Old Program, New Banks: Online Banks in Small Business Lending

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Abstract

Technological innovation has spurred the growth of online banks specializing in particular activities across broad geographic areas. We analyze the consequences of online banks' specialization in the government's SBA program, which provides loan guarantees to motivate lending to higher-risk borrowers. Online bank SBA loans default about twice as frequently but still earn higher rates of return than other lenders. Key to this return is the targeting of higher guarantees, which generates a cross-subsidy of 2% from traditional lenders and the government to online banks. Through this targeting, online banks expand credit access in the most economically troubled counties by 30%.

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In recent decades, changes to bank regulation and innovation in financial technology have caused a dramatic shift in the lending landscape away from traditional brick-and-mortar banks to shadow banks, fintech lenders, and online banks (Buchack, Matvos, Piskorski, and Seru, 2018; Jagtiani and Lemieux, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019; Gopal and Schnabl, 2022). These new lenders differ from traditional banks in terms of borrower profile (Bao and Huang, 2021; Balyuk, Berger, and Hackney, 2022) and the scope of their product offering (Benetton, Buchak, and Robles-Garcia, 2022) leading to a more specialized business model. While much of the research has focused on differences in regulatory burden and the role of nonbank fintech lenders on consumer lending, advances in financial technology and differences in business models have also produced a new class of bank whose operations are primarily online and lend to small businesses. These online banks are depository institutions that use streamlined platforms and technology to make lending decisions and reach a broader pool of borrowers. Like nonbank fintech lenders, online banks are not restricted by geography and may use a specialized model to target specific assets or loan characteristics that they view as attractive (Erel and Liebersohn, 2022; Di and Pattison, 2023).

In this paper, we hypothesize that online banks focus on a narrow scope of products for a set of borrowers that are riskier and not ripe for cross-selling. Indeed, we observe that online banks feature a more specialized business model than traditional banks and target specific loan profiles. One area of specialization is lending through the Small Business Administration (SBA) 7(a) program, which guarantees portions of loans to higher-risk borrowers. We find that online banks utilize features of the SBA loan program to secure the highest guarantee rates and charge higher interest rates. Despite online bank loans being about twice as likely to default and be charged off, these banks earn higher rates of return than other lenders. As lender costs to participate in the SBA program do not depend on the probability of default, this behavior generates a cross-subsidy of 2% of the loan size from traditional lenders and the government to online banks.

We find the loan profile that online banks target are concentrated in more economically disadvantaged counties. Therefore, in targeting higher guarantees, online banks lend more in poor and underserved areas, effectively increasing credit supply in these regions. Consistent with this focus, we do not find this credit expansion to be driven by outsized lending to minorities and women. The behavior of online banks mirrors that of fintech nonbanks, suggesting that technology and specialization rather than solely differences in regulatory burden that drives increased credit access through fintech lenders.

We focus our analysis on small business lending because it is an economically relevant area that is being transformed by non-traditional lenders. As of 2019, small businesses generated 44% of all economic activity in the US (Office Of Advocacy, 2019). Within the universe of small business loans, SBA lending is estimated to account for about 8% of all loans in 2016 (Gopal and Schnabl, 2022). The SBA provides comprehensive information on its loans that is typically unavailable in other data sources. SBA lenders are required to report loan terms and status, borrower name, address, and industry, and the lender name and address. This granularity is unique among small business lending data sources and allows us to track outcomes and estimate profitability on a loan-level basis.

The SBA operates by incentivizing its partner-lenders to make loans to high-risk small business borrowers by guaranteeing a percent of the loan. Only SBA-approved lenders can participate in these programs and lenders are required to pay a small "ongoing servicing fee" and a "guarantee fee" which is a fixed upfront cost based on loan amount and term length. SBA loans come with maximum loan amounts, interest rates, term lengths, and fund uses that depend on the specific program. As a government program, the SBA discloses how much government funding was needed each year. The SBA has the goal of achieving a "zero-subsidy rate," meaning that it generates adequate funds through guarantee fees and recovered collateral to offset the cost of paying the guarantees on defaulted loans. During our sample period, the SBA had a zero-subsidy rate from 2014 to 2019 but required supplemental government funds from 2010 to 2013 (Small Business Administration, 2022). The fees are based only on loan size and term length and do not depend on the percent of the loan guaranteed or the borrower's risk. SBA fees act as a transfer from lenders with low levels of SBA default to lenders with high levels of SBA default (Stillerman, 2021). As a result, there is cross-subsidization from lenders and borrowers, and in years where supplemental funds were needed, the government, to other lenders. This provides an additional facet to our analysis in understanding how online banks interact with other, more traditional, lenders.

