farm size (see Section 5.2 for details). Figure 2 presents the estimated effect of subsidy exposure on farm concentration using the estimator defined by De Chaisemartin and D'Haultfœuille (2020) to accommodate continuous treatment. The county-level midpoint farm size increases by about 390 acres, or about 52%, over the full sample period.

[Insert Figure 2 Here]

The first-stage estimates reveal a strong relationship between subsidy exposure and subsequent farm consolidation, with an unconditional correlation of 52%. Figure 3 illustrates this relationship. Panel A plots the increase in farm concentration over time, and Panel B shows the geographic distribution of direct payments.

[Insert Figure 3 Here]

As shown in the following sections, the first-stage F-statistics exceed the Stock and Yogo (2005) thresholds for weak instruments, satisfying the relevance condition. This supports the interpretation that the policy alters the structure of farms.

The second-stage estimates capture how exogenous changes in borrower structure affect the organization of local credit markets. The baseline second-stage specification is:

$$Y_{i,t} = \beta_2 \ \ \widehat{Farm\ Concentration}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}, \tag{2}$$

where subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The outcome variable $Y_{i,t}$ represents various measures of the structure of local banking markets at the county level, including the Bank Deposits $\text{HHI}_{i,t}$. All variables are measured in five-year intervals from 1994 to 2014. The vector of control variables $\mathbf{X_{i,t-2}}$ includes the lagged economic variables, log income per $\text{capita}_{i,t-2}$ and $\text{employment rate}_{i,t-2}$, aligned with the timing of the farm data in the first stage.

To examine heterogeneity across bank size, I construct separate county-level measures of banking network presence for small and large banks. I estimate the first stage of the IV model using OLS and the second stage using a Poisson model, following the approach of Cohn, Liu, and Wardlaw (2022). This method addresses the high incidence of zeros in the data: about 22% of county-year observations in my sample do not contain a large bank. Specifically, I apply a control function approach following Wooldridge (2015). I first estimate the first stage via OLS, then obtain the residual and include it as a correction term in the Poisson model:

$$\begin{aligned} &E\left[Y_{i,t} \,\middle|\, Farm\ Concentration_{i,t-2},\ \hat{\varepsilon}_{i,t-2}, \mathbf{X}_{i,t-2}, \gamma_i,\ \delta_t,\ \phi_{d(i,t)}\right] \\ &\qquad = \exp\left(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\right), \end{aligned} \tag{3}$$

where subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The vector of control variables $\mathbf{X_{i,t-2}}$ includes the same control variables as in Equation 2, with the addition of the log number of $\text{branches}_{i,t-2}$ to compare counties with similar pre-existing banking infrastructure. Because the model is estimated in two stages, I bootstrap the full procedure 1,000 times, clustering standard errors at the county level to preserve the panel structure. All analyses separating large and small banks, excluding linear probability models, follow this estimation strategy. For ease of interpretation, coefficients in these tables are reported as decimal percentages.[5]

[5] All Poisson (PPML) coefficients are reported as implied percentage changes. The relevant tables report $e^{\beta} - 1$ in decimal percentage form rather than the raw Poisson estimate β. For example, a reported coefficient of 0.70 corresponds to a 70% increase in the outcome ($e^{0.53} - 1 = 0.70$).

7 Empirical Results

I estimate the causal effect of subsidy-induced farm consolidation on local banking structure, credit allocation, and retail credit pricing. I show that as farms become more concentrated, lending activity and market share shift toward large banks, particularly those specializing in agricultural lending. By contrast, small banks respond primarily through internal consolidation. These changes in local banking structure are reflected in consumer credit markets, where households face higher borrowing costs and earn lower returns on deposits.

7.1 Farm Concentration and Bank Consolidation

In this section, I first establish that fixed subsidy payments lead to increased farm concentration, and then examine whether this consolidation among farms translates into greater concentration in local banking markets. Fixed-cash subsidies may have exogenously shifted farm consolidation in two ways. First, prior literature finds that increased liquidity and reduced financial risk encourage farms to expand acreage and specialize production (O'Donoghue and Whitaker (2010); Thakor (2023)). Because the commodity crops covered under the program exhibit increasing or non-negative returns to scale, increases in subsidy exposure shift farm size in a common direction across counties and crops (Duffy (2009); Langemeier (2013); Sumner (2014)). Second, by reducing idiosyncratic income volatility, these subsidies may improve farms' access to credit. Together, these mechanisms may encourage larger farms to grow, accelerating structural change in the agricultural sector.

Columns 1 and 2 of Table 2 show that a within-county one-standard-deviation increase in county-level subsidy payments increases farm concentration by about 105–110 acres using Equation 1. For the average corn farmer in my sample, an additional 110 base acres would generate $2,068 in extra fixed cash payments.[6]

[Insert Table 2 Here]

As farms grow and consolidate, the structure of agricultural borrowing may change, such that the average borrower becomes larger, but the number of commercial borrowers declines. In local credit markets, particularly in rural areas where agriculture is a core industry, this change in borrower composition may reduce the number of potential clients and change the nature of credit demand. Banks better able to serve larger borrowers may gain market share, while other banks may exit, merge, or be acquired. This mechanism reflects a broader insight

[6]The average historical program yield for corn in my sample is 79 bushels per acre. At the 2002 payment rate of $0.28 per bushel and the program's adjustment factor of 0.85, an additional 110 base acres would generate: 79*0.28*110*0.85 = $2,068.

from IO that as demand becomes more concentrated, supply often consolidates in response (Snyder (1996)).

To test this mechanism, I estimate the effect of farm concentration on local banking market concentration using Equation 2. Columns 3 and 4 of Table 2 show that a within-county one-standard-deviation increase in farm concentration raises local banking market concentration, measured through the county-level bank deposits HHI, by about 249 points or about 8% increase relative to the unconditional mean. This change is economically meaningful, comparable to a county moving from the 10th to the 25th percentile of the banking concentration distribution within my sample or if one out of seven banks exited a county.[7]

Areas with greater borrower consolidation should exhibit larger increases in banking concentration. Following Saidi and Streitz (2021), I estimate changes in bank deposits HHI across deciles of fitted lagged farm concentration using a control function approach. Figure 4 shows that bank deposits HHI increases steadily across deciles, consistent with greater borrower consolidation leading to greater banking concentration.

[Insert Figure 4 Here]

I then construct a counterfactual that removes the subsidy-induced component of consolidation to assess its contribution to the observed increase in banking concentration. I find that absent the subsidy program, local banking concentration would have been about 12% lower by 2014. To address concerns about autocorrelated residuals, I also show that the results hold in a first-difference specification (Table A.2).

Finally, I compare the IV estimates to OLS estimates that do not correct for the endogeneity of farm consolidation. Columns 5 and 6 of Table 2 present the results. These coefficients are smaller in magnitude than the IV estimates, suggesting that the endogeneity of farm concentration generates a downward bias. One potential source of this bias is urbanization. As the local population increases, farmland may be converted to residential or commercial uses, reducing the midpoint farm size and mechanically lowering measured concentration. Panel A of Figure 5 shows that counties with faster population growth have lower observed than predicted farm concentration, on average. At the same time, banking concentration may increase due to urban market dynamics or the exit of small rural banks. Panel B of Figure 5 shows a positive relationship between population growth and Bank Deposits $\text{HHI}_{i,t}$, after controlling for log income per $\text{capita}_{i,t-2}$, employment $\text{rate}_{i,t-2}$, and fixed effects for county, year, and state-level banking deregulation. The relationship between population growth and farm and bank concentration suggests a negative correlation

[7] Assuming deposits are initially evenly distributed across the five banks and that when one bank exits, its deposits are reallocated equally to the six remaining banks.

between farm concentration and local banking market concentration, which would bias the OLS estimates downward.

[Insert Figure 5 Here]

If farm consolidation drives changes in the structure of agricultural credit markets, the effect should be muted in urban areas where farming is not a major economic activity. I find no relationship between farm concentration and banking concentration in urban counties (Table 3). Although the number of urban observations is small, the strength of the instrument increases, and the estimated effect grows larger in progressively more rural areas. These results suggest that consolidation effects are strongest where the consolidating sector is central to the local economy and, more broadly, that the observed relationships are not driven by broader macroeconomic trends in banking.

[Insert Table 3 Here]

7.2 Farm Concentration and the Structure of Local Credit Markets

Borrower consolidation also alters the competitive dynamics between banks. Unlike traditional buyer-supplier relationships, the bank-firm relationship involves information processing and monitoring costs. Small community banks have historically relied on relationship lending to serve smaller or more opaque borrowers effectively (Berney, Haynes, and Ou (1999); Carter et al. (2004); Berger et al. (2005)). However, as farms consolidate and grow, they become more attractive to large banks capable of offering larger loans, more sophisticated products, and lower rates through access to wholesale funding (LaDue and Duncan (1996); DeYoung, Hunter, and Udell (2004); Park and Pennacchi (2009)). Large banks also face fewer regulatory constraints on lending limits, allowing them to issue larger loans (Office of the Comptroller of the Currency (2004)).

It follows that large banks are more likely than small banks to enter markets with increasingly concentrated borrowers. Table 4 presents the results. Large banks are four times more likely than small banks to be present in consolidated markets following a within-county one-standard-deviation increase in farm concentration. These results suggest that large banks respond to shifts in the composition and scale of local credit demand.

[Insert Table 4 Here]

To further assess banks' responses to farm consolidation, I examine two outcomes: branch networks and deposits per capita. The former captures banks' investment behavior: specifically, whether they are committing physical resources to a market (Cohen and Mazzeo

(2010)). The latter reflects borrower behavior: namely, revealing preferences for different types of institutions. Table 5 shows that large banks increase their deposits per capita by about 30% more than small banks following a within-county one-standard-deviation increase in farm concentration. A similar pattern emerges for branch networks. Large banks expand their local branch presence by about 17%, compared to 10% for small banks. These findings indicate that large banks capture a disproportionate share of market growth in areas with consolidated borrowers.

[Insert Table 5 Here]

The results remain largely unchanged when the sample is restricted to the pre-2009 period to control for the potential confounding effects of the 2008 Financial Crisis (Table A.3).

I then construct a simple counterfactual that reallocates subsidy-induced deposits-per-capita growth across small and large agricultural banks in proportion to their observed local market shares. If the subsidy-driven increase in deposits per capita had been distributed according to these fixed local market shares, small agricultural banks would have had about 24% higher deposit growth, or about an additional $66 million per county on average, in markets where large banks operate. Moreover, absent the subsidy program, deposits-per-capita growth at large agricultural banks would have been about 42% lower, while small agricultural banks' deposits per capita would have dropped only 6%.

Rather than expanding, small banks appear to consolidate. Mergers and acquisitions among small banks increase by 39%, whereas all other merger activity is not meaningfully affected (Table 6). These results suggest that, facing competitive pressure from larger institutions and shifting credit demand, small banks opt for defensive consolidation rather than expansion. The remaining small banks thus become fewer but larger, further diminishing the presence of community lenders in rural markets.

[Insert Table 6 Here]

These findings align with theoretical predictions that structural shifts in downstream markets, such as the rise of larger borrowers, can trigger consolidation among upstream suppliers (Galbraith (1952); Snyder (1996)). Within agricultural markets, as large farms dominate local credit demand, small banks may be compelled to merge to remain viable. Rather than expanding, they consolidate internally, altering the composition and competitiveness of the local banking sector.

Lending capacity constraints may explain banks' differential responses to borrower consolidation. In areas where lending limits are more likely to bind, such as where farms face higher fixed production costs and need to finance larger upfront investments, large banks

should gain more market share. I calculate the five-year average economic cost per acre for each major commodity crop between 1990 and 1995. For each county, I construct a weighted average of these costs based on the share of each crop's harvested acres, before the start of the subsidy program. Counties with economic costs above the national median are classified as high-cost, while those below are low-cost (Figure A.2).

Table 7 reports the tests for high- and low-cost counties. Large banks' deposits per capita grow an additional 33% in high-cost counties relative to their deposits-per-capita growth in low-cost counties. The reverse holds for small banks. In high-cost counties, small banks increase deposits per capita by only 7%, compared with about 18% in low-cost counties. These results indicate that when higher costs constrain small banks' lending capacity, borrowers move toward larger institutions. Branch expansion, by contrast, is stronger in low-cost counties for both large and small banks. In these areas, farms can expand more easily, increasing the expected returns to lending and encouraging a larger number of banks to finance investment and expand their branch networks.

[Insert Table 7 Here]

7.3 Farm Concentration and Agricultural Loan Growth

If borrower consolidation increases credit demand among large farms, we should observe a corresponding increase in agricultural loan volumes. Because Call Reports are at the bank level, I interpolate agricultural loan volumes to the bank-branch level within each county (see Section 5 for details). Table 8 presents the results. Large banks increase their share of total agricultural lending growth by about 50%. Disaggregating agricultural loans into real estate and non-real estate loans, both categories increase significantly for large banks. Small banks, on the other hand, experience growth only in non-real estate loans of about 12%.

[Insert Table 8 Here]

A potential explanation for the difference in lending growth between large and small banks is regulatory lending limits. The OCC restricts banks from lending more than 25% of their capital and surplus to a single borrower. In 2004, the OCC acknowledged this issue, noting that farm consolidation had "resulted in fewer, but larger, farms with expanded credit needs" and that existing limits were too restrictive for community banks (Office of the Comptroller of the Currency (2004)). Rising land values and production costs further increased average loan sizes, tightening these constraints. For example, by 2012, a typical loan could cover only half the acreage it did in 2001 (Ellinger (2012)).

7.4 Farm Concentration and the Structure of Agricultural Banking

The effects of farm consolidation should be more concentrated in the parts of the banking market most directly connected to agriculture. A within-county one-standard-deviation increase in farm concentration increases the agricultural loan-based HHI by about 531–540 points, or 15% of the unconditional mean (Table 9, Columns 1 and 2), double the effect on the deposit-based HHI reported in the baseline results in Table 2.

[Insert Table 9 Here]

For the remainder of this section, I restrict the sample to banks with greater exposure to the farm sector, defined as those institutions holding more than 5% of their assets in farm loans in any of the last five years. Among these banks, a within-county one-standard-deviation increase in farm concentration increases the deposit-based HHI by about 25% relative to the unconditional mean (Table 9, Columns 3 and 4), which is more than three times larger than the estimate for all banks. These findings suggest that as consolidation leaves fewer but larger borrowers, market concentration increases most among banks operating within the consolidating industry.

