Industry Specialization and Small Business Lending

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Abstract

This paper examines the rise and competitive impact of industry-specialized small business lenders. Using loan-level data with detailed industry codes from the Small Business Administration (SBA), we document a recent increase in lenders that originate loans nationally but to a limited number of industries. We then examine the impact of these industry-specialized lenders on credit availability and banking competition. Exploiting the staggered entry of a large, specialized lender, we find significant increases in total SBA-backed lending with no evidence of substitution from other lenders. We then explore potential mechanisms behind the increase in lending.

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1. Introduction

Two central challenges facing small business lenders are information opacity and business heterogeneity (Mills, 2019*b*). Information about a small business is difficult to acquire and communicate (Berger and Udell, 1995; Petersen and Rajan, 1994) and each small business is different, making it difficult to generalize knowledge from one business to others. Both challenges are closely tied to distance. Proximity aids in the collection and transfer of information, leading to better risk assessment and fewer defaults among nearby borrowers (Petersen and Rajan, 2002; DeYoung, Glennon and Nigro, 2008; Agarwal and Hauswald, 2010). But lending only to nearby borrowers can heighten the challenge of business heterogeneity, since the smaller pool of potential borrowers limits the scope for a lender to specialize in certain types of businesses. In contrast, a lender covering a larger area could focus only on certain industries, perhaps developing industry-specific expertise or making industry-specific investments in underwriting or marketing.

Small business lenders face this trade-off between geographic specialization - lending in specific locations to a variety of industries - and industry specialization - lending to specific industries across a variety of locations. Historically, lenders have nearly all chosen the former. The median distance between branches of small business lenders and their borrowers remains less than ten miles, and credit availability is tightly linked to the presence of nearby banks (Nguyen, 2019; Granja, Leuz and Rajan, 2022). In this paper, we document the recent rise of remote, industry-specialized lenders, i.e., institutions that lend nationally but specialize in a narrow set of industries. Based on loan-level data from the Small Business Administration (SBA) 7(a) program, the percentage of SBA loans (in dollars) accounted for by these specialized lenders has increased from less than 2% in 2001 to more than 17% in 2017. These specialists develop expertise in advertising, underwriting, or monitoring in their specific industries, and we find evidence that specialists exhibit improved loan performance relative to other lenders in the same industry.

The main focus of this paper is whether industry-specialized lenders complement or substitute for local lenders. If remote, specialized lenders complement existing lenders by lending to new borrowers, they may increase the total amount of lending and relax credit constraints common among small businesses. Additionally, for the targeted industries, remote specialists may weaken the link dependence of small businesses on nearby branches (Nguyen, 2019), leading to an increase in small business lending within underbanked areas. If specialized lenders serve as substitutes by competing for the same borrowers as local lenders, the greater competition may lead to better loan terms but have little impact on the total amount of loans or access to credit. In some cases, cream-skimming by competing new lenders can even lead to unraveling and a decline in credit availability (Detragiache, Tressel and Gupta, 2008; Gormley, 2014).

We examine the impact of industry-specialized lenders on lending in the small business credit market, in particular the market for SBA-guaranteed loans. The primary challenge is that specialized lending has grown steadily and endogenously over time, making it difficult to separate the impact of specialized lending from other factors. A second challenge is that commonly used data on small business lending do not contain detailed industry information. Previous papers examining industry concentration among lenders had to group businesses into 10-25 broad categories such as agriculture, construction, or energy, which are too coarse to detect specialization in narrowly defined industries.

To address these challenges, we examine entry by a specific industry-specialized lender, Live Oak Bank, within the SBA 7(a) lending program. Live Oak Bank is a prominent industry-specialized lender, originating more than 80% of its loans to just six industries. The bank lists industry-specific expertise as its primary advantage. Upon entering, Live Oak quickly accounts for around half of all SBA 7(a) lending to these industries. These large, staggered shocks to the supply of credit allow us to identify the impact of a sudden increase in industry-specialized lending on the market for SBA-guaranteed small business loans. The fact that Live Oak operates within the SBA program also allows us to use the SBA's loan-level data containing the full NAICS industry code for each loan from more than 800 distinct industries. In addition to providing a unique opportunity to identify the impact of specialized lending, this setting is interesting in its own right. SBA lending is an important source of credit for constrained small businesses, with a around a quarter employer small businesses applying for SBA loans (Federal Reserve Banks, 2016-2019), and Live Oak is the SBA program's largest lender, originating around 6% of SBA-backed dollars.

Exploiting the entry of this industry-specialized lender into its six industries, we estimate the impact on total lending and the competitive effect on other lenders within the market for SBA-guaranteed loans. Our strategy compares the evolution of lending in these six treated industries with lending in a group of control industries that Live Oak did not enter. We use the synthetic control method (Abadie and Gardeazabal, 2003; Abadie, Diamond and Hainmueller, 2010) to create a weighted average of control industries chosen to best match the treated industry's lending path during the pretreatment period.

We find that the industry-specialized lending significantly increased total SBA lending to the treated industries. Across the six treated industries, annual loan originations rise by 30-110 percentage points relative to the synthetic control. Moreover, there is no substitution away from other SBA lenders. Other institutions' SBA lending to the targeted industries remains unchanged upon Live Oak's entry. These results are robust to a variety of extensions and robustness checks and indicate that Live Oak originates loans to new borrowers who would not have obtained an SBA loan otherwise.

We lack the data to directly examine substitution from non-SBA commercial lending, but institutional features, existing evidence, and an empirical test all suggest that substitution from non-SBA bank lending is limited. One possibility is that specialized lending substitutes away from non-commercial alternatives, such as seller financing, which was historically common in several of the specialists' industries.

Next, we examine several mechanisms for the increase in lending that are related to industry specialization. Lenders themselves state that their ability to make these distant loans depends on their industry specialization and expertise. We find that specialized lenders focus on safer industries and industries where there is a weak relationship between distance and charge-offs. Consistent with expertise offsetting the costs of distant lending, we find that Live Oak Bank maintains similar charge-off rates to those of other lenders in the industries, despite lending at much greater distances.

Our main results focus on a single lender within the SBA program, so a natural question is whether these results generalize to other lenders and settings. Adapting the empirical strategy, we find similar average effects for other specialized lenders within the SBA program. For non-SBA lenders, detailed industry data on small business lending are not available, but other research and industry reports show that industry-specialized lending is increasingly prominent outside of SBA lending as well. Karen Mills, former Administrator of the SBA, describes the emergence of industry-specialized lenders as a key innovation in small business lending more generally (Mills, 2019*a*) and trade publications have highlighted the recent growth of specialty lending.[2] Additionally, Blickle, Parlatore and Saunders (2021) shows that industry-specialized commercial and industrial (C&I) lending exists even among large banks subject to stress testing. Similar to our setting, they find that there exists a group of extreme specialists, that specialization is associated with improved loan performance, and that industry specialization is increasing over time.

The main contributions of this paper are to document the growth in remote, industry-specialized small business lenders within the SBA program and to estimate the impact of entry by a specialized lender on credit availability. Our paper relates to a sizeable literature on the relationship between banks' portfolio concentration with sectors and their risk or returns. Winton (1999) and Stomper (2006) provide a theory analyzing the role of specialization and diversification in bank lending, and a corresponding empirical literature documents the presence and degree of banks' sectoral concentration and its relationship to loan performance (Acharya, Hasan and Saunders, 2006; Hayden, Porath and Westernhagen, 2007; Boeve, Duellmann and Pfingsten, 2010; Jahn, Memmel and Pfingsten, 2016; Tabak, Fazio and Cajueiro, 2011; Beck, De Jonghe and Mulier, 2022; Fricke and Roukny, 2020). Others examine lender specialization along dimensions other than industry, including the export market (Paravisini, Rappoport and Schnabl, 2021), collateral type (Gopal, 2019), and loan types (e.g. consumer or commercial) in the purchase of failed banks (Granja, Matvos and Seru, 2017). Our paper corroborates results finding better loan performance by specialists. In our setting, industry specialization is measured at a much finer level, with over 800 distinct industries, whereas the

[2]See American Banker (2013) and American Banker (2012) for examples of other niche lenders.

existing literature observes 20-40 broad sectors.

Recent work on bank specialization tests whether information advantages drive specialization and examines the implications of specialization for shock propagation. Paravisini, Rappoport and Schnabl (2021) shows that lenders specialize in certain export markets and that such specialization limits firms' abilities to easily substitute across lenders, thereby affecting the transmission of credit shocks. Consistent with information advantages, Giometti and Pietrosanti (2022) finds that specialized lenders offer less restrictive financial covenants to firms in the specialized industry, providing one mechanism that limits substitution away from specialized lenders. Also examining the interaction of specialization and credit shocks, Duquerroy et al. (2022) finds that bank closures disproportionately reduce borrowing in industries where the closed bank had specialized, while De Jonghe et al. (2020) and Jiang and Li (2022) find that lenders facing a negative credit shock reallocate credit toward sectors where they specialize. Our paper adds to this literature on the interaction of lender specialization and credit supply by providing new evidence on the effects of entry by a specialized lender.

Our focus on entry connects to the broader literature examining the competitive impact of new entrants in banking. One strand of this literature examines the entry of foreign (distant) banks and their impact on domestic (local) lenders after financial liberalization. Detragiache, Tressel and Gupta (2008) and Gormley (2014) develop theoretical models showing that competition from distant lenders can either increase or decrease aggregate lending. Empirical papers find that entry by foreign lenders sometimes reduces access to credit (Beck and Martinez Peria, 2010; Detragiache, Tressel and Gupta, 2008; Gormley, 2010) and sometimes increases access to credit (Giannetti and Ongena, 2009, 2012; Bruno and Hauswald, 2013; Claessens and Van Horen, 2014). A related literature examines the impact of increased competition caused by interstate banking deregulation within the United States (see, e.g., Black and Strahan (2002) and Cetorelli and Strahan (2006)). Related to industry expertise, Karakaya, Michalski and Örs (2022) focuses on broader sector specialization within manufacturing and uses interstate banking deregulation to identify the impact of entry by banks into new states. Lending grows in manufacturing sectors that the entering bank was more familiar with based on the businesses common in its home state. Others examine new competition from Fintech mortgage lenders (Buchak et al., 2018; Fuster et al., 2019) or peer-to-peer lenders (Tang, 2019; De Roure, Pelizzon and Thakor, 2022; Wolfe and Yoo, 2018; Jagtiani and Lemieux, 2017). Relative to these papers, we document the growth of a new type of lender (remote, industry-specialized small business lenders) and find that lenders specializing in certain sectors or industries can serve as complements to existing, local SBA small business lenders.

2. Setting and Data

Our analysis examines industry specialization within the market for Small Business Administration (SBA) 7(a) loans, which provides guarantees for small business loans. It is the SBA's largest funding program and an important source of credit for small businesses. In 2017, SBA 7(a) originated more than 60,000 loans totaling $25.45 billion, which makes up 10% of small business lending reported in the Community Reinvestment Act.[3] These SBA loans likely make up a larger share among employer small businesses (those with employees) and in certain industries where SBA lending is common. In the Small Business Credit Survey (Federal Reserve Banks, 2016-2019), 22-26% of employer small businesses seeking a loan or line of credit applied for an SBA loan. Of those that already held loans and did not apply in the last year, 17% held an SBA loan or line of credit.

To be eligible for a 7(a) loan, the borrower must run a for-profit small business that meets SBA industry-specific size standards. The program targets credit-constrained businesses. Lenders must satisfy the "credit elsewhere" requirement by documenting why the borrower could not obtain a loan on reasonable terms without the SBA guarantee, and also review whether funds are available from the personal resources of any applicants owning more than 20% of the small business. A 2008 survey of SBA borrowers finds that the large majority of 7(a) loans are used for new equipment (34%), financing working capital (23%), or to acquire a business (21%), and a smaller share is used to refinance another loan (8%) (Hayes, 2008).

Private lenders provide the capital for 7(a) loans. These lenders are mostly commercial banks, though there are also credit unions and other non-bank lenders. The private lenders make most decisions regarding the SBA loans subject to underwriting rules of the SBA such as a maximum interest rate and borrower requirements. The SBA provides the lender with a partial guarantee for the loan of up to 75-85%, depending on the loan size. In exchange, the lenders pay the SBA a fee that depends on the features of the loan and the amount guaranteed.

Although the loans are guaranteed, screening is still important. The SBA program serves a group of less creditworthy borrowers who could not obtain a loan on other terms, the guarantees are only partial, and the SBA monitors portfolio performance. The SBA can revoke Preferred Lender status for poor risk management or seek payment even for the guaranteed portion if a charge-off is attributable to technical deficiencies of the lender. Indeed, the bank we examine in our main analysis consistently lists loan delinquencies, credit losses, and possible repercussions from the SBA as the first risk factors in its annual report (Live Oak Bancshares,

[3]These loan amounts are not directly comparable, as CRA data do not include loans for more than $1 million while SBA 7(a) statistics do and the CRA only collects information from banks with assets over $1 billion. These larger institutions represent 70% of all outstanding small business loans made by banks (Haynes and Williams, 2018). In the CRA, small business loans are defined as those with original amounts of $1 million or less and were reported on the institution's Call Report or Thrift Financial Report as either "Loans secured by nonfarm or nonresidential real estate" or "Commercial and industrial loans."

Annual Report, 2016, 2018). As evidence of screening, Federal Reserve Banks (2016-2019) show that approval rates for SBA loans are similar or slightly lower, on average, than the approval rates when small businesses apply for non-SBA personal or business loans. Additionally, DeYoung, Glennon and Nigro (2008), DeYoung et al. (2011), and Huang (2020) provide empirical evidence of the importance of credit screening, default, and information asymmetries in lending through the SBA program.

Our main analysis uses data from the SBA Loan Data Report on all originated 7(a) loans between 2001 and 2017.[4] A key advantage of the data is that they contain the small businesses' industry and location, as well as each loan's amount, term, repayment status, and (starting in 2008) interest rate. We group businesses into industries by their 5-digit NAICS code, and businesses from more than 800 distinct industries obtain a 7(a) loan during our sample period. Using the lender identity and borrower location, we calculate the distance between each borrower and the closest branch of the institution making the loan.[5] To do so, we fuzzy match the SBA lender to bank branch networks in the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits. We match 92% of loans to branch networks, primarily missing loans from credit unions or other non-bank lenders because they are not included in the FDIC data. We then geocode the borrowers' addresses, matching 72%, and calculate the distance between the borrower and the closest branch of the lending institution. Although we only have the exact addresses geocoded for 72% of borrowers, all of our results using distance are robust to calculating distance using the borrower's county centroid, which is available for the full sample of bank loans. Internet Appendix B provides more details on the procedure for calculating distance.

3. Motivating Evidence

3.1. The Growth of Industry Specialization

We begin by documenting the existence and rise of remote, industry-specialized lenders within the SBA program. Figure 1 plots the relationship between each SBA lending institution's (log) median borrower-lender distance against its top-five industry share, defined as the share of the institution's loans extended to its five most common industries.[6] Two facts are evident. First, in all periods, there is a positive relationship between distant lending and industry concentration, reflecting a trade-off between geographic specialization and industry specialization. In the 2013-2017 period, institutions with a median borrower-lender distance

[4]We drop loans that were approved but canceled before origination.

[5]Since lending decisions and monitoring may not be done at the local branch, one may want to measure the distance between the borrower and the location where underwriting decisions are made, but these are not observed in the data. Granja, Leuz and Rajan (2022) also uses the location to the nearest branch and finds that this measure is correlated with lenders' information and borrowers' credit risks.

[6]For each period, we restrict the sample to lenders who originate at least 50 loans in that period. Additionally, we drop loans to the most common industry "limited-service restaurants," which make up 9.5% of all SBA loans. Among the other industries, none make up more than 2.2% of SBA loans. To calculate the top-five share, let S_{ijt} be the share of institution j's loans to industry i during period t. The top-five share for institution j during period t is the sum of its largest five S_{ijt} shares.

less than 10 miles had an average top-five share of 23%, while lenders with a median borrower-lender distance of more than 100 miles had an average top-five share of 40%.[7] Second, the three periods in Figure 1 reveal an increasing number of institutions with a high degree of both distant lending and industry concentration. To highlight this growth, we classify a lender as a remote specialist if its median borrower-lender distance exceeds 100 miles and its top-five industry share exceeds 32% (the 90^{th} percentile during the 2001-2006 period) and mark these institutions as solid circles in Figure 1.[8]

Figure 2 shows the annual number of remote specialists (as defined above) and their share of total SBA lending between 2001 and 2017. The number of lenders classified as remote specialists increased from less than 10 to more than 40 over this period. Additionally, remote industry specialists make up a larger share of SBA lending, from less than 1.6% in 2001 to 17.4% in 2017. These graphs show a steady increase in industry-specialized lending that accelerates after 2012. A natural question is whether these trends in specialization are unique to SBA lending. While our data are limited to the SBA program, external evidence suggests an increase in non-SBA specialized lending as well. Blickle, Parlatore and Saunders (2021) finds that industry-specialized C&I lending exists even among large banks subject to stress testing. Additionally, Karen Mills, the former Administrator of the Small Business Administration, emphasizes that specialization by lenders in specific industries is a key innovation of emerging small business lenders within and outside of the SBA program (Mills, 2019*a*), and trade publications have also highlighted the general rise of niche or specialty lending.[9]

3.2. Potential Benefits of Industry Specialization

What advantages do industry-specialized lenders have over local lenders in identifying profitable or low-risk borrowers? First, industry-specialized lenders can select industries with lower risks or less competitive markets. In Section 6, we show that Live Oak Bank, the subject of our case study, enters industries with low charge-off rates and industries where there is a weaker relationship between distant lending and loan performance. We also examine this for all specialized lenders in Internet Appendix C, which characterizes the specialists identified in Figure 1 and shows that their chosen industries tend to have below-average charge-off rates. Second, industry specialization may facilitate expertise that offsets the disadvantages of distant lending or helps the specialist appeal to new borrowers. For example, specialized lenders hire industry experts and develop industry-specific underwriting guidelines and performance metrics. Consistent with

[7] In Internet Appendix Tables A.1 and A.2, we show the positive relationship between distance and concentration is statistically significant and robust to additional controls and measures of distance. Additionally, to partially address the concern that this may be related to the SBA guarantee, we show that the relationship between distance and lending is similar for loans with a low ($\leq 50\%$) or high ($> 50\%$) SBA guarantee (Internet Appendix Figure A.1).

[8] Internet Appendix E provides additional discussion of this primary definition of remote specialist and demonstrates robustness to alternative thresholds and definitions.

[9] See American Banker (2013) and American Banker (2012) for examples of other niche lenders.

expertise, we find that specialized lenders experience better loan performance than other lenders within the same industries (Internet Appendix C.2). To provide a sense of the magnitude, these estimates imply that a lender originating 52% of its loans to an industry would offset the additional risk of lending to a borrower 100 miles away. This relationship between concentration and the probability of default remains similar when adding several geographic and loan controls.

These advantages of specialization are consistent with what specialized lenders themselves identify as their primary advantages: industry-specific expertise, practices, and investments. Live Oak Bank, which we examine in our empirical strategy, states, "We are one of the nation's top originators of small business loans primarily because our expertise in specific industries enables us to lend to business owners who haven't had access to capital in the past" (Live Oak Bank, n.d.). In particular, Live Oak develops expertise by hiring industry experts prior to lending. United Community Bank, another specialized SBA lender, reports that it mitigates the risk of "working with more borrowers it doesn't know well" by "originating SBA loans only within specific industries it has decided to cultivate after studying them carefully" (Schneider, 2016). Additionally, specialists use industry-specific underwriting criteria or collateral assessment to better evaluate credit risks. For example, specialists describe how general lenders do not understand the cash flow issues unique to specific industries,[10] or the off-balance-sheet assets (e.g., medical records, goodwill) unique to independent pharmacies and veterinary and dental practices.[11] As a result, local lenders may overestimate the risk of certain industries because they apply uniform, general underwriting criteria.

Finally, a specialist's industry-specific focus allows them to engage in industry-specific marketing (e.g. trade shows), build industry-specific networks (e.g. hiring industry insiders), and offer tailored advice in a way that is not feasible for general lenders. These unique potential advantages of industry-specialized lending may allow them to either identify new, profitable borrowers or to offer better rates and products to existing ones. The trade-off is that industry-specialized lenders must make more distant loans to serve a large enough pool of borrowers, and distance makes it difficult to collect soft information and monitor businesses. Additionally, specialists are more at risk to industry-specific shocks, while geographically concentrated lenders are exposed to area-specific shocks. As stated by Live Oak Bank, "the risk associated with industry concentration is mitigated by the geographical diversity of the overall loan portfolio" (Live Oak Bancshares, Annual Report, 2016).

[10]Concerning Live Oak's lending to Registered Investment Advisors (RIAs), "[O]ne of Live Oak's biggest advantages is that it understands the RIA industry and many banks don't ... A lot of lenders are uncomfortable with the RIA industry ... They don't understand this is a business without a lot of cash flow," states Jamie Carvallo, co-founder of Park Sutton Advisors LLC, quoted in Shidler (2013).

[11]First Financial Bank states, "Commercial banks are asset based lenders, and when it comes to a veterinary practice, the largest asset is usually an off-balance sheet asset – Patient files, Goodwill, etc. An SBA loan can be collateralized in different ways to make it possible to acquire the loan." (First Financial Bank, 2018*b*)

4. Empirical Strategy

Our goal is to examine the impact of remote, industry-specialized lenders on the availability of small business credit within the SBA program. Do specialized lenders complement or substitute for existing, primarily local lenders? What is their impact on the total amount of lending? Lending may increase or, as in the theoretical models of Detragiache, Tressel and Gupta (2008) and Gormley (2014), cream-skimming by new lenders may cause unraveling and a decline in credit availability. We investigate these questions by examining a case study of the largest remote, specialized SBA lender: Live Oak Bank. This case study of a prominent, remote specialized lender (and the largest SBA lender by volume) is of interest in its own right. Moreover, the size and entry strategy of Live Oak Bank provide a unique setting to estimate the competitive impact of entry by a remote lender, and provide evidence about the potential for specialized lending to complement existing lenders. In an extension, we adopt a similar strategy to assess whether the results of this case study generalize to other specialized SBA lenders.

4.1. Background: Live Oak Bank

Live Oak Bank was founded in 2007 as a niche lender, at first focused exclusively on SBA lending to veterinary practices, but soon expanding to other industries. Our strategy will exploit Live Oak's staggered entry into these industries, which generates a sudden increase in industry-specialized lending, to assess its impact on lending markets. Live Oak operates almost exclusively in the market for government-guaranteed loans, predominately within the SBA 7(a) program and, to a lesser extent, with loans guaranteed by the U.S. Department of Agriculture.

As seen in Figure 1, Live Oak exhibits the two key features of remote, industry-specialized lenders. Live Oak gave 95% of its SBA loans to borrowers more than 100 miles from its single headquarters in North Carolina and 80% of its loans went to just six industries. Table 1 reports Live Oak's main industries (those with at least 50 loans), as well as Live Oak's post-entry share of SBA loans (number and dollar amount) in that industry as of 2017 and the month that Live Oak first originated a loan to the industry.

Our analysis examines entry into the six industries where Live Oak has given the most loans: veterinarians, dentists, investment advice establishments, pharmacies, broilers, and funeral homes. Live Oak's share of the total SBA volume in dollars, at around 50%, is even greater. Live Oak's combination of size, industry concentration, and staggered entry generates sharp increases in total lending to these industries. When Live Oak enters, it provides a significant share of subsequent lending, ranging from 12% of SBA loans to offices of dentists to 58% of SBA loans to investment advice establishments. We exclude Live Oak's loans in its remaining industries because it either entered in mid-2015, so there is a short post-period, or the loans made up only a small share of lending to that industry and therefore are unlikely to have had a measurable impact.

4.2. Sample Construction: Treatment and Control Industries

We use data from the SBA 7(a) Loan Data Report to construct annual counts of all approved SBA 7(a) loans by industry (5-digit NAICS code) from 2001-2017.[12] These counts are of all 7(a) loans, so include term loans (68%) and revolving lines of credit (32%), and new loans as well as refinances.[13] Of the initial 835 5-digit NAICS industries receiving SBA loans, we drop the industries where Live Oak made a small number of loans, leaving the six primary Live Oak industries and the control industries where Live Oak made zero loans. Thus, the control industries face no competition from Live Oak. To ensure consistency in industry definitions, we also drop industries that had a change in their 5-digit NAICS code between 1997 and 2012, leaving 466 industries. Finally, we retain only the industries that have at least one SBA 7(a) loan approved for each year between 2001 and 2017. We also require the industries to average at least 20 loans per year during the period 2001-2006, so that the donor pool is similar in size to the industries that Live Oak enters. The final sample consists of a balanced panel from 2001-2017 of annual loan originations for 219 control industries and the six treated industries that Live Oak has entered.

4.3. Synthetic Control Method

To estimate the effect of Live Oak's entry, we compare the path of total lending in the six entered (treated) industries to a comparison group of other control industries. For the comparison group, we use the synthetic control method (Abadie and Gardeazabal, 2003; Abadie, Diamond and Hainmueller, 2010) to construct a synthetic match for each treated industry. The synthetic match is a weighted combination of the control industries where the weights are chosen to best match the pretreatment lending trajectory of the treated industry.

Our setting is well suited for the synthetic control method. First, the synthetic control method requires large treatment shocks because the small number of treated units makes it difficult to distinguish small treatment effects from other idiosyncratic shocks (Abadie, 2021). Table 1 shows that, after entry, Live Oak originated 12-58% of SBA loans to these industries. Outside of Dentists, Live Oak's loans amount to a shock of one to three times the pretreatment standard deviation of lending within the treated industries. Second, the industries that Live Oak did not enter provide a natural comparison group. These are loans to other small businesses that meet the SBA's requirements and, as discussed in the last section, we limit the donor pool of control industries to those that receive at least 20 loans annually during the pretreatment period.

Formally, consider a panel of I industries over T years with industry 1 as the single treated industry,

[12] We drop canceled loans and loans given to borrowers in the U.S. territories. We begin in 2001 because, prior to 2001, many 7(a) loans are missing the industry code.

[13] We examine the robustness to using counts of only term loans, which comprise more than 99% of Live Oak's loans. We cannot distinguish between new loans and refinances, but refinances account for only 8% of SBA 7(a) loans (Hayes, 2008).

which Live Oak enters in year T_0+1. Our outcome Y_{it} is the annual number of new SBA loans to industry i in year t, divided by the loans to industry i in 2006. This normalization converts all outcomes to percentages relative to 2006, which allows us to compare growth in industries of different sizes. We choose 2006 as the base year because it is the year before Live Oak began lending.

Let Y_{it} be the observed SBA loan originations to industry i in year t and, using potential outcomes notation, let $Y_{1t}(1)$ and $Y_{1t}(0)$ be the potential loan originations to industry 1 during year t with and without treatment (Live Oak's entry). Our goal is to estimate the causal effect of entry on lending to industry 1, $\tau_{1t} = Y_{1t}(1) - Y_{1t}(0) = Y_{1t} - Y_{1t}(0)$ for periods $t > T_0$. We only observe $Y_{1t}(1)$ for the treated industry during the post-treatment period, so estimating the treatment effect requires an estimate of the counterfactual number of loans that would have been given out if Live Oak had not entered, i.e., $Y_{1t}(0)$.

To estimate this counterfactual, we assume that the potential outcome under no treatment for all industries i follows the factor model

$$Y_{it}(0) = \delta_t + \lambda_t \mu_i + \varepsilon_{it} \tag{1}$$

where δ_t is a time fixed effect, λ_t is a vector of unobserved common factors, μ_i is a vector of unknown factor loadings, and ε_{it} is an unobserved, industry-level transitory shock with zero mean. As Abadie, Diamond and Hainmueller (2010) shows, if there is a set of weights $(w^*_{2t}, \ldots, w^*_{It})$, with $w^*_{it} \geq 0$ and $\sum_i w^*_{it} = 1$, such that a weighted combination of the outcomes of control industries equals the outcome of the treated industry for all pretreatment periods,

$$\sum_{i=2}^{I} w^*_i Y_{i1} = Y_{11}, \quad \sum_{i=2}^{I} w^*_i Y_{i2} = Y_{12}, \quad \ldots, \quad \sum_{i=2}^{I} w^*_i Y_{iT_0} = Y_{1T_0}, \tag{2}$$

then $\hat{\tau}_{1t} = Y_{1t} - \sum_{i=2}^{I} w^*_i Y_{it}$ for $t > T_0$, provides an asymptotically unbiased estimator as the number of pretreatment periods grows. In practice, there is not a set of weights such that equations in (2) will hold exactly, so the estimation procedure chooses weights such that the equation holds approximately. Specifically, for each treated industry j, with treatment occurring in period $T_0^j + 1$, we solve the following optimization problem:

$$\begin{aligned} \{w_i^{j*}\} = &\underset{\{w_i^j\}_{i \in \text{Control}}}{arg\,min} \sum_{t \leq T_0^j} [Y_{jt} - \sum_{i \in \text{Control}} w_i^j Y_{it}]^2 \\ s.t. &\textstyle\sum_{i \in \text{Control}} w_i^j = 1 \\ \text{and} \quad &w_i^j \geq 0 \quad \forall i. \end{aligned}$$

The weights $w_i^{j^*}$ minimize the pretreatment mean squared prediction error between lending in the treated industry j and the synthetic control.[14] With the optimal weights, the synthetic control for treated industry

[14]In matching, we include all pretreatment outcomes Y_{jt} from the pre-treatment period as covariates and use the default

j is $\hat{Y}_{jt}(0) = \sum_{i \in \text{Control}} w_i^{j*} Y_{it}$. The estimated impact of Live Oak entering on the total loan volume in industry j is the overall treatment effect

$$\widehat{\tau}_{jt}^{\text{overall}} = Y_{jt} - \hat{Y}_{jt}(0).$$

This overall treatment effect reflects the combination of Live Oak's new lending and the competitive effect of Live Oak's entry on other lenders

$$\underbrace{\widehat{\tau}_{jt}^{\text{overall}}}_{\text{Overall Effect}} = \underbrace{Y_{jt}^{\text{Live Oak}}}_{\text{Live Oak Lending}} + \underbrace{\widehat{\tau}_{jt}^{\text{comp}}}_{\text{Competitive Effect}}. \tag{3}$$

The direct effect of Live Oak's additional lending, $Y_{jt}^{\text{Live Oak}}$, is the number of loans that Live Oak originated to industry j in year t (normalized by total lending to industry j in 2006). These loans may have crowded out other SBA lenders, in which case the competitive effect $\widehat{\tau}_{jt}^{\text{comp}} < 0$. Alternatively, if Live Oak primarily complements existing lenders, $\widehat{\tau}_{jt}^{\text{comp}} \approx 0$. Following equation (3), we estimate $\widehat{\tau}_{jt}^{\text{comp}}$ as the difference between the overall treatment effect and Live Oak lending: $\widehat{\tau}_{jt}^{\text{overall}} - Y_{it}^{\text{Live Oak}}$.[15] Thus, we estimate both the overall effect on lending and the competitive effect on other lenders.