Within the SBA data, we classify lenders into one of five mutually exclusive categories, with online banks being the category of interest. We define online banks as FDIC-insured institutions that do not require any face-to-face interaction to secure a small business loan. We then examine which markets they lend to. We find that the market share of online banks is higher in counties with low per capita income, high unemployment, and low levels of competition from banks. These areas are typically associated with lower levels of credit supply and are underserved by existing financial institutions (Jagtiani and Lemieux, 2018). In addition to higher market share, we find that online banks lend more dollars in these economically depressed areas. In the lowest per capita income tercile counties, online banks lend about 30% more than in other counties. To provide causal evidence that changes in credit access are driven primarily by online banks' supply decisions, we utilize a regulatory change that negatively impacted the ability to securitize SBA loans. As online banks disproportionately securitize their SBA loans compared to other lenders, we find a significant reduction in credit supply from online banks following this change. This suggests that the changes in credit access in disadvantaged communities are likely driven by online banks expanding the supply of credit. Although the total credit supply increases in these geographies, we document that this effect is not explained by increased credit access to minorities or women-owned businesses.

Next, we examine the motivation behind online banks lending to underserved markets. The literature has shown that lenders generally take loan guarantees into account when pricing loans and making lending decisions (Bachas, Kim, and Yannelis, 2021). We hypothesize that online banks may target particular loan characteristics, such as high guarantees and higher interest rates, that they view as attractive. We suspect that online banks are best able to locate borrowers that fit these loan profiles in economically disadvantaged areas. Analyzing the relationship between SBA guarantees and local economic variables, we find higher guarantees are associated with lower per capita income, higher unemployment, lower competition from financial institutions, lower credit scores, higher rates of subprime borrowers, and higher poverty rates. Given the guarantee percentages are not explicitly based on these factors, we take these findings as evidence of online banks' targeting strategy.

In comparing the behavior of online banks and other lenders in the SBA 7(a) program, we find that, on average, online bank loans are larger in size and longer in term. Additionally, online bank loans come with higher interest rates. As hypothesized, we find that online bank loans have on average four percentage points higher SBA guarantee rates (0.2 standard deviations). We also find that the bunching of loan amounts around higher guarantee rate cut-offs, documented in Bachas, Kim, and Yannelis (2021), comes mainly from these online banks. Using a specification with borrower-year fixed effects, we document that online lenders make loans with higher guarantee rates, even when strictly comparing two loans to the same borrower in the same year from two different lenders. These higher guarantees imply that online bank loans, on average, have a lower cost of default to the lender. As expected with a lower cost of default, online banks are willing to make riskier loans that default more frequently and have larger charge-offs.

This combination of higher guarantees and higher defaults suggests that online bank loans cost the SBA more. Testing this, we apply methodology of Bachas, Kim, and Yannelis (2021) to calculate an expected guarantee subsidy as the predicted SBA payment relative to loan amount, net of fees. The average expected guarantee subsidy is 2% for online bank loans and 0% for loans of other lenders. In looking at actual rather than expected subsidy, we calculate SBA costs net of fees. We find that the SBA reimburses lenders for 5% of online bank loans compared to 2% of loans from other lenders. Since the SBA often breaks even through fee and collateral collection, these findings imply that online lenders are benefiting from the fees paid by other lenders and the collateral recovered from borrowers. Since the guarantee fee is based on loan size and term rather than on guarantee percent, we interpret this as a transfer from other lenders, borrowers, or, in times where the SBA does not have a zero-subsidy rate, the government, to online banks. Additionally, we find that the charge-off rates and SBA losses of online bank loans are indistinguishable across economic markets, suggesting that online banks do target specific loan characteristics across geographies.