It follows that farm consolidation should have a larger effect on the market structure of agricultural banks than on commercial banks overall. Table 10 reports that large agricultural banks are about 15% more likely to be present and expand their branch networks by 53% in consolidated markets. By contrast, small agricultural banks show no meaningful increase in presence or expansion. Moreover, large agricultural banks experience a 74% increase in deposits per capita, compared to a 21% increase for small agricultural banks. Both groups see greater growth than in the main sample, but large agricultural banks exhibit the largest expansion, with per capita deposits growing at three times the amount of large banks overall. Large agricultural banks are also nearly four times more likely to be present in rural counties experiencing farm consolidation than large banks overall, indicating that their market expansion is closely tied to shifts in agricultural credit demand.

[Insert Table 10 Here]

These findings suggest that both bank size and industry specialization affect responsiveness to borrower consolidation. As agricultural production becomes increasingly concentrated, the large, agriculturally specialized institutions gain market share disproportionately.

Table 11 presents tests of agricultural lending growth among agricultural banks. Most of the growth in agricultural lending is driven by large agricultural banks, across both loans

collateralized by farmland and loans used to finance agricultural production. These results support earlier evidence that the specialized institutions expanding their branch networks and deposit bases in response to borrower consolidation are also leading the growth in credit supply.

[Insert Table 11 Here]

Lastly, the results are monotonic with respect to the 5% threshold: as the share of agricultural lending drops below 5%, the effects weaken (Tables A.4 and A.5).

7.5 Farm Concentration and Interest Rates on Broader Consumer Products

IO theory suggests that buyer consolidation can influence prices through two distinct channels. First, consolidated buyers may gain bargaining power over suppliers, allowing them to negotiate more favorable prices and pushing lenders to compete on price for all buyers in the market (Snyder (1996); Chipty and Snyder (1999)). Second, consolidation may trigger restructuring on the supplier side, leading to concentration among the most efficient suppliers, which can result in unchanged or even higher prices (Galbraith (1952); Tirole (1988); Farrell and Shapiro (1990)). In the context of agricultural credit markets, Kropp and Whitaker (2011) find that farms with a greater share of base acres, and thus larger fixed cash payments relative to similarly sized farms, obtain lower interest rates on their operating loans.

However, the broader effects of borrower consolidation and local banking market structure on consumer financial products are less clear. New banks entering consolidated markets may lower consumer interest rates to attract customers. Yet, banks may raise rates if they can segment consumer markets from consolidated borrowers (Inderst and Valletti (2011)). These responses may also differ between large and small banks. Large banks tend to offer lower deposit rates due to access to wholesale funding, while small banks may offer higher deposit rates to attract local retail deposits and fund their lending activities (Park and Pennacchi (2009)). Thus, as large banks expand into consolidated markets, average deposit rates may decline.

To assess these spillover effects, I examine how borrower-side consolidation affects the pricing of consumer deposit and loan products, focusing on rural credit markets. Among deposit products, I focus on three commonly offered types: time, savings, and checking deposits. These deposit types differ in liquidity, interest elasticity, and their role in bank funding strategies. Liquid deposits, such as savings and checking deposits, make up banks'

core funding base, providing a stable and relatively inelastic source of funds. Because these deposits are less sensitive to rate changes and are typically not withdrawn even when interest rates fall, they allow banks to maintain low-cost funding. In contrast, time deposits are more rate-sensitive and often used to fund longer-term lending, such as commercial or agricultural loans (Drechsler, Savov, and Schnabl (2017); Supera (2021)). I use real, inflation-adjusted interest rates in all analyses. In addition to the baseline farmland and local economic condition controls from the first- and second-stage specifications, I control for changes in local household and farm credit demand by including county-level measures of total deposits and total farm interest expenses in logs.

Table 12 shows that a within-county one-standard-deviation increase in farm concentration is associated with a 24-basis-point decline in the county-level average savings deposit interest rate, which represents about a 20% reduction relative to the unconditional mean. County-level time deposit interest rates remain relatively flat on average, possibly to preserve funding for agricultural or commercial lending. Finally, checking deposit interest rates decline by about 13 basis points.

[Insert Table 12 Here]

I next examine the effects on consumer credit, focusing on auto loans. These are among the most widely reported and standardized consumer lending products in the RateWatch data. Because auto loans require relatively little soft information, they allow meaningful comparisons across banks of different sizes and structures (Keys et al. (2010)). The county-level average interest rate offered on auto loans increases by 88 basis points. These results suggest that the resulting change in market structure between borrowers and banks leads to less competitive loan terms for consumers more broadly. I also re-estimate the specification in first differences to confirm that the results are not driven by persistent county-level trends or non-stationarity (Table A.6).

8 Robustness

This section examines the instrument, tests for direct subsidy effects on credit markets, controls for the role of nonbank lenders in local banking market structure, and assesses whether the subsidy program shifted government lending.

8.1 Instrument Relevance and Terrain Ruggedness

The instrument should only predict consolidation where consolidation is physically feasible. To capture how difficult it is to expand farm size in a given county, I use the USDA–ERS

Terrain Ruggedness Index (Figure A.1). I divide counties into those above and below the top quartile of ruggedness. In areas with rugged terrain, where farm consolidation is more difficult, the first-stage relationship weakens and the F-statistic falls below the Stock and Yogo (2005) threshold. In contrast, the instrument remains strong in less rugged counties (Table A.7). This result indicates that subsidy exposure predicts consolidation only where consolidation can occur, supporting the interpretation that the instrument does not identify broader shocks.

8.2 Farm Concentration and Crop Insurance

Crop insurance reduces downside risk, improves credit access, and supports farm expansion (Cornaggia (2013); Azzam et al. (2021); Ifft et al. (2024)), so rising take-up during this period may affect the main results. However, controlling for the log total county-level number of crop insurance policies leaves the first- and second-stage estimates largely unchanged (Table A.8). This result suggests that the observed consolidation effects are primarily driven by fixed subsidy payments.

8.3 Subsidy Exposure and Local Banking Structure

Direct payments act as a liquidity shock and increase survivorship among farms, reinforcing that the observed consolidation reflects expansion rather than distress-driven failures (Burfisher and Hopkins (2003); Key and Roberts (2006); Kropp and Katchova (2011)). At the same time, subsidy-driven improvements in farm liquidity raise a potential concern that subsidies may influence local banking structure directly, for example by lowering farms' default risk. However, because the same subsidies also lead to changes in farm size distribution, a simple OLS regression of banking structure on subsidies would conflate this potential direct effect with the indirect effect operating through farm consolidation. To assess whether subsidies have an economically meaningful direct effect on banking outcomes, separate from the consolidation channel, I set up a falsification test motivated by the logic of local irrelevance for IVs (D'Haultfœuille, Hoderlein, and Sasaki (2024)). Formally, under the exclusion restriction, the local irrelevance condition implies that subsidy exposure should not affect banking outcomes in counties where it does not induce changes in farm consolidation.

Following Acemoglu et al. (2022), which applies the intuition of D'Haultfœuille, Hoderlein, and Sasaki (2024), I classify counties by their predicted responsiveness of consolidation to subsidy exposure and group them into terciles. Counties in the bottom tercile, where subsidies have minimal predicted impact on consolidation, can be interpreted as "never-takers". In these counties, subsidy exposure does not have a meaningful effect on banking structure (Table A.9, Panel A).

In contrast, counties in the top tercile experience substantial subsidy-induced increases in farm consolidation. Given farm consolidation alters the nature and amount of credit demanded, the reduced-form effect of subsidies on local banking structure is expected to be positive in these counties. Consistent with this hypothesis, I find that subsidy exposure has a stronger reduced-form relationship with banking outcomes in counties in the top tercile (Table A.9, Panel B). This pattern, null effects for never-takers and meaningful effects for compliers, suggests that subsidies affect banking structure primarily through consolidation, rather than through a direct credit-risk or liquidity channel.

8.4 Farm Credit System and Commercial Banks

Nonbank lenders may also affect the structure of local commercial banking. In agricultural credit markets, the Farm Credit System (FCS) is the main alternative to commercial banks. Established in 1916 as a government-sponsored enterprise, the FCS is a borrower-owned cooperative system whose goal is to provide credit to farmers and ranchers who historically faced limited access to commercial bank financing. FCS institutions may lend only to persons owning agricultural land or engaged in the production of agricultural commodities, and they are prohibited from offering non-farm loans. In 2016, the FCS held nearly 41% of the farm sector's total debt, relative to the 42% share held by commercial banks.[8]

If the FCS absorbs a share of the additional credit demand generated by consolidated farms, then the extent to which borrower consolidation reorganizes local banking markets may be reduced. Because the FCS competes with commercial banks for agricultural borrowers, counties with more FCS branches may experience different levels of commercial bank concentration, deposit holding, or branching activity. To address this possibility, I control for the log number of FCS branches in each county. The estimated effects of farm consolidation on commercial bank outcomes remain similar (Table A.10). These findings suggest that although the FCS is an important competitor in agricultural lending, its local presence does not affect the observed reorganization of commercial banks in consolidating agricultural markets.

8.5 Farm Concentration and Direct Loans by the USDA's Farm Service Agency (FSA)

Although my main results show that fixed subsidy payments lead to increased farm consolidation, one alternative mechanism is that these payments reduce income risk and encourage new entry into farming. Cash subsidies may also simply increase credit demand

[8]See Farm Credit System (`https://www.congress.gov/crs_external_products/RS/HTML/RS21278.html`).

more broadly rather than specifically among large, consolidating operations. If either of these mechanisms were at work, we would expect to see a rise in federal direct loans, which are targeted to small, new, or socially disadvantaged farmers. However, I find no evidence that subsidy-induced consolidation affects the number or volume of direct loans at the county-year level (Table A.11).

Because consolidation is measured as the county-level midpoint farm size, these results support the interpretation that subsidies primarily facilitate the expansion of existing farms rather than widespread entry. New entry by small farms would reduce, not raise, the midpoint size. The absence of a response in direct loans points to a consolidation effect driven by incumbents, not by a broad-based expansion in credit access.

9 Conclusion

In this paper, I introduce a novel driver of bank consolidation: the consolidation and growth of large borrowers. Using U.S. agriculture as a setting, I show that farm consolidation, driven by fixed cash subsidies, changes the local banking market structure. Stable, predictable subsidies enable larger farms to invest and expand, resulting in a borrower pool that is increasingly concentrated among high-income, creditworthy operations.

These larger farms have greater financing needs, making them more aligned with the operating models of large banks. The likelihood of large-bank presence significantly increases in rural counties undergoing borrower consolidation. Moreover, large banks expand both their deposit bases and branch networks, particularly when they already have exposure to agricultural lending.

However, large banks are also more responsive to negative income shocks. When farm incomes declined in the decade following the subsidy shock, the earlier expansion reversed. Between 2015 and 2019, the top 30 banks reduced their farm loan portfolios by $3.9 billion, or 17.5%.[9] JPMorgan Chase had expanded its farm lending by 76% between 2008 and 2015 to $1.1 billion, but later pulled back, reducing its farm lending by about 22%.[10] Thus, while borrower consolidation may attract large-scale lenders in the short run, it may also reduce long-run financial stability.

[9] See Rabobank takes on US agriculture's lending gap as large banks exit (https://www.bankingdive.com/news/rabobank-us-agriculture-lending-gap) and Big banks exiting farm loan business (https://www.proag.com/news/big-banks-exiting-farm-loan-business/).

[10] See Wall Street banks bailing on troubled U.S. farm sector (https://www.reuters.com/article/business/wall-street-banks-bailing-on-troubled-us-farm-sector).

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Table 1. Descriptive Statistics

The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). Subscript i represents the county and t represents the year. $Farm\ Concentration_{i,t-2}$ is the midpoint farm size at the county level. $Bank\ Deposits\ HHI_{i,t}$ is the Herfindahl-Hirschman Index, a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. $Probability\ of\ Large\ Bank_{i,t}$ and $Probability\ of\ Small\ Bank_{i,t}$ are indicator variables for whether a large or small bank, respectively, is present in a county in a given year. $Number\ of\ Large\ Bank\ Branches_{i,t}$ and $Number\ of\ Small\ Bank\ Branches_{i,t}$ refer to the number of branches operated by large and small banks at the county level, respectively. $Large\ Banks'\ Deposits\ Per\ Capita_{i,t}$ and $Small\ Banks'\ Deposits\ Per\ Capita_{i,t}$ measure total deposits per capita held at large and small banks, respectively. $Large\ Acquires\ Small_{i,t}$ measures the total number of mergers or acquisitions in which a large bank acquires a small bank, aggregated over five-year intervals. $Small\ Acquires\ Small_{i,t}$ and $Large\ Acquires\ Large_{i,t}$ measure the number of mergers between two small or two large banks, respectively, also aggregated over five-year intervals. $Total\ Agricultural\ Loans_{i,t}$ is the total imputed agricultural loan volume at the county level, disaggregated by bank size. $Agricultural\ Real\ Estate\ Loans_{i,t}$ and $Agricultural\ Non\text{-}Real\ Estate\ Loans_{i,t}$ represent county-level imputed loan volumes secured by farmland and used to finance agricultural production, respectively. $Urban_{i,t}$ is an indicator variable for whether the county is classified as large central metropolitan areas by the National Center for Health Statistics (NCHS). $Metro_{i,t}$ is an indicator variable for whether the county is a broader metropolitan area, and $Rural_{i,t}$ is an indicator variable for whether the county is a non-core area. $Savings\ Deposit\ Rate_{i,t}$ is the real interest rate offered on $10,000 money market accounts, and $Time\ Deposit\ Rate_{i,t}$ is the real interest rate offered on 12-month $10,000 certificates of deposit. $Checking\ Deposit\ Rate_{i,t}$ is the real interest rate offered on interest-bearing checking accounts. $Auto\ Loan\ Interest\ Rate_{i,t}$ is the real interest rate offered on auto loans. The instrument, $Subsidy\ Amount_{i,t}$, is a continuous measure of the predicted value of total fixed subsidy payments in a given county-year. Control variables include measures of land availability (idle cropland, pastureland, and fallow or unharvested cropland in acres from the prior Census of Agriculture), local economic conditions, and pre-existing banking infrastructure (county-level employment rate, log income per capita, and total number of branches).