4.4. Identification

In this section, we discuss and evaluate the assumptions necessary to identify the treatment effects of Live Oak's entry. Our model representing the impact of entry on lending can be written as[16]

$$Y_{it} = \alpha_i + \delta_t + \sum_{m=0}^{M} \tau_{it} z_{i,t-m} + C_{it} + \epsilon_{it}$$

where α_i are industry fixed effects, δ_t are time fixed effects, and τ_{it} represents the industry-time-specific treatment effect of Live Oak's entry into industry i. The indicators $z_{i,t-m}$ equal one if industry i is treated as of period $t-m$. Our setting is a standard case of staggered adoption, in which the treatment z_{it} is binary and absorbing, i.e., $z_{it'} \geq z_{it}$ for all i and $t' \geq t$. The term ϵ_{it} is an industry-year shock that is uncorrelated with Live Oak's entry. Our goal is to estimate the treatment effects for the group of treated industries, i.e., τ_{it} for $i \in$ Treated.

The term C_{it} represents unobserved confounds that are correlated with entry decisions. For example, C_{it} would reflect scenarios where treated industries experience above-average growth or respond differently to the business cycle. When ignored, these confounding trends would lead to biased estimates of the treatment

procedure of "synth" in Stata, which uses a regression-based approach to obtain variable weights in the V-matrix of Abadie, Diamond and Hainmueller (2010). As discussed in detail in Kaul et al. (2022), this is equivalent to the minimization procedure above.

[15] This estimator is identical to estimating $\widehat{\tau}_{jt}^{\text{comp}}$ with a synthetic control on the outcome of normalized aggregate loan counts that exclude Live Oak's loans. The equivalence holds because the synthetic control is chosen using only on pretreatment observations and so is not affected by dropping Live Oak's lending, all of which occurs post-treatment.

[16] This section follows the notation and specification of Freyaldenhoven et al. (2021), which discusses many of these issues in a general setting. The synthetic control can account for unit-specific fixed effects when, in the pretreatment period, the weighted average of the outcomes for the synthetic control units exactly equals the average outcome for the treated unit (Arkhangelsky et al., 2021). In practice, this holds only approximately.

effect. With no restrictions on the confound C_{it}, any time-path of lending after entry could be explained by some pattern of confound shocks. Thus, to identify the treatment effects τ_{it} we must place restrictions on the confound C_{it}. The identifying assumption in our synthetic control strategy is that the confounds follow the structure

$$C_{it} = \lambda_t \mu_i$$

where λ_t is a vector of unobserved common factors and μ_i is a vector of unknown factor loadings. This structure allows, for example, each industry to have a different response (μ_i) to the aggregate economy (λ_t). It also accounts for the possibility that Live Oak enters industries based on their pre-existing trends, or that it enters industries less affected by the business cycle. Our assumption is more flexible than that of a difference-in-difference specification, which would impose that $C_{it} = 0$ or, by including linear trends, that $C_{it} = \mu_i t$.

However, our estimates would be biased if the common factors do not fully control for confounds in the treated industries. For example, the identification assumption would be violated if Live Oak enters industries when they anticipate abnormal future growth that deviates from the factor model. Similarly, the assumption would be violated if other specialized lenders would have entered the same industries but were deterred by Live Oak's entry. We investigate the possible violations of our identification assumption in several ways. First, we examine Live Oak's public documents and interviews about how they select the entered industries. Second, under the stronger identifying assumption of parallel trends across all industries, we diagnose potential bias by examining the pretrends of the treated and control industries. Third, our strategy exploits the exact timing of entry by Live Oak. We argue that the role of omitted variables are likely to be small relative to this large, discrete entry event. Finally, we include several additional robustness checks to address specific concerns.

4.4.1. Determinants of Entry

In its annual reports, interviews, and articles, Live Oak attributes its entry decisions to an industry's historical repayment performance, level of competition, and Live Oak's ability to develop industry expertise through research and hiring experts.[17] The bank analyzes historical SBA data and payment records to select industries. Characteristics such as average industry risk are fixed within an industry and so are captured by industry fixed effects. Other components of risk may vary over time with historical trends or with macroeconomic shocks (e.g. cyclicality), and so are captured by the industry-specific factor loadings

[17] "Our Emerging Markets group identifies new verticals by methodically analyzing payment records, level of competition, and most importantly, conducts a relentless search for a Domain Expert that not only understands the industry but also is a fit with our unique culture." (Live Oak Bancshares, Annual Report, 2018). Also, see Streeter (n.d.) and Bank To Bank (2016).

and time-varying factors. Thus, we control for the historical characteristics and trends that are the primary determinants of entry decisions. In its annual reports, interviews, and publicly available information, there is no indication that Live Oak chooses industries (verticals) based on temporary shocks or expectations of sudden growth in the industries. Rather than responding to short-term fluctuations, entry decisions are based on long-term trends or fixed characteristics and require industry-specific investments (e.g. hiring experts, developing expertise) that generate fixed costs of entry. This is consistent with our identification assumption, which assumes that, conditional on being in the treatment group, the *exact timing of entry* is not correlated with systematic deviations from the factor model.

4.4.2. Diagnosing Bias from Pretrends

We also diagnose the potential bias from such shocks by graphically examining pretrends among the treated industries under the stronger assumption from difference-in-differences that $C_{it} = 0$, i.e. there are no confounders. To do so, we estimate the standard event study model

$$Y_{it} = \alpha_i + \delta_t + \sum_{m=-10, m\neq -1}^{5} \beta_m \Delta z_{i,t-m} + \beta_{6+} z_{i,t-6} + \beta_{-11+}(1 - z_{i,t+10}) + \epsilon_{it}. \tag{4}$$

where Δ denotes the first difference operator. Note that $\Delta z_{i,t-m}$ is an indicator for whether industry i was treated exactly m periods before t, $z_{i,t-6}$ is an indicator for whether it was treated 6 or more periods before t, and $(1 - z_{i,t+10})$ is an indicator for whether it was treated more than 10 periods after t.[18] The parameters β_m can be interpreted as the cumulative treatment effects at different horizons for an event occurring at $m = 0$. To better detect short-term trends, we group the data into semi-annual bins so that time t reflects a six-month period when estimating the model.

Figure 3(a) reports the β_m coefficients from the event study, along with both pointwise confidence intervals and 95% simultaneous, sup-t confidence bands (Montiel Olea and Plagborg-Møller, 2019), which cover the entire parameter vector with 95% probability. The event study is estimated on the main analysis sample, consisting of all treatment and control industries from 2001-2017. Figure 3(a) also plots the linear pretrend over the five years prior to entry.[19] The figure reveals stable coefficients leading up to entry in period 0, indicating that the treated and control industries were trending similarly up to the point of Live Oak's entry. Then, in the 1.5 years after entry, there is a 50 percentage point increase in lending to the treated industries.

A separate issue is that the dynamic treatment effects may be heterogeneous across industries, which

[18] These binned endpoints are needed so that the omitted period consists only of $m = -1$ (see, e.g. Freyaldenhoven et al. (2021)).

[19] The linear pretrend (β) in event time is estimated from the equation, as in Freyaldenhoven et al. (2021),

$$Y_{it} = \alpha_i + \delta_t + \beta \cdot r + \sum_{m=0}^{5} \beta_m \Delta z_{i,t-m} + \beta_{6+} z_{i,t-6} + \beta_{-11+}(1 - z_{i,t+10}) + \epsilon_{it}.$$

where r equals event time m when $-10 \leq m \leq 0$ and $r = 0$ otherwise. The pretrend β is then extrapolated into the post-period.

complicates the interpretation of the estimates in specification (4). Panel (b) implements the doubly-robust event-time estimator of Callaway and Sant'Anna (2020), which provides estimates of a well-defined average treatment effect in a staggered adoption setting such as ours. Again, the estimates show smaller and stable coefficients prior to treatment then a sharp increase in the first 1.5 years after Live Oak's entry. Note that the synthetic control also addresses the potential for heterogeneous treatment effects by estimating the separate treatment effects $\widehat{\tau}_{jt}$ for each treated industry j and post-treatment period t, thereby avoiding issues present when estimating an average treatment effect in a two-way fixed effects model with staggered adoption (e.g. Callaway and Sant'Anna (2020); De Chaisemartin and d'Haultfoeuille (2020); Goodman-Bacon (2021)).

As seen in Figure 3, Live Oak's entry generates a sudden, roughly 50 percentage point increase in lending (relative to 2006 baseline) in the first 1.5 years after entry. Increases of a large magnitude are consistent with the summary statistics in Table 1, in which Live Oak makes roughly 30-50% of SBA loans to these industries after entry. Moreover, lending rises immediately after Live Oak's entry, then levels off in the subsequent periods. If confounding variables were to explain the pattern of coefficients, they must follow a similar pattern around the exact timing of Live Oak's entry. Given that Live Oak Bank does not report entering industries in response to immediate, short-term shocks, we think it is unlikely that confounders would follow this pattern around entry.

4.4.3. Potential Bias from Spillovers

The identification assumption also requires no spillovers, meaning that Live Oak's entry into a treated industry does not affect the control industries. Given that general lenders often make loans to dozens or hundreds of industries, we expect that Live Oak's entry into a single industry is unlikely to have significant spillover effects on overall lending practices. If there are spillover effects, however, we think it is most likely that lenders may divert resources away from the industries Live Oak enters and into other non-treated industries. This would increase lending to the control industries, relative to the treated industry, potentially leading to a downward bias in our estimates of Live Oak's overall effect on lending and the competitive effect. In such a case, correcting the bias would reinforce the results we find in Section 5. There is, however, a concern that other remote lenders follow Live Oak into the treated industries in a way that is not captured by the trends allowed in the factor model. We address this concern directly by reporting results from an alternative sample that excludes other remote loans (those with a distance more than 100 miles) from the industry loan counts.

4.5. Inference

To evaluate the statistical significance of the results, we use the permutation inference procedures of Abadie (2021) and Abadie and L'hour (2021). We provide an overview of the inference procedure here and formally define the test statistics in Internet Appendix D. For each treated industry j, we generate an empirical distribution of placebo treatment effects by iteratively estimating a synthetic control for each of the 219 control industries, assigning the entry year for industry j as the placebo treatment date. We then assess the statistical significance of the actual treatment effect by comparing its magnitude against the distribution of placebo treatment effects.[20] If the actual treatment effect, i.e. the change in lending the treated industry, is an outlier relative to the placebo distribution, we conclude that it is unlikely to be due to chance.

We focus on three test statistics for inference. The first is each industry's average treatment effect (ATE) during the first four post-treatment years (the longest period available for all treated industries). One concern with the average treatment effect test statistic is that some of the placebo synthetic controls may have a poor pretreatment fit, making the estimated placebo treatment effects in the post-period less credible. For this reason, our second test statistic is the ratio of the four-year post-treatment fit to the pretreatment fit, where fit is measured by the root mean squared prediction error (RMSPE) between the industry and its synthetic control as in Abadie, Diamond and Hainmueller (2010) and Abadie (2021). For these first two test statistics, we compare the magnitude of the treated industry's test statistic to the corresponding distribution of placebo test statistics, and calculate the p-value as the share of placebo statistics that are larger (in absolute value) than that of the treated industry. Finally, we also conduct a joint inference test using the method of Abadie and L'hour (2021), which extends the permutation methods to cases with multiple treated units. This joint test employs a rank-based test statistic to compare the combined treatment effects of the six treated industries against the distribution of combined treatment effects generated by iteratively selecting random sets of six industries.

5. Results

5.1. Main Results

Figure 4 plots the paths of each treated industry and its synthetic control.[21] In most cases, the synthetic control closely approximates the trajectory of lending during the pretreatment period prior to Live Oak's entry. However, the fit of the synthetic control is not equally good across all industries. In particular, the MSPE for Broilers is 0.33, which is 16 times larger than the second-largest MSPE. When there is no good pretreatment fit, synthetic controls are asymptotically biased and Abadie, Diamond and Hainmueller (2010) and Abadie (2021) recommend against using synthetic controls in such cases. For this reason, we report joint summary statistics that both include and exclude Broilers.

[20]Following Abadie (2021), we include the actually treated industry in the placebo distribution, so it is formed from 220 estimated treatment effects.

[21]Internet Appendix Table A.3 shows the donor pool industries that make up the synthetic controls.

Turning to the post-period, the gaps between the treated industry and the synthetic control in Figure 4 indicate large increases in total lending upon Live Oak's entry. Each treated industry increases, often sharply, relative to the synthetic control. For most industries, lending to the synthetic control remains relatively flat while lending to the treated industry increases sharply. For Veterinarians, lending to the synthetic control declines sharply, as lending to many industries did at the start of the recession, while lending to the treated industry remains stable. Thus, Live Oak's lending caused Veterinarians to avoid the declines in lending present in other similar industries. In all cases, lending in the treated industry rises relative to the synthetic control as Live Oak's entry generated increases in total SBA lending to these industries. These loan counts contain both term loans and revolving lines of credit. Nearly all ($> 99\%$) of Live Oak's loans are term loans, so we provide estimates with the sample restricted to SBA 7(a) term loans (Appendix Figure A.5) and find similar results, with larger percentage increases for Funeral Homes, Investment Advice, and Pharmacies but a less persistent increase for Dentists.

Figure 5 plots the estimated overall treatment effects $\hat{\tau}_{jt}^{\text{overall}}$, which are the gaps between lending in the treated industry and its synthetic control. A potential concern is that other remote lenders may enter the same industries after Live Oak, which would generate increases in lending that we would mistakenly attribute to Live Oak's entry. To address this concern, Figure 5 also plots the treatment effects estimated from annual loan counts that exclude non-Live-Oak remote loans.[22] Except for "Broilers," all industries demonstrate a good pretreatment fit and a sharp growth in overall lending upon Live Oak's entry. As seen in the figure, the treatment effects are similar when non-Live-Oak remote loans are excluded, indicating that the growth in total lending is largely due to Live Oak's entry and not due to subsequent entry by other remote lenders.

The overall treatment effect estimates reflect the combination of Live Oak's new lending and the competitive effect of Live Oak's entry on other lenders. As discussed in Section 4, we can isolate the competitive effect by subtracting Live Oak's loans from the overall effect $\widehat{\tau}_{jt}^{\text{comp}} = \widehat{\tau}_{jt}^{\text{overall}} - Y_{it}^{\text{Live Oak}}$. Figure 6 plots the estimates of the competitive effect from synthetic controls using the full sample and the subsample excluding remote loans. The competitive effects are generally close to zero (or slightly positive), indicating that, upon Live Oak's entry, other SBA lenders continued lending similar amounts to the treated industries. There is no evidence of substitution away from other SBA lenders, suggesting that Live Oak's loans were given to borrowers who would not have otherwise received an SBA loan.

[22] Remote loans are those with a borrower-lender distance above 100 miles, with distance computed using county centroids. The small share of loans missing the county measure of borrower-lender distance (largely from credit unions and nonbanks) are also dropped.

5.2. Average Effects and Statistical Significance

To assess the average treatment effects and their statistical significance, we use the permutation-based inference outlined in Section 4.5. Figure 7 shows the distribution of these placebo treatment effects for each of the treated industries, along with the actual treatment effect estimate from the full sample in black.[23] In the figure, the treatment effects for the actually treated industries are not only positive, but also large relative to the distribution of placebo effects. Table 2 provides a formal comparison using the average treatment effect during the first four post-treatment years, and r_j, the ratio of the post- to pre-treatment RMSPEs.

Across the six treated industries, the average treatment effect in Panel A column 1 is a 21-112 percentage point increase in annual lending, with most two-sided p-values significant at conventional levels (column 2).[24] The average effects are largest for Investment Advice, Broilers, Pharmacies, and Funeral Homes and smaller for Dentists and Veterinarians, reflecting that Live Oak's entry caused the largest percentage changes in the industries that previously had fewer SBA loans.[25] When using r as the test statistic in Panel A columns 3 and 4, four of the treated industries have p-values below 0.1. The two that do not, Funeral Homes and Broilers, are those with the worst pretreatment fit (quantified in Internet Appendix Table A.4) which explains their relatively low value for r_j. Across both test statistics, the joint inference p-values for overall significance are also highly significant and are similar when excluding Broilers, which has a poor pretreatment fit.

Despite these large increases in lending by Live Oak, Panel A columns 5-8 confirm that the competitive effects on other lenders are small, mostly positive, and statistically insignificant individually (except for r_j for Veterinarians) and jointly insignificant.[26] Panel B, which excludes loans from other remote lenders, largely corroborates the results of Panel A. The results in Panel B columns 3 and 4 are generally smaller and often have a p-value above 0.1. The joint test statistic, however, demonstrates that the effect sizes remain large relative to the permutation distribution, with a p-value less than 0.01. Overall, Table 2 shows that Live Oak's entry generated large and statistically significant increases in overall SBA lending with no indication of substitution away from existing lenders.

5.3. Substitution Within and Outside of SBA Lending

[23] Following Abadie, Diamond and Hainmueller (2010), the plot excludes placebo industries with a poor pretreatment fit, i.e., a pretreatment MSPE more than 20 times that of the average MSPE among the treated industries.

[24] The exception is Dentists, with a p-value of 0.19. That the impact on Dentists is smaller is expected because Live Oak made up only 12% of the post-entry loans in that industry, while it made up at least 30% in the other treated industries.

[25] Between 2001-2006, there were more than 800 SBA loans to dentists annually, 370 to Veterinarians, and fewer than 200 in each of the remaining industries.

[26] Although the r_j test statistic for Veterinarians in Table 2 column 7 is significant, this is due to increased volatility in the post-period but not a decline in lending. As seen in the τ statistic in column 5, there was only a 1% fall lending during this time.

5.3.1. Intensive Margin vs. Extensive Margin

The results above, with annual loan counts as the dependent variable, suggest there was no substitution away from existing lenders on the number of loans (extensive margin). But substitution in the dollar amount of lending (intensive margin) could still occur if firms take smaller loans from existing lenders. We examine the intensive margin response by repeating the analysis above, but replacing the dependent variable with the loan volume, i.e. the annual dollar amount of lending, to each industry. Table 3 reports the average treatment effects and p-values, and Internet Appendix Figure A.3 plots the patterns of lending volumes for the treated industries and the synthetic controls. Similar to the earlier analysis, the intensive margin results indicate sharp increases in lending volume upon Live Oak's entry, with no evidence of substitution away from existing lenders, and the joint test of the combined treatment effects is significant at the one percent level. The magnitudes of the treatment effects have the same ranking across industries as those for loan counts (compared in Internet Appendix Figure A.4). The magnitudes are larger, consistent with Live Oak originating loans that are large relative to other loans in their industries (discussed in Section 6). As before, the competitive effects on the intensive margin are smaller, generally positive, and statistically insignificant.

Live Oak may also cause substitution from other remote, specialized SBA lenders.[27] To the extent that other specialists are captured by the synthetic control, our estimates account for this substitution as well. However, it is possible that Live Oak substituted for lending from other potential remote specialists who would have entered the treated industries if Live Oak had not. In this case, if Live Oak had not increased lending to these industries, another specialized lender would have. In light of this possibility, one can view our estimates, particularly those excluding remote loans, as the substitution effect on existing *nonspecialized* lenders. This substitution effect is important, as nonspecialized lenders still make up the large majority of SBA lending (Figure 2).

5.3.2. Additional Evidence on Substitution Within SBA Lending

The zero competitive effect indicates that Live Oak did not substitute for existing SBA lenders. To further investigate substitution within SBA lending, we check whether Live Oak's borrowers have previously obtained an SBA loan from another institution. At the time the Live Oak borrowers in our six industries obtain their first Live Oak loan, only 2.9% had a previous SBA loan from another institution in our 2001-2017 sample. For comparison, 13.8% of other SBA borrowers who originated a loan in 2014 had a previous SBA loan.[28] Of those with a previous loan, the size of their Live Oak loan exceeded the amount of their previous

[27] There are too few specialized lenders to directly examine Live Oak's impact on their lending patterns. As suggestive evidence about deterrence, however, we note that several remote specialists entered Live Oak's industries after Live Oak's entry (Internet Appendix Table A.5). Additionally, for the two specialized lenders operating in a treated industry before Live Oak, there was not a noticeable decline in lending upon Live Oak's entry (Internet Appendix Figure A.2).

[28] We chose 2014 as the comparison year because it is the median year for Live Oak's loans.

loan by an average of $813,000 (median $750,000). Thus, upon entry, Live Oak lends largely to new SBA borrowers and, in the few cases where a borrower has obtained a previous SBA loan, Live Oak originates large loans that may not have been approved by other SBA institutions.

5.3.3. Substitution From Non-SBA Lending

Perhaps Live Oak caused substitution away from non-SBA lending. Institutional features, external evidence, and indirect evidence using a proxy for total lending, however, suggest that substitution between SBA and non-SBA lending is likely limited. First, the "credit elsewhere" test of the SBA 7(a) loan program requires SBA lenders to certify that the borrower could not obtain a loan on reasonable terms without an SBA guarantee. This credit elsewhere test does seem to be enforced, and lenders often refer borrowers to the SBA program after they fail to qualify for a conventional loan.[29] As argued in Bachas, Kim and Yannelis (2021), lenders specialized in SBA lending, such as Live Oak, are most likely to comply with the credit elsewhere test as they would face the largest costs from violations, which could lead to exclusion from the SBA program. Additionally, other SBA loans are likely the closest substitutes with regards to loan features, collateral requirements, and loan durations.[30] Given that we find no substitution within the SBA program, it is likely that substitution from commercial lending outside of SBA lending is also limited. External evidence also suggests that SBA-guaranteed lending increases the supply of credit rather than substituting for non-SBA alternatives. Bachas, Kim and Yannelis (2021) examine heterogeneity in the elasticity of SBA lending with respect to the guarantee rate across areas, finding estimates consistent with limited substitution between SBA and non-SBA lending. Additionally, Brown and Earle (2017) finds that SBA lending leads to increases in employment, which would not occur if SBA loans simply crowded out non-SBA alternatives.

We also empirically examine the impact of Live Oak's entry on a proxy for total industry lending from The Risk Management Association's (RMA) eStatement Studies. Financial institutions provide the RMA with financial statements collected from commercial borrowers or applicants, and the RMA collects information from hundreds of financial institutions including nine of the ten largest banks (Lisowsky, Minnis and Sutherland, 2017). Small business borrowers provide financial statements (e.g. tax returns, income statements, balance sheets) as a part of the loan application and monitoring process, so these counts provide a proxy for total lending.[31] Berger, Minnis and Sutherland (2017) shows a strong correlation between these

[29]Temkin (2008) surveyed 23 banks that originate SBA loans about their application of the "credit elsewhere" requirement, and the surveys suggest that "the lenders are aware of the credit elsewhere requirement and adhere to the requirement." Lender representatives report that most SBA applicants are referred to the program if (i) the business shows insufficient net operating income to obtain a conventional loan, (ii) the collateral is limited, or (iii) the borrower does not have sufficient equity for the down payment.

[30]Live Oak's 2017 Annual Report states that "[i]f we lose our status as a Preferred Lender, we may lose some or all of our customers to lenders who are SBA Preferred Lenders."

[31]See, for example, `https://www.nerdwallet.com/article/small-business/how-to-qualify-for-small-business-loans`.

financial statements and the size of the bank's commercial and industrial lending portfolio. Live Oak is not a participant in the RMA survey during our sample period, so the RMA data provide a proxy for total industry lending excluding Live Oak, i.e., the competitive effect. Applying our same strategy to industry-year counts of financial statements in Internet Appendix F, we find no statistically significant declines in financial statements in the treated industries. The p-values indicate that more than 50% of the placebo industries experienced larger declines in lending. Overall, while we cannot directly examine non-SBA lending, the institutional features, external evidence, and the test using financial statements all suggest that substitution from non-SBA lending is limited and unlikely to fully offset the observed growth in SBA lending within the treated industries.

Live Oak's entry may have caused borrowers to switch from non-commercial, such as financing from friends and family or seller financing. In several of Live Oak's industries (pharmacies, dentists, veterinarians, and funeral homes), commercial loans were generally unavailable for acquisitions. Much of the value of these businesses is in goodwill, which makes for poor collateral in the event of default, and some buyers had little wealth (e.g. new dentists and veterinarians with student loans). As a result, acquisitions were historically financed by the seller without a commercial loan from a bank. Live Oak and other specialized lenders have likely generated some substitution away from these seller-financed loans.

5.3.4. Real Effects

The increase in commercial financing through the SBA program could generate a measurable impact on employment or establishment counts in these industries. SBA lending provides nearly 20% of loans to employer small businesses (Federal Reserve Banks, 2016-2019), and perhaps a larger share in the treated industries, where SBA lending is more common.[32] Internet Appendix G and Table G.1 and uses the synthetic control approach to examine the impact of Live Oak's entry on employment and charge-off rates. There is some evidence of an increase in employment and establishment for investment advice agencies (p-values less than 0.1), which is the industry where Live Oak's impact was largest. Overall, the changes in employment and establishment counts are jointly insignificant. The lack of significant real effects is not surprising, as even a significant increase in total SBA lending may not have a measurable impact on employment or establishments. Brown and Earle (2017) finds that SBA lending increased employment by only 3-3.5 jobs per million dollars in lending. Effect sizes of this magnitude would not be apparent in national employment counts. Additionally, many SBA loans are used for the purchase of existing practices or expansions of existing businesses, which would not change the establishment counts.

[32]First Financial Bank, an SBA lender, reports that SBA lending is the most common form of lending to independently owned veterinarian practices and pharmacies (First Financial Bank, 2018*a*,*b*).

5.4. Extensions and Robustness

5.4.1. Sensitivity to Changes in Design

We summarize results from several diagnostic checks suggested by Abadie (2021) that examine the sensitivity of our results to the design of the synthetic control. We find that the results are robust to backdating the treatment timing by 1-3 years (Internet Appendix Figure A.6), dropping individual industries from the donor pool (Internet Appendix Figure A.7), and using different predictors (average pre-treatment charge-off rates number of loans) for the synthetic control (Internet Appendix Figure A.8).[33] We also compare our synthetic control method to a simple difference-in-difference approach in Internet Appendix Figure A.9. Even with this simple comparison group, it is evident that total lending in each treated industry increases upon Live Oak's entry, although the parallel trends restriction fails to hold in the pretreatment period. This gives further support to the synthetic control strategy, which improves upon this simple average by selecting a weighted average of industries that better match the pretreatment lending path of each treated industry. To make the comparison between the two strategies precise, Internet Appendix Table A.4 shows that the MSPE from the simple average is 2.6 to more than 7,500 times larger than that of the synthetic control.

5.4.2. Other Specialized Lenders and External Validity

Given that this case study focuses on a single lender, a natural question is whether the results apply to other remote specialists. In this section, we extend the analysis to provide suggestive evidence about the other remote specialists identified in Figure 1. While Live Oak's staggered entry and lending volume make it uniquely suited for the synthetic control analysis, we can estimate the average impact of a broader set of remote, specialized lenders on total lending.

For industry j in year t, we estimate the following specification:

$$Loans_{jt} = \beta_0 + \beta_1 SpecLoans_{jt} + \delta_j + \tau_t + \epsilon_{jt}. \tag{5}$$

The outcome $Loans_{jt}$ is the total number of new SBA loans originated to industry j during year t, and the explanatory variable $SpecLoans_{jt}$ is the total number of specialized loans (defined below) originated to industry j during year t. The parameter of interest is β_1, which captures the impact of an increase in specialized lending on total lending. For example, if $\beta_1 \approx 0$, additional lending by a specialized lender in an industry j does not alter the total number of loans to industry j, implying that specialized lending substitutes for other SBA lending. Alternatively, if $\beta_1 \approx 1$, it indicates that specialized lending complements other SBA lending and increases the total quantity of SBA loans. The primary concern with this exercise

[33] One concern is that the gap in lending between the treated and control industries is due to heterogeneity in the cyclicality of the industries, especially during the Great Recession. These robustness checks also help address this concern about cyclicality, since they show that (i) the results are robust to selecting industries of similar risks (i.e., matching on charge-off rates) and (ii) the differences emerge only after Live Oak enters.

is that specialized lending may be correlated with ϵ_{jt}. For example, specialized lenders may enter industries that are growing quickly or trending differently. Although we allow for industry-specific linear trends in some specifications, residual correlation between $SpecLoans_{jt}$ and ϵ_{jt} would lead to biased estimates of β_1. Thus, unlike our synthetic control analysis of Live Oak Bank, we view this exercise as providing only suggestive evidence of the impact of other remote specialized lenders on total SBA lending.

We define a loan as a specialized loan if it (i) is from a lender remote, specialized lender using the definition from Section 3 and (ii) is to an industry in which the lender originates at least 10% of its SBA loans (all measured during the period 2013-2017).[34] This second requirement allows the definition of a specialist to vary within a lender across industries, since not all loans from a specialized lender are to the industries in which they specialize. The estimates, however, are similar when criterion (ii) is removed and we simply count all loans from a remote, specialized lender as specialized loans (see Internet Appendix E).

Table 4 reports the estimates, with Panel A including industry and year fixed effects and Panel B adding industry-specific linear trends. As a benchmark, column 1 estimates the impact of Live Oak loans on total lending. Consistent with the lack of substitution found in the main analysis, the estimates in column 1 are close to one, indicating an additional loan from Live Oak increases total lending by roughly one loan. Although the estimate exceeds one in Panel A, it falls below one in Panel B, reflecting some sensitivity to the controls for industry-specific linear trends. Column 2 broadens the explanatory variable to include loans from all specialized lenders including Live Oak. Column 3 excludes all Live Oak loans from the outcome and explanatory variable. To avoid bias caused by other remote lenders entering the same industry, Column 4 drops Live Oak loans and all non-specialized remote loans (borrower-lender distance of more than 100 miles) from the counts forming the dependent variable. Estimates in all columns are close to one, indicating an increase in lending with little substitution, and generally statistically significant. They remain similar when allowing for industry-specific linear trends in Panel B. This provides suggestive evidence that the estimates from Live Oak's entry may also apply to other remote specialized lenders. We examine the sensitivity of the estimates in Table 4 to changes in the definition of specialized lenders in Internet Appendix E, including different thresholds for distance, concentration, and size in our primary definition of remote specialists, and also across a definition of specialized lending based on Paravisini, Rappoport and Schnabl (2021) and another using an industry-level HHI measure, as in Giometti and Pietrosanti (2022). The estimates and statistical significance are similar across alternative measures of specialization.