Recent policy events have increased the significance of our findings of online bank behavior and cross-subsidization. Historically, nonbanks have only been granted limited involvement in SBA programs. To accelerate the disbursement of funds during the COVID pandemic, the SBA permitted fintech nonbanks to participation in its PPP program (Erel and Liebersohn, 2020). This decision to allow nonbank participation has resulted in the removal of restrictions on nonbank involvement in other SBA programs. As of May 2023, nonbanks are now permitted complete participation in 7(a) lending.[1] Therefore, it has become increasingly important to understand how lenders with specialized business models that utilize technology to make loans remotely impact SBA lending.

This paper relates to four major areas of the literature. First, it contributes to the literature that documents changes in lending driven by advances in technology. Nonbanks, primarily driven by fintech lenders, have filled credit gaps following the 2008 financial crisis (Gopal and Schnabl, 2022). Implementation of algorithms, big data, and digital footprints allow lenders to make decisions based on hard information faster and more effectively (Berg, Burg, Gombović, and Puri, 2019; Fuster, Plosser, Schnabl, and Vickery, 2019; Balyuk, Berger, and Hackney, 2022; Bartlett, Morse, Stanton, and Wallace, 2022). Since the COVID-19 pandemic, the growth in digital banking has accelerated as lenders have been compelled to improve online services to meet customer needs and expectations, changing the way borrowers approach financing (Pearce and Borkenhagen, 2021). While the majority of papers in this space focus on fintech nonbanks, He, Jiang, Xu, and Yin (2021) document that banks are increasing their spending on information

[1] https://www.federalregister.gov/documents/2022/11/07/2022-23597/small-business-lending-company-sblc-moratorium-rescission-and-removal-of-the-requirement-for-a-loan

technology to remain competitive with fintech lenders. We differ from previous literature as we examine the effects of the growth and behavior driven by specialization and technological innovation of online banks rather than that of nonbanks driven by regulatory differences.

Second, we add to a literature that focuses on bank specialization (Paravisini, Rappoport, and Schnabl, 2023). The business model specialization we document is somewhat at odds with banks generating profits by undertaking a broad set of depository activities, lending activities, and exploiting the synergies between them (Egan, Lewellen, and Sunderam, 2021). A commonly cited benefit of banks is the ability to cross-sell products to customers. For larger firms, this cross-selling is in the form of future loans, debt underwriting, and other investment banking services (Yasuda, 2005; Ljungqvist, Marston, and Wilhelm Jr., 2006; Bharath, Dahiya, Saunders, and Srinivasan, 2007; Neuhann and Saidi, 2018). For retail and small business customers, the cross-selling is typically additional loans or credit cards, brokerage accounts, or other non-credit services (Puri and Rocholl, 2008; Santikian, 2014; Benetton, Buchak, and Robles-Garcia, 2022). We document that these online banks have a business model that focuses on borrowers that likely not ripe for cross-selling.

Third, an important aspect of this paper is the SBA program. Much work has been done analyzing the efficacy of the SBA program and its impact on the US economy (Krishnan, Nandy, and Puri, 2014; Brown and Earle, 2017). There is a recent literature on government guarantees and subsidies and the effect of these policies on lender behavior. Bachas, Kim, and Yannelis (2021) show loan bunching around guarantee thresholds and find that raising guarantee rates causes the per-loan amount to increase. These guarantees create a redistribution of credit from low-risk to high-risk firms. Because of the decreased cost of default, lenders take on greater levels of risk and are less motivated to collect information on their borrowers (Stillerman, 2021). By concentrating on the behavior of online banks, which can target borrowers across markets, we expand the understanding of the efficacy of the SBA in modern lending, how lenders view guarantees, and whether the guarantees are having their intended effect.