Variable	Mean	SD	P10	P50	P90	N
Main Dependent Variables						
Farm Concentration$_{i,t-2}$ (Acres)	752	833	65	327	2,072	13,808
Bank Deposits HHI$_{i,t}$	3,123	2,011	1,308	2,540	5,474	13,808
Probability of Large Bank$_{i,t}$	0.78	0.42	0.00	1.00	1.00	13,808
Probability of Small Bank$_{i,t}$	0.96	0.20	1.00	1.00	1.00	13,808
Number of Large Bank Branches$_{i,t}$	13	29	0	3	33	13,808
Large Banks' Deposits Per Capita$_{i,t}$ ($)	7,498	24,887	0	5,684	15,437	13,808
Number of Small Bank Branches$_{i,t}$	9	10	1	7	19	13,808
Small Banks' Deposits Per Capita$_{i,t}$ ($)	11,814	9,679	1,552	9,836	24,462	13,808
Large Acquires Small$_{i,t}$	0.09	0.33	0	0	1	13,808
Small Acquires Small$_{i,t}$	0.15	0.42	0	0	1	13,808
Large Acquires Large$_{i,t}$	0.14	0.42	0	0	1	13,808
Large Banks' Total Agricultural Loans$_{i,t}$ ($1,000s)	18,669	42,814	0	5,592	46,237	13,808
Small Banks' Total Agricultural Loans$_{i,t}$ ($1,000s)	39,647	55,144	287	17,635	108,395	13,808
Large Banks' Agricultural Real Estate Loans$_{i,t}$ ($1,000s)	8,459	18,633	0	2,699	21,705	13,808
Small Banks' Agricultural Real Estate Loans$_{i,t}$ ($1,000s)	18,548	24,808	117	8,876	49,037	13,808
Large Banks' Agricultural Non-Real Estate Loans$_{i,t}$ ($1,000s)	9,997	26,468	0	1,879	24,897	13,808
Small Banks' Agricultural Non-Real Estate Loans$_{i,t}$ ($1,000s)	20,755	33,478	3	6,312	61,592	13,808
Direct Loan Amounts$_{i,t}$ ($1,000s)	431	890	0	89	1,258	13,808
Number of Direct Loans$_{i,t}$	12	24	0	3	35	13,808
Urban$_{i,t}$	0.01	0.12	0.00	0.00	0.00	14,059
Metro$_{i,t}$	0.53	0.50	0.00	1.00	1.00	14,059
Rural$_{i,t}$	0.45	0.50	0.00	0.00	1.00	14,059

Variable	Mean	SD	P10	P50	P90	N
Agricultural Banks' Dependent Variables						
Number of Large Agricultural Bank Branches$_{i,t}$	0.97	3.18	0	0	3	13,808
Large Agricultural Banks' Deposits Per Capita$_{i,t}$ ($)	1,160	3,299	0	0	3,979	13,808
Number of Small Agricultural Bank Branches$_{i,t}$	4.11	4.66	0	3	10	13,808
Small Agricultural Banks' Deposits Per Capita$_{i,t}$ ($)	8,344	10,252	0	4,355	22,557	13,808
Interest Rate Dependent Variables						
Savings Deposit Rate$_{i,t}$ (%)	-1.15	0.56	-1.74	-1.19	-0.46	42,328
Time Deposit Rate$_{i,t}$ (%)	-0.07	1.16	-1.55	-0.10	1.60	42,470
Checking Deposit Rate$_{i,t}$ (%)	-1.63	0.35	-2.04	-1.71	-1.16	36,906
Auto Loan Interest Rate$_{i,t}$ (%)	4.57	1.60	2.23	4.91	6.45	36,341
Instrument						
Total Subsidy Amount$_{i,t}$ ($1,000s)	1,369	2,193	0	277	4,265	13,808
Control Variables						
Income Per Capita$_{i,t-2}$ ($)	36,523	9,217	27,227	34,930	47,124	13,808
Employment Rate$_{i,t-2}$	0.50	0.13	0.34	0.49	0.66	13,808
Population$_{i,t-2}$	63,234	115,890	5,909	25,013	149,639	13,808
State-Level Deregulation Index$_{i,t}$	1	2	0	1	4	13,808
Number of Branches$_{i,t}$	22	36	3	11	49	13,808
Idle Land$_{i,t-7}$ (Acres)	9,577	13,477	751	4,851	23,274	13,808
Unharvested Cropland$_{i,t-7}$ (Acres)	20,072	35,616	1,047	7,868	48,167	13,808
Pastureland$_{i,t-7}$ (Acres)	142,326	273,841	6,864	40,479	387,947	13,808

Table 2. Effect of Farm Consolidation on Bank Concentration

This table reports the first- and second-stage results from an instrumental variable strategy to estimate the effect of a within-county one-standard-deviation increase in farm concentration on the bank deposits Herfindahl-Hirschman Index (HHI). The specifications for the first and second stages, respectively, are: $\textit{Farm Concentration}_{i,t} = \beta_1 \textit{Subsidy Amount}_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $Y_{i,t} = \beta_2 \widehat{\textit{Farm Concentration}}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). Columns 1 and 2 report the first-stage regressions, where the dependent variable is $\textit{Farm Concentration}_{i,t-2}$, measured as the lagged midpoint farm size at the county level. In all second-stage regressions, $\textit{Farm Concentration}_{i,t-2}$ is expressed in within-county standardized units. Columns 3 and 4 report the second-stage results, where the dependent variable is the bank deposits HHI. Columns 5 and 6 reports the OLS estimates of farm concentration on bank deposits HHI. The outcome variable, $\textit{Bank Deposits HHI}_{i,t}$, is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county. The instrument, $\textit{Subsidy Amount}_{i,t-2}$, is a continuous within-county standardized measure of the predicted value of total fixed subsidy payments in a given county-year. In the first stage, the control variables account for county-level land availability using lagged measures of idle cropland, pastureland, and cropland left fallow, lost to crop failure, or otherwise unharvested from the prior Census of Agriculture. In both stages, I also control for local economic conditions using the county-level employment $\text{rate}_{i,t-2}$ and log income per $\text{capita}_{i,t-2}$. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage		Second Stage		OLS	
	Farm Concentration		Bank Deposits HHI			
Farm Concentration$_{i,t-2}$					20.814**	17.355*
					(9.062)	(9.018)
$\widehat{\text{Farm Concentration}}_{i,t-2}$			252.230***	249.142***		
			(38.588)	(39.072)		
Subsidy Amount$_{i,t-2}$	105.220***	110.368***				
	(5.492)	(6.126)				
Log Income Per Capita$_{i,t-2}$		178.020**		-87.181		32.540
		(69.535)		(122.951)		(116.971)
Employment Rate$_{i,t-2}$		-150.858		301.403		329.287
		(156.737)		(325.595)		(315.061)
Idle Land$_{i,t-7}$		26.547***				-9.600
		(5.250)				(7.675)
Unharvested Cropland$_{i,t-7}$		-15.546***				-9.239
		(3.808)				(7.740)
Pastureland$_{i,t-7}$		2.786				0.106
		(6.042)				(6.212)
Observations	13,808	13,808	13,808	13,808	13,808	13,808
R-squared	0.851	0.852	0.931	0.931	0.920	0.921
F-statistic	367.05	98.84	367.05	98.84	5.28	5.08
Deregulation Index FE	No	Yes	No	Yes	No	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	751.7	751.7	3,123	3,123	3,123	3,123

Table 3. Rural vs. Urban: Effect of Farm Concentration on Bank Concentration

This table reports the first- and second-stage results from an instrumental variable strategy to estimate the effect of a within-county one-standard-deviation increase in farm concentration on the bank deposits Herfindahl-Hirschman Index (HHI) by county type. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1 Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $Y_{i,t} = \beta_2\ \widehat{Farm\ Concentration}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). Columns 1 and 4 restrict the sample to $Urban_{i,t}$ counties, classified as large central metropolitan areas by the National Center for Health Statistics (NCHS). Columns 2 and 5, and Columns 3 and 6, restrict the sample to $Metro_{i,t}$, or broader metropolitan, and $Rural_{i,t}$, or non-core, counties, respectively. Means and standard deviations are calculated within the relevant subsample. The dependent variable is the bank deposits HHI. The $Bank\ Deposits\ HHI_{i,t}$ is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. The controls are the same set of first- and second-stage controls as in Table 2. F-statistics are from the first stage. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage			Second Stage		
	Farm Concentration			Bank Deposits HHI		
	Urban	Metro	Rural	Urban	Metro	Rural
Subsidy Amount$_{i,t-2}$	45.79	71.65***	89.75***			
	(54.71)	(6.82)	(6.77)			
$\widehat{\text{Farm Concentration}}_{i,t-2}$				136.69	133.54**	293.99***
				(202.87)	(52.93)	(65.87)
Observations	193	7,394	6,015	193	7,394	6,015
F-statistic	1.09	35.61	54.22	1.09	35.61	54.22
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	611.4	716.6	792.3	1,790	2,427	3,925

Table 4. Effect of Farm Concentration on the Probability of Large and Small Bank Presence

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on the probability of the presence of a large or small bank, respectively. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1 Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $Y_{i,t} = \beta_2\ \widehat{Farm\ Concentration}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). The outcome variable is an indicator variable for whether a large or small bank is present in the county in a given year, respectively. Small banks are those with less than \$10 billion in inflation-adjusted assets, and large otherwise. $\widehat{Farm\ Concentration}_{i,t-2}$ is the fitted lagged within-county standardized midpoint farm size estimated in the first stage. The controls are the same set of first-stage controls as in Table 2. In both stages, I also control for local economic conditions using the county-level employment rate$_{i,t-2}$, log income per capita$_{i,t-2}$, and log number of branches$_{i,t-2}$. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Large Bank	(2) Small Bank
	Probability of Entering	
$\widehat{\text{Farm Concentration}}_{i,t-2}$	0.04**	0.01***
	(0.02)	(0.01)
Observations	13,808	13,808
F-statistic	95.06	95.06
County Controls	Yes	Yes
Deregulation Index FE	Yes	Yes
County & Year FE	Yes	Yes
Mean of Dependent Variable	0.78	0.960

Table 5. Effect of Farm Concentration on the Presence and Deposit Share of Large and Small Banks

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on bank presence and deposits-per-capita growth by bank size. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $E\big[Y_{i,t}\,\big|\,Farm\ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. For this specification, I use a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). In Columns 1 and 3, the outcome variable is $Branches_{i,t}$, which is the county-level number of branches owned by large and small banks, respectively. In Columns 2 and 4, the outcome variable is $Deposits\ Per\ Capita_{i,t}$, which is the deposits per capita in large and small banks, respectively. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. The controls are the same set of first- and second-stage controls as in Table 4. Log population$_{i,t-2}$ is included in the first stage regression for Columns 2 and 4 to adjust for the per-capita scaling of the dependent variable. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Large Bank		Small Bank	
	Branches	Deposits Per Capita	Branches	Deposits Per Capita
Farm $\widehat{\text{Concentration}}_{i,t-2}$	0.168***	0.266**	0.101***	0.202***
	(0.040)	(0.105)	(0.021)	(0.026)
Observations	13,808	13,808	13,808	13,808
F-statistic	95.06	81.18	95.06	81.18
County Controls	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	14	8,468	9	11,936

Table 6. Effect of Farm Concentration on Bank Acquisitions by Bank Size

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on bank acquisitions by bank size. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $E\big[Y_{i,t}\,\big|\,Farm\ \ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. For this specification, I use a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). In Column 1, the outcome variable is $Large\ Acquires\ Small_{i,t}$, which measures the total number of mergers or acquisitions in which a large bank acquires a small bank, aggregated over five-year intervals. Columns 2 and 3 report $Small\ Acquires\ Small_{i,t}$ and $Large\ Acquires\ Large_{i,t}$, which capture the total number of mergers or acquisitions occurring between two small banks and between two large banks, respectively, also aggregated over five-year intervals. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. The controls are the same set of first- and second-stage controls as in Table 4. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
		Acquisition Type	
	Large Acquires Small	Small Acquires Small	Large Acquires Large
Farm $\widehat{\text{Concentration}}_{i,t-2}$	0.012	0.385***	-0.102
	(0.143)	(0.114)	(0.109)
Observations	13,808	13,808	13,808
F-statistic	95.06	95.06	95.06
County Controls	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes
Mean of Dependent Variable	0.399	0.392	0.576

Table 7. High- vs. Low-Cost Counties: Effect of Farm Concentration on the Presence and Deposit Share of Large and Small Banks

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on bank presence and deposits-per-capita growth by bank size and average county per-acre farming costs. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $E\big[Y_{i,t}\,\big|\,Farm\ \ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. For this specification, I use a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). Panel A includes counties with per-acre average economic costs above the nationwide median, and Panel B includes counties that are below the nationwide median. Economic costs per acre for each major commodity crop are calculated as the five-year average (1990–1995) from the Farm Costs and Returns Survey (FCRS) compiled by the U.S. Department of Agriculture's Economic Research Service (ERS). The measure is constructed as a time-invariant, county-level weighted average of per-acre economic costs, where weights are each crop's share of harvested acreage from the 1992 Census of Agriculture. Means and standard deviations are calculated within the relevant subsample. Across both panels, in Columns 1 and 3, the outcome variable is $Branches_{i,t}$, which is the county-level number of branches owned by large and small banks, respectively. In Columns 2 and 4, the outcome variable is $Deposits\ Per\ Capita_{i,t}$, which is the deposits per capita in large and small banks, respectively. Small banks are those with less than \$10 billion in inflation-adjusted assets, and large otherwise. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. The controls are the same set of first- and second-stage controls as in Table 5. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. High-Cost Counties

	(1)	(2)	(3)	(4)
	Large Bank		Small Bank	
	Branches	Deposits Per Capita	Branches	Deposits Per Capita
$\widehat{\text{Farm Concentration}}_{i,t-2}$	0.092**	0.329*	0.059***	0.065**
	(0.043)	(0.150)	(0.021)	(0.027)
Observations	6,905	6,905	6,905	6,905
F-statistic	56.29	45.12	56.29	45.12
County Controls	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	13	7,431	10	11,212