[34] Internet Appendix Table A.5 lists the lenders and industries that are classified as specialized lenders.

6. Mechanisms and Loan Characteristics

The case study of Live Oak shows that entry by an industry-specialized lender can increase SBA lending, but what explains the increase? In this section, we expand on this by investigating specific mechanisms that may explain the increase in lending caused by Live Oak Bank. We find that Live Oak Bank targeted a subset of industries with low charge-off rates and where the relationship between distance and charge-off rates is weak. This strategy of selecting safe industries that are well-suited for distant lending is only available to industry-specialized lenders. We also find, consistent with industry expertise, Live Oak maintains similar charge-off rates to those of other lenders within these industries, despite significantly increasing total originations and lending distances. Live Oak also tends to originate larger, longer loans at lower interest rates than those offered by other lenders.

6.1. Industry Selection

One advantage of specialists is that they can target a subset of industries that are safer, better suited for distant lending, or less competitive. Table 5 shows how the charge-off rates and interest rates in Live Oak's industries differ from those in other industries. The variable of interest is "LO industry," an indicator for whether the loan was in one of Live Oak's six industries. Importantly, the sample excludes all loans from Live Oak, so the estimates are not confounded by Live Oak's lending. As seen in column 1, Live Oak enters safer industries. Live Oak's industries have three-year charge-off rates 0.69 percentage points lower than other industries, and this difference remains significant when loan-level controls for loan size and term are added in column 2. Columns 3 and 4 show that distant loans are also safer in these industries, with the interaction term LO industry $\times\, log(dist)$ nearly offsetting the positive relationship between distance and charge-off rates. Viewing the relationship between distance and charge-offs as a proxy for the importance of soft information in lending decisions, these results are consistent with Live Oak entering industries where soft information is less important.

Although these industries have lower charge-off rates, columns 5-8 show that the lower risk is not reflected in the interest rates charged by other lenders. Indeed, columns 7 and 8 show that interest rates rise more rapidly with distance in these industries, even though columns 3 and 4 show that charge-off rates rise more slowly. Thus, Live Oak entered industries that were lower risk, but where other lenders were not pricing this lower risk into interest rates.

6.2. Loan Performance and Characteristics

Another advantage is that specialization may facilitate industry expertise. The evidence from industry-specialized lenders reported in Section 3 that specialized lenders have better loan performance suggests this plays a role. To investigate whether Live Oak's loans are consistent with industry expertise, we examine within-industry loan performance and characteristics. This analysis focuses on the years immediately after Live Oak's entry, and one may expect industry expertise to develop over time. Live Oak, however, credits its advantage to hiring an industry expert and developing an understanding of the industry before they enter, so the industry expertise would be available immediately upon entry.

Table 6 columns 1-4 investigate within-industry charge-off rates for Live Oak and other lenders in the sample of loans to the six treated industries.[35] The variable of interest is "Live Oak loan," an indicator for whether Live Oak originated the loan. Columns 1 (with industry fixed effects) and 2 (adding loan-level controls) show that Live Oak experiences similar charge-off rates to other lenders in these industries, despite significant increases and the number of borrowers and borrower-lender distances. Columns 3 and 4 add controls for the log of borrower-lender distance and its interaction with the indicator for Live Oak loans. For other lenders in these industries, there is the standard positive relationship between distance and charge-off rates. Live Oak, however, exhibits no significant relationship between distance and charge-off rates; the small positive coefficient on $log(dist)$ is completely offset by the interaction term Live Oak loan $\times \log(dist)$.[36] Internet Appendix Figure A.10 reports results from semi-parametric versions of these regressions and finds a similar relationship between distance and charge-off rates. These regressions show that Live Oak finds new, low-risk borrowers and maintains similar charge-off rates to those of other lenders, despite significantly increasing total originations.

We also compare interest rates in Table 6 columns 5-8. Live Oak's interest rates are 12.6 basis points lower than those of other lenders (column 5), or 6.9 basis points lower after controlling for loan size and term. Columns 7 and 8 reveal that these differences in interest rates are driven by distant loans. Other lenders increase rates by around 5 basis points for every 100 log-point increase in distance, while Live Oak's interest rates do not vary with distance. In addition to these interest rate differences, Live Oak tends to originate larger, longer-term loans than those offered by other lenders. Since 2008, Live Oak's average loan size was $1.08 million (2010 dollars), compared with an average loan size of $459,000 for other lenders in the treated industries. Live Oak's average term was 209 months, compared with an average term of 149 months for other lenders. Together, these results suggest that the increase in total lending may be driven, in part, by Live Oak originating larger, longer loans at lower interest rates than those offered by other lenders.

[35] To focus on similar loans, we restrict the sample to loans for more than $100,000 (in 2010 dollars) because 96% of Live Oak's loans are above $100,000. Because the maximum SBA guarantee threshold changes at $150,000, we also estimate these regressions on the sample of loans over $150,000. We find similar estimates in Tables A.8 and A.9, except the relationship between distance and charge-offs is weaker (though still significant in Table A.9). We also repeat the regressions with county fixed effects in tables A.10 and A.11, and the results are very similar to those in the main table.

[36] The results are similar if we calculate distances based on county centroids, which is available for all bank loans in the sample (Internet Appendix Table A.6).

6.3. Geography and Local Credit Supply

In addition to providing different types of loans, Live Oak may expand lending if it originates distant loans in locations underserved by existing lenders. We find limited evidence for this channel. Live Oak's borrowers are not located farther from physical branches of SBA lenders than borrowers from local banks. The borrower-lender distance distributions of local and remote borrowers are very similar (Internet Appendix Figure A.11). Indeed, 99% of remote SBA borrowers are within 10 miles of a branch of a bank that grants SBA loans. We also examine the proximity to high-volume Preferred Lenders Program (PLP) SBA lenders, which is an important determinant of access to the SBA program (Brown and Earle, 2017). Within the six treated industries, Live Oak's borrowers were slightly more likely to have a branch of a PLP lender in their county. Thus, we do not find evidence that physical distance to an SBA lender explains the growth in lending after Live Oak's entry.

It is still possible that Live Oak advances credit to borrowers in areas that have limited credit supply despite being close to PLP lenders. To examine this, we test for heterogeneity in Live Oak's impact across areas with low and high credit supply using four different measures of credit supply based on the area's (i) SBA lending per capita, (ii) small business lending per capita, (iii) the share of residents that are credit constrained, and (iv) state-level creditor protections (asset exemptions). Each measure has advantages and disadvantages, but together they allow us to examine heterogeneity in Live Oak's impact across multiple dimensions. We then reestimate the main synthetic control model, but restrict the sample loans originated in low-credit-supply areas and high-credit-supply areas, respectively. We do this separately for each treated industry and each measure of credit supply, summarizing the results here and reporting the full analysis in Internet Appendix H.

Live Oak's entry generated sizable lending increases in both low- and high-credit-supply areas, so Live Oak's impact was not confined solely to areas with limited credit supply. However, the impact may still have been larger in low-credit-supply areas. Comparing the magnitudes across areas, there is not a consistent pattern that holds across all industries and measures of credit supply. For the measure based on SBA lending, there was more loan growth in low-credit areas relative to high-credit areas in all six industries. Arguably, this measure of credit supply may be most relevant for Live Oak's borrowers, since SBA loans are intended to serve borrowers who are unable to obtain reasonable loans without the SBA guarantee. For the remaining three measures of credit supply, however, there is not a clear pattern of heterogeneity between low- and high-credit areas.

7. Conclusion

Remote industry specialization offers a very different approach than the local lending that has historically characterized small business finance. This paper documents recent growth in industry-specialized lenders, which grew from 2% of SBA originations to 17% in 2017. We then examine the effects of entry by the largest of these remote, specialized lenders with the SBA program, Live Oak Bank. Upon Live Oak's entry into specific industries, total SBA lending increases sharply with no evidence of declines from other lenders. Examining specialization, we show that Live Oak (and other specialized lenders) targets safer industries and experiences better loan performance within those industries, consistent with industry expertise. This setting demonstrates that remote, industry-specific lending has the potential to expand credit markets.

While our focus is within the SBA program, specialized lending is increasingly prominent outside of this setting. Industry experts and trade publications have highlighted the emergence of specialized or "vertical" small business lenders (Mills, 2019*a*; American Banker, 2013, 2012) and similar specialization exists among larger commercial lenders (Blickle, Parlatore and Saunders, 2021). Additional research is needed to understand the broader impact of industry-specialized lenders outside of the market for SBA-guaranteed loans. Concerning real effects on the broader economy, growth in specialized lending may lead to changes in labor markets, entrepreneurship, and banking outcomes. If industry specialization increases the supply of loans to certain industries, it may alter the industrial composition of small businesses. Already, Live Oak Bank and other remote lenders have altered the industry composition of SBA 7(a) lending. Concerning banking and risk management, specialized lenders are less exposed to regional economic downturns but more exposed to industry-specific risks, which affects credit risk and risk-sharing across the economy. We leave these issues for future research.

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Table 1: **Live Oak's Industries**

Industry	**Live Oak Loans**	**Share of Live Oak's Loans**	**Share of SBA Loans**	**Share of SBA Volume**	**Live Oak's Entry Month**
Veterinarians	1,455	0.25	0.33	0.49	06/2007
Offices of Dentists	1,038	0.18	0.12	0.27	03/2009
Investment Advice	814	0.14	0.58	0.75	02/2013
Pharmacies	799	0.14	0.30	0.56	11/2009
Broilers	520	0.09	0.37	0.60	04/2014
Funeral Homes	311	0.05	0.28	0.41	09/2011
Self-Storage	131	0.02	0.34	0.53	05/2015
Insurance Agencies	105	0.02	0.09	0.20	11/2015
Breweries	97	0.02	0.09	0.20	04/2015
Physicians	80	0.01	0.02	0.06	09/2012
Other	378	0.07	0.01	0.03	

This table shows the industries where Live Oak Bank has approved at least 50 loans, ordered by the number of loans. Industries with less than 50 loans are classified as "Other." "Share of Live Oak's Loans" is the share of Live Oak's 2007-2017 loans going to that industry. The columns "Share of SBA Loans" and "Share of SBA Volume" show Live Oak's post-entry share of SBA loans in each industry by number and by dollar amount, respectively. "Entry Month" is the month that Live Oak first approved a loan to that industry.

Table 2: **Average Treatment Effect and Inference**

	Overall Effect				Competitive Effect			
Industry	τ	p-val.	r	p-val.	τ	p-val.	r	p-val.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Sample:	All Loans							
Veterinarians	0.30	(0.06)	387.94	(0.01)	-0.01	(0.96)	173.81	(0.02)
Pharmacies	0.45	(0.05)	117.54	(0.03)	0.18	(0.26)	46.93	(0.11)
Dentists	0.21	(0.19)	69.89	(0.06)	0.13	(0.37)	50.09	(0.10)
Funeral Homes	0.61	(0.02)	4.81	(0.58)	0.18	(0.20)	1.46	(0.85)
Investment Advice	1.12	(0.02)	45.61	(0.05)	0.10	(0.35)	6.78	(0.39)
Broilers	1.04	(0.02)	1.90	(0.84)	0.29	(0.10)	0.56	(0.99)
Joint Inference		(<0.01)		(0.02)		(0.15)		(0.29)
Joint Inf. (excl. Broilers)		(<0.01)		(<0.01)		(0.30)		(0.10)
Panel B. Sample:	Excluding Other Remote Loans							
Veterinarians	0.26	(0.06)	4.68	(0.53)	-0.04	(0.68)	1.82	(0.84)
Pharmacies	0.59	(0.01)	176.64	(<0.01)	0.32	(0.07)	94.18	(0.01)
Dentists	0.38	(0.04)	15.11	(0.16)	0.31	(0.09)	12.49	(0.17)
Funeral Homes	0.41	(0.04)	7.73	(0.18)	-0.02	(0.81)	1.49	(0.83)
Investment Advice	0.92	(0.02)	20.51	(0.02)	-0.09	(0.41)	2.93	(0.57)
Broilers	0.61	(0.02)	1.76	(0.81)	-0.14	(0.28)	0.46	(0.99)
Joint Inference		(<0.01)		(0.02)		(0.22)		(0.71)
Joint Inf. (excl. Broilers)		(<0.01)		(0.01)		(0.29)		(0.47)

This table reports estimates of the overall effect on lending and the competitive effect on lending, as well as the corresponding p-values. Panel A shows estimates for the full sample, and Panel B shows estimates from the sample dropping non-Live-Oak remote loans. The test statistic τ_j^j is the average effect during the first four post-treatment years, and r_j^j is the ratio of the post- to pretreatment root MSPEs. The bottom two rows of each panel report p-values from the joint inference procedure using $B = 5,000$ random permutations. See Section 4.5 for details on the test statistics and inference procedures.

Table 3: **ATE and Inference: Loan Volume**

	Overall Effect				Competitive Effect			
Industry	τ	p-val.	r	p-val.	τ	p-val.	r	p-val.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Sample:	All Loans							
Veterinarians	0.40	(0.20)	58.17	(0.20)	-0.21	(0.52)	26.85	(0.52)
Pharmacies	1.33	(0.05)	111.96	(0.12)	0.32	(0.48)	25.75	(0.48)
Dentists	0.34	(0.46)	60.68	(0.23)	0.15	(0.74)	41.96	(0.35)
Funeral Homes	2.11	(0.02)	187.25	(0.03)	0.57	(0.16)	55.73	(0.17)
Investment Advice	11.54	(<0.01)	127.38	(0.02)	1.13	(0.11)	12.57	(0.49)
Broilers	4.00	(0.01)	15.99	(0.37)	0.64	(0.26)	2.59	(0.90)
Joint Inference		(<0.01)		(<0.01)		(0.14)		(0.33)
Joint Inf. (excl. Broilers)		(<0.01)		(<0.01)		(0.20)		(0.17)
Panel B. Sample:	Excluding Other Remote Loans							
Veterinarians	0.39	(0.17)	3.59	(0.78)	-0.22	(0.38)	2.36	(0.89)
Pharmacies	1.29	(0.03)	41.93	(0.10)	0.29	(0.51)	9.59	(0.48)
Dentists	0.40	(0.40)	3.61	(0.83)	0.21	(0.64)	2.38	(0.92)
Funeral Homes	1.74	(0.02)	50.59	(0.03)	0.20	(0.53)	5.68	(0.65)
Investment Advice	11.68	(<0.01)	121.05	(0.01)	1.27	(0.07)	12.99	(0.24)
Broilers	3.50	(0.01)	26.68	(0.07)	0.13	(0.69)	1.79	(0.92)
Joint Inference		(<0.01)		(0.05)		(0.37)		(0.93)
Joint Inf. (excl. Broilers)		(<0.01)		(0.11)		(0.25)		(0.85)

This table repeats Table 2, replacing the dependent variable with the dollar volume of loans (normalized by the 2006 loan volume).

Table 4: **Impact of Other Remote Lenders on SBA Lending**

Outcome:	All SBA Loans	All SBA Loans	All SBA Loans (excl. Live Oak)	All SBA Loans (excl. Live Oak & other remote)
	(1)	(2)	(3)	(4)
Panel A: Industry and Year Fixed Effects				
Live Oak loans	1.264***			
	(0.138)			
Spec. loans		1.114***		
		(0.226)		
Spec. loans (excl. Live Oak)			1.236*	0.865
			(0.695)	(0.533)
Observations	4,199	4,199	4,199	4,199
Panel B: Industry and Year Fixed Effects, Industry-Specific Linear Trends				
Live Oak loans	0.784***			
	(0.201)			
Spec. loans		1.095***		
		(0.331)		
Spec. loans (excl. Live Oak)			1.383***	0.951**
			(0.528)	(0.440)
Observations	4,199	4,199	4,199	4,199

Sample consists of industry-year observations for 2001-2017, restricted to industries that average at least 30 loans per year during 2001-2007. The table reports estimates from equation (5). The outcome is the total number of SBA loans for each industry-year (excluding some loan types in columns 3 and 4) and the explanatory variable is the total number of loans from Live Oak (column 1) or all remote, specialized lenders (columns 2) or remote, specialized lenders excluding Live Oak (columns 3-4) in each industry-year. Panel A includes industry and year fixed effects, and Panel B adds controls for industry-specific linear trends. Standard errors are clustered at the industry level.

Table 5: **Live Oak's Industry Selection**

Sample: Excludes Live Oak loans								
Dependent variable:	Charge-off Indicator				Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LO industry	-0.00690***	-0.00387***			-0.00417	0.000626		
	(0.00116)	(0.00117)			(0.00933)	(0.00925)		
$log(dist)$			0.00312***	0.00290***			0.0421***	0.0384***
			(0.000172)	(0.000178)			(0.00137)	(0.00139)
LO industry$\times log(dist)$			-0.00280***	-0.00226***			0.00593*	0.0148***
			(0.000445)	(0.000444)			(0.00354)	(0.00347)
Observations	63,492	63,492	63,492	63,492	63,492	63,492	63,492	63,492
Mean of Dep. Var.	0.00879	0.00879	0.00879	0.00879	5.691	5.691	5.691	5.691
Year FE	X	X	X	X	X	X	X	X
Loan char.		X		X		X		X
Industry FE			X	X			X	X

The sample consists of loans for amounts over $100,000 (in 2010 dollars) that were originated between 2008-2017. Live Oak's loans are dropped and loans to Live Oak industries outside of the largest six are dropped. Interest rate data are available from 2008Q4 and observations missing the interest rate are dropped. The dependent variable is either an indicator for whether the loan was charged off within three years of origination or the loan's interest rate (in percentage points). LO industry is an indicator for whether the loan was originated to one of the six Live Oak industries. Loan characteristics include the share guaranteed and dummies for ventiles of the size of the loan and the term length. Industry fixed effects are indicators for the 5-digit NAICS code.

Table 6: **Live Oak's Charge-off Rates and Interest Rates**

Sample: Loans in the six treated industries								
Dependent variable:	Charge-off Indicator				Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Live Oak loan	-0.000444	0.000612	0.00253	0.00443	-0.126***	-0.0694***	-0.0201	0.0486
	(0.00110)	(0.00119)	(0.00649)	(0.00655)	(0.0176)	(0.0189)	(0.103)	(0.102)
$log(dist)$			0.000346*	0.000482**			0.0492***	0.0575***
			(0.000209)	(0.000219)			(0.00332)	(0.00343)
Live Oak loan×$log(dist)$			-0.000673	-0.000866			-0.0481***	-0.0526***
			(0.000986)	(0.000989)			(0.0156)	(0.0154)
Observations	10,368	10,368	10,368	10,368	10,368	10,368	10,368	10,368
Mean of Dep. Var	0.00222	0.00222	0.00222	0.00222	5.655	5.655	5.655	5.655
Year FE	X	X	X	X	X	X	X	X
Loan char.		X		X		X		X
Industry FE	X	X	X	X	X	X	X	X

The sample consists of loans to the six treated industries for amounts over $100,000 (in 2010 dollars) that were originated between 2008-2017. Interest rate data are available from 2008Q4 and observations missing the interest rate are dropped. The dependent variable is either an indicator for whether the loan was charged off within three years of origination or the loan's interest rate (in percentage points). Live Oak loan is an indicator for whether Live Oak originated the loan. Loan characteristics include the share guaranteed and dummies for ventiles of the size of the loan and the term length. Industry fixed effects are indicators for the 5-digit NAICS code.

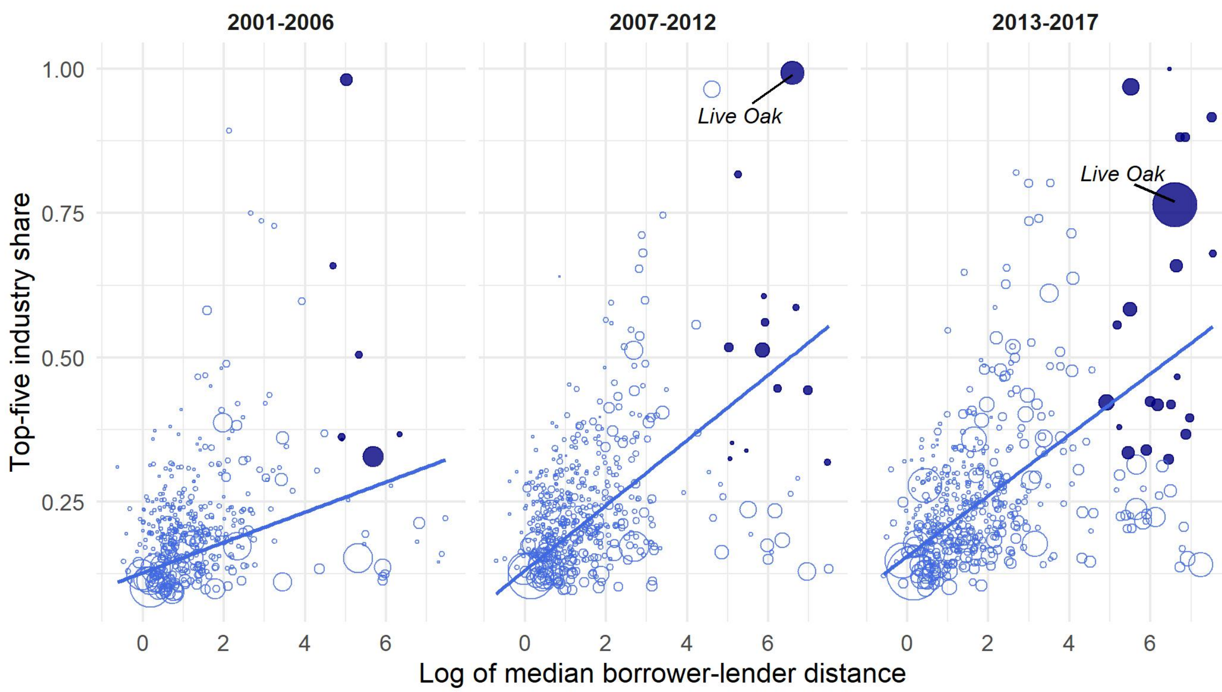


Figure 1: **SBA Lenders' Distance and Industry-Specialization**

These figures plot SBA institutions' (log) median borrower-lender distance against their top-five industry share for three periods. Each circle represents an institution and its size reflects the dollar amount of SBA loans it originated during the period. The sample is restricted to institutions originating at least 50 loans during the respective periods. The solid circles are remote, industry specialists (according to our classification in Section 3).

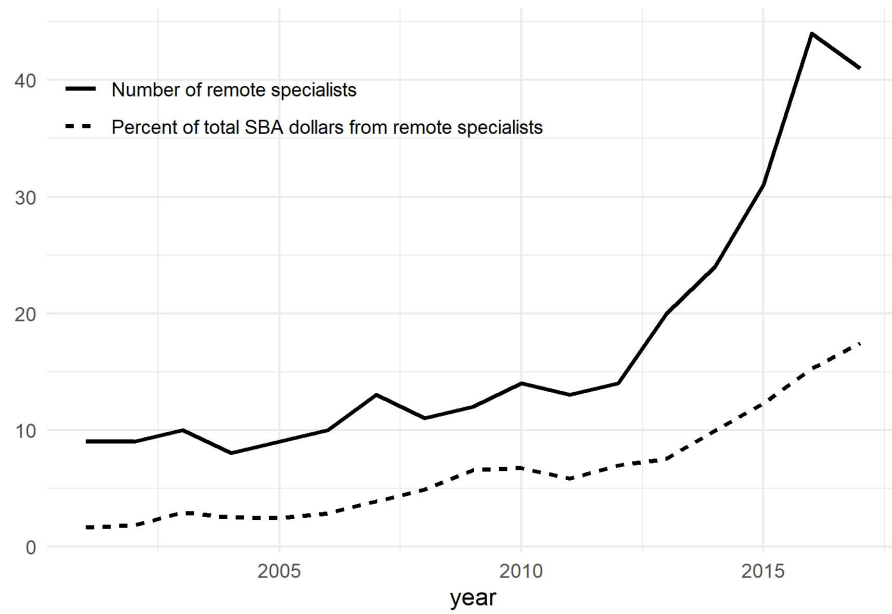
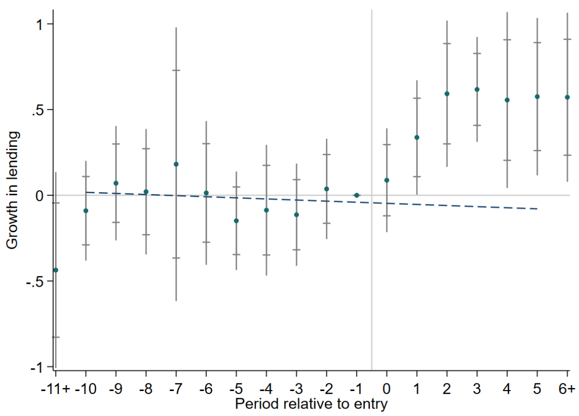
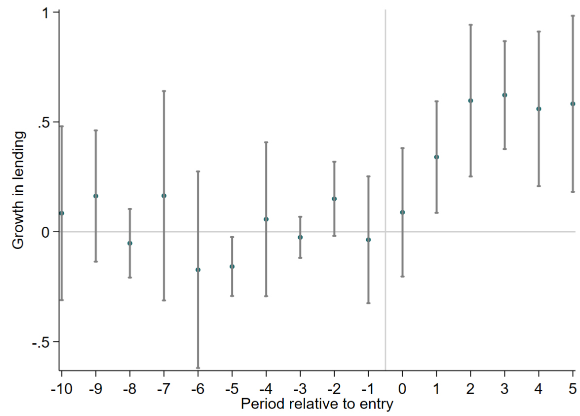


Figure 2: **Growth in Remote, Industry-Specialized Lenders**
The figure shows the number of SBA 7(a) remote, industry specialists (according to the classification in Section 3) and percent of SBA loan amounts originated by these specialists for each year from 2001-2017. We exclude institutions that originated fewer than 10 SBA loans in a year.



(a)



(b)

Figure 3: **Event study estimates**
The event study is estimated on the sample of all treatment and control industries in the main analysis sample from 2001-2017 (Section 4.2). Panel (a) reports estimates of β_m from specification (4), along with pointwise 95% confidence intervals (inner bars) and the 95% simultaneous, sup-t confidence bans of Montiel Olea and Plagborg-Møller (2019) (outer lines). The dashed blue line shows the linear pretrend over the five years prior to entry (see text for details). Panel (b) reports estimates of the dynamic average treatment on the treated using the estimator of Callaway and Sant'Anna (2020), along with their 95% simultaneous confidence bands.

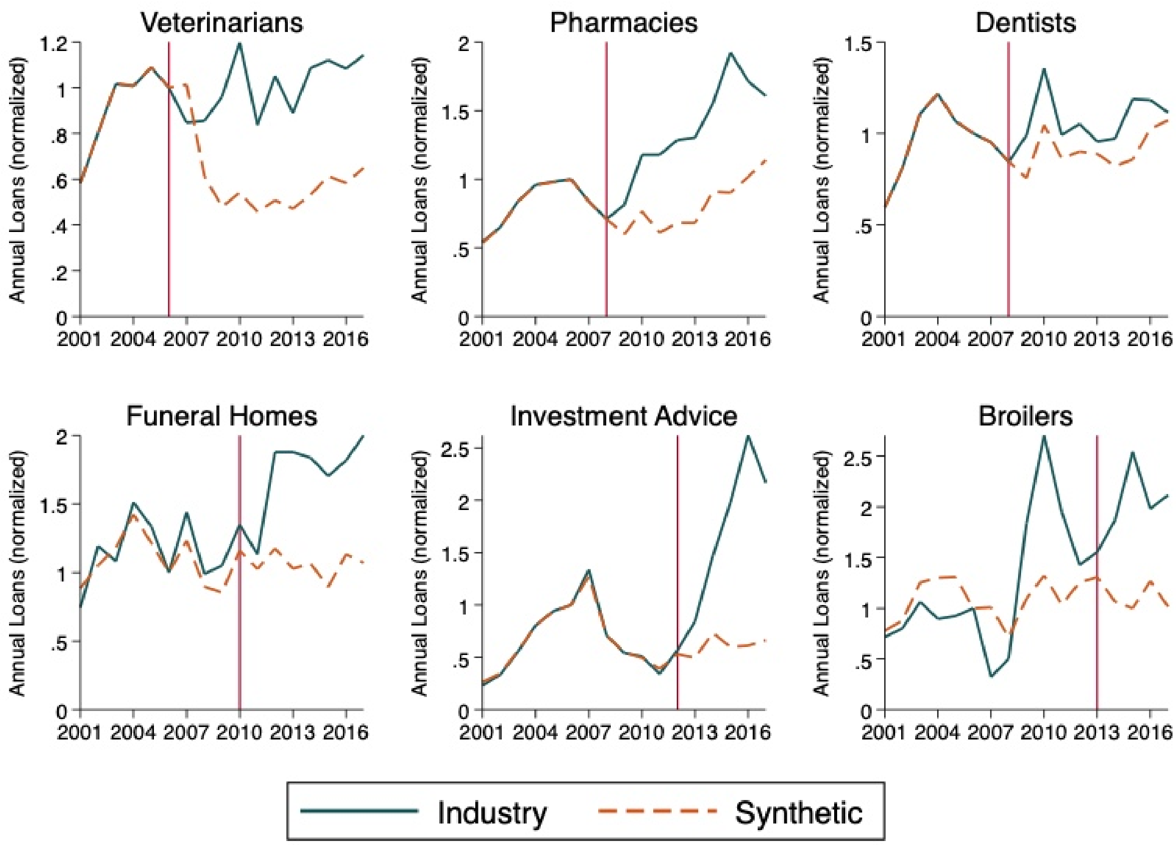


Figure 4: **Annual Lending: Treated vs. Synthetic Control**
This figure shows the growth in the annual number of SBA 7(a) loans in each industry (with 2006 loans normalized to one) for the treated industries and the synthetic control. The synthetic controls are formed by matching on all pretreatment years beginning in 2001, with no additional covariates. The vertical line shows the year before Live Oak entered.

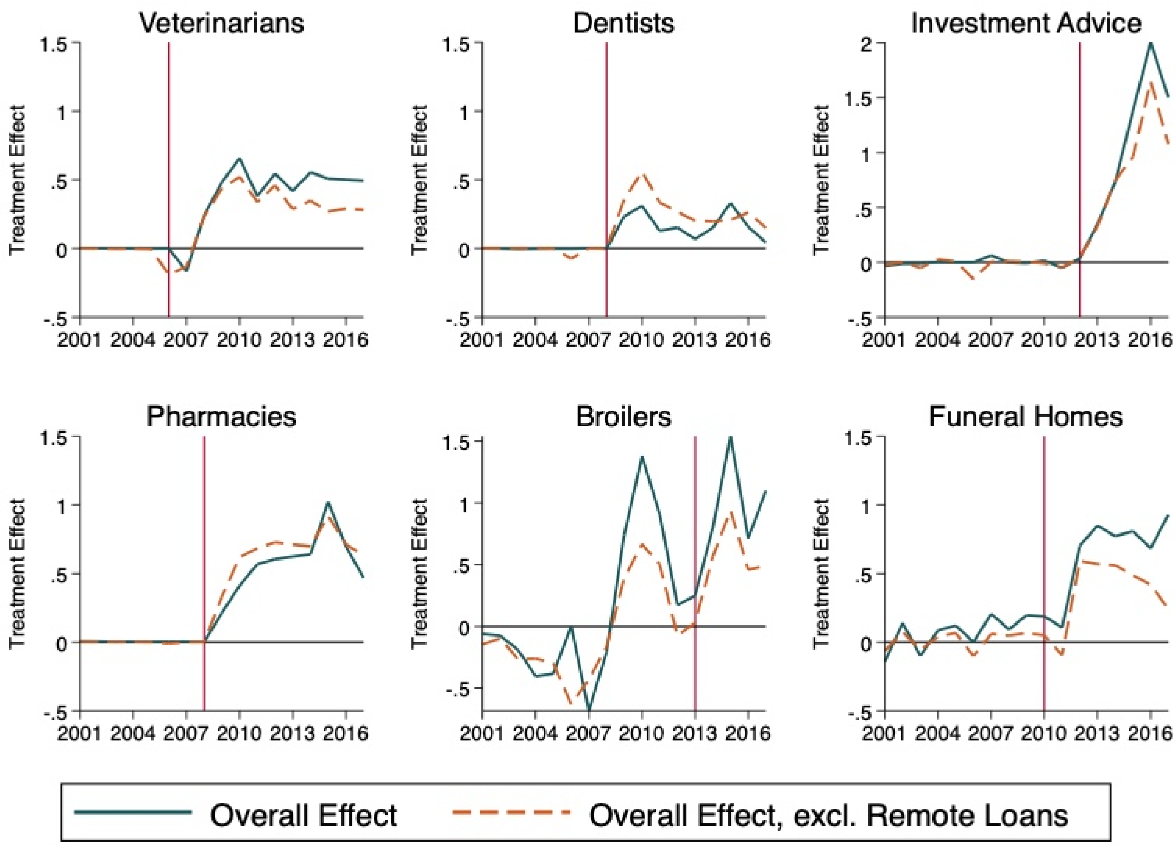


Figure 5: **Overall Effect of Entry**

Synthetic control estimates of the overall treatment effect on annual lending for each treated industry. The "Overall Effect" is for all loans, and "Overall Effect, excl. Remote Loans" excludes non-Live-Oak remote loans (loans with distance > 100 miles). The vertical line shows the year before Live Oak entered.

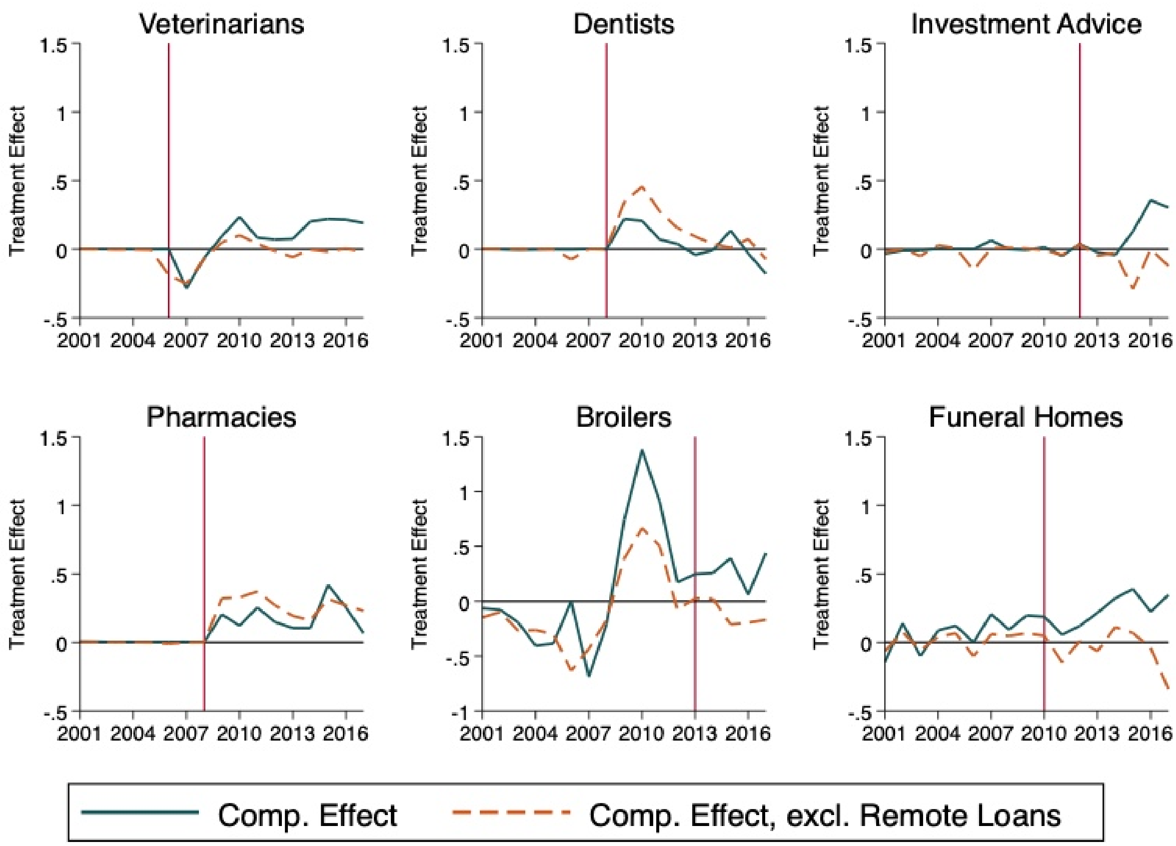


Figure 6: **Competitive Effect of Entry**

Synthetic control estimates of the competitive treatment effect on annual lending for each treated industry. The "Competitive Effect" is for all (non-Live-Oak) loans, and "Comp. Effect, excl. Remote Loans" excludes loans with borrower-lender distances > 100 miles. The vertical line shows the year before Live Oak entered.

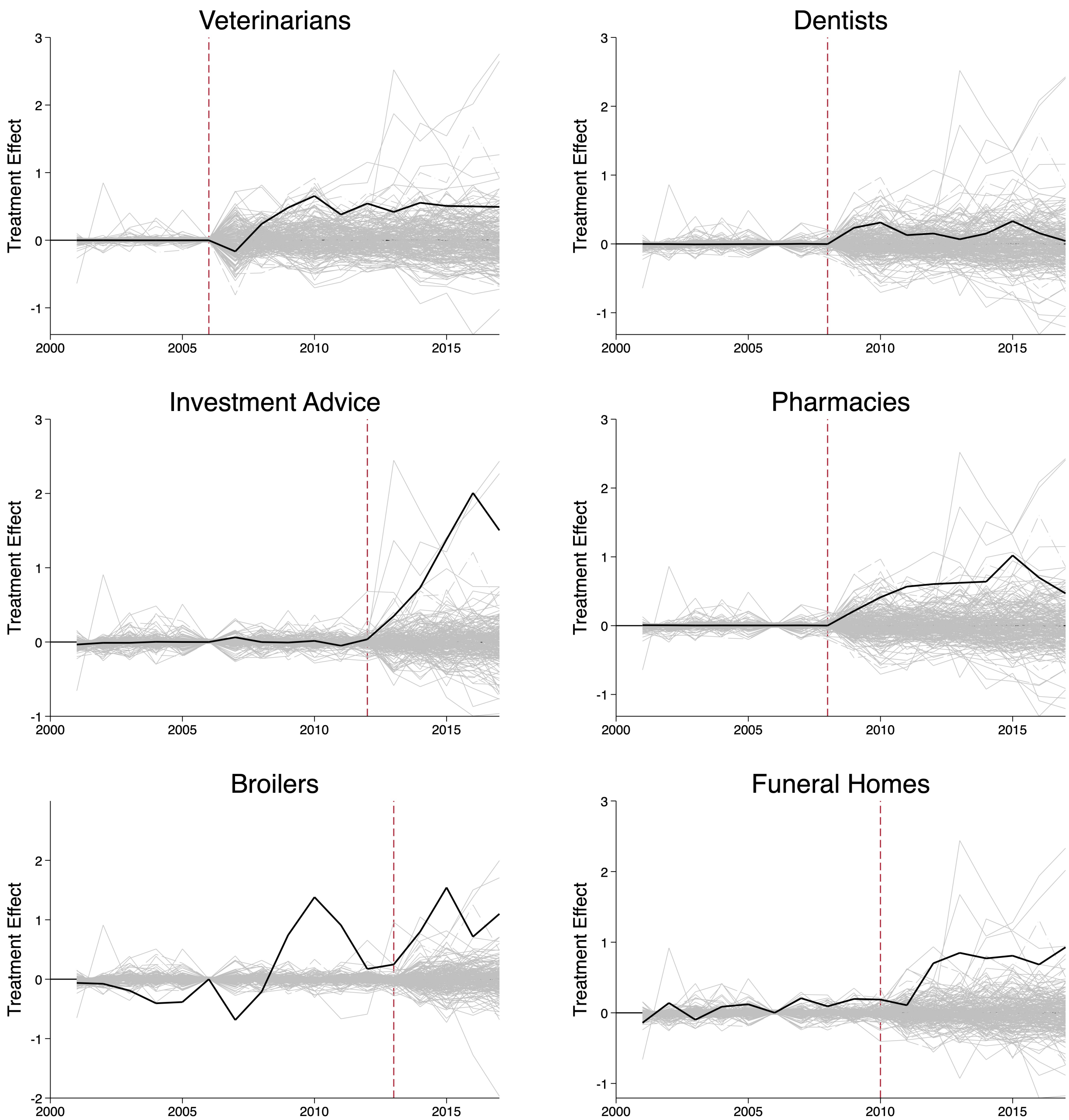


Figure 7: **Treated and Placebo Treatment Effects**
The bold line shows the gap for the industry that Live Oak entered, while the gray lines show the gap for the placebo industries. The figure omits industries with a pretreatment MSPE more than 20 times that of the average MSPE among the treated industries. The vertical line shows the year before Live Oak entered.

INTERNET APPENDIX

"Industry Specialization and Small Business Lending"

Wenhua Di Nathaniel Pattison

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A Appendix Tables and Figures

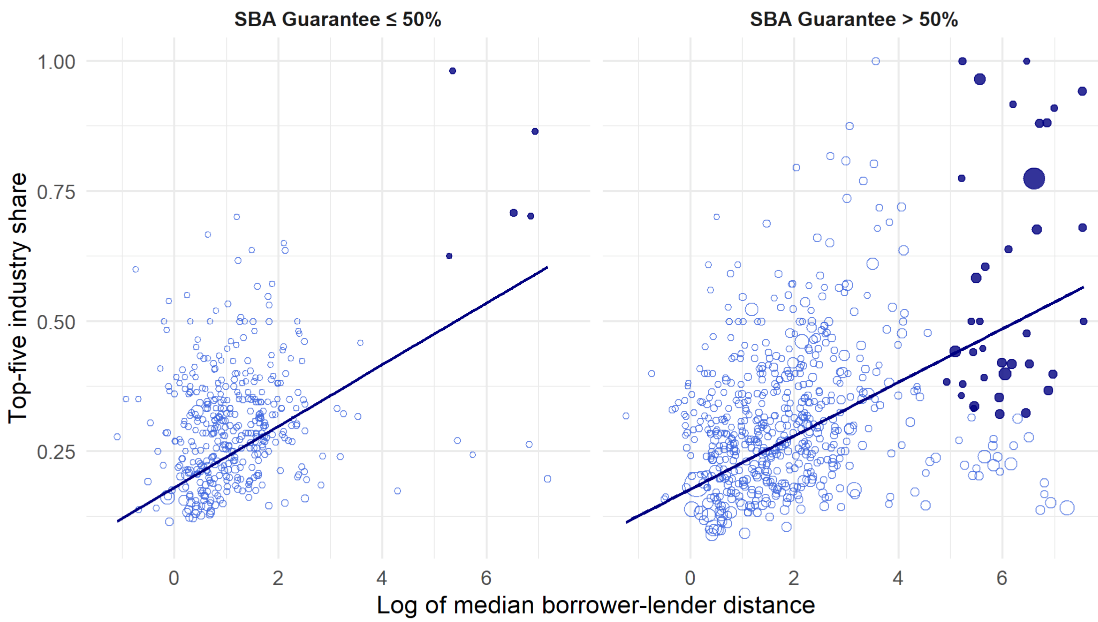


Figure A.1: **Distance and concentration by the SBA guarantee amount (2013-2017)**
These figures plot institutions' (log) median borrower-lender distance against their top-five industry share for the period 2013-2017. The shares and distances are formed separately for loans with a low ($\leq$ 50%) or high ($>$ 50%) SBA guarantee. Each circle represents an institution and its size reflects the dollar amount of SBA loans it originated during the period. The sample is restricted to institutions originating at least 20 loans in the guarantee category during 2013-2017. The solid circles are remote, industry specialists (according to our classification in the text).

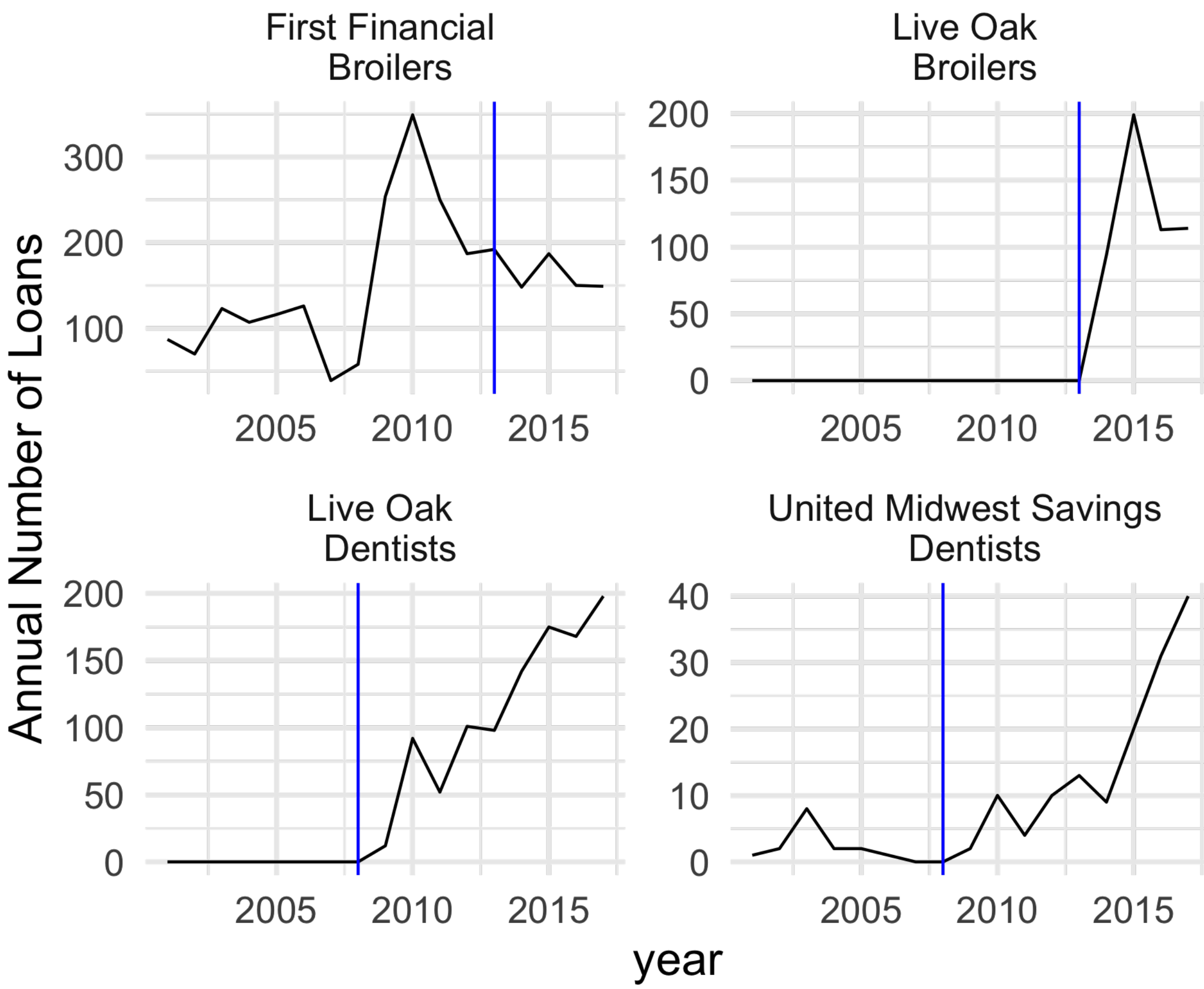


Figure A.2: **Live Oak and Other Specialized Lenders**
The figure plots the annual number of loan originated by the two specialized lenders who were already operating within the treated industries at the time of Live Oak's entry. The vertical bar shows the year prior to Live Oak's entry.

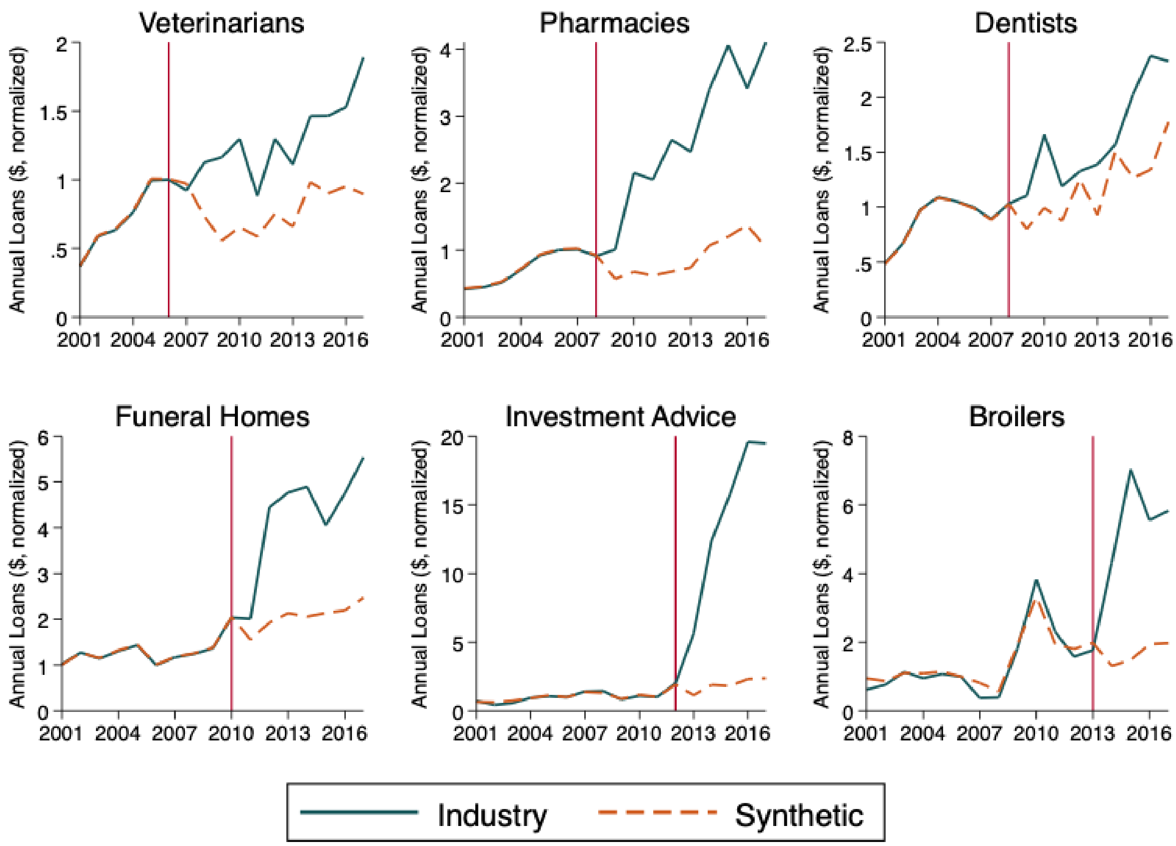


Figure A.3: **Loan Volume: Treated vs. Synthetic Control**
This figure repeats Figure 4, replacing the dependent variable with the dollar volume of loans (normalized by the 2006 loan volume).

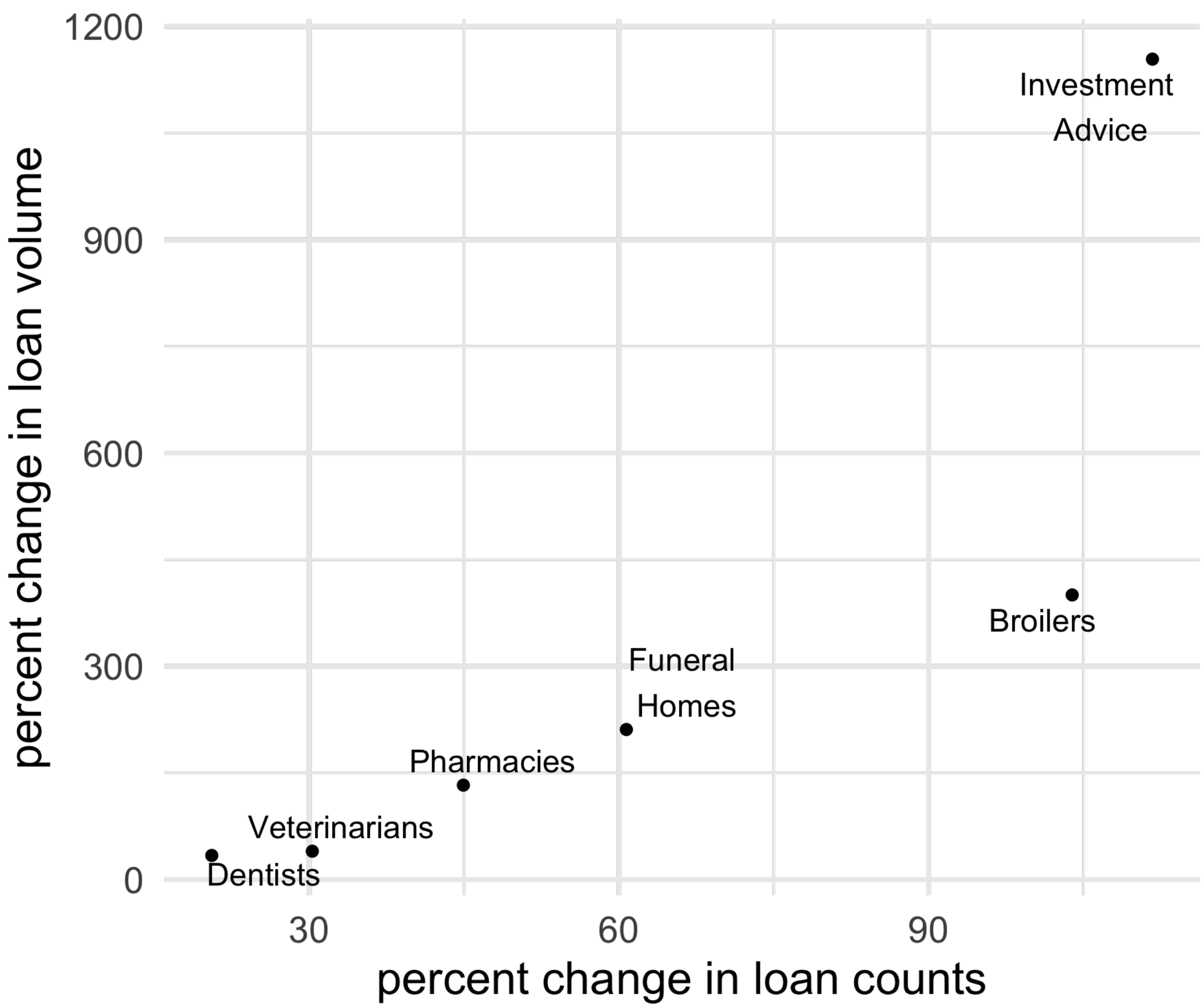


Figure A.4: **ATE for Loan Counts vs. Loan Volume**
This figure compares the average treatment effects during years 0-4 for the specifications using loan counts and loan volumes, respectively, as the dependent variable. The estimates of the average treatment effects are reported in Table 2 and Table 3.

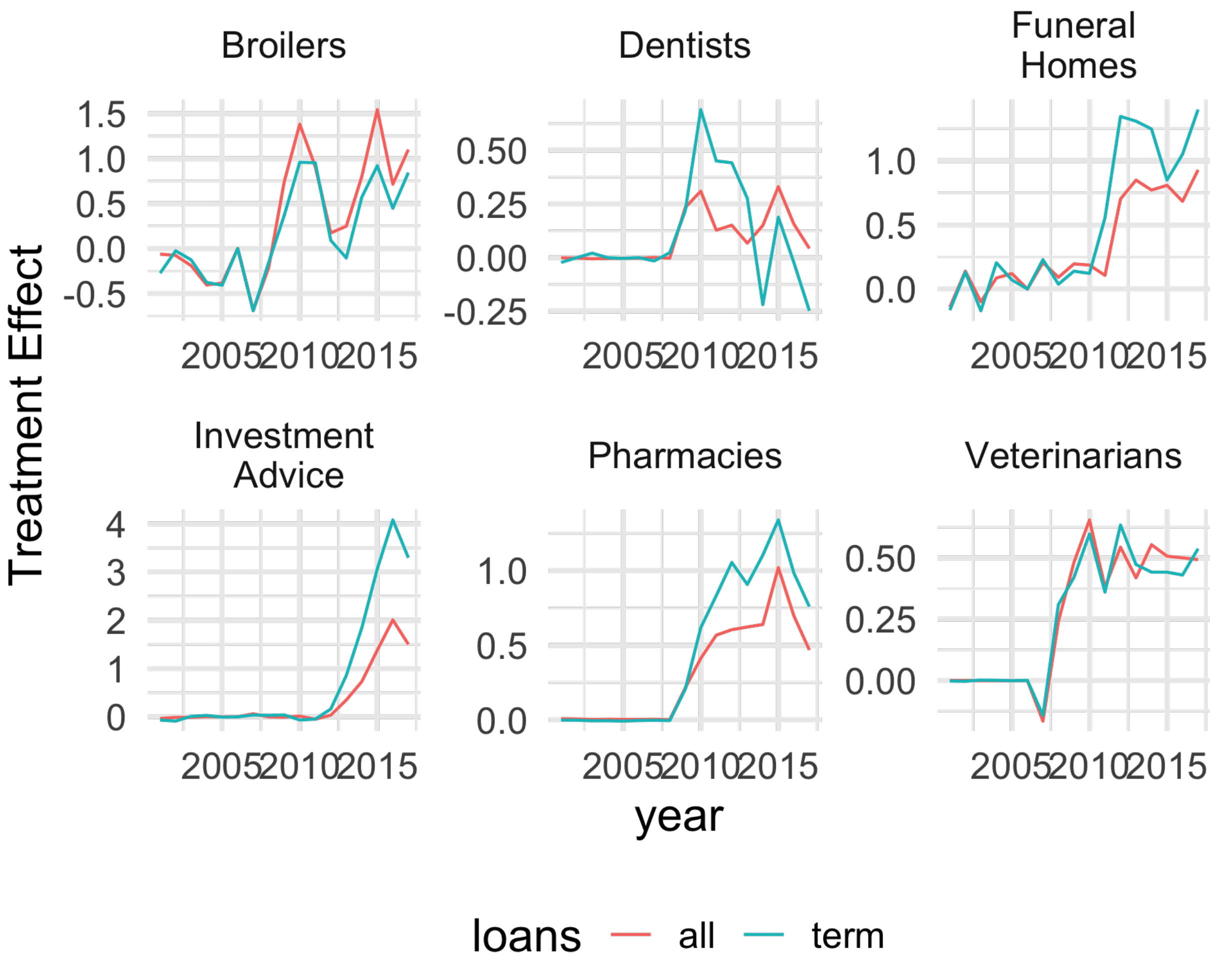


Figure A.5: **Term Loan: Treated vs. Synthetic Control**
This figure compares the main estimates from Figure 4 using counts of all loans (both term and lines of credit) against estimates using counts of only term loans.

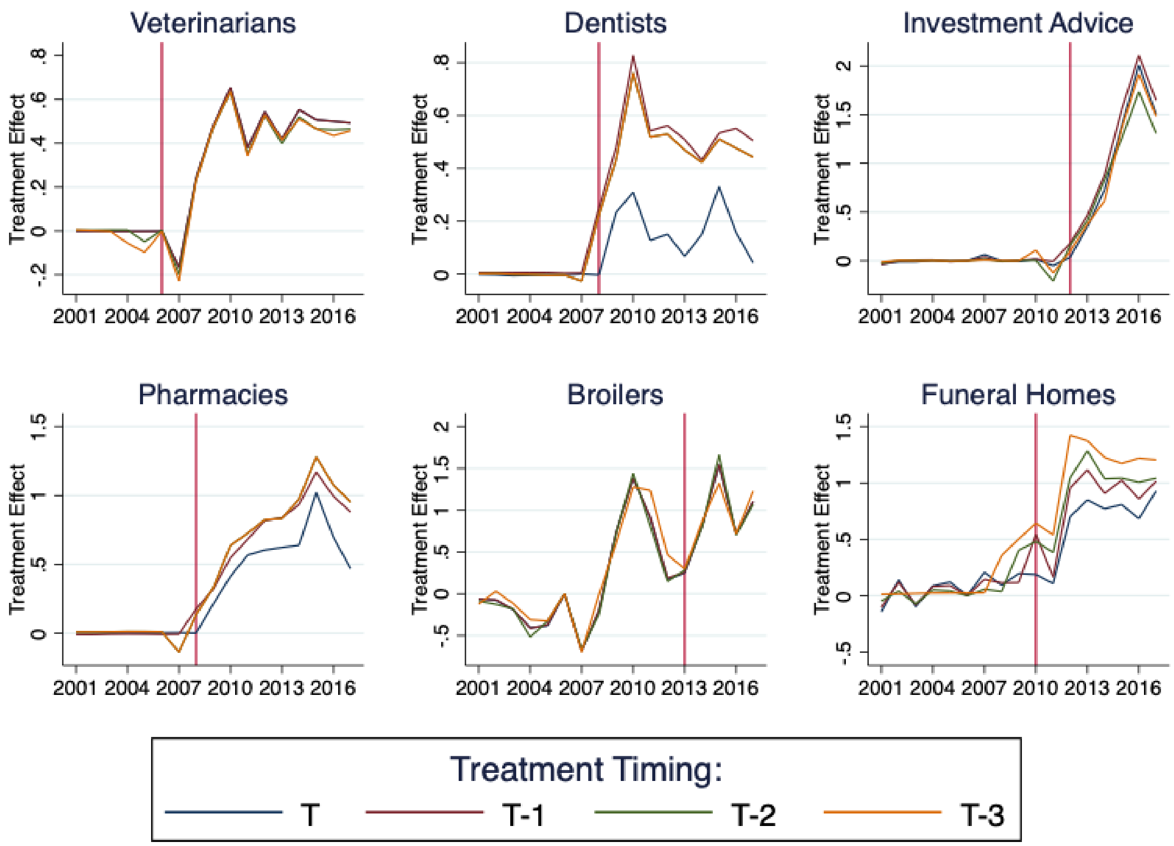


Figure A.6: **Sensitivity to Treatment Timing**
This figure reports treatment effects from four synthetic control estimates, varying the treatment timing $T-3$ through T, where T is the true treatment timing. The vertical line shows the year before Live Oak entered.