Panel B. Low-Cost Counties

	(1)	(2)	(3)	(4)
	Large Bank		Small Bank	
	Branches	Deposits Per Capita	Branches	Deposits Per Capita
$\widehat{\text{Farm Concentration}}_{i,t-2}$	0.094**	0.091	0.120***	0.184***
	(0.038)	(0.058)	(0.024)	(0.026)
Observations	6,903	6,903	6,903	6,903
F-statistic	54.99	51.19	54.99	51.19
County Controls	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	13	7,566	8	12,416

Table 8. Effect of Farm Concentration on Agricultural Loan Growth

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on agricultural loan growth by bank size. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $E\big[Y_{i,t}\,\big|\,Farm\ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. For this specification, I use a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). In Columns 1 and 2, the outcome variable, $Total\ Agricultural\ Loan\ Growth_{i,t}$, is large or small banks' growth in total agricultural loan volume in a given county-year relative to the prior period's total agricultural loan volume. The outcome variable in Columns 3 and 4 is $Real\ Estate\ Loan\ Growth_{i,t}$, and the outcome variable in Columns 5 and 6 is $Non\text{-}Real\ Estate\ Loan\ Growth_{i,t}$; both are similarly measuring the loan growth by bank size relative to the prior period's total volume by relevant loan type. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. Small banks are those with less than \$10 billion in inflation-adjusted assets, and large otherwise. The controls are the same set of first- and second-stage controls as in Table 4. In the first-stage, I also control for the prior period's log total loan volume by relevant loan type. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Large Bank	(2) Small Bank	(3) Large Bank	(4) Small Bank	(5) Large Bank	(6) Small Bank
	Total Agricultural Loan Growth		Real Estate Loan Growth		Non-Real Estate Loan Growth	
$\widehat{\text{Farm Concentration}}_{i,t-2}$	0.499***	0.069**	0.501***	0.022	0.344***	0.120***
	(0.108)	(0.030)	(0.150)	(0.041)	(0.089)	(0.030)
Observations	13,808	13,808	13,808	13,808	13,808	13,808
F-statistic	95.71	95.71	95.38	95.38	95.71	95.71
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.49	0.73	0.58	0.95	0.72	0.75

Table 9. Effect of Farm Consolidation on Agricultural Lending and Bank Concentration

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on the Herfindahl-Hirschman Index (HHI) of agricultural loans and agricultural bank deposits. The specifications for the first and second stages, respectively, are: $\textit{Farm Concentration}_{i,t} = \beta_1 \textit{Subsidy Amount}_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $Y_{i,t} = \beta_2 \widehat{\textit{Farm Concentration}}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). In Columns 1 and 2, the dependent variable is *Agricultural Loan HHI*$_{i,t}$, which is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared total agricultural loan shares held by each bank within a county. For Columns 3 and 4, the sample is further restricted to agricultural banks, which I define as those holding more than 5% of their total assets in farm loans in any of the last five years. I then calculate *Bank Deposits HHI*$_{i,t}$, which is analogous to the calculation in Columns 1 and 2 but using the sum of squared deposit shares held by each agricultural bank within a county. $\textit{Farm Concentration}_{i,t-2}$ is the lagged within-county standardized midpoint farm size. The controls are the same set of first- and second-stage controls as in Table 2. F-statistics are from the first stage. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively

	(1)	(2)	(3)	(4)
	All Banks		Agricultural Banks	
	Agricultural Loans HHI		Bank Deposits HHI	
$\widehat{\text{Farm Concentration}}_{i,t-2}$	531.43***	539.99***	413.74***	449.57***
	(56.19)	(55.00)	(55.93)	(56.54)
Observations	13,808	13,808	13,808	13,808
F-statistic	367.03	98.84	367.03	98.84
County Controls	No	Yes	No	Yes
Deregulation Index FE	No	Yes	No	Yes
County & Year FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	3,531	3,531	1,800	1,800

Table 10. Agricultural Banks: Effect of Farm Concentration on Large and Small Banks

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on agricultural (ag) bank presence and deposits-per-capita growth by bank size. The specification for the first stage is: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$. The specifications for the second stages are: $Y_{i,t} = \beta_2\ \widehat{Farm\ Concentration}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$ in Columns 1 and 4 and $E\big[Y_{i,t} \,\big|\, Farm\ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$ in the remaining columns using a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). The sample is further restricted to agricultural banks, which I define as those holding more than 5% of their total assets in farm loans in any of the last five years. In Columns 1 and 4, the outcome variable, $Probability\ of\ Entry_{i,t}$, is an indicator variable for whether a large or small ag bank is present in the county in a given year, respectively. In Columns 2 and 5, the outcome variable is $Branches_{i,t}$, which is the county-level number of branches owned by large and small ag banks, respectively. In Columns 3 and 6, the outcome variable is $Deposits\ Per\ Capita_{i,t}$, which is the deposits per capita in large and small ag banks, respectively. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. Small banks are those with less than \$10 billion in inflation-adjusted assets, and large otherwise. The controls are the same set of first- and second-stage controls as in Table 4. Log population$_{i,t-2}$ is included in the first stage regression for Columns 3 and 6 to adjust for the per-capita scaling of the dependent variable. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Large Agricultural Bank			Small Agricultural Bank		
	Probability of Entry	Branches	Deposits Per Capita	Probability of Entry	Branches	Deposits Per Capita
$\widehat{\text{Farm Concentration}}_{i,t-2}$	0.147***	0.534***	0.736***	0.008	-0.003	0.206***
	(0.021)	(0.127)	(0.140)	(0.009)	(0.020)	(0.031)
Observations	13,808	13,808	13,808	13,808	13,808	13,808
F-statistic	98.83	98.83	86.93	98.83	98.83	86.93
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.32	2	2,310	0.77	5	9,948

Table 11. Agricultural Banks: Effect of Farm Concentration on Agricultural Loan Growth

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on agricultural loan growth by bank size and only among agricultural (ag) banks. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $E\big[Y_{i,t} \,\big|\, Farm\ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. For this specification, I use a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). The sample is further restricted to agricultural banks, which I define as those holding more than 5% of their total assets in farm loans in any of the last five years. In Columns 1 and 2, the outcome variable, $Total\ Agricultural\ Loan\ Growth_{i,t}$, is large or small banks' growth in total agricultural loan volume in a given county-year relative to the prior period's total agricultural loan volume. The outcome variable in Columns 3 and 4 is $Real\ Estate\ Loan\ Growth_{i,t}$, and the outcome variable in Columns 5 and 6 is $Non\text{-}Real\ Estate\ Loan\ Growth_{i,t}$; both are similarly measuring the loan growth by bank size relative to the prior period's total volume by relevant loan type. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. The controls are the same set of first- and second-stage controls as in Table 8. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Large Ag Bank	(2) Small Ag Bank	(3) Large Ag Bank	(4) Small Ag Bank	(5) Large Ag Bank	(6) Small Ag Bank
	Total Agricultural Loan Growth		Real Estate Loan Growth		Non-Real Estate Loan Growth	
$\widehat{\text{Farm Concentration}}_{i,t-2}$	1.226***	0.076**	1.246**	0.058	0.802***	0.066*
	(0.257)	(0.035)	(0.351)	(0.051)	(0.183)	(0.034)
Observations	13,808	13,808	13,808	13,808	13,808	13,808
F-statistic	79.49	79.49	79.01	79.01	79.14	79.14
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.14	0.46	0.16	0.60	0.13	0.46

Table 12. Effect of Farm Concentration on Offered Interest Rates, 2002 to 2014

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on the average annual real interest rates advertised by banks in the county. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1 Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $Y_{i,t} = \beta_2\ \widehat{Farm\ Concentration}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data on an annual level (see Section 5 for variable and sample construction details). Columns 1–3 report deposit interest rates and Column 4 reports auto lending interest rates. All outcome variables are county-level averages of the interest rates offered by banks within each county and are expressed in real, inflation-adjusted terms. The outcome variable in Column 1 is the offered interest rate on savings deposit accounts, defined as $10K money market accounts. The outcome variables in Columns 2 and 3 are the offered interest rates on time deposit accounts, defined as 12-month $10K certificates of deposit, and checking deposit accounts, defined as interest-bearing checking accounts, respectively. The outcome variable in Column 4 is the offered interest rate on auto loans. $\widehat{Farm\ Concentration}_{i,t-2}$ is the fitted lagged within-county standardized midpoint farm size estimated in the first stage and carried forward annually until the next census observation. The controls are the same set of first- and second-stage controls as in Table 2. In both stages, I also control for local credit demand using county-level annual log total deposits and log total farm interest expenses. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Savings Deposits	(2) Time Deposits	(3) Checking Deposits	(4) Auto Loans
$\widehat{\text{Farm Concentration}}_{i,t-2}$	-0.236***	-0.022	-0.133***	0.875***
	(0.040)	(0.029)	(0.027)	(0.116)
Observations	36,539	36,657	36,614	29,399
F-statistic	52.50	52.50	52.50	52.50
Deregulation Index	Yes	Yes	Yes	Yes
Credit Demand Controls	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	-1.208	-0.564	-1.629	4.850

Figure 1. Timeline of U.S. Farm Policy Changes from 1996 to 2014

This figure illustrates the timeline of base acre reference periods and key policy events under successive U.S. farm bills. The 1996 Federal Agriculture Improvement and Reform (FAIR) Act introduced fixed direct payments based on average planted acres from 1981 to 1985. The 2002 Farm Security and Rural Investment (FSRI) Act expanded the program to include oilseeds and allowed base acres to be updated to reflect average plantings from 1998 to 2001. The program was renewed in the 2008 Food, Conservation, and Energy Act and ended in the 2014 Agricultural Act.

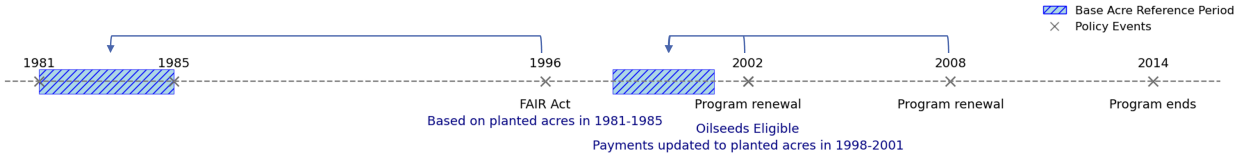


Figure 2. Effect of Subsidies on Farm Concentration

Estimates are obtained using the difference-in-differences estimator developed by De Chaisemartin and D'Haultfœuille (2020), which accommodates continuous treatments and addresses biases in two-way fixed effects models. The specification is: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The observations are at the county-year level. The sample is restricted to non-metropolitan counties with available Census of Agriculture data from 1987 to 2012 (see Section 5 for variable and sample construction details). The outcome variable is $Farm\ Concentration_{i,t}$, which is the midpoint farm size. $Subsidy\ Amount_{i,t}$ is a within-county standardized continuous measure of the estimated value of total fixed subsidy payments in a given county-year. The controls are the same set of first-stage controls as in Table 2. Coefficient estimates are plotted with 95% confidence intervals based on standard errors clustered by county.

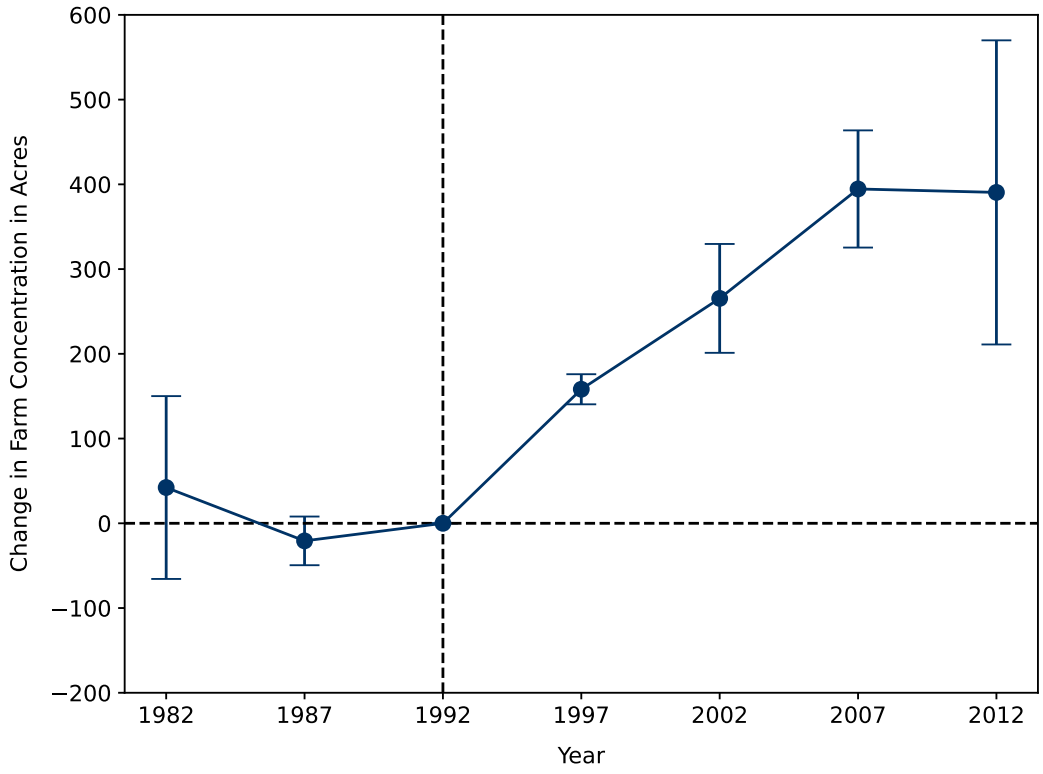
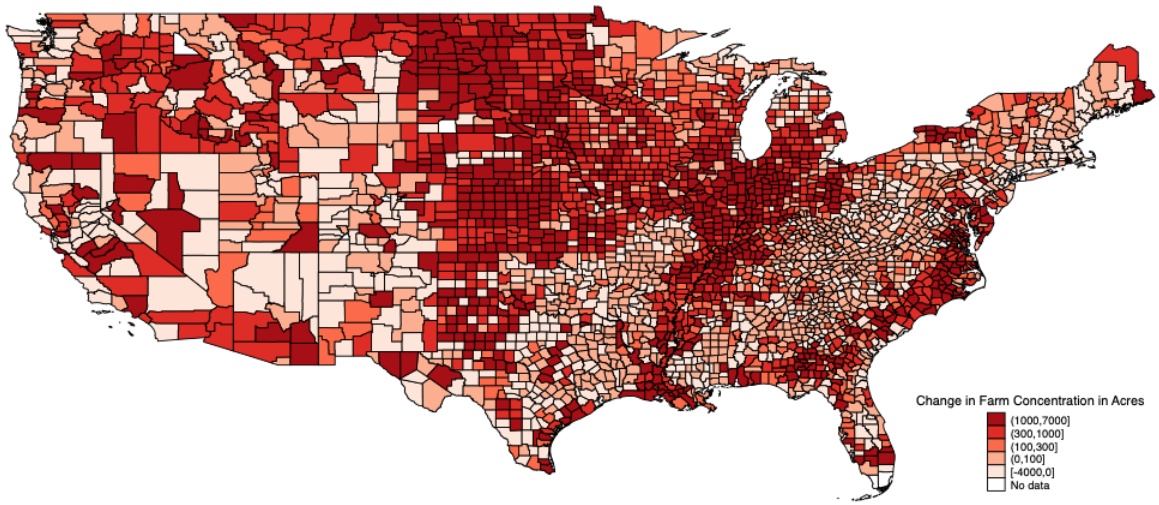


Figure 3. Changes in County-Level Farm Concentration and Program Payments

Panel A shows the change in farm concentration between 1992 and 2012, and Panel B shows the total fixed payments paid per county over the same period.