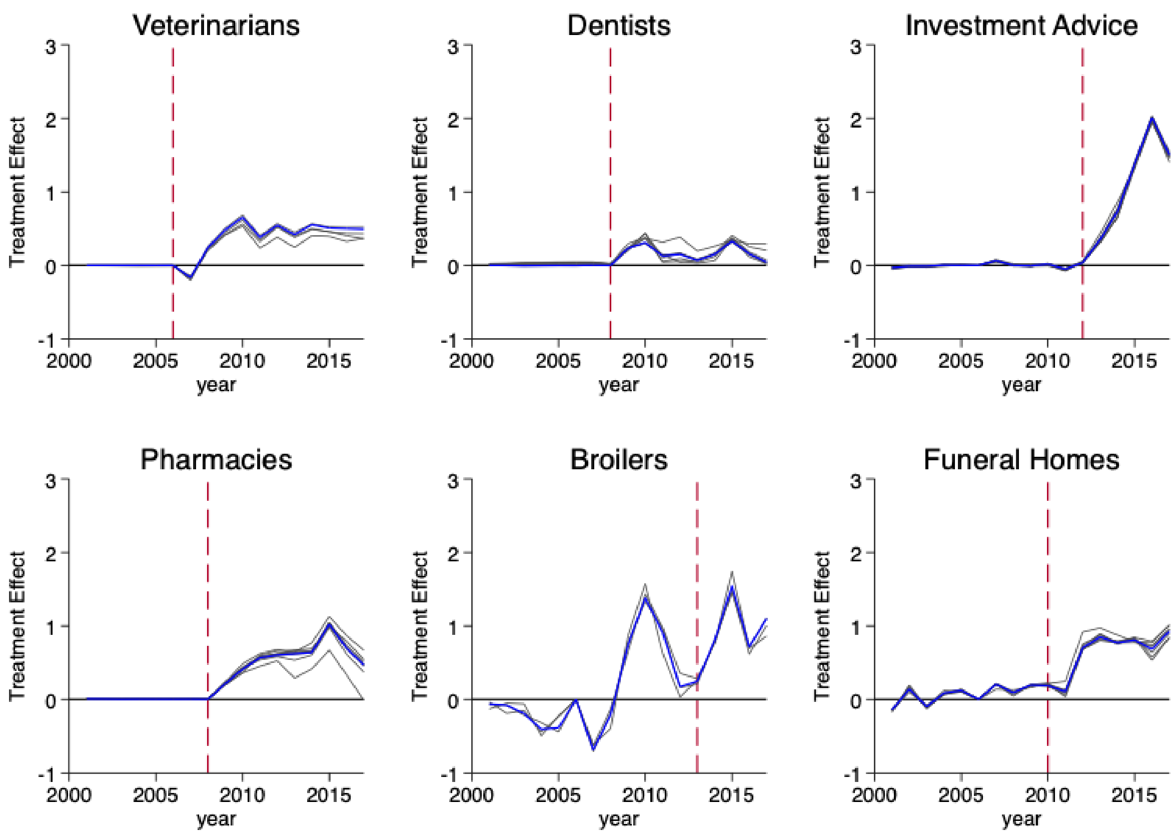


Figure A.7: **Sensitivity to the Donor Pool**

This figure reports leave-one-out treatment effect estimates. For each treated industry, we construct leave-one-out donor pools by iteratively dropping each control unit with a weight of at least 0.01 in the synthetic control of Figure 4 and re-estimating the treatment effects. The blue line shows the treatment effect when all industries are included. The vertical line shows the year before Live Oak entered.

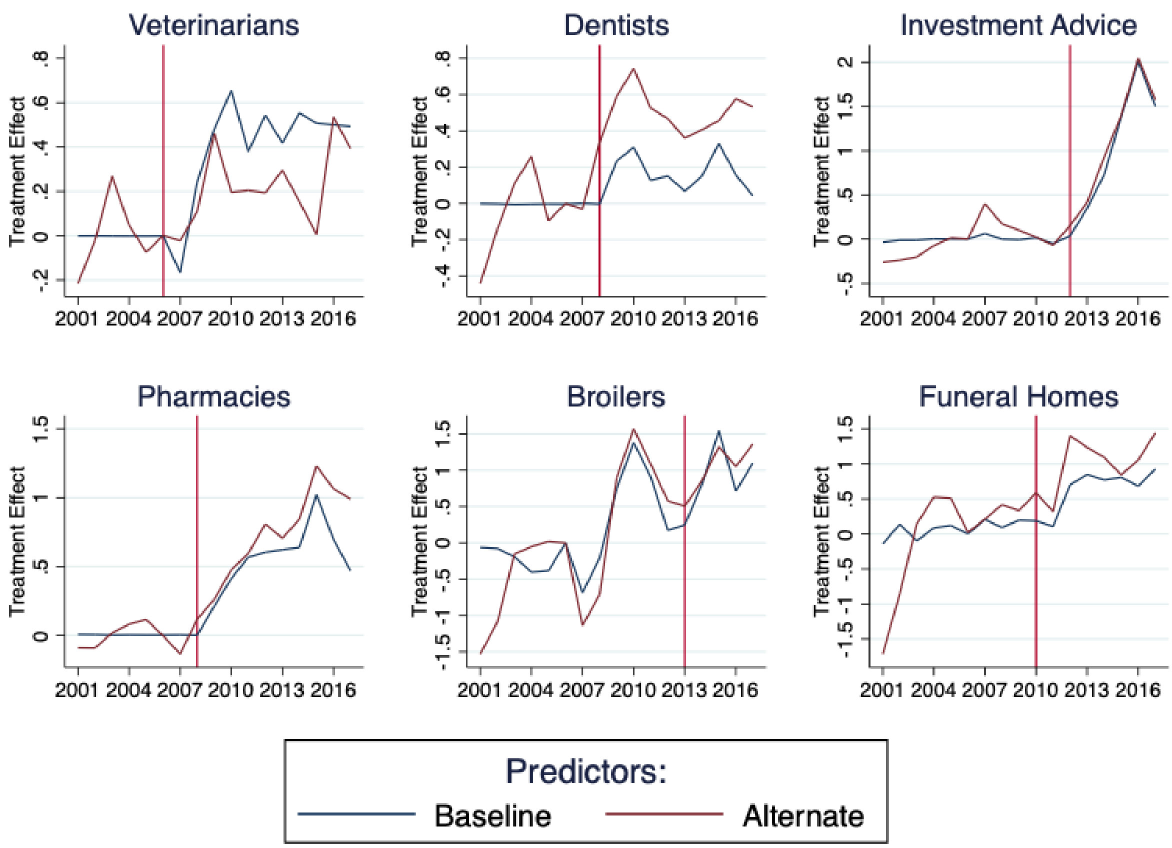


Figure A.8: **Sensitivity to Alternative Predictors**
The Baseline specification using all pre-treatment outcomes as controls. The Alternative matches units on the average pre-treatment controls for the number of observations, charge-off rate, and normalized lending, with each average taken over the pre-treatment period.

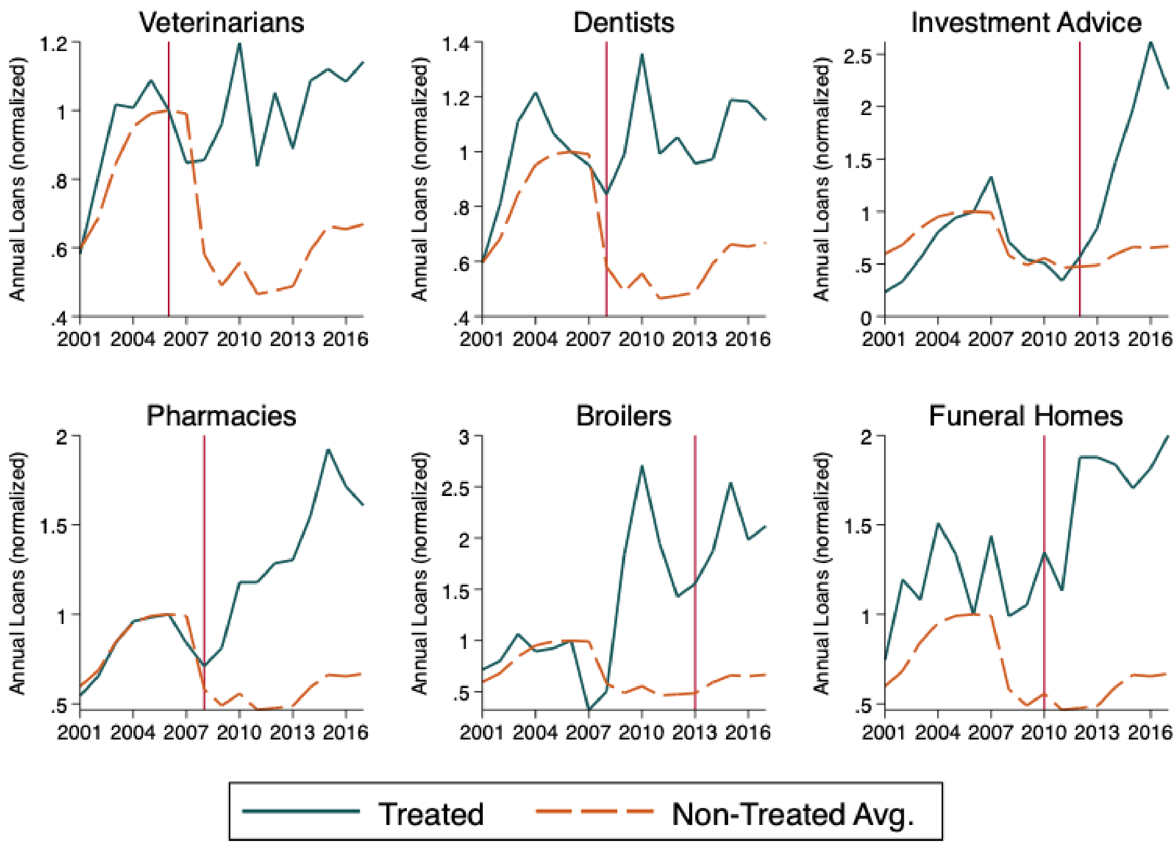
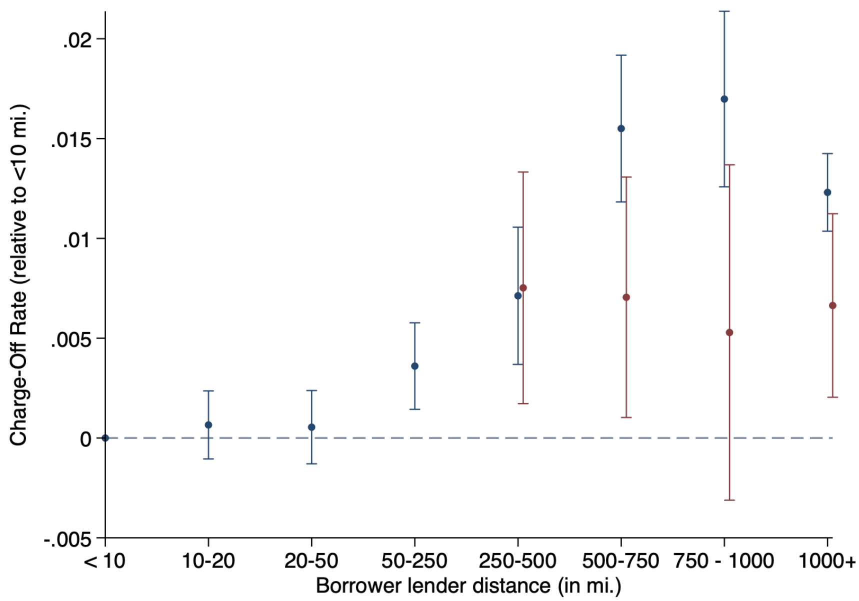
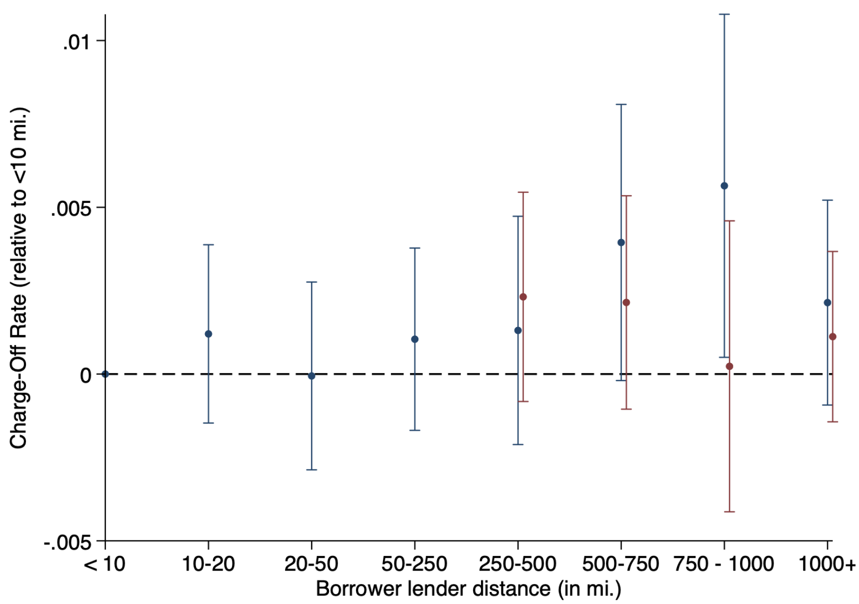


Figure A.9: **Annual Lending: Treated vs. Simple Comparison Group**
This figure shows the growth in the annual number of SBA 7(a) loans in each industry (with 2006 loans normalized to one) for the treated industries and the simple average of all control industries. In each panel, the non-treated group consists of the ten control industries whose average annual lending between 2001 and 2006 was closest to that of the treated industry. The vertical line shows the year before Live Oak entered.

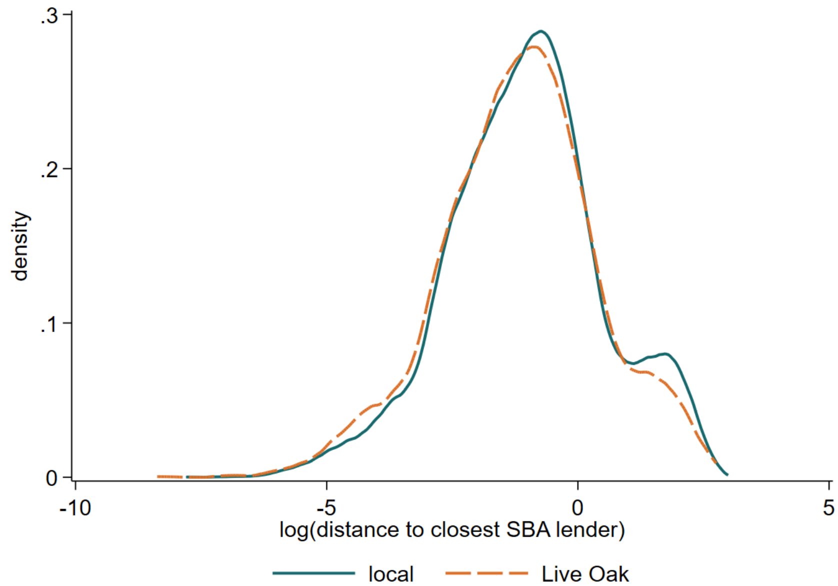


(a) All industries

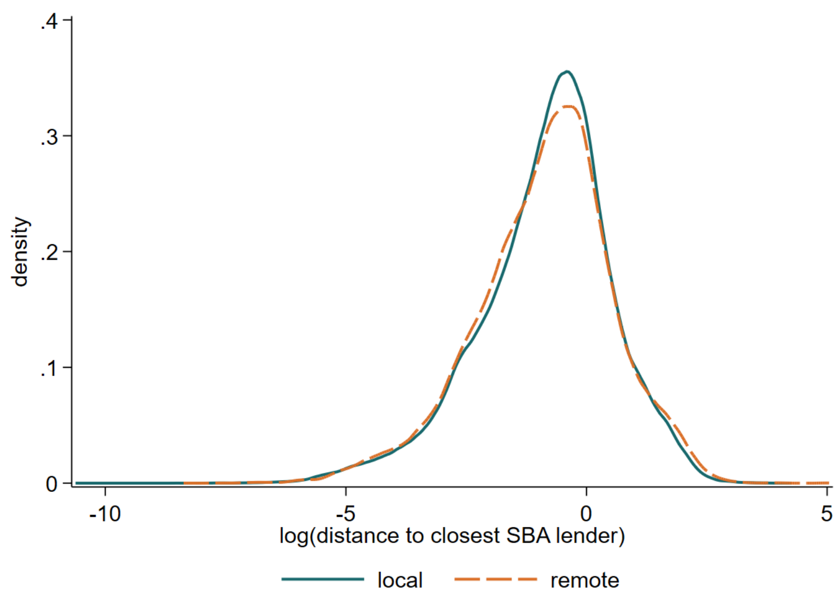


(b) Live Oak industries only

Figure A.10: **Distance and Charge-off Rates (Flexible Specification)**
We estimate the specification in Table 6 column 2 with the 3-year charge-off rate as the dependent variable, but replace the independent variable $log(dist)$ with a set of dummy variables for different distances (shown on the horizontal axis). We interact these dummies with an indicator for Live Oak and an indicator for non-Live-Oak lenders. These figures report the coefficients on these indicators, along with 95% confidence intervals, from a sample containing loans from all industries (figure a) and a sample containing only Live Oak's six industries. In both sets of regressions, Live Oak experiences better loan performance in distant loans, though the differences are only statistically significant in figure a. We do not report coefficients for Live Oak for loans of less than 250 miles, because Live Oak makes very few of these loans and the confidence interval spans the entire vertical axis.



(a) Comparison of local loans and Live Oak loans (in Live Oak industries)



(b) Comparison of local loans and remote loans

Figure A.11: **Distance to Closest SBA Branch**
This graph shows the similarity in the distribution of the distance between borrowers and the closest branch of any institution that grants SBA loans for local and remote between 2007 and 2017. The first figure compares local loans (from a lender within 100 miles) to Live Oak loans for borrowers in the six treated industries. The second figure compares local loans to remote loans (from a lender more than 100 miles away). Distance is calculated according to the procedure described in Section B, except it is the distance to the closest branch of any SBA lender.

Table A.1: **Institutions' Lending Distance and Portfolio Concentration**

	Dependent variable: Institution's Top Five Share					
	(1)	(2)	(3)	(4)	(5)	(6)
log(med. distance)	0.0244***	0.0304***	0.0140***	0.0131**		
	(0.00453)	(0.00398)	(0.00273)	(0.00544)		
Share 100+ mi.					0.222***	0.123***
					(0.0335)	(0.0251)
Observations	5,278	5,278	5,278	1,705	5,278	5,278
Mean Dep. Var.	0.430	0.430	0.430	0.318	0.430	0.430
Year FE	X	X	X	X	X	X
Inst. volume ventiles		X	X	X	X	X
Inst. FE			X	X		X
Balanced panel				X		

Observations are at the institution-year level from 2007-2017 and standard errors are clustered at the institution level. The dependent variable is the share of an institution's loan portfolio in its top five industries. Share 100+ mi. is the share of the institution's loans given to borrowers more than 100 miles from the closest branch. The sample is restricted to institution-year observations with at least 10 loans. Institution volume ventiles are ventile indicators for the number of SBA loans each year.

Table A.2: **Institutions' Lending Distance and Industry Concentration (HHI)**

	Dependent variable: Bank's Industry Concentration (HHI)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(med. distance)	146.5***	162.0***	75.95***	42.41**		
	(23.96)	(23.09)	(14.74)	(17.80)		
Share 100+ mi.					1,264***	695.4***
					(192.8)	(142.3)
Observations	5,278	5,278	5,278	1,705	5,278	5,278
Mean Dep. Var.	985.6	985.6	985.6	686.5	985.6	985.6
Year FE	X	X	X	X	X	X
Inst. volume ventiles		X	X	X	X	X
Inst. FE			X	X		X
Balanced panel				X		

Observations are at the institution-year level from 2007-2017 and standard errors are clustered at the institution level. The sample is restricted to institution-year observations with at least 10 loans. The industry HHI for lender b in year t is defined as $HHI_{bt} = \sum_i S_{ibt}^2$, where S_{ibt} is the percent of lender b's loans given to industry i in year t. The HHI is increasing in industry concentration and takes a value from close to 0 (least concentrated) to 10,000 (all loans to a single industry). Institution volume ventiles are ventile indicators for the number of SBA loans each year.

Table A.3: **Industries Comprising Synthetic Controls (Donor Pool)**.

Industry	Synthetic Makeup	Weight
Broilers and Other Meat Type		
	Fluid Power Valve and Hose Fitting Manufacturing	0.14
	Logging	0.54
	Motion Picture Theaters (except Drive-Ins)	0.31
Pharmacies and Drug Stores		
	Continuing Care Retirement Communities	0.10
	Mobile Food Services	0.02
	Motion Picture Theaters (except Drive-Ins)	0.09
	Other Residential Care Facilities	0.04
	Precision Turned Product Manufacturing	0.04
	Recreational Vehicle Dealers	0.23
	Services for the Elderly and Persons with Disabilities	0.10
	Used Household and Office Goods Moving	0.02
Investment Advice		
	Audio and Video Equipment Manufacturing	0.09
	Child and Youth Services	0.04
	Direct Title Insurance Carriers	0.21
	Lessors of Other Real Estate Property	0.13
	Mortgage and Nonmortgage Loan Brokers	0.09
	Motor Vehicle Body Manufacturing	0.04
	Other Support Activities for Road Transportation	0.35
	Tour Operators	0.05
Veterinary Services		
	Fish and Seafood Markets	0.10
	Other Residential Care Facilities	0.04
	Photofinishing Laboratories (except One-Hour)	0.07
	Theater Companies and Dinner Theaters	0.05
Offices of Dentists		
	Agents and Managers for Artists, Athletes, Entertainers, and Other Pub	0.01
	All Other Miscellaneous Electrical Equipment and Component Manufacturi	0.16
	Fluid Power Valve and Hose Fitting Manufacturing	0.02
	Motion Picture Theaters (except Drive-Ins)	0.16
	Other Residential Care Facilities	0.26
	Other Support Activities for Air Transportation	0.09
	Packaging and Labeling Services	0.14
Funeral Homes and Funeral Services		
	All Other Miscellaneous Electrical Equipment and Component Manufacturi	0.16
	Child and Youth Services	0.09
	Logging	0.15
	Marinas	0.22
	Motion Picture Theaters (except Drive-Ins)	0.28
	Rendering and Meat Byproduct Processing	0.07
	Scenic and Sightseeing Transportation, Water	0.04

* Shows all industries with weight above 0.01. Industries with a weight of less than 0.01 are excluded.

Table A.4: **Comparison of Pre-Treatment Fit**

	(1) MSPE - Comparison Mean	(2) MSPE - Synthetic Control	(3) Ratio (1)/(2)
Veterinarians	.0095	1.2e-06	7,665.0
Offices of Dentists	.029	9.7e-06	2,982.5
Investment Advice	.044	.00079	55.3
Pharmacies	.0054	.000016	332.0
Broilers	.86	.33	2.6
Funeral Homes	.21	.02	10.6

This table compares the pre-treatment fit, measured by the mean squared prediction error (MSPE), for when the comparison group is either the simple average of all controls (column 1) or the synthetic control (column 2). Column 3 reports the ratio of the two MSPE calculations.

Table A.5: **Other Remote Lenders and Industries**

Bank	Industry	Year of First Loan	Bank's Share of Loans (2013-2017)	Bank's Loans in Industry (2001-2017)
Bank of George	Hotels (except Casino Hotels) and Motels	2015	0.83	90
Carver State Bank	Insurance Agencies and Brokerages	2016	0.93	70
Citizens Bank	Offices of Chiropractors	2015	0.15	34
Citizens Bank	Gasoline Stations with Convenience Stores	2001	0.11	28
Citizens Bank	Hotels (except Casino Hotels) and Motels	2001	0.10	77
Civis Bank	Gasoline Stations with Convenience Stores	2012	0.12	9
Civis Bank	Hotels (except Casino Hotels) and Motels	2010	0.12	14
Crestmark Bank	Insurance Agencies and Brokerages	2014	0.69	93
Crestmark Bank	Hotels (except Casino Hotels) and Motels	2014	0.13	18
FinWise Bank	Offices of Lawyers	2014	0.56	82
First Bank	Hotels (except Casino Hotels) and Motels	2016	0.10	20
First Chatham Bank	Child Day Care Services	2013	0.20	27
First Colorado National Bank	Hotels (except Casino Hotels) and Motels	2007	0.18	53
First Financial Bank	Broilers and Other Meat Type	2001	0.66	2592
First Financial Bank	Pharmacies and Drug Stores	2012	0.16	208
Meadows Bank	Retail Bakeries	2011	0.12	48
Meadows Bank	Child Day Care Services	2012	0.10	40
Mission Valley Bank	Hotels (except Casino Hotels) and Motels	2015	0.28	25
Mission Valley Bank	Funeral Homes and Funeral Services	2015	0.16	14
NOA Bank	Hotels (except Casino Hotels) and Motels	2009	0.38	163
NOA Bank	Gasoline Stations with Convenience Stores	2009	0.10	51
Spirit of Texas Bank, SSB	Beauty Salons	2009	0.27	462
Spirit of Texas Bank, SSB	Other Personal Care Services	2009	0.26	345
The MINT National Bank	Hotels (except Casino Hotels) and Motels	2014	0.67	74
The MINT National Bank	Gasoline Stations with Convenience Stores	2014	0.14	15
Titan Bank, National Association	Offices of Dentists	2013	0.30	27
United Community Bank	Offices of Dentists	2001	0.18	117
United Community Bank	Veterinary Services	2001	0.15	93
United Midwest Savings Bank	Offices of Dentists	2001	0.21	155

A lender is classified as a remote specialized lender if it has a median lending distance greater than 100 miles, a top-five industry share above 32%, and at least 50 total SBA loans (all measured during the period 2013-2017). We consider that lender to specialize in a specific industry if (in 2013-2017), at least 10% of that lender's loans are to the industry.

Table A.6: **Charge-off Rates and Interest Rates - County Distance Measure**

Sample: Loans in the six treated industries								
Dependent variable:	Charge-off Indicator				Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Live Oak loan	-0.000875	0.000515	-0.000830	0.00153	-0.123***	-0.0625***	0.129	0.207**
	(0.000825)	(0.000898)	(0.00502)	(0.00506)	(0.0141)	(0.0152)	(0.0846)	(0.0842)
$log(dist)$			0.000281	0.000470**			0.0659***	0.0763***
			(0.000195)	(0.000202)			(0.00328)	(0.00337)
Live Oak loan$\times log(dist)$			-0.000159	-0.000393			-0.0738***	-0.0797***
			(0.000770)	(0.000771)			(0.0130)	(0.0128)
Observations	15,569	15,569	15,569	15,569	15,569	15,569	15,569	15,569
Mean of Dep. Var	0.00193	0.00193	0.00193	0.00193	5.656	5.656	5.656	5.656
Year FE	X	X	X	X	X	X	X	X
Loan char.		X		X		X		X
Industry FE	X	X	X	X	X	X	X	X

This table repeats Table 6, using distance measured using the borrower's county-centroid. The sample consists of loans to the six treated industries for amounts over $100,000 (in 2010 dollars) that were originated between 2008-2017. Interest rate data are available from 2008Q4 and observations missing the interest rate are dropped. The dependent variable is either an indicator for whether the loan was charged off within three years of origination or the loan's interest rate (in percentage points). Loan characteristics include the share guaranteed and dummies for ventiles of the size of the loan and the term length. Industry fixed effects are indicators for the 5-digit NAICS code.

Table A.7: **Live Oak Industry Selection - County Distance Measure**

Sample: Excludes Live Oak loans								
Dependent variable:	Charge-off Indicator				Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LO industry	-0.00685***	-0.00380***			-0.00837	-0.00247		
	(0.000929)	(0.000935)			(0.00762)	(0.00758)		
$log(dist)$			0.00317***	0.00313***			0.0517***	0.0478***
			(0.000167)	(0.000171)			(0.00135)	(0.00137)
LO industry$\times log(dist)$			-0.00296***	-0.00241***			0.0121***	0.0217***
			(0.000433)	(0.000430)			(0.00350)	(0.00344)
Observations	90,969	90,969	90,969	90,969	90,969	90,969	90,969	90,969
Mean of Dep. Var.	0.00840	0.00840	0.00840	0.00840	5.693	5.693	5.693	5.693
Year FE	X	X	X	X	X	X	X	X
Loan char.		X		X		X		X
Industry FE			X	X			X	X

This table repeats Table 5, using distance measured using the borrower's county-centroid. The sample consists of loans for amounts over $100,000 (in 2010 dollars) that were originated between 2008-2017. Live Oak's loans are dropped. Interest rate data are available from 2008Q4 and observations missing the interest rate are dropped. The dependent variable is either an indicator for whether the loan was charged off within three years of origination or the loan's interest rate (in percentage points). Loan characteristics include the share guarantee and dummies for ventiles of the size of the loan and the term length. Industry fixed effects are indicators for the 5-digit NAICS code.

Table A.8: **Charge-off Rates and Interest Rates - Loans Above $150,000**

Sample: Loans in the six treated industries								
Dependent variable:	Charge-off Indicator				Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Live Oak loan	0.000418	0.00123	0.00215	0.00351	-0.126***	-0.0753***	0.0229	0.0900
	(0.000968)	(0.00104)	(0.00562)	(0.00566)	(0.0180)	(0.0192)	(0.103)	(0.103)
$log(dist)$			2.07e-05	0.000141			0.0501***	0.0574***
			(0.000188)	(0.000196)			(0.00345)	(0.00356)
Live Oak loan $\times log(dist)$			-0.000274	-0.000428			-0.0546***	-0.0598***
			(0.000854)	(0.000856)			(0.0157)	(0.0155)
Observations	9,406	9,406	9,406	9,406	9,406	9,406	9,406	9,406
Mean of Dep. Var	0.00159	0.00159	0.00159	0.00159	5.638	5.638	5.638	5.638
Year FE	X	X	X	X	X	X	X	X
Loan char.		X		X		X		X
Industry FE	X	X	X	X	X	X	X	X

This table repeats Table 6, restricting the sample to loans above $150,000. The sample consists of loans to the six treated industries for amounts over $100,000 (in 2010 dollars) that were originated between 2008-2017. Interest rate data are available from 2008Q4 and observations missing the interest rate are dropped. The dependent variable is either an indicator for whether the loan was charged off within three years of origination or the loan's interest rate (in percentage points). Loan characteristics include the share guaranteed and dummies for ventiles of the size of the loan and the term length. Industry fixed effects are indicators for the 5-digit NAICS code.

Table A.9: **Live Oak Industry Selection - Loans Above $150,000**

Sample: Excludes Live Oak loans								
Dependent variable:	Charge-off Indicator				Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LO industry	-0.00431***	-0.00273***			0.0262***	0.0110		
	(0.000959)	(0.000971)			(0.00966)	(0.00965)		
$log(dist)$			0.000464***	0.000762***			0.0350***	0.0364***
			(0.000157)	(0.000158)			(0.00155)	(0.00155)
LO industry$\times log(dist)$			-0.000399	-0.000379			0.0137***	0.0162***
			(0.000374)	(0.000373)			(0.00371)	(0.00365)
Observations	51,436	51,436	51,436	51,436	51,436	51,436	51,436	51,436
Mean of Dep. Var.	0.00527	0.00527	0.00527	0.00527	5.654	5.654	5.654	5.654
Year FE	X	X	X	X	X	X	X	X
Loan char.		X		X		X		X
Industry FE			X	X			X	X

This table repeats Table 5, restricting the sample to loans above $150,000. The sample consists of loans for amounts over $100,000 (in 2010 dollars) that were originated between 2008-2017. Live Oak's loans are dropped. Interest rate data are available from 2008Q4 and observations missing the interest rate are dropped. The dependent variable is either an indicator for whether the loan was charged off within three years of origination or the loan's interest rate (in percentage points). Loan characteristics include the share guarantee and dummies for ventiles of the size of the loan and the term length. Industry fixed effects are indicators for the 5-digit NAICS code.

Table A.10: **Charge-off Rates and Interest Rates - County FE**

Sample: Loans in the six treated industries								
Dependent variable:	Charge-off Indicator				Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Live Oak loan	0.000524	0.00153	0.00328	0.00480	-0.124***	-0.0628***	-0.218	-0.0480
	(0.00125)	(0.00134)	(0.00943)	(0.00952)	(0.0195)	(0.0205)	(0.145)	(0.144)
$log(dist)$			0.000485**	0.000622**			0.0462***	0.0534***
			(0.000236)	(0.000248)			(0.00364)	(0.00376)
Live Oak loan$\times log(dist)$			-0.000734	-0.000870			-0.0168	-0.0352
			(0.00142)	(0.00143)			(0.0219)	(0.0217)
Observations	10,353	10,353	10,353	10,353	10,353	10,353	10,353	10,353
Mean of Dep. Var	0.00222	0.00222	0.00222	0.00222	5.655	5.655	5.655	5.655
Year FE	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X
Loan char.		X		X		X		X
Industry FE	X	X	X	X	X	X	X	X

This table repeats Table 6, including county fixed effects. The sample consists of loans to the six treated industries for amounts over \$100,000 (in 2010 dollars) that were originated between 2008-2017. Interest rate data are available from 2008Q4 and observations missing the interest rate are dropped. The dependent variable is either an indicator for whether the loan was charged off within three years of origination or the loan's interest rate (in percentage points). Loan characteristics include the share guaranteed and dummies for ventiles of the size of the loan and the term length. Industry fixed effects are indicators for the 5-digit NAICS code.

Table A.11: **Live Oak Industry Selection - County FE**

Sample: Excludes Live Oak loans								
Dependent variable:	Charge-off Indicator				Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LO industry	-0.00710***	-0.00402***			-0.0541***	-0.0385***		
	(0.00123)	(0.00123)			(0.00972)	(0.00958)		
$log(dist)$			0.00314***	0.00289***			0.0417***	0.0376***
			(0.000179)	(0.000184)			(0.00140)	(0.00142)
LO industry$\times log(dist)$			-0.00282***	-0.00221***			0.000708	0.0103***
			(0.000458)	(0.000457)			(0.00360)	(0.00353)
Observations	63,455	63,455	63,455	63,455	63,455	63,455	63,455	63,455
Mean of Dep. Var.	0.00879	0.00879	0.00879	0.00879	5.691	5.691	5.691	5.691
Year FE	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X
Loan char.		X		X		X		X
Industry FE			X	X			X	X

This table repeats Table 5, including county fixed effects. The sample consists of loans for amounts over $100,000 (in 2010 dollars) that were originated between 2008-2017. Live Oak's loans are dropped. Interest rate data are available from 2008Q4 and observations missing the interest rate are dropped. The dependent variable is either an indicator for whether the loan was charged off within three years of origination or the loan's interest rate (in percentage points). Loan characteristics include the share guarantee and dummies for ventiles of the size of the loan and the term length. Industry fixed effects are indicators for the 5-digit NAICS code.

B Appendix: Matching Procedure

In this appendix, we describe the procedure used to construct a measure of borrower-lender distance.

B.1 Matching SBA Lenders to FDIC Summary of Deposits

The SBA 7(a) loan data contain the name and address of the institution that is currently assigned the loan. 5,815 institutions originated SBA loans between 2001 and 2017. For these institutions, we conduct a series of probabilistic matches using bank name, address, city, state, and zip code to link the SBA lending institutions to institutions in the 2017 FDIC Summary of Deposits. First, the matching procedure produces a match score between 0 and 1 based on the similarity of the text in the variables listed above, with more weight given to the bank name and address, since they are more likely to uniquely identify banks.[1] Of the 5,815 unique institutions, we find an exact match for 3,041. After checking for accuracy, we also count the roughly 800 additional institutions with a bigram match score greater than 0.98 as a match. For those with a score less than 0.98, we conduct a clerical review to determine whether the best match is accurate. After this first round of matching, we conduct a second round of matching and clerical review using different weights for the variables. We then manually match any unmatched institution that gave more than 100 SBA loans between 2001 and 2017 (provided that the institution is a bank and is not closed). Overall, we match 75% of the 5,815 institutions and these institutions provide 91.8% of SBA loans from 2001-2017. The majority of unmatched SBA institutions are credit unions or non-bank lenders, for which we do not have bank branch locations in the FDIC Summary of Deposit data, or they are closed banks whose assets were transferred.

B.2 SBA Lenders' Branch Locations

Having matched banks in the SBA data to banks in the FDIC Summary of Deposits, we construct historical branch networks. The FDIC Summary of Deposits contains annual counts and locations for bank branches from 1994-2017. For each matched SBA lender, we can therefore determine its branch locations at the time the loan was originated. The matches are imperfect, however, since the SBA 7(a) data contain the institution currently assigned the loan, rather than the institution that originated the loan. Bank closures, mergers, and acquisitions will generate differences between the banks currently assigned the loan and the bank that originated the loan. For example, BankBoston merged with Bank of America in 2004, and all of its branches were converted to Bank of America. Consequently, an SBA loan originated by BankBoston in 2001 may appear in the SBA data as currently held by Bank of America. To construct historical branch networks in light of these changes in bank structure, for each branch in each year from 2001-2017, we use the FDIC's Reports

[1] Specifically, we first standardize the bank names and addresses, then use reclink command in Stata. To assess similarity, reclink uses bigram comparison to score two strings based on the number of common 2-4 consecutive letter combinations. The first probabilistic match uses relative weights of 14 (out of 20) given to the name, 8 given to the address, 4 given to city, and 4 given to the zip code. The second match uses the same variables, but weights of 16,4,4, and 4. In both, we require state to match exactly.

of Structure Changes to determine the bank that holds that branch as of 2017. For example, we consider a branch to be a part of Bank of America's network if that branch is a Bank of America branch or would later become a Bank of America branch. That is, for a given year t, we consider a branch to be a part of an institution j's network in year t if that branch either (i) belongs to institution j in year t or (ii) would become a branch of institution j by 2017.

Another possible source of error is that banks may transfer loan assignments, even if there were no changes in bank structure. In order to gauge the error introduced by transfers of assignments, we compare loans of the top 100 lenders in FY2012 from the 2012 Coleman Report to the top 100 lenders in FY2012 based on who is currently assigned the loan. These top 100 lenders provided 59% of all SBA loans and 60% of SBA volume in FY2012. Of the top 100 lenders, we are able to match 70 in our 2017 data. The unmatched banks are due to name changes, closures, mergers, and acquisitions between 2012 and 2017. Of the matched banks, the number of loans attributed to them in our data is very similar to the loans attributed to them in the 2012 Coleman Report (see Figure B.1), suggesting that absent changes in bank structure, banks rarely transfer the assignment of SBA loans.

B.3 Borrower-Lender Distance

Starting with the 962,527 non-canceled SBA loans from 2001-2017 (and dropping the 179 that are missing industry info), we are able to match 885,166 to a lending institution in the FDIC Summary of Deposits. We then run these loans through the Census Geocoder, using the borrower's listed address, and are able to match 629,946 of the addresses to a latitude and longitude. Our results are also robust to using borrower-lender distance constructed using the centroid of the borrower's county, which is available for all borrowers. Then, based on the borrower's institution and year, we match each borrower to the historical branch network for that institution.[2] Finally, we calculate the (Haversine) distance between the borrower and (i) the closest branch of the institution that originated the loan and (ii) the closest branch of any SBA lender.[3]

[2]We drop the 1.5% of branches that are missing longitude and latitude data.
[3]The Haversine distance, which is the shortest distance over the earth's surface.

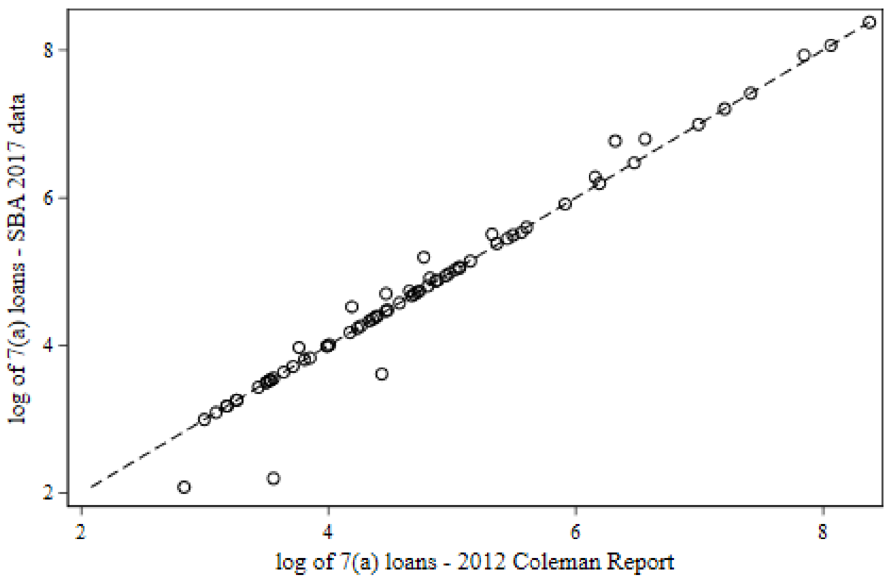


Figure B.1: **Difference between Counts at Origination in 2012 and Counts Recorded in 2017**

C Appendix: Characterizing Remote Specialists

C.1 Descriptive Characteristics

We briefly characterize the specialists and their chosen industries. Internet Appendix Table C.1 lists the 21 specialized lenders in the 2013-2017 period, along with their median borrower-lender distance and top-five share. We also list the institutions in which they specialize in Internet Appendix Table C.2. Among the 21 lenders classified as remote specialists in the 2013-2017 period, the average of the median borrower-lender distance is 677 miles and the average top-five share is 58%. Of the industries they specialize in, defined as those making up more than 10% of the lender's portfolio, hotels and gas stations are most commonly selected, and health professionals (chiropractors, dentists, pharmacists, and veterinarians) and financial or legal professionals (insurance agencies, investment advisers, and lawyers) are also common. There is also a variety of other industries, including funeral homes, bakeries, and daycare services.

These industries are likely selected, at least in part, because they have lower payment risk for lenders. The average three-year charge-off rate (from 2007-2012) for all industries receiving SBA loans was 7.5%, while the average charge-off rate for industries chosen by specialists (weighted by the number of specialists) is 2.8%. We also gathered industry characteristics from The Risk Management Association (RMA) and IBISWorld Industry Reports, which provide detailed information about market characteristics, industry conditions, and characterizes industries along ten dimensions. Compared to the fifteen most common industries in the SBA data, the specialists' industries tend to have higher capital intensity, greater regulation and greater industry assistance (defined as protection, direct or indirect government assistance, and support from associations and trade groups).

C.2 Industry Concentration and Loan Performance

If industry concentration facilitates expertise in lending to these industries, concentrated lenders may experience better loan performance within the industries where they focus. To investigate this idea, we examine whether loans from concentrated lenders perform better than loans from less concentrated lenders. As mentioned, concentrated lenders tend to focus on industries with lower charge-offs, which would lead to better loan performance even in the absence of expertise. So that our estimates will not be driven by this industry selection, our regressions will include industry fixed effects and thus compare across lenders within the same industry.

Using the loan-level data, we estimate the following regression for a loan i from lender b to industry j originated in year t:

$$Chargeoff_{ibjt} = \alpha + \beta_0 log(dist_{ibjt}) + \beta_1 IndustryShare_{bjt} + X_{ibjt}\gamma + \delta_j + \tau_t + \epsilon_{ibjt} \qquad (1)$$

where $Chargeoff_{ibjt}$ is an indicator for whether loan i from lender b originated to industry j during year t was charged off within three years of origination. The variable $log(dist_{ibjt})$ is the log of the distance between the borrower and the closest branch of the lender originating the loan. The main specification also includes loan-level controls for size and term length (X_{ibjt}) and industry (δ_j) and year (τ_t) fixed effects. Some specifications also include additional loan-level controls, state-by-year fixed effects, and lender-specific fixed effects.

Our measure of industry concentration, $IndustryShare_{bjt}$, is the share of total loans from lender b in year t that went to industry j. We focus on contemporaneous shares as our primary measure. If lenders build expertise (e.g. by hiring industry experts) then increase lending to the industry, current lending shares reflect expertise. However, if expertise are developed through past exposure to an industry, it may be more appropriate to use a lagged measure. In robustness checks, we find a similar effect using lagged shares. Moreover, contemporaneous and lagged shares are highly correlated - the coefficient of correlation is 0.92.[4] The coefficient of interest, β_1, captures the correlation between the probability that a loan in industry j is charged off within three years and the lender's $IndustryShare_{bjt}$. If β_1 is negative, it would reflect that lenders giving a larger share of their loans to an industry experience lower charge-off rates relative to other lenders. Since the specification includes industry fixed effects, β_1 reflects how the probability of charge-offs varies among loans given to the same industry. In some specifications, we add the interaction of the share of loans to an industry and borrower-lender distance, to examine whether industry concentration can mitigate the disadvantages of lending at a distance.

Table C.3 reports the results of specification (1). Consistent with the prior literature on distance and lending, the positive coefficient on the $log(dist)$ in Column 1 indicates that the probability of default increases with borrower-lender distance, controlling for loan characteristics (dummies for ventiles of loan size and term length). Column 2 adds the share of loans that a lender makes to the industry. The negative coefficient on the share in the industry indicates that having a greater share of loans to an industry is correlated with lower charge-off rates within that industry (relative to less concentrated lenders). To provide a sense of the magnitude, these estimates imply that an industry share of 52% would offset the additional risk of a 100-mile loan. The offsetting threshold is higher for more distant loans and lower for closer ones. This negative relationship between concentration and the probability of default remains similar when adding state-by-year fixed effects in Column 3. Column 4 includes the interaction of the "Share in industry" with the log of borrower-lender distance. The coefficient is negative and significant, suggesting that concentration in lending can mitigate the disadvantages of lending at a distance. Columns 5-8 repeat these specifications, but add institution fixed effects. The coefficients decrease in magnitude, but remain statistically significant. Thus, even within an institution, loan performance is better in the industries where the institution is more concentrated. However, adding institution fixed effects causes the interaction of industry share with $log(dist)$ to become statistically insignificant and slightly positive (column 8).

[4] An alternative measure concentration could be the *number* of loans a bank gave to the industry. This measure, however, would potentially conflate the effects of bank size and concentration. Instead, we adopt the common approach of using a measure that is comparable across banks of different sizes and then controlling directly for bank size in the regressions (Acharya, Hasan and Saunders, 2006, Hayden, Porath and Westernhagen, 2007, Berger, Minnis and Sutherland, 2017).

Table C.1: **List of Remote Lenders**

Institution	B-L distance	Top-5 Share	Industries	Share of lender's loans (%)	Share of SBA loans (%)	Ratio of column (5) to (6)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bank Of George	1,828	92	Hotels (except Casino Hotels) and Motels	83	1.7	49
			Lessors of Miniwarehouses and Self-Storage Units	2.8	0.23	12
Carver State Bank	640	100	Insurance Agencies and Brokerages	93	0.87	108
			Other Electronic and Precision Equipment Repair and Maintenance	4	0.25	16
Citizens Bank	399	42	Offices of Chiropractors	15	0.96	15
			Gasoline Stations with Convenience Stores	11	1.1	10
Civis Bank	187	38	Gasoline Stations with Convenience Stores	12	1.1	11
			Hotels (except Casino Hotels) and Motels	12	1.7	7.1
Crestmark Bank	830	88	Insurance Agencies and Brokerages	69	0.87	79
			Hotels (except Casino Hotels) and Motels	13	1.7	7.9
Evolve Bank & Trust	634	32	Veterinary Services	8.6	0.81	11
			Offices of Dentists	7.1	1.8	3.9
Finwise Bank	1,885	68	Offices of Lawyers	56	1.1	49
			Electronic Shopping	7.5	0.54	14
First Bank	363	34	Hotels (except Casino Hotels) and Motels	10	1.7	6.2
			Funeral Homes and Funeral Services	9.9	0.34	29
First Chatham Bank	671	42	Child Day Care Services	20	1.2	16
			Car Washes	6.7	0.77	8.7
First Colorado National Bank	1,062	40	Hotels (except Casino Hotels) and Motels	18	1.7	11
			Drycleaning and Laundry Services (except Coin-Operated)	6.5	0.48	14
First Financial Bank	249	97	Broilers and Other Meat Type	66	0.65	101
			Pharmacies and Drug Stores	16	0.68	24
Live Oak Banking Company	734	76	Investment Advice	19	0.53	36
			Offices of Dentists	18	1.8	9.9
Meadows Bank	233	34	Retail Bakeries	12	0.38	31
			Child Day Care Services	10	1.2	8.4
Mission Valley Bank	176	56	Hotels (except Casino Hotels) and Motels	28	1.7	17
			Funeral Homes and Funeral Services	16	0.34	47
Noa Bank	244	58	Hotels (except Casino Hotels) and Motels	38	1.7	23
			Gasoline Stations with Convenience Stores	10	1.1	9.1
Spirit Of Texas Bank, Ssb	769	66	Barber Shops	27	2	13
			Other Personal Care Services	26	0.73	36
T Bank, National Association	972	37	Car Washes	9.9	0.77	13
			Child Day Care Services	7.6	1.2	6.2
The Mint National Bank	947	88	Hotels (except Casino Hotels) and Motels	67	1.7	40
			Gasoline Stations with Convenience Stores	14	1.1	12
Titan Bank, National Association	781	47	Offices of Dentists	30	1.8	17
			Lessors of Nonresidential Buildings (except Miniwarehouses)	5.6	0.62	9
United Community Bank	136	42	Offices of Dentists	18	1.8	10
			Veterinary Services	15	0.81	18
United Midwest Savings Bank	480	42	Offices of Dentists	21	1.8	12
			Funeral Homes and Funeral Services	7.9	0.34	23

This table lists the 2013-2017 institutions in Figure 1 that are classified as remote specialists (according to our definition). Column 1 reports the institution's name. Columns 2 and 3 report the institution's median borrower-lender distance and its top-five share, calculated over 2013-2017. Column 4 lists the top two industries for each institution's and Column 5 lists the share of the institution's SBA loans going to that industry. For comparison, Column 5 lists the share of all SBA loans going to that industry. Finally, Column 7 shows the ratio of Column 5 to Column 6, which gives the share of the industry within each specialist institution relative to the industry's overall SBA share.

Table C.2: **List of Specialists' Industries**

Industry	Specialists (#)	Share of specialists' loans (%)	Share of SBA loans (%)	Ratio of column (3) to (4)	Charge-off rate (%)
(1)	(2)	(3)	(4)	(5)	(6)
Barber Shops	1	27	2	13	9.4
Broilers and Other Meat Type	2	39	0.65	60	0.73
Child Day Care Services	2	15	1.2	12	4.2
Funeral Homes and Funeral Services	1	16	0.34	47	1.2
Gasoline Stations with Convenience Stores	4	12	1.1	11	3.2
Hotels (except Casino Hotels) and Motels	9	31	1.7	19	0.97
Insurance Agencies and Brokerages	2	81	0.87	93	5.9
Investment Advice	1	19	0.53	36	9.2
Offices of Chiropractors	1	15	0.96	15	4.2
Offices of Dentists	4	22	1.8	12	0.85
Offices of Lawyers	1	56	1.1	49	3.5
Other Personal Care Services	1	26	0.73	36	9.3
Pharmacies and Drug Stores	2	15	0.68	21	1.7
Retail Bakeries	1	12	0.38	31	6.6
Veterinary Services	2	15	0.81	18	0.9
Overall SBA Average					7.5

This table reports the industries in which the institutions in Table C.1 specialize. The table includes any industry in which a specialist lender listed in Table C.1 originated at least 5% of its loans during the 2013-2017 period. Column 1 reports the industries and Column 2 reports the number of specialists giving at least 10% of its loans to the industry. Column 3 reports the share of the specialists' loans to that industry (or the average share when the number of specialists in that industry is greater than 1). For comparison, Column 4 reports the share of all 2013-2017 SBA loans that go to that industry, and Column 5 reports the ratio of Column 3 to Column 4. Finally, Column 6 reports the three-year charge-off rate for each industry during, calculated during the 2007-2012 period.

Table C.3: **Lender Portfolio Concentration and Loan Performance (within Industry)**

	Dependent variable: Indicator for Charge-off within 3 Years							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$log(dist)$	0.00476***	0.00500***	0.00437***	0.00521***	0.00208***	0.00210***	0.00252***	0.00208***
	(0.000362)	(0.000358)	(0.000332)	(0.000401)	(0.000388)	(0.000388)	(0.000369)	(0.000425)
Share in industry		-0.0441***	-0.0333***	-0.0391***		-0.0170***	-0.0174***	-0.0176***
		(0.00340)	(0.00284)	(0.00386)		(0.00428)	(0.00416)	(0.00507)
Share$\times log(dist)$				-0.00298**				0.000268
				(0.00144)				(0.00129)
Observations	255,874	255,874	255,874	255,874	255,874	255,874	255,874	255,874
Industry FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Loan char.	X	X	X	X	X	X	X	X
State-by-year FE			X				X	
Inst. FE					X	X	X	X

Using the loan-level data, we estimate the following regression for a loan i from lender b to industry j originated in year t:

$$Chargeoff_{ibjt} = \alpha + \beta_0 log(dist_{ibjt}) + \beta_1 IndustryShare_{bjt} + X_{ibjt}\gamma + \delta_j + \tau_t + \epsilon_{ibjt}$$

where $Chargeoff_{ibjt}$ is an indicator for whether loan i from lender b originated to industry j during year t was charged off within three years of origination. Observations are at the loan level from 2007-2014 and standard errors are clustered at the industry (5-digit NAICS) level. Loan characteristics include dummies for ventiles of the size of the loan and the term length. The state in the state-by-year fixed effects is determined by the location of the borrower's business.

D Appendix: Inference

This appendix covers the three test statistics use to assess statistical significance.

Each industry is observed for periods $t = 1, \ldots, T$, and let T_0^j be the last pretreatment period for treated industry j. For each treated industry j of the J treated industries, we estimate a placebo synthetic control for each control industry i by assigning it the treatment timing $T_0^j + 1$. Let $J+1, \ldots, J+I+1$ index the I control industries. $\widehat{Y}_{it}^j(0)$ is the predicted lending in period t produced by the placebo synthetic control for industry i when it is assigned treatment time T_0^j.

We summarize the treatment effects during the post-period with two test statistics. The first test statistic is the average treatment effect in the first four years of the post-treatment period:

$$\tau_i^j = \frac{1}{4} \sum_{t=T_0^j+1}^{T_0^j+4} (Y_{it} - \widehat{Y}_{it}^j(0)).$$

One concern with this test statistic is that some of the placebo synthetic controls may have a poor pretreatment fit, making the estimated placebo treatment effects less credible. For this reason, Abadie, Diamond and Hainmueller (2010) and Abadie (2021) suggest also using the ratio of the post-treatment fit to the pretreatment fit as another test statistic, where fit is measured by the root mean squared prediction error (RMSPE):

$$r_i^j = \frac{\left(\frac{1}{4}\sum_{t=T_0^j+1}^{T_0^j+4}\left(Y_{it} - \widehat{Y}_{it}^j(0)\right)^2\right)^{1/2}}{\left(\frac{1}{T_0^j}\sum_{t=1}^{T_0^j}\left(Y_{it} - \widehat{Y}_{it}^j(0)\right)^2\right)^{1/2}}.$$

The p-value based on the permutation distribution of each test statistic t (either τ or r) for treated industry j is

$$p_j(t) = \frac{1}{I+1}\left(1 + \sum_{i=J+1}^{J+I+1} \mathbb{1}\left(t_i^j \geq t_j^j\right)\right).$$

Finally, we also conduct joint inference using the method of Abadie and L'hour (2020), which extends the permutation methods to cases with multiple treated units. Let the true treated units be $D^{(0)} = \{1, \ldots, J\}$ and assign this group to iteration $b = 0$. We then form B random samples of J control industries $D^{(b)} = \{i_1^{(b)}, \ldots, i_J^{(b)}\}$ with control industry $i_j^{(b)}$ assigned the treatment timing of treated industry j. For each iteration $b = 1, \ldots, B$ and each $j \in \{1, \ldots, J\}$, we first compute the placebo treatment effect $\widehat{T}_j^{(b)} = \tau_{i_j^{(b)}}^j$ (and, in a separate procedure, $\widehat{T}_j^{(b)} = r_{i_j^{(b)}}^j$). Then, we calculate the ranks $R_1^{(0)}, \ldots, R_J^{(0)}, \ldots, R_1^{(B)}, \ldots, R_J^{(B)}$ associated with the absolute values of the $J \times (B+1)$ treatment effects $\widehat{T}_1^{(0)}, \ldots, \widehat{T}_J^{(0)}, \ldots, \widehat{T}_1^{(B)}, \ldots, \widehat{T}_J^{(B)}$. Using these rankings, we calculate the sum of ranks for each permutation $SR^{(b)} = \sum_{i=1}^{J} R_i^{(b)}$. The joint p-value is

$$p = \frac{1}{B+1} \sum_{b=0}^{B} \mathbb{1}\left(SR^{(b)} \geq SR^{(0)}\right).$$

Let the true treated units be $D^{(0)} = \{1, \ldots, J\}$ and assign this group to iteration $b = 0$. We then form B random samples of J control industries $D^{(b)} = \{i_1^{(b)}, \ldots, i_J^{(b)}\}$ with control industry $i_j^{(b)}$ assigned the treatment timing of treated industry j. For each iteration $b = 1, \ldots, B$ and each $j \in \{1, \ldots, J\}$, we first compute the placebo treatment effect $\widehat{T}_j^{(b)} = \tau_{i_j^{(b)}}^{j}$ (and, in a separate procedure, $\widehat{T}_j^{(b)} = r_{i_j^{(b)}}^{j}$). Then, we calculate the ranks $R_1^{(0)}, \ldots, R_J^{(0)}, \ldots, R_1^{(B)}, \ldots, R_J^{(B)}$ associated with the absolute values of the $J \times (B+1)$ treatment effects $\widehat{T}_1^{(0)}, \ldots, \widehat{T}_J^{(0)}, \ldots, \widehat{T}_1^{(B)}, \ldots, \widehat{T}_J^{(B)}$. Using these rankings, we calculate the sum of ranks for each permutation $SR^{(b)} = \sum_{i=1}^{J} R_i^{(b)}$. The joint p-value is

$$p = \frac{1}{B+1} \sum_{b=0}^{B} \mathbb{1}\left(SR^{(b)} \geq SR^{(0)}\right).$$

In summary, we compare the ranks of the treatment effect sizes in the actually treated industries to the distributions ranks from randomly chosen placebo industries. The joint test statistic is statistically significant if the sum of its ranks are an outlier relative to the distribution of summed ranks from the placebo industries.

E Appendix: Definition of Specialized Lenders

Although remoteness and industry specialization are continuous quantities, we define a discrete group of "remote specialized" lenders in order to document the rise of these lenders in Figure 2 and when examining their impact in Table 4. This appendix discusses the choices behind our primary definition, then examines the sensitivity of the results to alternative definitions.