Panel A. Change in Farm Concentration between 1992 and 2012



Panel B. Change in Total Program Payments between 1992 and 2012

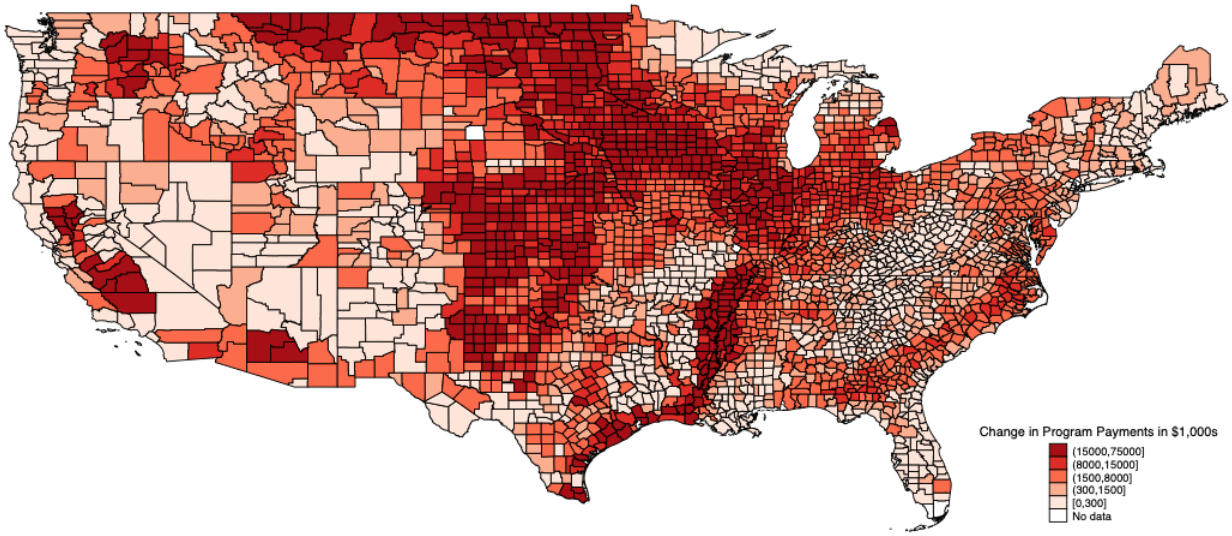


Figure 4. Farm Concentration and Bank Concentration

This figure illustrates the effect of fitted Farm Concentration$_{i,t-2}$ on the Bank Deposits Herfindahl-Hirschman Index$_{i,t}$ (HHI), following Saidi and Streitz (2021). The plotted coefficients are estimated from the first- and second-stage regressions, with 95% confidence intervals. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $Y_{i,t} = \sum_{k=2}^{10} \beta_k Farm\ Concentration_{i,t-2} + \beta_{11}\hat{\varepsilon}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. For this specification, I use a control function approach to allow for nonlinearities and omit the first decile. The controls are the same set of first- and second-stage controls as in Table 2. The outcome variable, Bank Deposits HHI$_{i,t}$, is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county.

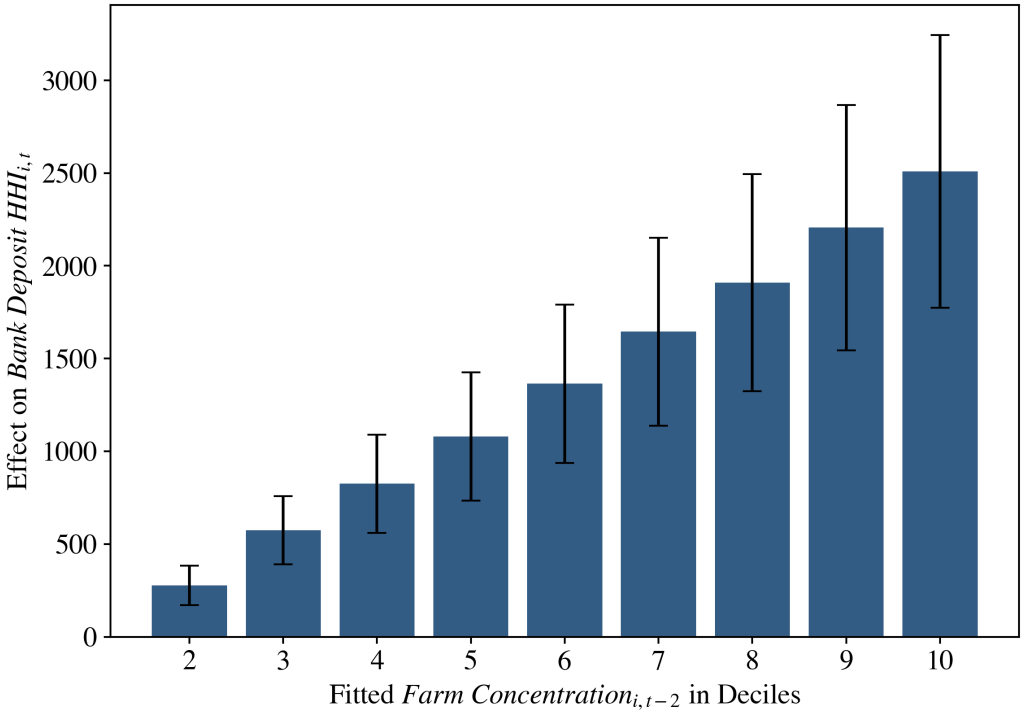
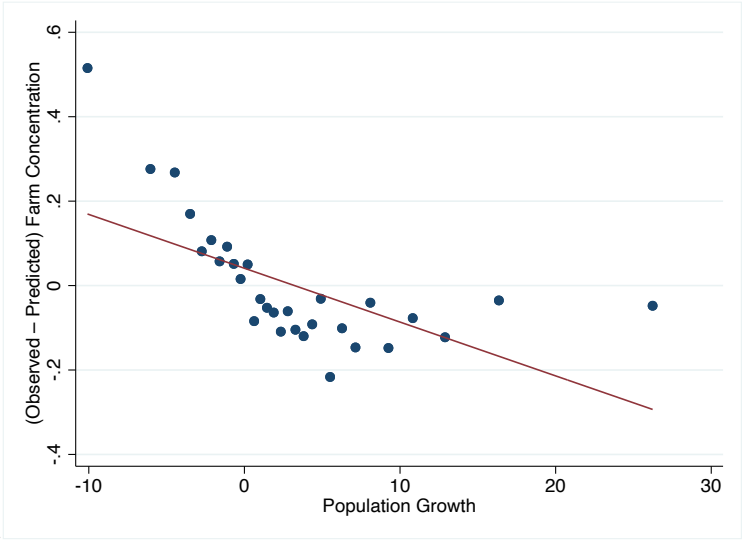


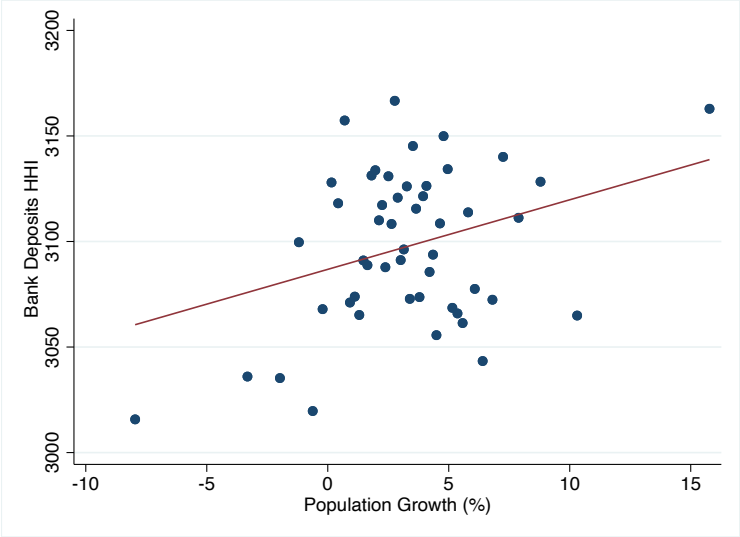
Figure 5. Relationship Between Population Growth and Farm and Bank Concentration

Panel A plots the relationship between changes in observed and predicted farm concentration (Observed – Predicted) Farm Concentration and county-level population growth. The first-stage specification is: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The controls are the same set of first-stage controls as in Table 2. Panel B plots Bank Deposits $\text{HHI}_{i,t}$ against population growth, including the same set of second-stage controls and fixed effects as in Table 2.

Panel A. Residual Farm Concentration and Population Growth



Panel B. Bank Concentration and Population Growth



Appendix A. Additional Analyses

Table A.1. Alternative Lag Structures: Effect of Farm Concentration on Large and Small Banks

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on measures of local banking markets by bank size with alternative time lags for the second stage. The specification for the first stage is: $Farm\ Concentration_{i,t} = \beta_1 Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$. The specifications for the second stages are: $Y_{i,t} = \beta_2\ \widehat{Farm\ Concentration}_{i,t-k} + \mathbf{X}'_{i,t-k}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$ in Column 1 and $E\big[Y_{i,t} \,\big|\, Farm\ Concentration_{i,t-k}, \hat{\varepsilon}_{i,t-k}, \mathbf{X}'_{i,t-k}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-k} + \mathbf{X}'_{i,t-k}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-k} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$ in Columns 2–5 using a control function approach. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). In Panels A and B, the first stage is lagged by three and four years, respectively, to test the sensitivity of the results to alternative lag structures. In Column 1, the outcome variable, *Bank Deposits* $HHI_{i,t}$, is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county. In Columns 2 and 4, the outcome variable is $Branches_{i,t}$, which is the county-level number of branches owned by large and small banks, respectively. In Columns 3 and 5, the outcome variable is *Deposits Per Capita*$_{i,t}$, which is the deposits per capita in large and small banks, respectively. $Farm\ Concentration_{i,t-k}$ is the within-county standardized midpoint farm size, lagged by either three or four years. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. In the first stage, the control variables account for county-level land availability using lagged measures of idle cropland, pastureland, and cropland left fallow, lost to crop failure, or otherwise unharvested from the prior Census of Agriculture. Log population$_{i,t-k}$ is included in the first stage regression for Columns 3 and 5 to adjust for the per-capita scaling of the dependent variable. In both stages, I also control for local economic conditions using the county-level employment rate$_{i,t-k}$ and log income per capita$_{i,t-k}$. In Columns 2–5, I additionally control for pre-existing banking infrastructure by including the log number of bank branches$_{i,t-k}$ in the county. F-statistics are from the first stage. Coefficients are reported as decimal percentages in Columns 2–5. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. First Stage Lagged Three Years

	(1)	(2)	(3)	(4)	(5)
		Large Bank		Small Bank	
	Bank Deposits HHI	Branches	Deposits Per Capita	Branches	Deposits Per Capita
$\widehat{\text{Farm Concentration}}_{i,t-3}$	215.34***	0.166***	0.406***	0.103***	0.227***
	(38.29)	(0.059)	(0.122)	(0.020)	(0.028)
Observations	13,808	13,808	13,808	13,808	13,808
F-statistic	99.44	96.40	81.38	96.40	81.380
County Controls	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	3,120	15	8,787	9	11,759

Panel B. First Stage Lagged Four Years

	(1)	(2)	(3)	(4)	(5)
		Large Bank		Small Bank	
	Bank Deposits HHI	Branches	Deposits Per Capita	Branches	Deposits Per Capita
$\widehat{\text{Farm Concentration}}_{i,t-4}$	218.37***	0.114**	0.449***	0.111***	0.234***
	(37.67)	(0.046)	(0.113)	(0.019)	(0.029)
Observations	13,808	13,808	13,808	13,808	13,808
F-statistic	98.56	95.44	81.48	95.44	81.48
County Controls	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	3,114	13	8,146	8	11,497

Table A.2. First Differences: Effect of Farm Concentration on Bank Concentration

This table reports the first- and second-stage results from an instrumental variable strategy to estimate the effect of a within-county one-standard-deviation change in farm concentration on the change in the bank deposits Herfindahl-Hirschman Index (HHI). To correct for autocorrelation, this specification uses first differences, where the first and second stage, respectively, are: $\Delta Farm\ Concentration_{i,t} = \beta_1\ \Delta Subsidy\ Amount_{i,t} + \Delta \mathbf{X}'_{i,t}\mathbf{\Gamma} + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $\Delta Y_{i,t} = \beta_2\ \Delta Farm\ \widehat{Concentration}_{i,t-2} + \Delta \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). Columns 1 and 2 report the first-stage regressions, where the dependent variable is $\Delta Farm\ Concentration_{i,t-2}$, measured as the change in the midpoint farm at the county level. In all second-stage regressions, $\Delta Farm\ Concentration_{i,t-2}$ is expressed in within-county standardized units. Columns 3 and 4 report the second-stage results, where the dependent variable is the change in bank deposits HHI. The $\Delta Bank\ Deposits\ HHI_{i,t}$ is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county, differenced each period. The instrument, $\Delta Subsidy\ Amount_{i,t-2}$, is a continuous within-county standardized measure of the predicted change of total fixed subsidy payments in a given county-year. The controls are the same set of first- and second-stage controls as in Table 2, but in first differences. F-statistics are from the first stage. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	First Stage		Second Stage	
	Δ Farm Concentration		Δ Bank Deposits HHI	
Δ Farm $\widehat{\text{Concentration}}_{i,t-2}$			167.97**	147.37**
			(78.80)	(58.57)
Δ Subsidy Amount$_{i,t-2}$	35.65***	46.46***		
	(3.99)	(4.28)		
Δ Log Income Per Capita$_{i,t-2}$		85.21		-53.92
		(65.63)		(89.32)
Δ Employment Rate$_{i,t-2}$		-98.60		68.90
		(128.13)		(275.72)
Δ Idle Land$_{i,t-7}$		24.41***		
		(4.64)		
Δ Unharvested Cropland$_{i,t-7}$		13.87***		
		(4.39)		
Δ Pastureland$_{i,t-7}$		7.14		
		(5.21)		
Observations	13,166	13,166	13,166	13,166
F-statistic	77.42	35.23	77.42	35.23
Deregulation Index FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	119.5	119.5	12.65	12.65

Table A.3. Pre-2009: Effect of Farm Concentration on Large and Small Banks

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on measures of local banking markets by bank size before the 2008 Financial Crisis. The specification for the first stage is: $Farm\ Concentration_{i,t} = \beta_1 Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$. The specifications for the second stages are: $Y_{i,t} = \beta_2\ \widehat{Farm\ Concentration}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$ in Column 1 and $E\big[Y_{i,t} \,\big|\, Farm\ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$ in Columns 2–5 using a control function approach. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). The sample is further restricted to pre-2009 years to exclude the potential confounding effects of the 2008 Financial Crisis. In Column 1, the outcome variable, $Bank\ Deposits\ HHI_{i,t}$, is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county. In Columns 2 and 4, the outcome variable is $Branches_{i,t}$, which is the county-level number of branches owned by large and small banks, respectively. In Columns 3 and 5, the outcome variable is $Deposits\ Per\ Capita_{i,t}$, which is the deposits per capita in large and small banks, respectively. $Farm\ Concentration_{i,t-2}$ is the within-county standardized midpoint farm size, lagged by two years. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. In Columns 1 and Columns 2–5, the controls are the same set of controls as in Table 4 and Table 5, respectively. F-statistics are from the first stage. Coefficients are reported as decimal percentages in Columns 2–5. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
		Large Bank		Small Bank	
	Bank Deposits HHI	Branches	Deposits Per Capita	Branches	Deposits Per Capita
$\widehat{\text{Farm Concentration}}_{i,t-2}$	303.81***	0.195***	0.265**	0.111***	0.187***
	(70.08)	(0.070)	(0.111)	(0.039)	(0.039)
Observations	8,512	8,512	8,512	8,512	8,512
F-statistic	42.25	41.33	36.25	41.33	36.25
County Controls	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	3,151	19	7,739	11	12,233

Table A.4. Alternative Definition of Agricultural Banks: Effect of Farm Concentration on Large and Small Banks

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on bank presence and deposit-per-capita growth by bank size and restricted to only agricultural (ag) banks. The specification for the first stage is: $Farm\ Concentration_{i,t} = \beta_1 Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$. The specifications for the second stages are: $Y_{i,t} = \beta_2\ \widehat{Farm\ Concentration}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$ in Columns 1 and 4 and $E\big[Y_{i,t}\,\big|\,Farm\ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$ in the remaining columns using a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). The sample is further restricted to agricultural banks, which I define as those holding more than 1% of their total assets in farm loans in any of the last five years. In Columns 1 and 4, the outcome variable, $Probability\ of\ Entry_{i,t}$, is an indicator variable for whether a large or small bank is present in the county in a given year, respectively. In Columns 2 and 5, the outcome variable is $Branches_{i,t}$, which is the county-level number of branches owned by large and small ag banks, respectively. In Columns 3 and 6, the outcome variable is $Deposits\ Per\ Capita_{i,t}$, which is the deposits per capita in large and small ag banks, respectively. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. The controls are the same set of first- and second-stage controls as in Table 10. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Large Agricultural Bank			Small Agricultural Bank		
	Probability of Entry	Branches	Deposits Per Capita	Probability of Entry	Branches	Deposits Per Capita
$\widehat{\text{Farm Concentration}}_{i,t-2}$	0.073***	0.229***	0.575***	0.020**	0.037*	0.203***
	(0.02)	(0.058)	(0.080)	(0.01)	(0.021)	(0.027)
Observations	13,808	13,808	13,808	13,808	13,808	13,808
F-statistic	99.10	99.10	83.63	99.10	99.10	83.63
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.67	7	5,032	0.90	7	10,502

Table A.5. Alternative Definition of Agricultural Banks: Effect of Farm Concentration on Agricultural Loan Growth

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on agricultural loan growth by bank size and only among agricultural (ag) banks. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $E\big[Y_{i,t} \,\big|\, Farm\ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). The sample is further restricted to agricultural banks, which I define as those holding more than 1% of their total assets in farm loans in any of the last five years. In Columns 1 and 2, the outcome variable, $Total\ Agricultural\ Loan\ Growth_{i,t}$, is large or small banks' growth in total agricultural loan volume in a given county-year relative to the prior period's total agricultural loan volume. The outcome variable in Columns 3 and 4 is $Real\ Estate\ Loan\ Growth_{i,t}$, and the outcome variable in Columns 5 and 6 is $Non\text{-}Real\ Estate\ Loan\ Growth_{i,t}$; both are similarly measuring the loan growth by bank size relative to the prior period's total volume by relevant loan type. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. Small banks are those with less than \$10 billion in inflation-adjusted assets, and large otherwise. The controls are the same set of first- and second-stage controls as in Table 8. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Large Ag Bank	(2) Small Ag Bank	(3) Large Ag Bank	(4) Small Ag Bank	(5) Large Ag Bank	(6) Small Ag Bank
	Total Agricultural Loan Growth		Real Estate Loan Growth		Non-Real Estate Loan Growth	
$\widehat{\text{Farm Concentration}}_{i,t-2}$	0.531***	0.073**	0.545***	0.023	0.360***	0.123***
	(0.107)	(0.029)	(0.149)	(0.040)	(0.088)	(0.030)
Observations	13,808	13,808	13,808	13,808	13,808	13,808
F-statistic	76.80	76.80	76.37	76.37	76.69	76.69
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.49	0.73	0.58	0.95	0.72	0.75

Table A.6. First Differences: Effect of Farm Concentration on Offered Interest Rates, 2003 to 2014

This table shows the second-stage estimates of the effect of a within-county one-standard-deviation increase in the change in farm concentration on the change in the average annual real interest rates advertised by banks in the county using an instrumental variable strategy. To correct for autocorrelation, this specification uses first differences, where the first and second stage, respectively, are: $\Delta Farm\ Concentration_{i,t} = \beta_1\ \Delta Subsidy\ Amount_{i,t} + \Delta \mathbf{X}'_{i,t}\mathbf{\Gamma} + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $\Delta Y_{i,t} = \beta_2\ \Delta \widehat{Farm\ Concentration}_{i,t-2} + \Delta \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data on an annual level (see Section 5 for variable and sample construction details). Columns 1–3 report the change in deposit interest rates and Column 4 reports the change in auto lending interest rates. All outcome variables are changes in county-level average offered bank interest rates, expressed in real, inflation-adjusted terms. The outcome variable in Column 1 is the change in offered interest rates on savings deposit accounts, defined as $10K money market accounts. The outcome variables in Columns 2 and 3 are the change in offered interest rates on time deposit accounts, defined as 12-month $10K certificates of deposit, and checking deposit accounts, defined as interest-bearing checking accounts. The outcome variable in Column 4 is the change in offered interest rates on auto loans. $\Delta\ \widehat{Farm\ Concentration}_{i,t-2}$ is the change in the fitted lagged within-county standardized midpoint farm size estimated in the first stage and interpolated annually until the next census observation. The controls are the same set of first- and second-stage controls as in Table 12, but in first differences. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Δ Savings Deposits	(2) Δ Time Deposits	(3) Δ Checking Deposits	(4) Δ Auto Loans
$\Delta\widehat{\text{Farm Concentration}}_{i,t-2}$	-0.143***	-0.008	-0.054***	0.269***
	(0.023)	(0.024)	(0.015)	(0.063)
Observations	29,526	29,637	29,613	23,269
F-statistic	17.70	17.70	17.70	17.70
Deregulation Index	Yes	Yes	Yes	Yes
Credit Demand Controls	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	-0.073	-0.219	-0.011	-0.289

Table A.7. Flat vs. Rugged: Effect of Cash Subsidies on Farm Concentration

This table reports the effect of a within-county one-standard-deviation increase of subsidy amounts on farm concentration across counties with different levels of terrain ruggedness. The specification is: $\textit{Farm Concentration}_{i,t} = \beta_1 \textit{Subsidy Amount}_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). The dependent variable is $\textit{Farm Concentration}_{i,t}$, measured as the within-county standardized midpoint farm at the county level. Means and standard deviations are calculated within the relevant subsample. The instrument, $\textit{Subsidy Amount}_{i,t}$, is a continuous within-county standardized measure of the predicted value of total fixed subsidy payments in a given county-year. Counties are classified as rugged if their average Terrain Ruggedness Index (TRI), calculated by the Economic Research Service (ERS), falls in the top quartile of the national distribution. All other counties are classified as flat. The controls are the same set of first-stage controls as in Table 2. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Flat	(2) Rugged
	Farm Concentration	
Subsidy Amount	159.834***	36.190***
	(10.764)	(8.198)
Observations	10,368	3,440
R-squared	0.838	0.855
F-statistic	67.66	5.72
County Controls	Yes	Yes
Deregulation Index FE	Yes	Yes
County & Year FE	Yes	Yes
Mean of Dependent Variable	892.43	327.72

Table A.8. Effect of Farm Concentration on Bank Concentration, Controlling for Crop Insurance Coverage

This table reports the first- and second-stage results from an instrumental variable strategy to estimate the effect of a within-county one-standard-deviation increase in farm concentration on the bank deposits Herfindahl-Hirschman Index (HHI). The specifications for the first and second stages, respectively, are: $\textit{Farm Concentration}_{i,t} = \beta_1 \textit{Subsidy Amount}_{i,t} + \beta_3 \textit{Log Crop Insurance Policies}_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $Y_{i,t} = \beta_2 \widehat{\textit{Farm Concentration}}_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). Columns 1 and 2 report the first-stage regressions, where the dependent variable is $\textit{Farm Concentration}_{i,t-2}$, measured as the midpoint farm size at the county level. In all second-stage regressions, $\textit{Farm Concentration}_{i,t-2}$ is expressed as within-county standardized units. Columns 3 and 4 report the second-stage results, where the dependent variable is the bank deposits HHI. The outcome variable, $\textit{Bank Deposits HHI}_{i,t}$, is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county. The instrument, $\textit{Subsidy Amount}_{i,t-2}$, is a continuous within-county standardized measure of the predicted value of total fixed subsidy payments in a given county-year. I include crop insurance, $\textit{Log Crop Insurance Policies}_{i,t-2}$, measured as the log total number of crop insurance policies in the county-year. The controls are the same set of first- and second-stage controls as in Table 2. F-statistics are from the first stage. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	First Stage		Second Stage	
	Farm Concentration		Bank Deposits HHI	
$\widehat{\text{Farm Concentration}}_{i,t-2}$			266.71***	257.70***
			(38.84)	(39.04)
Subsidy Amount$_{i,t-2}$	105.03***	109.53***		
	(5.52)	(6.15)		
Log Crop Insurance Policies$_{i,t-2}$	23.41***	22.95***		
	(4.29)	(4.33)		
Log Income Per Capita$_{i,t-2}$		187.38***		-90.82
		(69.36)		(123.20)
Employment Rate$_{i,t-2}$		-137.03		400.12
		(156.05)		(839.58)
Idle Land$_{i,t-7}$		26.94***		
		(5.24)		
Unharvested Cropland$_{i,t-7}$		-16.29***		
		(3.82)		
Pastureland$_{i,t-7}$		2.66		
		(6.05)		
Observations	13,808	13,808	13,808	13,808
F-statistic	183.13	79.31	183.13	79.31
Deregulation Index FE	No	Yes	No	Yes
County & Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	751.7	751.7	3,123	3,123

Table A.9. Falsification Test: Direct Effect of Subsidy Amount on Large and Small Banks

This table reports reduced form estimates of the effect of a within-county one-standard-deviation increase in subsidy amounts on measures of local banking markets by bank size. The specifications are: $Y_{i,t} = \beta_1\ Subsidy\ Amount_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$ in Column 1 and $E\big[Y_{i,t} \,\big|\, Subsidy\ Amount_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_1\ Subsidy\ Amount_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$ in Columns 2–5. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). In this sample, I include urban counties. Counties are sorted into terciles based on the predicted long-run change in farm concentration attributable to subsidies. Panels A and B report results for the bottom and top terciles, respectively. In Column 1, the outcome variable, $Bank\ Deposits\ HHI_{i,t}$, is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county. In Columns 2 and 4, the outcome variable is $Branches_{i,t}$, which is the county-level number of branches owned by large and small banks, respectively. In Columns 3 and 5, the outcome variable is $Deposits\ Per\ Capita_{i,t}$, which is the deposits per capita in large and small banks, respectively. $Subsidy\ Amount_{i,t-2}$ is the within-county standardized subsidy amount, lagged by two years. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. In Columns 1 and Columns 2–5, the controls are the same set of controls as in Table 4 and Table 5, respectively. F-statistics are from the first stage. Coefficients are reported as decimal percentages in Columns 2–5. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Bottom Tercile of Predicted Farm Consolidation