E.1 Primary Definition

Qualitatively, we define a remote, specialized lender as a lender that makes loans to distant borrowers, is concentrated in few industries, and makes a sufficiently large number of SBA loans. In our primary definition of remote specialization, we implement these three qualitative requirements using the following thresholds:

(i) remote: the lender's median borrower-lender distance exceeds 100 miles[5]

(ii) specialized: the lender's top-five industry share exceeds 32%, where the top-five share for a lender is the share of loans in its portfolio that go to firms in that lender's five most common industries

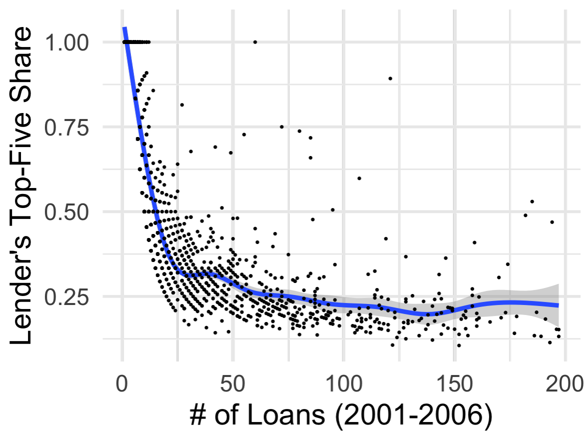
(iii) size: the lender must originate at least 50 loans during the relevant period (2001-2006, 2007-2012, or 2013-2017).[6]

The first two criteria define thresholds for "remote" and "specialized" which capture the obvious aspects of being a remote, industry-specialized lender. The purpose of the size criteria (iii) is to avoid mistakenly classifying small lenders as industry specialists. Lenders that originate very few SBA loans will *mechanically* have high top-five share. For example, lenders with fewer than five loans in the period will all have a top-five share of 100% because their loans must go to at most five industries. To illustrate, Figure E.1(a) plots each lender's number of loans against its top-five share. Among lenders that originate 25 or more loans, their top-five shares average around 25%. In contrast, lenders with few SBA loans have much higher top-five shares, and all lenders with five or fewer loans have a top-five share that equals 100%. Other definitions of a lender's industry concentration of a lender (Herfindahl-Hirschman Indexes, top-N shares, the definition from Paravisini, Rappoport and Schnabl (2021)) are still based on the share of a lender's portfolio, and so will also mark small lenders as highly concentrated. The purpose of the size criteria (iii) is to exclude these small lenders from being classified as specialists.

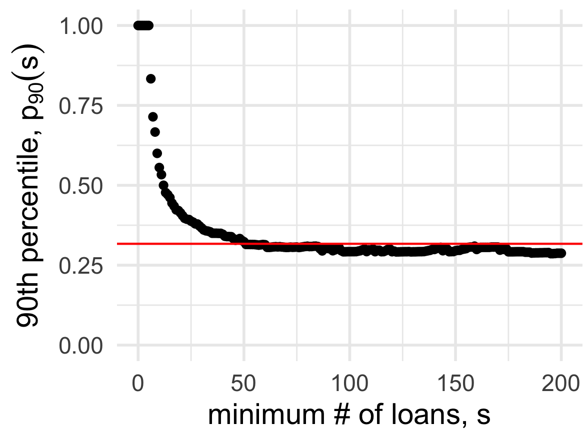
For the same reason, we exclude these small lenders from Figure 1 and when calculating the 90^{th}-percentile of distribution of industry concentration that forms the threshold for the specialized

[5]Among 2001-2006 lenders with at least 50 loans during this period, the 90^{th} percentile for median B-L distance was 15 miles. The 95th percentile is roughly 100 miles, so our criterion corresponds to the 95th percentile from this distribution. We use 100 miles, rather than the 90^{th} percentile of 15 miles, because 15 miles is still quite close and so does not correspond with our concept of "remote lending" with little face-to-face interaction.

[6]When using year-by-year (rather than multi-year period) definitions of remote lending in Figure 2, we implement this as the lender must originate at least 10 loans in the year.



(a)



(b)

Figure E.1: **Small Lenders and Top-Five Shares**
Panel (a) plots each lender's number of SBA 7(a) loans against that lender's top-five share, both calculated during the period 2001-2006. Each point represents a lender, and the curve shows a smoothed conditional expectation function, fit with generalized additive model and default smoothing basis in R "mgcv" package. Panel (b) plots the corresponding 90^{th} percentile of the top-five share distribution, $p_{90}(s)$ for different the minimum size cutoff, s, from criteria (iii) in the primary definition of remote specialized lenders. In the primary definition, $s = 50$, i.e., lenders must originate at least 50 loans. The red line shows $p_{90}(50)$ from our primary definition.

criteria (ii). Including small lenders in the distribution would exaggerate the degree of industry concentration within the SBA market. To see this, let $p_{90}(s)$ be the 90^{th} percentile when the minimum size cutoff is s, so that our baseline 32% threshold is $p_{90}(50) = 0.32$. Figure E.1(b) shows how 90^{th} percentile $p_{90}(s)$ varies with the minimum size cutoff, s. For $p_{90}(0)$, we include all lenders who were active at any point between 2001-2013, setting the 2001-2006 top-five share to zero for lenders that were inactive during 2001-2006. The 90^{th} percentile is stable for $s \geq 50$, varying between 0.32 and 0.29, with the red line showing $p_{90}(50) = 0.32$. The 90^{th} percentile rises rapidly when small lenders are included, however. For $s \leq 5$ which contains when we include inactive lenders ($s = 0$), the 90^{th} percentile is 1.0, or 100% of loans in the top-five share. This, again, reflects that small lenders have high industry concentrations simply because they originate few loans.

One can think of the lender size minimum in criterion (iii) as requiring sufficient sample size to identify industry specialization. Dropping the small lenders does not significantly alter statistics about SBA lending because, while small lenders are numerous, they account for a small share of SBA lending. For example, 47% of the lenders in the 2001-2006 period originate five or fewer loans, but these lenders account for only 1.1% of total SBA loans and 1.4% of SBA dollars. In contrast, the lenders we include, those with at least 50 loans, account for more than 93% of SBA loans and 92% of SBA dollars. Thus, by focusing on these larger lenders, we avoid falsely classifying small lenders as "industry specialists" while still retaining the group of lenders that provide nearly all

SBA loans.[7]

Importantly, we exclude small lenders only when defining which lenders are remote specialists. The loans from small lenders *are included* in the total loan counts used throughout the analysis. Additionally, we examine the sensitivity of this percentile to the minimum size threshold s, and later in this section we examine the robustness of Table 4 to alternative thresholds.

E.2 Alternative Definitions of Remote Specialists

In this section, we examine the sensitivity of the results in Table 4 to alternative definitions of remote, specialized lending. First, we maintain our primary definition, but alter the specific thresholds used for the remote, specialized, and size criteria. Second, we remove the industry share requirement from the definition of specialized lending in Table 4. Then, we investigate the robustness to alternative definitions of specialization using a measure based on Paravisini, Rappoport and Schnabl (2021) and another based on the industry-level Herfindahl-Hirschman Index (HHI).

Alternative Thresholds

In Table 4, the definition of remote, specialized lenders requires the lender's median lending distance to exceed 100 miles, its top-five share to exceed 32%, and the lender to have originated at least 50 loans during the period 2013-2017. We examine the sensitivity of Table 3 to changes in these thresholds. Specifically, we vary the remote threshold within $\{50, 100, 150\}$ miles, the specialized share threshold within $\{0.25, 0.32, 0.6\}$, and the size threshold within $\{25, 50, 100\}$. The values for the specialized share and the size threshold were chosen to span much of the range shown in Figure E.1(b). With three choices for each threshold, there are 27 possible permutations, including the main definition with the thresholds $(100, 0.32, 50)$.

We estimate Table 4 specifications A1-A4 and B1-B4 under each of the 27 possible permutations. Figure E.2 reports the point estimates and statistical significance from the 26 new permutations as well as the main estimates from Table 4. Overall, the estimates remain similar across the alternative definitions of remote, specialized lenders. The specifications A1 and B1 are unaffected, since those specifications use only specialized loans from Live Oak bank which is not affected by the choice of thresholds. The alternative point estimates from the remaining specifications are generally centered around the main point estimates, or slightly larger in magnitude, across the other 26 definitions of specialized lending. The statistical significance also remains similar. The only robustness estimates with any p-values above 0.1 are those in specifications A3 and A4, which are both marginally significant in the main results of Table 4 as well. As the estimates are all fairly close to one, they continue to suggest that lending by remote, specialized lenders increases the total quantity of SBA credit.

[7] The shares reported for small and large lenders are similar in the 2007-2012 and 2013-2017 periods, with small lenders accounting for 2% or less of total lending and large lenders counting for more at least 86% in all periods.

Sensitivity to Industry Share

Table 4 uses the definition of a specialized *loan* as well as a remote, specialized *lender*. A specialized loan is a loan that (i) is from a remote, specialized lender and (ii) goes to an industry in which that specialized lender originates at least 10% of its loans. The second criterion allows the definition of remote, specialized lending to vary across industries within a lender, acknowledging the fact that a specialized lender can also make loans to industries in which it does not specialize. For example, First Financial Bank originated 97% of its loans to just four industries, but the remaining 3% of loans were spread across 17 other industries.

However, the results of the paper are robust to simply counting all loans from a remote specialized lender as a specialized loan. In the set of estimates "No Industry Share" in Figure E.3, we implement this by dropping the second criterion and counting all loans from a remote, specialized lender as a specialized loan.[8] The point estimates are similar or slightly larger in magnitude than the baseline and all are statistically significant at the 5% level.

In Figure E.4, we also show how the share of loans accounted for by remote, specialized lenders would change depending on whether we include all loans from specialized lenders or only those to industries making up at least 10% of the lender's portfolio. Since we exclude loans that do not exceed the 10% portfolio threshold, the share of SBA loans attributed that are remote and specialized is slightly lower, but follows the same trend as that reported in Figure 2.

Alternative Definitions of Specialization

We examine alternative definitions of "specialization" which are not based on a lender's top-five share. Across alternative definitions, the estimates remain similar across alternative definitions of specialization. To ease comparisons, Figure E.3 shows the estimates from the alternative specifications alongside those from the main estimates. The individual estimates and standard errors are reported in the tables at the end of this section.

The first alternative definition, labeled "Outlier" in Figure E.3, is based on Paravisini, Rappoport and Schnabl (2021), which identifies banks that specialize in the export markets of certain countries as those whose portfolio share of lending to a country is an outlier, defined as exceed the 75^{th}-percentile plus 1.5 interquartile ranges of the country-specific portfolio share distribution. To implement the outlier definition of Paravisini, Rappoport and Schnabl (2021) in our setting, we first calculate the share S_{ij} of each lender i's loans that are originated to industry j during the period 2013-2017.[9] We then classify a lender i^* as "specialized" in industry j^* if $S_{i^*j^*}$ is an outlier in the distribution of S_{ij^*} across lenders, where an outlier is defined as exceeding the 75^{th}-percentile plus 1.5 interquartile ranges of the distribution. "Remote specialized" lenders in industry j^* are those that meet the definition of specialized lenders and also have a lender-specific median borrower-lender distance exceeding 100 miles. Note that, like our primary definition of "specialized

[8] The estimates and standard errors are reported in Table E.1.

[9] For the reasons discussed in Section E.1, we again restrict the sample to lenders with at least 50 loans during the 2013-2017 period when forming the distribution of industry shares of the lending portfolio.

loan," this definition varies across lenders *and industries*. Table E.2 reports the estimates when using the outlier definition from Paravisini, Rappoport and Schnabl (2021), and they are similar in magnitude and significance to those in the main Table 4.

As the second alternative definition, we replace the definition of "specialized" in our primary definition by one based the industry Herfindahl–Hirschman index of the lender's portfolio, a standard measure of concentration. This measure was also applied to bank specialization in Giometti and Pietrosanti (2022). The industry HHI for lender b in period t is defined as $HHI_{bt} = \sum_i S_{ibt}^2$, where S_{ibt} is the percent of lender b's loans given to industry i in year t. The HHI is increasing in industry concentration and takes a value from close to 0 (least concentrated) to 10,000 (all loans to a single industry). We then classify a lender as specialized if that lender's loan portfolio in 2013-2017 exceeds the 90^{th} percentile of the HHI distribution for all lenders with at least 50 loans during the period 2001-2006. The estimates again are similar to the main estimates in both magnitude and statistical significance.

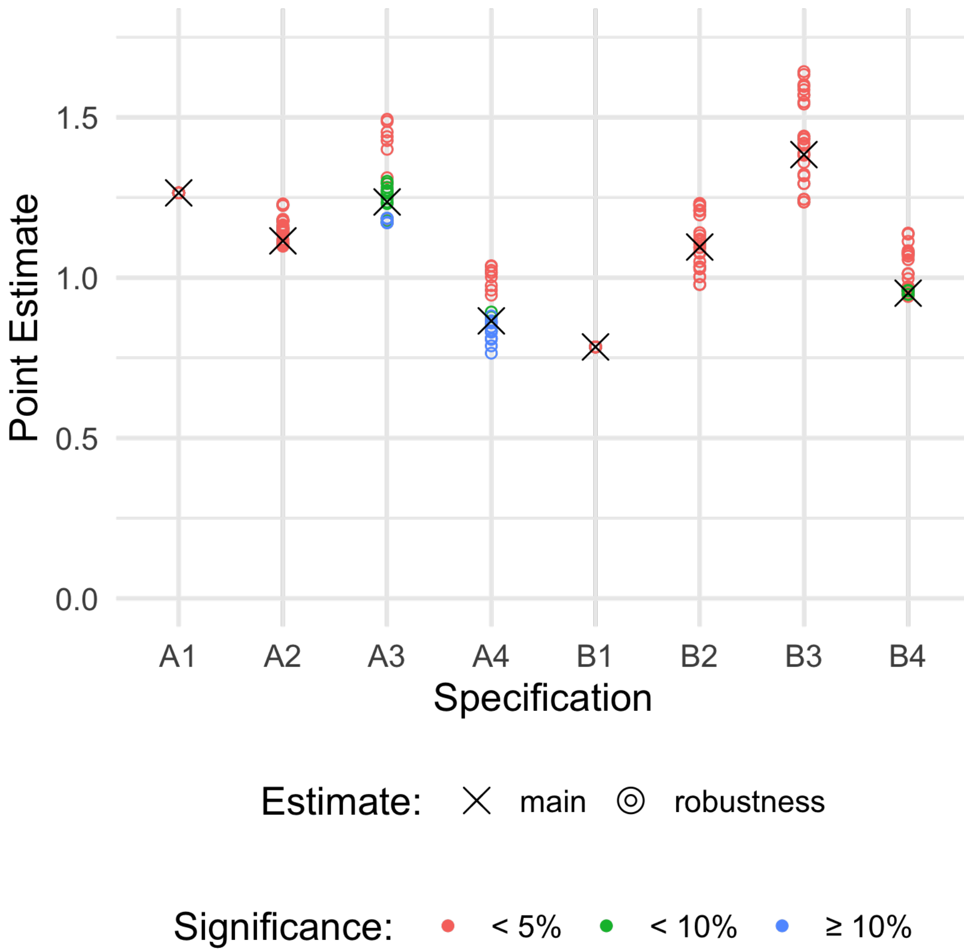


Figure E.2: **Robustness to Changes in Thresholds**
This figure examines the robustness of Table 4 specifications A1-A4 and B1-B4 to changes in the thresholds of the definition for remote, specialized lenders. Specifically, we vary the remote threshold within {50, 100, 150} miles, the specialized share threshold within {0.25, 0.32, 0.6}, which is based on the figure above, and the size threshold within {25, 50, 100}. The points show the coefficient estimates from the 27 possible permutations of these changes, while the crosses show the location of the main estimates in Table 4 .

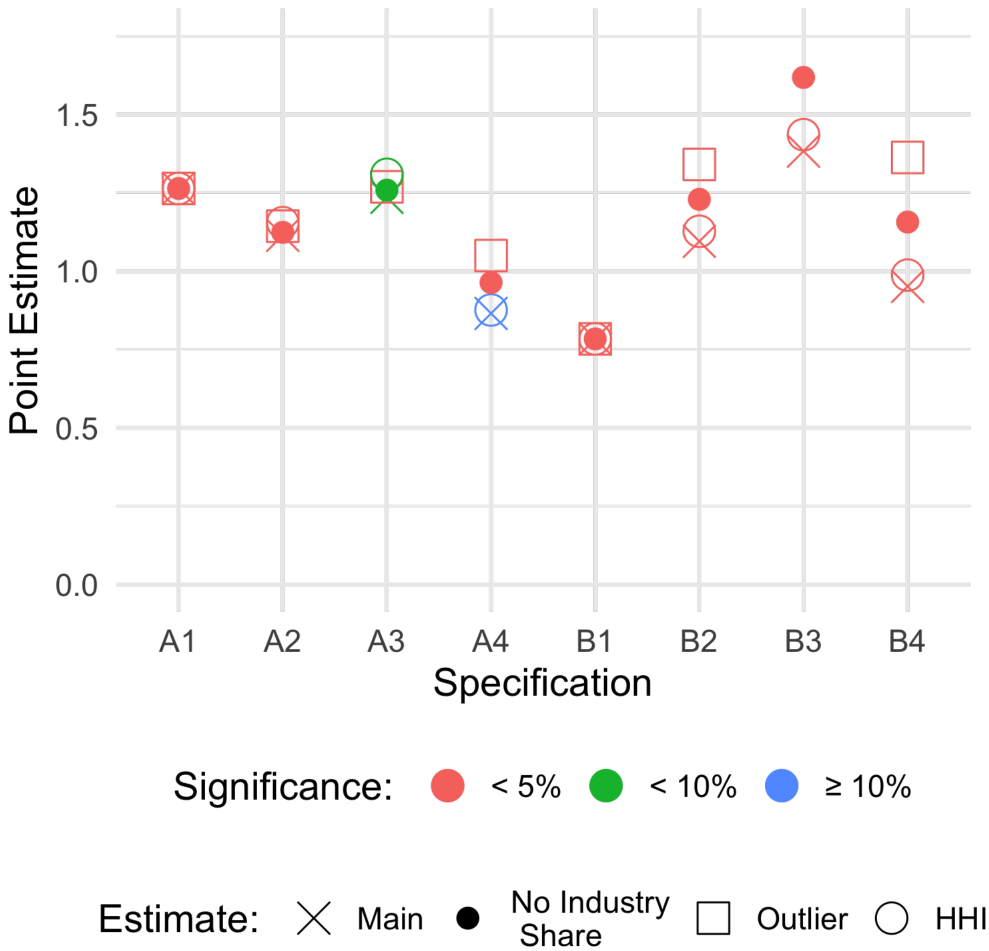


Figure E.3: **Robustness to Alternative Definitions**
This figure examines the robustness of Table 4 specifications A1-A4 and B1-B4 to alternative definitions of remote, specialized lenders. "No Industry Share" removes the industry share requirement from the specialized loan definition. "Outlier" uses the outlier definition of specialized loan, as in Paravisini, Rappoport and Schnabl (2021). "HHI" uses a definition based on the Herfindahl-Hirschman index, as in Giometti and Pietrosanti (2022). See Section E.2 for details of the alternative definitions.

Table E.1: **No Industry Share Threshold**

Outcome:	All SBA Loans	All SBA Loans	All SBA Loans (excl. Live Oak)	All SBA Loans (excl. Live Oak & other remote)
	(1)	(2)	(3)	(4)
Panel A: Industry and Year Fixed Effects				
Live Oak loans	1.264***			
	(0.138)			
Spec. loans		1.124***		
		(0.216)		
Spec. loans (excl. Live Oak)			1.259*	0.964**
			(0.654)	(0.474)
Observations	4,199	4,199	4,199	4,199
Panel B: Industry and Year Fixed Effects, Industry-Specific Linear Trends				
Live Oak loans	0.784***			
	(0.201)			
Spec. loans		1.229***		
		(0.305)		
Spec. loans (excl. Live Oak)			1.619***	1.157***
			(0.503)	(0.353)
Observations	4,199	4,199	4,199	4,199

This table repeats the regressions of Table 4 , but classifies all loans from a remote, specialized lender as a specialized loan.

Table E.2: **Definition based on Paravisini et al. (2021)**

Outcome:	All SBA Loans	All SBA Loans	All SBA Loans (excl. Live Oak)	All SBA Loans (excl. Live Oak & other remote)
	(1)	(2)	(3)	(4)
Panel A: Industry and Year Fixed Effects				
Live Oak loans	1.264***			
	(0.138)			
Spec. loans		1.144***		
		(0.269)		
Spec. loans (excl. Live Oak)			1.269**	1.050**
			(0.637)	(0.435)
Observations	4,199	4,199	4,199	4,199
Panel B: Industry and Year Fixed Effects, Industry-Specific Linear Trends				
Live Oak loans	0.784***			
	(0.201)			
Spec. loans		1.341***		
		(0.282)		
Spec. loans (excl. Live Oak)			1.808***	1.363***
			(0.422)	(0.214)
Observations	4,199	4,199	4,199	4,199

This table repeats the regressions of Table 4 , but uses an alternative definition of a “remote, specialized loan” based on the definition in Paravisini, Rappoport and Schnabl (2021). See text in Section E.2 for details on the definition.

Table E.3: **Definition based on HHI**

Outcome:	All SBA Loans	All SBA Loans	All SBA Loans (excl. Live Oak)	All SBA Loans (excl. Live Oak & other remote)
	(1)	(2)	(3)	(4)
Panel A: Industry and Year Fixed Effects				
Live Oak loans	1.264***			
	(0.138)			
Spec. loans		1.155***		
		(0.228)		
Spec. loans (excl. Live Oak)			1.309*	0.876
			(0.727)	(0.568)
Observations	4,199	4,199	4,199	4,199
Panel B: Industry and Year Fixed Effects, Industry-Specific Linear Trends				
Live Oak loans	0.784***			
	(0.201)			
Spec. loans		1.127***		
		(0.337)		
Spec. loans (excl. Live Oak)			1.436***	0.987**
			(0.547)	(0.443)
Observations	4,199	4,199	4,199	4,199

This table repeats the regressions of Table 4 , but uses the 90th percentile of the HHI distribution. See text in Section E.2 for details on the definition.

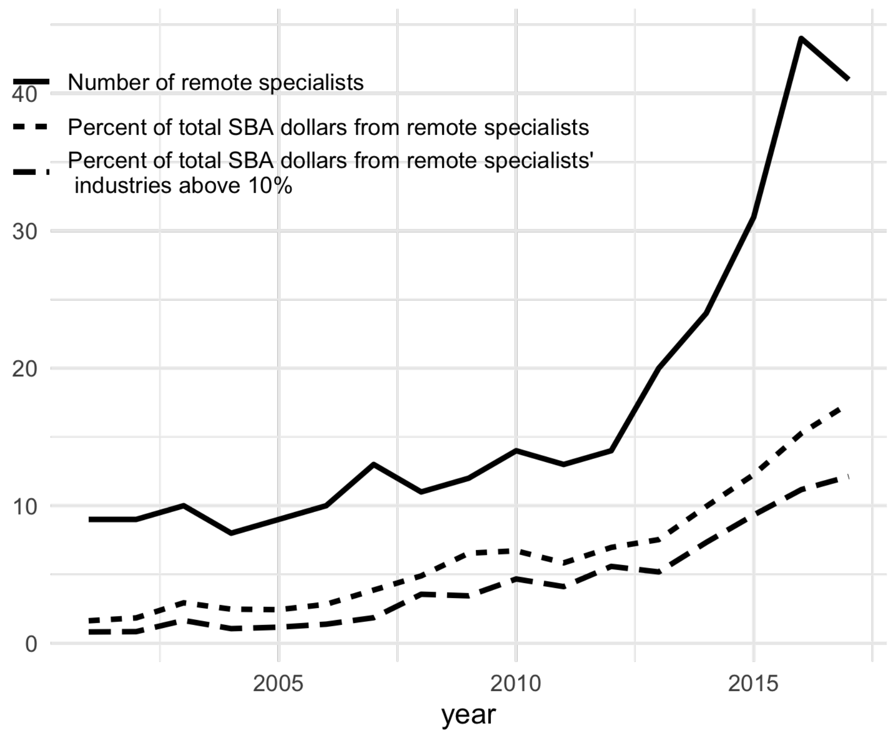


Figure E.4: **Growth in Remote, Industry-Specialized Lenders**
This figure repeats Figure 2, but includes an additional line showing the amount of lending accounted for by the remote specialists' larger industries. Specifically, the additional line shows the share of total SBA dollars accounted for by remote specialists' industries that make up at least 10% of the specialized lender's loans plus loans from Live Oak.

F Appendix: An Indirect Test of the Impact on Total Lending

We empirically examine the impact of Live Oak's entry on a proxy for total industry lending from The Risk Management Association's (RMA) eStatement Studies.[10] Financial institutions provide the RMA with financial statements collected from commercial borrowers or applicants. Although participation is voluntary, hundreds of financial institutions including nine of the ten largest banks provide these statements to the RMA (Lisowsky, Minnis and Sutherland, 2017). The RMA's eStatement Studies publishes counts of the number of financial statements collected by industry (6-digit NAICS). Financial statements can be collected due to loan originations, applications, or monitoring, and so are an imperfect proxy for total loan originations. Still, these counts of financial statements provide, to our knowledge, the only industry-specific measure of total (SBA and non-SBA) lending activity and Berger, Minnis and Sutherland (2017) shows a strong correlation between these financial statements and the size of bank's commercial and industrial lending portfolio. Our RMA data includes a balanced panel of annual financial statement counts for 63 industries from 2001-2017 and the data contain five of the six treated industries (the industry Broilers is not available in the RMA data).[11] Live Oak is not a participant in the RMA survey during our sample period, so the RMA data provide a proxy for total industry lending excluding Live Oak, i.e., the competitive effect.

Using the RMA industry-specific statement reports, we form annual counts of financial statements by industry (normalized by financial counts in 2006) and estimate treatment effects using a synthetic control for each industry (Internet Appendix Figure D.1). If Live Oak caused substitution from non-SBA to SBA lending, we would expect financial statements from these other lenders to fall. Instead, for most treated industries, the actual number of financial statements closely tracks the number predicted by the synthetic control in the post-period. Table D.1 columns 1-4 report the average treatment effect estimates (τ_j^j), the RMSPE ratio (r_j^j), and p-values for the RMA outcomes. With the null hypothesis as a decline in financial statements, we report left-tailed p-values in column 2 and one-sided r_j measures in column 3.[12] As seen in columns 1 and 2, there are no statistically significant declines in financial statements in the treated industries and the p-values indicate that more than 50% of the placebo industries experienced larger declines in lending. Similarly, the one-sided r statistics are generally insignificant in columns 3 and 4, though Funeral Homes is significant at the 5% level (but its average effect τ in columns 1 and 2 is small and insignificant). The p-values based on the joint inference procedure for both test statistics are insignificant, indicating no significant overall change in financial statements within the treated industries.

[10]For more detailed information on the participants and coverage of RMA's eStatement Studies, see Berger, Minnis and Sutherland (2017) and Lisowsky, Minnis and Sutherland (2017).

[11]Because we manually code the data from RMA, we selected a subset of industries from the SBA sample: the industries with at least 20 SBA loans per year and are able to be uniquely mapped from the 5-digit NAICS our the SBA analysis to the 6-digit NAICS in the RMA data. The resulting sample is 63 industries with complete data for 2001-2017.

[12]The one-sided r_i^j measure replaces $\left(Y_{it} - \widehat{Y}_{it}^j(0)\right)$ in the numerator of r_i^j with just its negative part (Abadie, 2021). Positive values for the numerator are coded as zero.

Overall, while we cannot directly examine non-SBA lending, the institutional features, external evidence, and the indirect test using financial statements all suggest that Live Oak's substitution from non-SBA lending is limited and unlikely to fully offset the observed growth in SBA lending within the treated industries.

Table D.1: **Impact on Proxy for Total Lending**

Competitive Effect: RMA Financial Statements

Industry	τ (1)	p-val. (2)	r (3)	p-val. (4)
Veterinarians	-0.33	(0.11)	21.80	(0.25)
Pharmacies	0.04	(0.77)	5.58	(0.35)
Dentists	0.59	(0.95)	0.00	(1.00)
Funeral Homes	-0.03	(0.54)	40.63	(0.02)
Investment Advice	-0.05	(0.56)	2.26	(0.44)
Joint Inference				
Joint Inf. (excl. Broilers)		(0.65)		(0.23)

This table reports the test statistics τ_j^j and r_j^j, as well as the p-values from the respective permutation distributions, when estimating a synthetic control on the outcome of counts of RMA financial statements (normalized by statement counts in 2006). The bottom two rows of each panel report p-values from the joint inference procedure using $B = 5,000$ random permutations. See Section 4.5 for details on the test statistics and inference procedures.

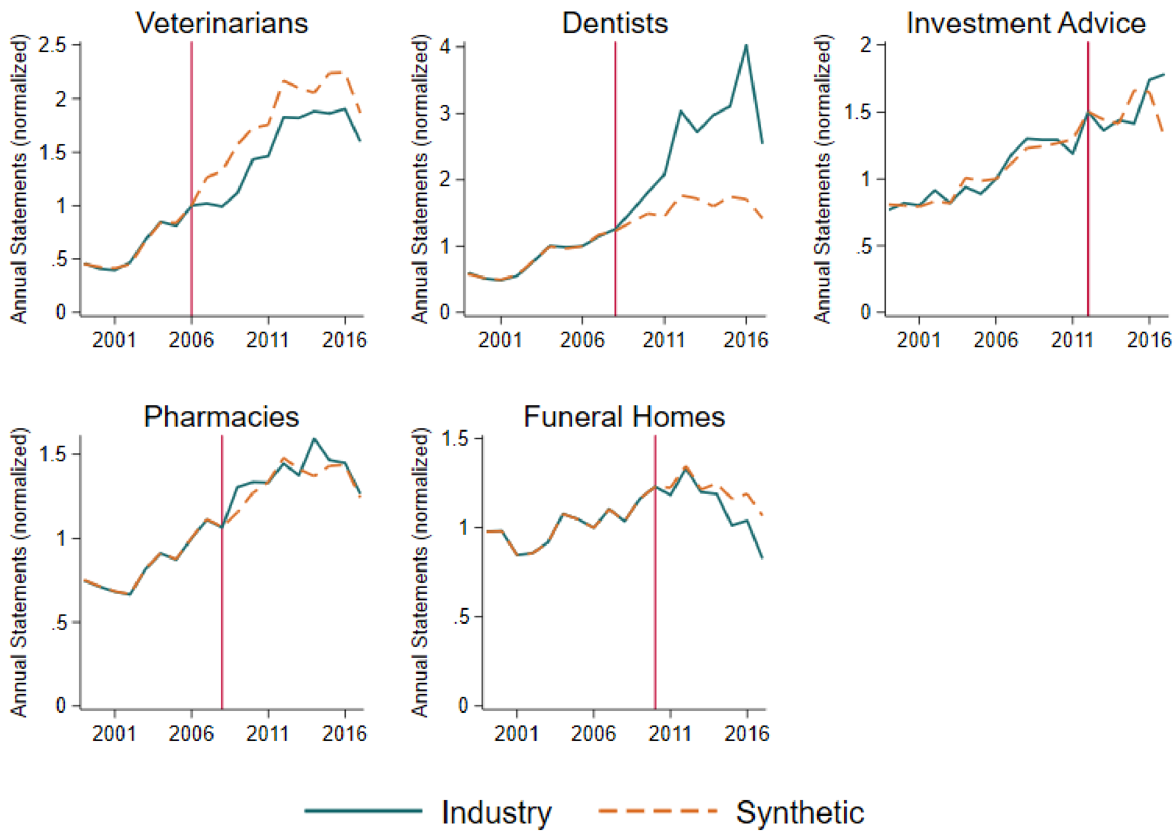


Figure D.1: **Synthetic Control using RMA Counts of Financial Statements**
This figure shows the change in counts of borrowers' financial statements collected by other lenders upon Live Oak's entry. The figure compares the number of statements collected in each industry (normalized by 2006 statement counts) that Live Oak enters to the normalized number of statements predicted by the synthetic control. The synthetic controls are formed by matching on all pre-treatment years beginning in 1999, with no additional covariates. The vertical line shows the year before Live Oak entered.
Source: The Risk Management Association's Annual eStatement Studies

G Appendix: Employment, Establishments, and Charge-offs

We examine the impact of Live Oak's entry on small business employment and charge-off rates. We use data on industry-level employment and establishment counts from the Quarterly Census of Employment and Wages (QCEW), which publishes data by NAICS code for workers in jobs covered by state unemployment insurance laws (95% of all jobs). We form national employment counts and establishment counts for businesses with 10-250 employees.[13] We drop industries where some employment counts for small businesses are not disclosed during the period 2001-2017, leaving a sample of 107 control industries and three treated industries (Veterinarians, Funeral Homes, and Broilers are dropped). We calculate 3-year charge-off rates by industry using information on charge-offs available in the SBA 7(a) data.[14] In the charge-off sample, we exclude Live Oak's loans in order to examine Live Oak's effects on the charge-off rates of other lenders and to investigate the possibility of cream-skimming by Live Oak would increase the charge-off rates of other lenders.