	(1)	(2)	(3)	(4)	(5)
		Large Bank		Small Bank	
	Bank Deposits HHI	Branches	Deposits Per Capita	Branches	Deposits Per Capita
Subsidy Amount$_{i,t-2}$	10.612	0.002	0.002	-0.006*	0.008*
	(7.052)	(0.001)	(0.004)	(0.003)	(0.005)
Observations	4,688	4,206	4,201	4,585	4,585
R-squared	0.91	0.95	0.81	0.72	0.82
County Controls	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	3,489	26	9,725	10	8,750

Panel B. Top Tercile of Predicted Farm Consolidation

	(1)	(2)	(3)	(4)	(5)
		Large Bank		Small Bank	
	Bank Deposits HHI	Branches	Deposits Per Capita	Branches	Deposits Per Capita
Subsidy Amount$_{i,t-2}$	26.757	0.029*	0.020	0.025**	0.022**
	(17.100)	(0.017)	(0.034)	(0.011)	(0.009)
Observations	4,682	4,115	4,115	4,682	4,682
R-squared	0.90	0.88	0.80	0.58	0.87
County Controls	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	2,643	11	7,982	11	16,422

Table A.10. Effect of Farm Concentration on Large and Small Banks, Controlling for Farm Credit System (FCS) locations

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on measures of local banking markets by bank size and controlling for Farm Credit System (FCS) historical branch locations. The specification for the first stage is: $Farm\ Concentration_{i,t} = \beta_1 Subsidy\ Amount_{i,t} + \beta_3 Log\ FCS\ Branches_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$. The specifications for the second stages are: $Y_{i,t} = \beta_2\ \widehat{Farm\ Concentration}_{i,t-2} + \beta_4 Log\ FCS\ Branches_{i,t} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \epsilon_{i,t}$ in Column 1 and $E\big[Y_{i,t} \,\big|\, Farm\ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, Log\ FCS\ Branches_{i,t}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \beta_4 Log\ FCS\ Branches_{i,t} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_5\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$ in the Columns 2–5 using a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). In Column 1, the outcome variable, $Bank\ Deposits\ HHI_{i,t}$, is a continuous variable ranging from 0 to 10,000 calculated as the sum of squared deposit shares held by each bank within a county. In Columns 2 and 4, the outcome variable is $Branches_{i,t}$, which is the county-level number of branches owned by large and small banks, respectively. In Columns 3 and 5, the outcome variable is $Deposits\ Per\ Capita_{i,t}$, which is the deposits per capita in large and small banks, respectively. $\widehat{Farm\ Concentration}_{i,t-2}$ is the within-county standardized midpoint farm size, lagged by two years. Small banks are those with less than $10 billion in inflation-adjusted assets, and large otherwise. In Columns 1 and Columns 2–5, the controls are the same set of controls as in Table 4 and Table 5, respectively. F-statistics are from the first stage. Coefficients are reported as decimal percentages in Columns 2–5. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
		Large Bank		Small Bank	
	Bank Deposits HHI	Branches	Deposits Per Capita	Branches	Deposits Per Capita
Farm $\widehat{\text{Concentration}}_{i,t-2}$	251.18***	0.172***	0.257**	0.103***	0.210***
	(39.31)	(0.041)	(0.094)	(0.021)	(0.026)
Log FCS Branches	-22.15	-0.030**	0.070	-0.021	-0.079***
	(30.08)	(0.015)	(0.146)	(0.017)	(0.020)
Observations	13,808	13,808	13,808	13,808	13,808
F-statistic	97.82	93.87	80.28	93.87	80.28
County Controls	Yes	Yes	Yes	Yes	Yes
Deregulation Index FE	Yes	Yes	Yes	Yes	Yes
County & Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	3,123	14	8,468	9	11,936

Table A.11. Falsification Test: Effect of Farm Concentration on Federal Government Loans

This table reports second-stage instrumental variable (IV) estimates of the effect of a within-county one-standard-deviation increase in farm concentration on access to subsidized loans. The specifications for the first and second stages, respectively, are: $Farm\ Concentration_{i,t} = \beta_1\ Subsidy\ Amount_{i,t} + \mathbf{X}'_{i,t}\mathbf{\Gamma} + \gamma_i + \delta_t + \phi_{d(i,t)} + \varepsilon_{i,t}$ and $E\big[Y_{i,t}\,\big|\,Farm\ \ Concentration_{i,t-2}, \hat{\varepsilon}_{i,t-2}, \mathbf{X}'_{i,t-2}, \gamma_i, \delta_t, \phi_{d(i,t)}\big] = \exp\big(\beta_2\ Farm\ Concentration_{i,t-2} + \mathbf{X}'_{i,t-2}\mathbf{\Gamma} + \beta_3\ \hat{\varepsilon}_{i,t-2} + \gamma_i + \delta_t + \phi_{d(i,t)}\big)$. Subscript i represents the county, t represents the year, and d represents state-level banking deregulation. For this specification, I use a control function approach. In the table, I include a hat on $Farm\ Concentration_{i,t-2}$ to indicate this is an IV regression. The county-year data are from merged bank and agriculture data (see Section 5 for variable and sample construction details). The outcome variables in Columns 1 and 2 are the $Total\ Amount_{i,t}$ and $Total\ Number_{i,t}$ of direct loans, respectively, issued at the county level by the federal government. These direct loans are specifically targeted toward small, new, or socially disadvantaged family farms that are unable to secure credit at reasonable rates from commercial banks. $Farm\ Concentration_{i,t-2}$ is the lagged within-county standardized midpoint farm size. The controls are the same set of first- and second-stage controls as in Table 4. F-statistics are from the first stage. Coefficients are reported as decimal percentages. Standard errors clustered at the county level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Direct Loan	
	Total Amount	Total Number
$\widehat{\text{Farm Concentration}}_{i,t-2}$	0.078	-0.255
	(0.267)	(0.210)
Observations	13,808	13,808
F-statistic	95.35	95.35
County Controls	Yes	Yes
Deregulation Index FE	Yes	Yes
County & Year FE	Yes	Yes
Mean of Dependent Variable	474,406	13.13

Figure A.1. Distribution of Counties by Average Terrain Ruggedness

This figure shows the distribution of average terrain ruggedness across U.S. counties, measured using the 2010 Terrain Ruggedness Index (TRI) from the USDA Economic Research Service (ERS). Counties are divided into quartiles based on the national TRI distribution, with the top quartile corresponding to an average ruggedness index greater than or equal to 28.

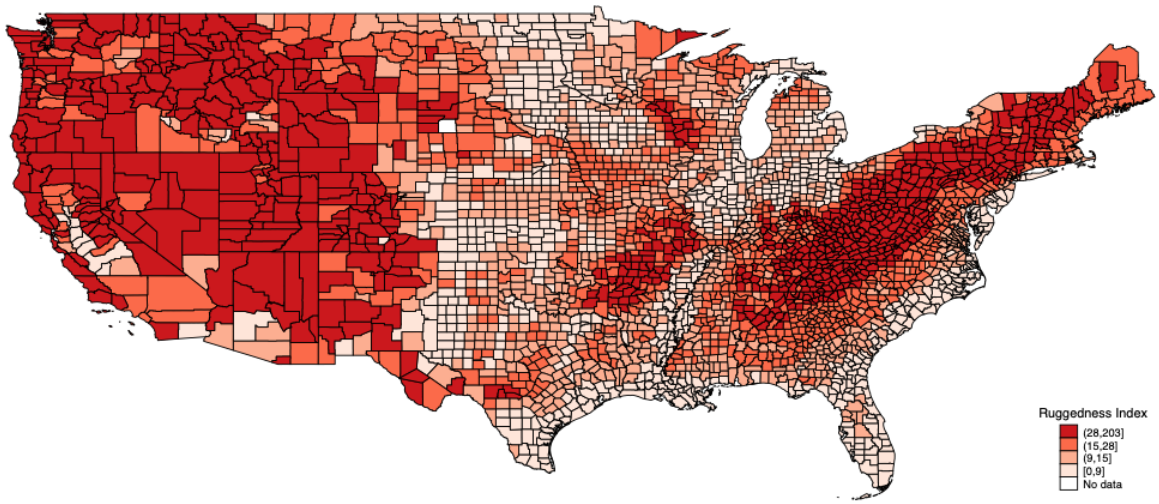
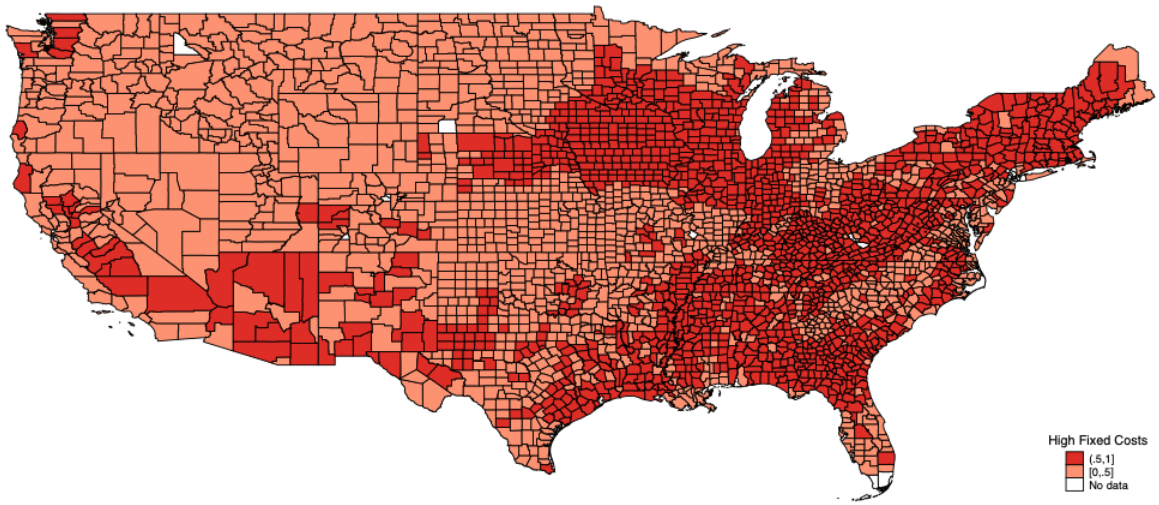


Figure A.2. Distribution of High- and Low-Cost Counties

This figure shows the distribution of U.S. counties classified as high- or low-cost based on per-acre economic costs. The measure is constructed as a time-invariant, county-level weighted average of per-acre economic costs, where weights are each crop's share of harvested acreage from the 1992 Census of Agriculture. Economic costs per acre for each major commodity crop are calculated as the five-year average (1990–1995) from the Farm Costs and Returns Survey (FCRS) compiled by the U.S. Department of Agriculture's Economic Research Service (ERS). Counties with weighted average costs above the national median are classified as high-cost, and those below the median as low-cost.



Appendix B. Data Methods and Technical Details

This appendix provides additional detail on the procedures used to construct key variables and allocate bank- and loan-level data to the county level for empirical analysis.

B.1 Estimating County-Level Agricultural Lending

Because agricultural loan volumes are reported at the bank level in the FFIEC Call Reports, I allocate each bank's total agricultural lending across the counties in which it operates using a demand-weighted procedure based on the Census of Agriculture. Specifically, I calculate each county's share of total farm interest expenses, aggregated across real estate and non-real estate loans, and use this share to allocate agricultural lending from each bank across counties. For example, if a bank operates in three counties and each county accounts for one-third of total farm interest expenses, I assign one-third of the bank's agricultural lending to each county. This process is repeated for each bank and year, then aggregated by county and by bank size group (small vs. large).

This method follows the approach used in Key, Burns, and Lyons (2019) and Ifft et al., (2024), which estimate spatial lending exposures using historical agricultural activity. While the method provides a proxy for local credit allocation, it has limitations. First, banks, particularly larger institutions with centralized lending divisions, may extend loans beyond the counties in which they maintain branches. Second, the method assumes that a bank's lending is proportional to local demand as measured by past interest expenses, which may not reflect current lending decisions. Nevertheless, this allocation approach provides a consistent basis for constructing county-level measures of agricultural lending intensity in the absence of branch-level loan data.

B.2 Instrument Construction and Interpolation

The instrumental variable leverages exogenous variation in fixed-cash subsidies introduced under the 1996 FAIR Act and subsequently extended and modified under the 2002 Farm Security and Rural Investment (FSRI) Act. Initially, payments were based on base acres and yields from 1981 to 1985, scaled by national per-acre payment rates. The 2002 FSRI Act permitted farmers to update base acres using planting data from 1998 to 2001 and expanded eligibility to include oilseeds such as soybeans and peanuts.

To construct predicted subsidy exposure, I combine each county's current base acre allocations with national payment rates by crop and year, following a continuous difference-in-differences design. Because base acres are fixed by legislation and national rates vary only over time, identification comes from differential county-level exposure based on historical

crop shares and program eligibility. This approach captures both the original 1996 eligibility criteria and the 2002 updates.

In the five-year panel, I compute predicted subsidies in each census year and use them as instruments for changes in farm structure. For the annual panel used in the RateWatch analysis, I estimate fitted values of farm concentration (midpoint farm size) from the first-stage regression in each census year and carry these values forward until the next census observation. Although this approach may introduce measurement error, it should bias results conservatively toward zero.

B.3 Lag Structure and Timing Alignment

To allow time for structural changes in agriculture to influence financial outcomes, all farm variables, including the midpoint and land-use controls, are lagged by two years in the five-year panel. In the annual panel, the timing of banking data (from the FDIC) reflects branch activity as of June of each year. To align RateWatch interest rate data with this calendar structure, I average weekly rates from July of the previous year through June of the current year.

B.4 USDA Direct Loan Program

To assess whether subsidy-driven borrower consolidation affects access to federal agricultural credit, I use administrative data from the USDA's Farm Service Agency (FSA) on direct loan issuance. These loans are targeted primarily toward family farms, defined as operations where the majority of the business is owned and operated by individuals within a family. The program is designed to assist small, new, or socially disadvantaged farmers, offering credit at reasonable rates to support farm ownership, operation, or expansion.