Table G.1 reports the average treatment effects, their p-values, and p-values for the r statistics for changes in employment (columns 1-3), establishments (columns 4-6), and charge-offs (columns 7-9).[15] Each outcome is normalized by the industry's 2006 values, so that the estimates of τ can be interpreted as percentage point changes (relative to the baseline of 2006). There is some evidence of an increase in employment and establishment for investment advice agencies (p-values less than 0.1), which is the industry where Live Oak's impact was largest. Overall, the changes in employment are jointly insignificant. Small effects on employment are consistent with the results of Brown and Earle (2017) which finds that SBA lending increased employment by only 3-3.5 jobs per million dollars in lending. Effect sizes of this magnitude would not be apparent in national employment counts. Finally, columns 7-9 show small and insignificant effects on charge-off rates of other lenders, consistent with the lack of cream-skimming.

[13] We choose these thresholds for small businesses because many counts for businesses with less than 10 or 250-499 employees are not disclosed.

[14] To calculate three-year charge-off rates for the full period 2001-2017, we expand the SBA data by merging charge-off data through 2020. Using business and lender names, addresses, and locations, we match 97% of loans to the more recent data.

[15] Internet Appendix Figure G.1 reports the synthetic controls.

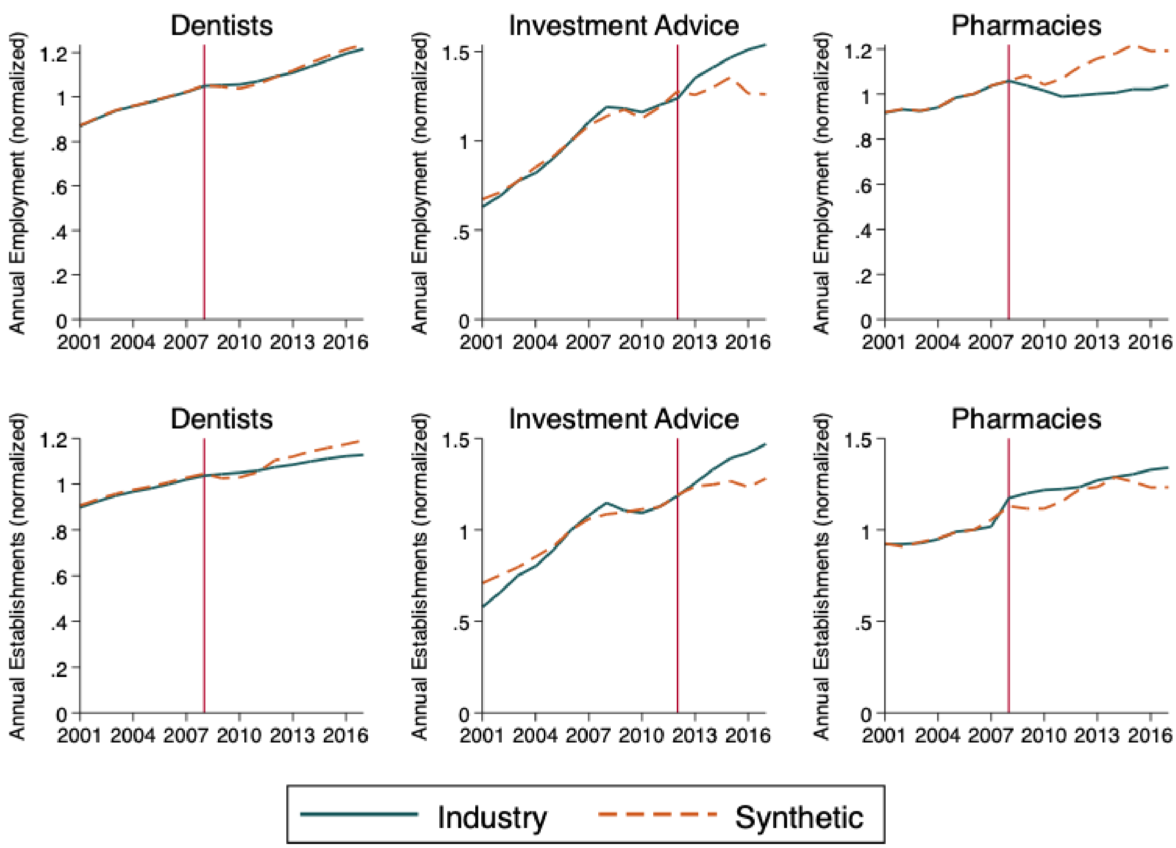


Figure G.1: **Impact on Employment and Establishment Counts**
Synthetic control estimates for employment (top row) and establishment counts (bottom row) of businesses with 10-250 employees (relative to 2006). Data are from the 2001-2017 Quarterly Census of Employment and Wages.

Table G.1: **Impact on Employment, Establishments, and Charge-offs**

	Industry Employment			Industry Establishments			3-Year Charge-off Rate ($\times$100)		
Industry	τ	p-val.	r p-val.	τ	p-val.	r p-val.	τ	p-val.	r p-val.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Veterinarians							-0.022	(0.49)	(0.16)
Pharmacies	-0.070	(0.38)	(0.20)	0.066	(0.28)	(0.86)	-0.005	(0.78)	(0.50)
Dentists	0.010	(0.81)	(0.72)	0.004	(0.96)	(0.94)	-0.012	(0.43)	(0.47)
Funeral Homes							-0.007	(0.49)	(0.47)
Investment Advice	0.141	(0.07)	(0.47)	0.103	(0.06)	(0.77)	-0.006	(0.55)	(0.67)
Broilers							-0.010	(0.41)	(0.67)
Joint Inference		(0.33)	(0.43)		(0.32)	(0.99)		(0.56)	(0.54)
Joint Inf. (excl. Broilers)		(0.31)	(0.42)		(0.32)	(0.99)		(0.60)	(0.45)

This table reports the test statistics τ_j^j p-values from the respective permutation distributions for τ_j^j and r_j^j for changes in employment counts, establishment counts, and three-year charge-off rates, all normalized so that 2006 values equals 1. Employment and establishment counts are from the QCEW for businesses with 10-250 employees. The bottom two rows of each panel report p-values from the joint inference procedure using $B = 5,000$ random permutations. See Section 4.5 for details on the test statistics and inference procedures.

H Appendix: Credit Supply and Geography

In this Appendix, we separately estimate the impact of Live Oak's entry on lending in low-credit-supply and high-credit-supply areas.[16] If Live Oak increases credit supply in areas that were previously constrained, we would expect the percentage increases in total lending to be larger in low-credit-supply areas than high-credit-supply areas. To implement this, we construct four measures of local credit supply, each with its advantages and disadvantages. We then reestimate the main synthetic control model, but restrict the sample to low- or high-credit-supply areas, respectively.

H.1 Defining Low- and High-Credit-Supply Areas

We construct four measures of credit supply across locations, and each measure has its advantages and disadvantages. The first measure is the county-level average number of SBA 7(a) loans per capita from 2001-2006 (prior to Live Oak's entry). An advantage of this measure is that it reflects the level of SBA credit granted in a county, which is likely the appropriate measure of credit supply for SBA borrowers, especially if SBA borrowers are truly unable to obtain credit without the guarantee. If there is substitution between SBA and non-SBA credit, however, total small business credit may be a more appropriate measure. Thus, our second measure consists of the county-level average number of small business loans per capita as measure in the Community Reinvestment Act data, which captures small business loans for less than \$1 million originated by banks with more than \$1 billion in assets.

A shortcoming of both of these measures is that they reflect the equilibrium quantity of credit, which depends on supply and demand. Rather than reflecting supply, low-credit areas may simply be areas where small businesses demand less credit. Our final two measures of credit supply therefore focus on factors that affect the risk of lending, and therefore the credit supply. First, we use the Credit Insecurity Index from the Federal Reserve Bank of New York (Hamdani et al., 2019), which provides a county-level index of the share of residents who are "credit constrained."[17] While this measure is based on consumer credit reports, it is still relevant for the supply of small business credit given that 87% of employer small businesses rely on the owners' personal credit scores to obtain financing (Federal Reserve Banks, 2016-2019). Our final measure of credit supply is based on state-level variation in asset exemption levels, which protect borrowers assets from seizure by creditors in the event of default. There is significant variation in the level of asset exemptions across states, and there is evidence that higher exemption levels decrease the supply of credit available to small firms (Berkowitz and White, 2004, Cerqueiro and Penas, 2017).[18] To define state-level

[16] Specifically, we apply the synthetic control strategy using the dependent variable Y_{it}^{Low}, which is the number of SBA loans originated to industry i in year t to borrowers in low-credit-supply areas. Similarly, we estimate a synthetic control using the dependent variable Y_{it}^{High}.

[17] The Credit Insecurity Index equals the share of adults without a credit score plus a measure of the share with a credit score but likely to have limited access to credit. Limited access is defined as having no revolving credit, utilization rate greater than 100%, a deep subprime credit score, or have a consistently delinquent credit history.

[18] There is also some evidence, however, that higher exemptions increase demand for small business credit, leading

exemptions, we use the maximum of the state and federal home and nonhome exemptions that are available to single filers in each state.

These four groupings of areas into low- or high-credit-supply areas are measured before Live Oak's entry (except for credit insecurity, where the earliest available date is 2007), so they measure credit conditions prior any effects from Live Oak's entry. The three measures of low credit – SBA, CRA, and credit insecurity – are positively correlated with correlation coefficients between 0.28 and 0.35. These measures, however, have a weak or negative covariance with the grouping based on exemption levels. Thus, the measures capture different aspects of credit supply.

H.2 Results: Heterogeneity by Credit Supply

With these four measures, we divide geographic locations into low- or high-credit-supply areas.[19] For each treated industry, the estimates are obtained from estimating a separate synthetic control where the loan counts are restricted to low-credit-supply areas, and separately, high-credit-supply areas.

We report the average treatment effect in years 0-3, which we report in Figure H.1 and Table H.1. We also report the full set of synthetic control estimates for low- and high-credit-supply areas, respectively, in Figures H.2 and H.3. The pattern of results shows that Live Oak's impact was not confined to low-credit-supply areas. Across all four measures, Live Oak's entry generated increases in lending in both low supply and high supply areas.

Although lending increased in both low- and high-supply areas, the increases may have been larger in low-supply areas. Indeed, for the measure of credit supply based on SBA lending, there was more credit growth in low credit areas relative to high credit areas in all six industries. This SBA-based measure could be the most appropriate measure of credit supply for Live Oak's borrowers, since eligibility for an SBA loan requires that the borrower be unable to receive other credit on reasonable terms. The other measures, however, do not show a consistent pattern that holds across all industries and measures of credit supply. Of the 24 combinations (6 industries and 4 measures of credit supply), 14/24 estimates from low-credit-supply areas are larger than the baseline estimates from the main model, while 11/23 estimates from the high-credit-supply areas are larger than the baseline estimates.[20] Table H.2 reports the same table with the calculated competitive effects. As in the main results, the competitive effects are generally positive, indicating that other lenders continued to lend to the treated industries. However, the competitive effect estimates in the low- and high-credit-supply split samples are generally large in magnitude than the baseline estimates

to a greater equilibrium quantity (Hackney, 2016).

[19] For the SBA and CRA measures, an area is defined as a low-credit-supply area if it has below-median lending per capita during the 2001-2006 period. For the Credit Insecurity Index, we defined a county as a low-credit-supply county if it has an insecurity index above the national average, where insecurity is measure in 2007. When using asset exemptions, we define a state as having a low credit supply if that state has above-median asset exemptions in the year 2006.

[20] For Broilers, there were zero SBA loans in high credit areas during 2006, when credit is measured using the Credit Insecurity Index. Since our strategy normalizes lending by the base year 2006 lending, we are not able to provide estimates for Broilers using this measure of credit supply.

reported in column (2), especially for the low-credit-supply areas.[21]

[21]This is partially mechanical, because all of these estimates reflect percentage changes from the 2006 lending amounts, and these 2006 lending amounts are lower in the split samples (especially in the low-credit-supply areas). The smaller denominator results in larger percentage changes. This effect is also evident in the magnitudes of the ATE effects in Table H.1.

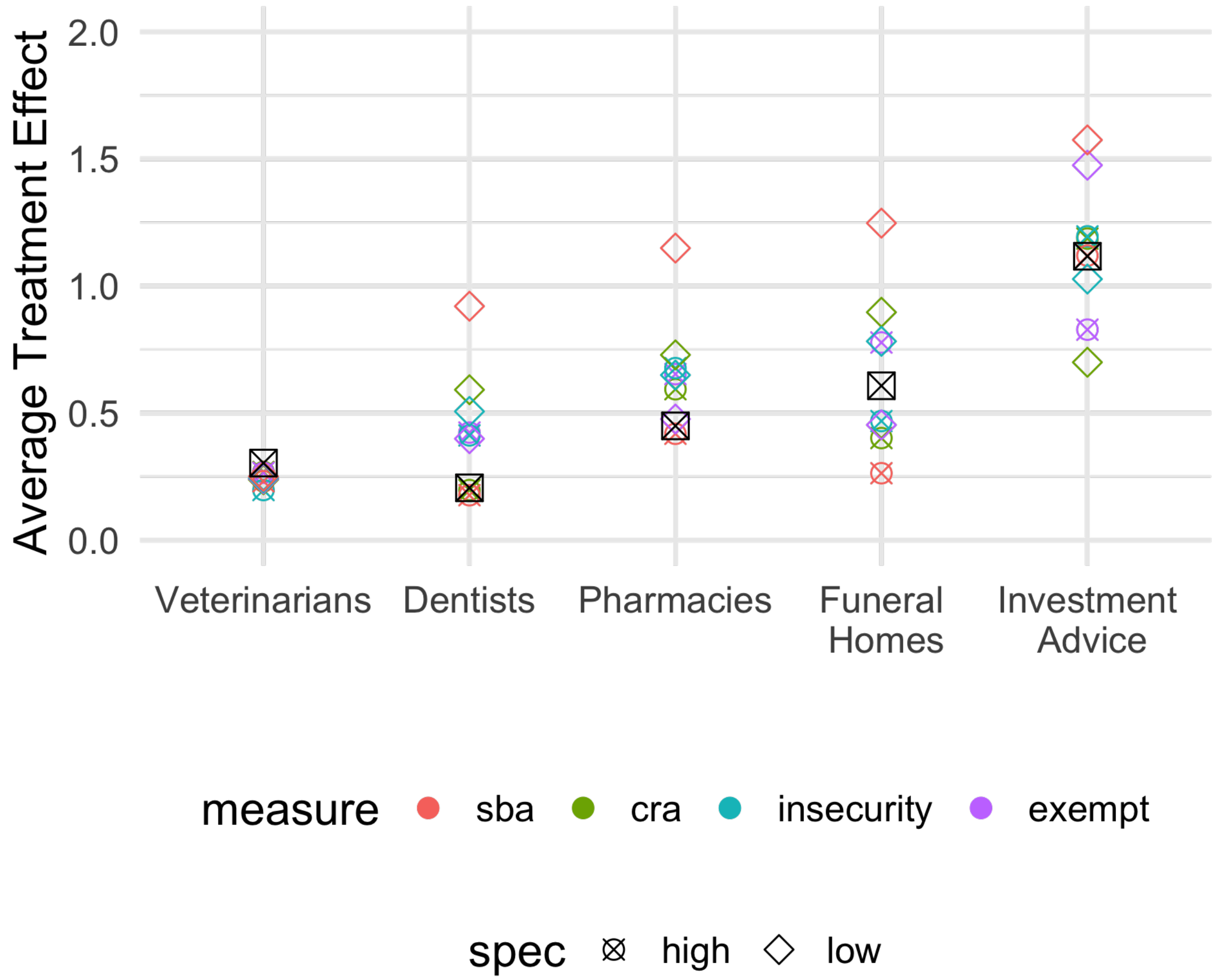


Figure H.1: **Comparison of Low- and High-Credit-Supply Areas**
This figure shows the average treatment effect during years 0-3 for high and low-credit-supply areas across the four measures of credit supply. The black boxes report the baseline estimates from the main model in the paper.

For each industry-measure-high/low pair, the estimates are obtained from estimating a separate synthetic control. For example, the Veterinarian-sba measure-low credit estimate is obtained from a synthetic control strategy for the treatment industry veterinarians, where the dependent variable is Y_{it}^{Low}, the quantity of loans in industry i and year t that are originated to borrowers located in low credit score areas, as defined by the SBA credit supply measure.

Table H.1: **ATE in Low and High Credit Supply Areas**

specification	industry	Average Treatment Effect				
		baseline	low credit		high credit	
	(1)	(2)	(3)	(4)	(5)	(6)
sba	Veterinarians	0.30	0.25	(-)	0.23	(-)
	Dentists	0.21	0.92	(+)	0.18	(-)
	Pharmacies	0.45	1.15	(+)	0.42	(-)
	Funeral Homes	0.61	1.25	(+)	0.26	(-)
	Investment Advice	1.12	1.57	(+)	1.12	(+)
	Broilers	1.04	12.17	(+)	-0.34	(-)
cra	Veterinarians	0.30	0.24	(-)	0.27	(-)
	Dentists	0.21	0.59	(+)	0.20	(-)
	Pharmacies	0.45	0.73	(+)	0.59	(+)
	Funeral Homes	0.61	0.90	(+)	0.40	(-)
	Investment Advice	1.12	0.70	(-)	1.19	(+)
	Broilers	1.04	0.38	(-)	7.36	(+)
insecurity	Veterinarians	0.30	0.25	(-)	0.20	(-)
	Dentists	0.21	0.51	(+)	0.41	(+)
	Pharmacies	0.45	0.65	(+)	0.68	(+)
	Funeral Homes	0.61	0.78	(+)	0.47	(-)
	Investment Advice	1.12	1.03	(-)	1.20	(+)
	Broilers	1.04	0.62	(-)		
exempt	Veterinarians	0.30	0.24	(-)	0.26	(-)
	Dentists	0.21	0.40	(+)	0.42	(+)
	Pharmacies	0.45	0.48	(+)	0.65	(+)
	Funeral Homes	0.61	0.45	(-)	0.78	(+)
	Investment Advice	1.12	1.48	(+)	0.83	(-)
	Broilers	1.04	0.01	(-)	17.05	(+)
				(+): 14/24		(+): 11/23

This table reports the average treatment effect (ATE) during years 0-3 for high and low-credit-supply areas across the four measures of credit supply. Column (1) reports the industry, column (2) reports the baseline (ATE) estimates from the main specification in the paper, column (3) reports the estimates when the sample is restricted to low-credit-supply areas, and column (4) indicates whether the estimate in column three is above (+) or below (-) the baseline estimates. Columns (5) and (6) repeat this, but for the high-credit-supply areas.

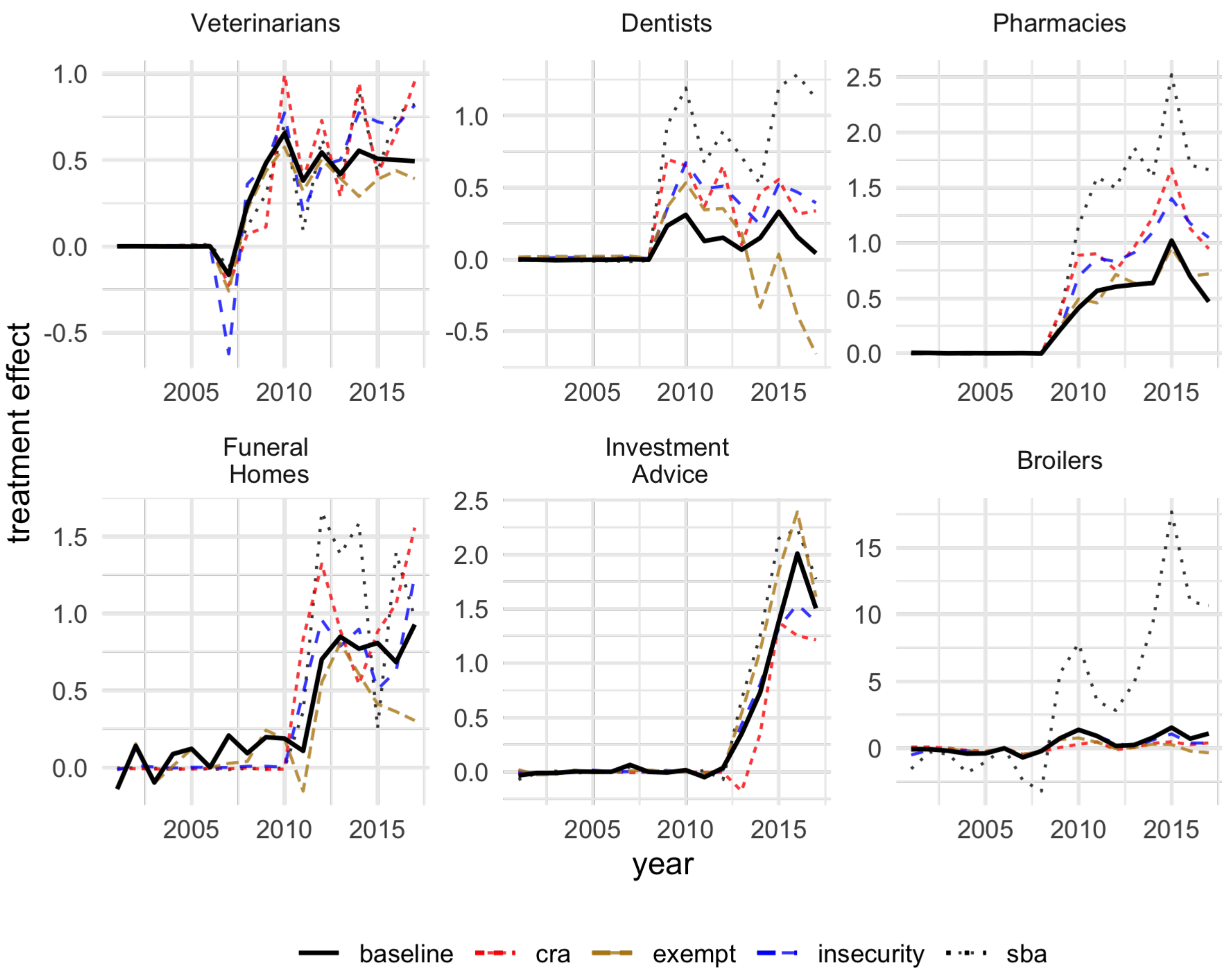


Figure H.2: **Low-Credit-Supply Areas**
This figure reports the treatment effect estimates from a synthetic control where the dependent variable is the number of loans (normalized by the 2006 level) in low-credit-supply areas. Low credit supply is defined according to the four separate measures (cra, exempt, insecurity, sba). The baseline estimates from the main specification in the text are reported for comparison.

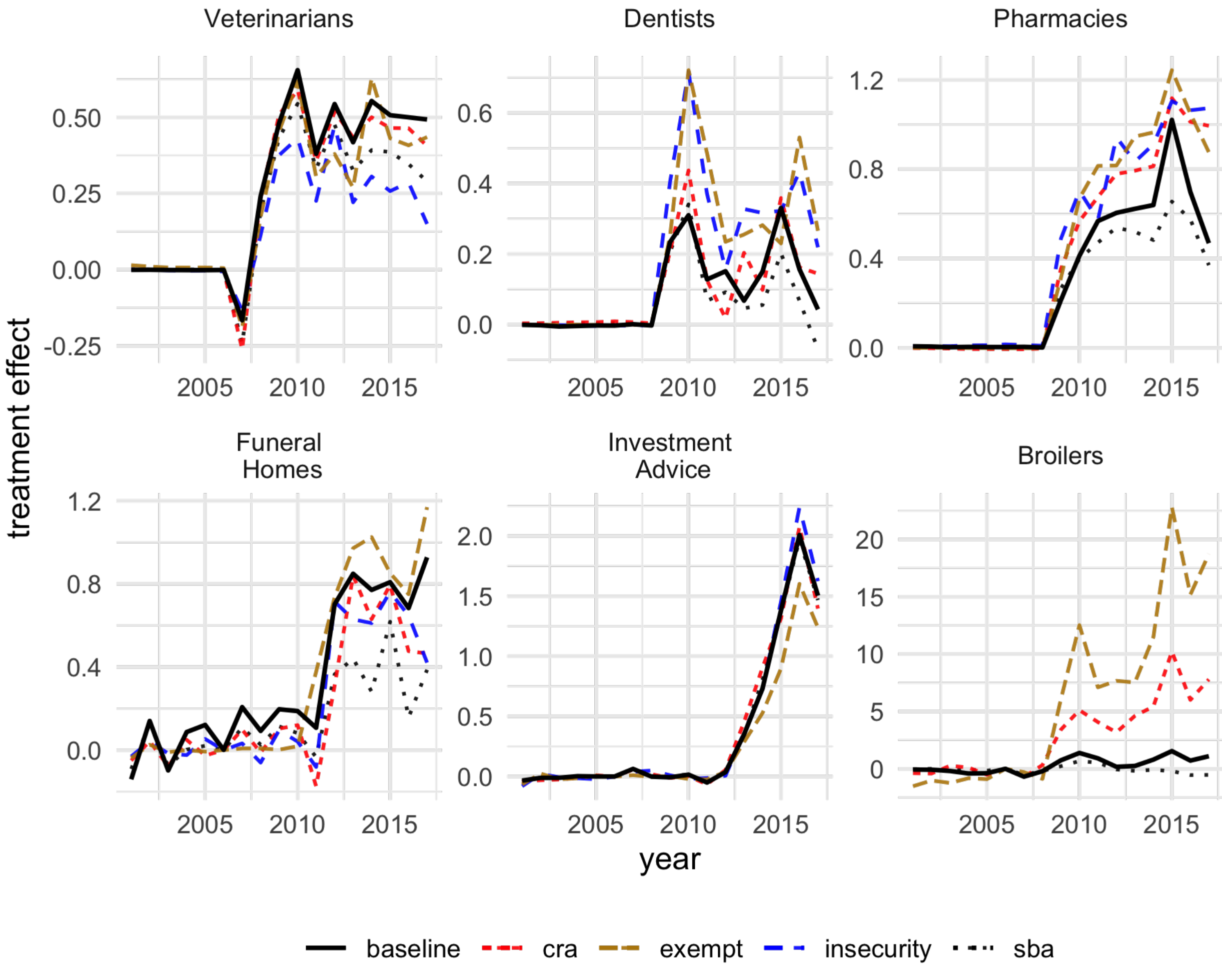


Figure H.3: **High-Credit-Supply Areas**

This figure reports the treatment effect estimates from a synthetic control where the dependent variable is the number of loans (normalized by the 2006 level) in high-credit-supply areas. High credit supply is defined according to the four separate measures (cra, exempt, insecurity, sba). The baseline estimates from the main specification in the text are reported for comparison.

Table H.2: **Competitive Effect in Low and High Credit Supply Areas**

specification	industry	Average Competitive Effect				
		baseline	low credit		high credit	
	(1)	(2)	(3)	(4)	(5)	(6)
sba	Veterinarians	-0.01	-0.20	(-)	-0.05	(-)
	Dentists	0.13	0.75	(+)	0.11	(-)
	Pharmacies	0.18	0.48	(+)	0.21	(+)
	Funeral Homes	0.18	0.70	(+)	-0.14	(-)
	Investment Advice	0.10	-0.00	(-)	0.15	(+)
	Broilers	0.29	4.94	(+)	-0.55	(-)
cra	Veterinarians	-0.01	-0.07	(-)	-0.04	(-)
	Dentists	0.13	0.52	(+)	0.12	(-)
	Pharmacies	0.18	0.46	(+)	0.31	(+)
	Funeral Homes	0.18	0.44	(+)	-0.02	(-)
	Investment Advice	0.10	0.02	(-)	0.15	(+)
	Broilers	0.29	-0.09	(-)	4.00	(+)
insecurity	Veterinarians	-0.01	-0.13	(-)	-0.08	(-)
	Dentists	0.13	0.43	(+)	0.34	(+)
	Pharmacies	0.18	0.40	(+)	0.37	(+)
	Funeral Homes	0.18	0.32	(+)	0.07	(-)
	Investment Advice	0.10	0.20	(+)	0.06	(-)
	Broilers	0.29	-0.02	(-)		
exempt	Veterinarians	-0.01	-0.06	(-)	-0.05	(-)
	Dentists	0.13	0.33	(+)	0.34	(+)
	Pharmacies	0.18	0.23	(+)	0.33	(+)
	Funeral Homes	0.18	0.03	(-)	0.33	(+)
	Investment Advice	0.10	0.37	(+)	-0.08	(-)
	Broilers	0.29	-0.29	(-)	8.36	(+)
				(+): 14/24		(+): 11/23

This table reports the average competitive effect (i.e., the ATE minus Live Oak's loans) during years 0-3 for high and low-credit-supply areas across the four measures of credit supply. Column (1) reports the industry, column (2) reports the baseline estimates of the competitive effect from the main specification in the paper, column (3) reports the estimates when the sample is restricted to low-credit-supply areas, and column (4) indicates whether the estimate in column three is above (+) or below (-) the baseline estimates. Columns (5) and (6) repeat this, but for the high-credit-supply areas.

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