Eligibility does not depend on a minimum credit score. Although applicants must demonstrate reasonable ability to repay and cannot be delinquent on other federal debt, individuals with no formal credit history may still qualify. The program includes both ownership and operating credit. Farm ownership loans can be used to purchase farmland or expand physical infrastructure, with a loan limit of $600,000 and repayment terms of up to 40 years. Operating loans are designed for inputs such as seed, livestock, or equipment, with a loan limit of $400,000 and repayment terms of up to seven years.

I use annual data on direct loans issued between 1994 and 2014, aggregating both the total number of loans and the dollar amount issued each year. These data allow me to examine whether borrower-side consolidation, triggered in part by fixed-cash subsidies, influences the scale and allocation of federally supported agricultural credit.

Internet Appendix

IA.1 Model Setup

This section presents a simple one-period model of a bank's optimization problem. The purpose of the model is to illustrate how fixed cash payments, such as agricultural subsidies, can increase lending amounts and reduce interest rates by increasing the borrower's pledgeable assets. In the model, cash is fully pledgeable in default and therefore acts as collateral, both raising the lender's recovery value and reducing the set of states in which default occurs. As a result, higher cash holdings allow lenders to extend larger loans at lower interest rates.

Assume there is a lender and a firm. The firm seeks bank financing for a project requiring upfront funding L. The project has a payoff X, where $X \sim N(\mu L, \sigma^2 L^2)$, so expected returns and risk scale with project size. The bank will choose an interest rate of r to maximize profits.

Assume the firm has cash $A \geq 0$ and has size (e.g., land) S. I assume cash and investment needs scale with size, $A = \pi_1 S$ and $L = \pi_2 S$, which implies that $A = \pi L$ for some constant π. If the firm defaults, it liquidates and the lender recovers a fraction ℓ of total resources, $\ell(A + X)$. Lastly, the bank incurs a cost C when it lends, and it will only lend if expected profits are non-negative.

IA.2 Equilibrium Interest Rate

For an interest rate r, the bank's expected profits are

$$E[\mathbb{1}_{X+A<L(1+r)} \max(0, \ell(A+X)) + \mathbb{1}_{X+A\geq L(1+r)} L(1+r)] - L - C.$$

The bank chooses r to maximize this value.

Using the formula for the expected value of a truncated normal distribution, I can rewrite this objective as

$$\ell\left(\Phi\left(\frac{(1+r)-\pi-\mu}{\sigma}\right) - \Phi\left(\frac{-\pi-\mu}{\sigma}\right)\right)\left((\mu+\pi) - \frac{\phi\left(\frac{(1+r)-\pi-\mu}{\sigma}\right) - \phi\left(\frac{-\pi-\mu}{\sigma}\right)}{\Phi\left(\frac{(1+r)-\pi-\mu}{\sigma}\right) - \Phi\left(\frac{-\pi-\mu}{\sigma}\right)}\sigma\right)L$$
$$+ L(1+r)\left(1 - \Phi\left(\frac{(1+r)-\pi-\mu}{\sigma}\right)\right) - L - C,$$

where ϕ and Φ denote the standard normal p.d.f. and c.d.f., respectively. The lending market is competitive, so the equilibrium interest rate rate will be the minimum rate such that the bank's expected profits are non-negative.

IA.3 Results

This section presents a numerical example to illustrate the basic mechanisms of the model. The results proceed in three steps. First, I show that an increase in borrowers' cash holdings raises expected lender profits, implying borrowers are more likely to receive financing and interest rates are lower. Second, the results imply that larger firms, or farms in my setting, whose scale mechanically increases both investment size and fixed cash payments, are better positioned to expand investment using financing due to lower interest rates. Third, I show that if larger borrowers use this improved access to credit to finance acquisitions, the resulting increasing returns to scale further raises expected returns and liquidation values, amplifying these effects. While the model abstracts from bank size heterogeneity, it suggests a channel through which borrower-side consolidation increases demand for large-scale lending, with implications for bank market structure.

IA.1 Cash Subsidies and Credit Market Outcomes

Figure IA.1 decomposes the lender's profits (before the lending cost C) into various components. As the interest rate increases, the firm's probability of default rises. Conditional on repayment, the lender's gains increase mechanically with the interest rate. Conditional on default, expected gains also increase with the interest rate because as rates increase, the set of payoffs which are defaulting increase. However, the gains upon default are lower than upon solvency for a given rate, so increasing rates beyond a point leads to lower expected profits.

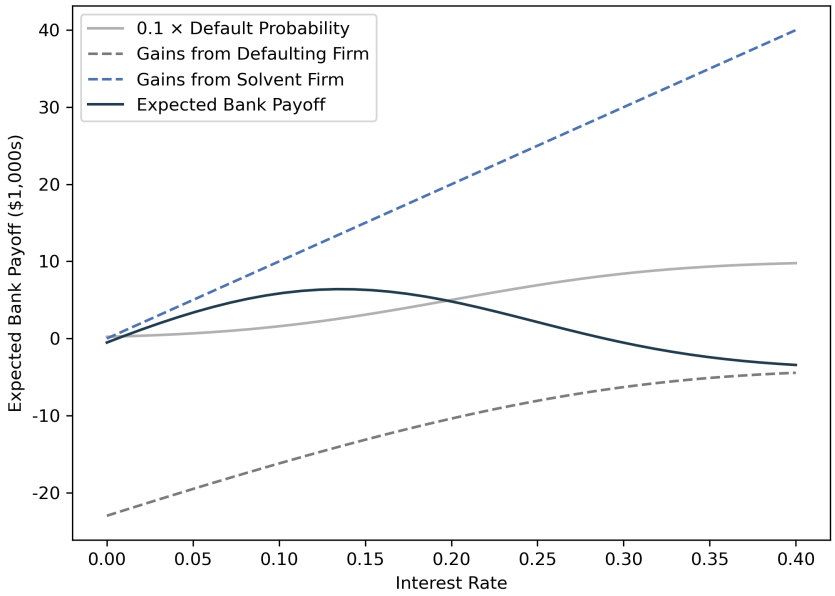


Figure IA.1. This figure illustrates the components of the decision problem of the lender. The parameter values are $L = 50{,}000$, $\pi = 0.15$, $\mu = 1.05$, $\sigma = 0.1$, and $\ell = 0.8$.

In the analysis that follows in this section, I'll study the results for firms with different cash allocations and sizes. To highlight the dynamics in my setting, it will be useful to view the firm in the model as an agricultural farm with varying levels of base acreage and scale. Figure IA.2 shows that the bank's profits before lending costs are increasing in the farm's cash holdings A, which for fixed L, can be interpreted as the number of base acres for a farm of given size. If a farm has more base acres, there are more states (realizations of project values) in which it does not default, leading to higher payoffs for the lender. The dotted horizontal lines indicate the level of lending costs, and the x values of the solid dots denote equilibrium interest rates. When the cost of lending is high, there is no interest rate at which the lender would lend to the farm with low base acreage, because profits would be negative at any given interest rate. In this case, such farms are credit rationed. When the cost is sufficiently low, the bank is willing to lend to farms with low base acreage, but only at a higher interest rate than for farms with greater base acreage.

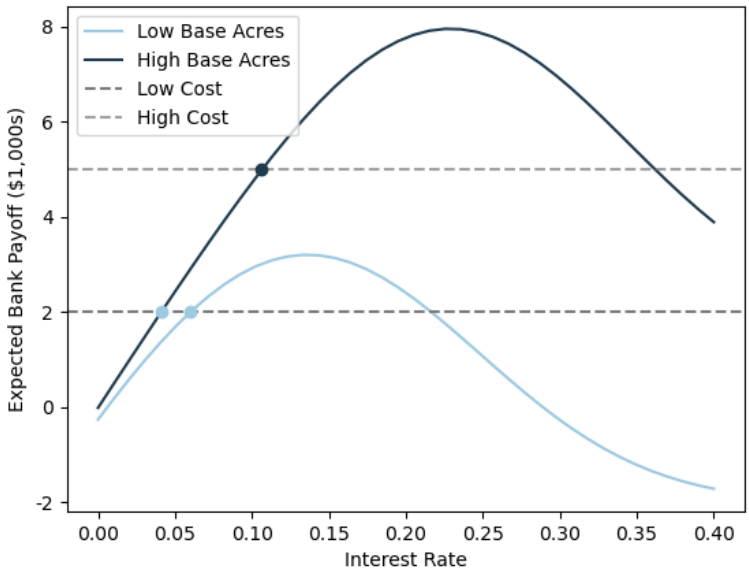


Figure IA.2. This figure shows bank profits as a function of rates for a farm with a large and small number of base acres. π is set to 0.15 (light blue) and 0.25 (dark blue). The other parameter values are $L = 50{,}000$, $\mu = 1.05$, $\sigma = 0.1$, and $\ell = 0.8$. Two lending cost levels, $C = 2{,}000$ and 4,000, are considered.

Figure IA.3 presents the analogous comparison for farms of different sizes. Expected lender profits increase with farm size through two channels. First, larger farms undertake larger projects. Second, because subsidies are tied to land, larger farms mechanically have greater base acreage and therefore higher cash holdings. As a result, sufficiently small farms are credit rationed when the cost of lending is high (holding lending costs fixed across farms). When the cost of lending is sufficiently low, the bank is willing to lend to both small and large farms, but charges the large farm a lower equilibrium interest rate. This result suggests that larger farms are better positioned to secure cheaper financing following the introduction of fixed subsidies, allowing them to fund larger upfront investments such as farmland acquisitions.

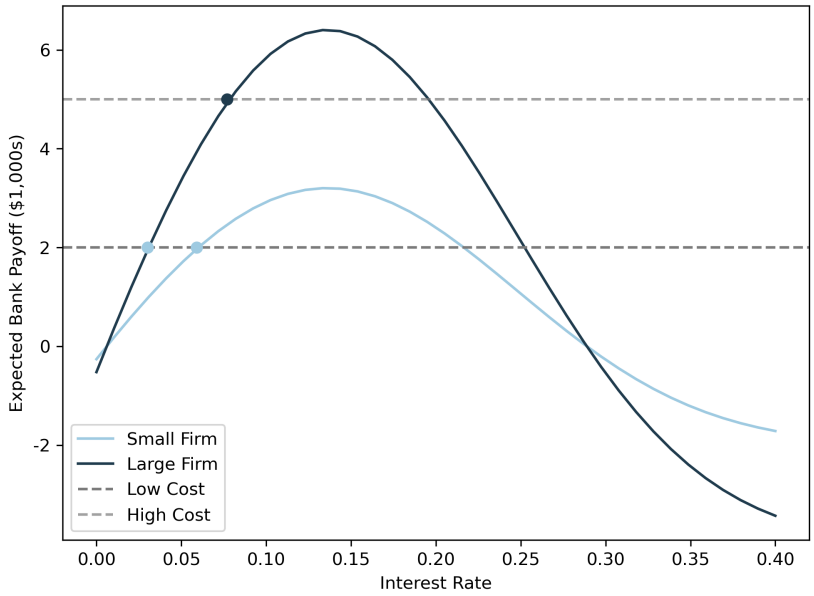


Figure IA.3. This figure shows bank profits as a function of rates for a large and small firm. L is varied from 50,000 to 100,000. The other parameter values are $\mu = 1.05$, $\sigma = 0.1$, $\pi = 0.15$, and $\ell = 0.8$. Two lending cost levels, $C =$ 2,000 and 4,000, are considered.

IA.2 Mergers and Increasing Returns to Scale

Lastly, I consider a setting in which firms may merge and, upon merging, their projects exhibit increasing returns to scale. I compare the bank's lending decision for two identical standalone firms with its decision for the merged firm. Increasing returns to scale are captured by assuming that the merged farm has a higher mean project return μ. The merged firm's project requires double the upfront investment and incurs double the monitoring cost relative to a single firm. Previously I considered differences in firm size while holding monitoring costs fixed across borrowers, which might seem inconsistent with the notion that the merged firm has monitoring cost of $2C$. Allowing monitoring costs to scale proportionally with firm size in the merger case is therefore conservative. Reducing the monitoring cost of lending to the merged firm below $2C$ would only strengthen the results.

Figure IA.4 shows that when two firms merge and exhibit increasing returns to scale, the bank's expected profit from lending to the merged firm exceeds the combined expected profit from lending to the two firms separately. Moreover, conditional on whether the bank is willing to lend to both the two separate firms and the merged firm, the merged firm is less likely to be credit rationed and can borrow at a lower equilibrium interest rate than the two standalone firms.

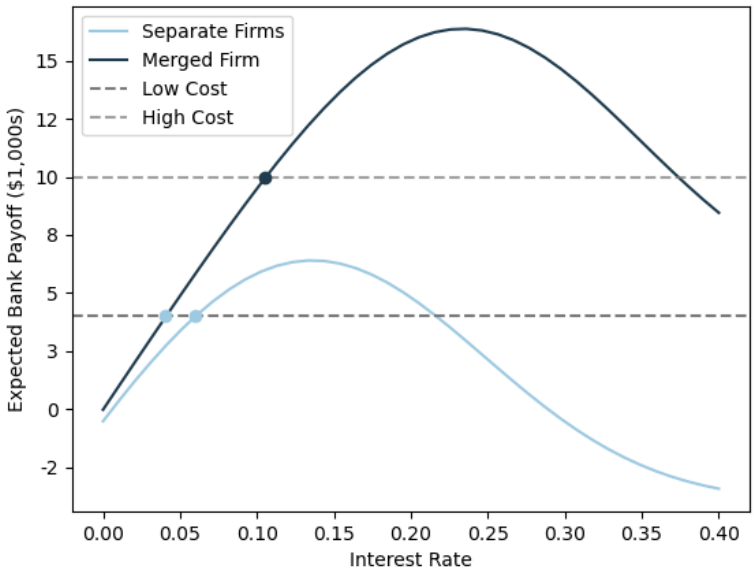


Figure IA.4. This figure compares expected bank profits under a merger with increasing returns to scale to profits when the bank lends to two firms separately. $\mu = 1.05$ when the firms are separate; under a merger, $\mu = 1.1 \cdot 1.05$. Each firm has $L = 50{,}000$. The other parameter values are $\sigma = 0.1$, $\pi = 0.15$, and $\ell = 0.8$. Two lending cost levels, $C = 2{,}000$ and 4,000, are considered, and the total cost of lending to both firms or the merged firm is $2C$.