Fourth, this paper relates to work on credit access. There is a broad literature that examines the impact of new lender types and increased competition on credit availability. The consensus is that the entrance of a new lender typically increases credit access (Black and Strahan, 2002; Cetorelli and Strahan, 2006; Rice and Strahan, 2010). Fintech lenders specifically have been found to expand consumer credit access into highly concentrated and economically challenging markets (Jagtiani and Lemieux, 2018; Cornelli, Frost, Gambacorta, Rau, Wardrop, and Ziegler, 2020). This suggests that fintech lenders have the potential to penetrate underserved markets, increasing credit availability. Di and Pattison (2023) present evidence of remote industry-specialized lenders in SBA lending, finding that entry of specialized lenders is associated with increased credit access within the industry. Though it is not always the case that new lenders expand credit access. For example, Gormley (2014) finds foreign lender entry has a negative effect on credit supply as foreign lenders tend to lend to only the best borrowers, reducing credit to all other firms. Therefore, while additional lenders usually lead to an expansion of credit access, certain lenders may have the opposite effect. This paper adds to this literature by focusing on the increased credit access to small businesses by online lenders as an unintended consequence of their specialized lending model. Most importantly, to the extent of our knowledge, this is first paper to document that such an increase in credit access implies a cross subsidization from traditional lenders, borrowers, and the government to online lenders.

I Institutional Background and Data

I.A SBA 7(a) Program

The SBA (Small Business Administration) was founded in 1953, its goal is to “grow businesses and create jobs” (Small Business Administration, 2012). The SBA attempts to realize this goal through its central programs, 7(a) and 504. These programs provide financing to small businesses that would otherwise have difficulty accessing credit. SBA funding is primarily used to support working capital, make PP&E purchases, expand into new markets, refinance existing debt, and create or acquire new business. These loans are made by participating financial institutions, with the SBA guaranteeing a portion (typically 50-90% depending on loan size and type) of the loan to offset the additional risk being taken on by the financial institution. For example, if an SBA loan with a guarantee of 75% defaults with a $50,000 remaining balance, the SBA assumes $37,500 of the loss and the financial institution assumes $12,500.

The effects of the SBA program have been examined by the literature. Krishnan, Nandy, and Puri (2014) find that the SBA program increases access to credit. Through this increased credit access, small businesses create jobs in local economies and participate in "productive projects that may otherwise not be taken up." Brown and Earle (2017) estimate the cost per job from SBA 7(a) and 504 loans to be between $21,580 and $25,450. They compare this to the cost per job of other government programs including the American Recovery and Reinvestment Act at $158,000 to $407,000 (Neumark, 2011) and the New Jobs Tax Credit at $37,500 to $75,000 (Bartik and Erickcek, 2010). This suggests that SBA loans are a comparatively low-cost government method of job generation.

We focus on the SBA's original and most common loan program, the 7(a). To qualify for a 7(a) loan, a small business must meet the following requirements. It must be a for-profit business, conduct business within the United States, and fit the SBA's definition for a small business. This definition varies across industry but is based on the firm's number of employees and its annual receipts ("total income plus cost of goods sold"). These businesses must also show that they have need for the loan, cannot get reasonable terms for funding elsewhere, have equity invested in the business, and have already expended alternative funding including personal resources. Additionally, any business that is delinquent on existing debt obligations to the US government is ineligible for a 7(a) loan.

During our sample period of 2010 to 2019, the maximum loan amount for any 7(a) loan is $5 million. Interest rates are decided by the lender and can be fixed or variable but must not exceed the SBA maximums which, during our sample period, were pegged to the LIBOR rate.[2] Within

[2]The SBA base rate transitioned to the prime rate or an optional peg rate in 2023 following the phase-out of

the 7(a) program, there are several loan types, referred to by the SBA as "delivery methods," that differ on loan purpose, loan amount, eligibility requirements, SBA turnaround time, and guarantee percentage. Descriptions of the main delivery methods with their accompanying guarantee rate can be found in Table A.2. For example, the Standard/Small 7(a) loan has a maximum loan amount of $5 million and a turnaround time of 5 to 10 business days. The SBA guarantees 85% of Standard/Small 7(a) loans that are less than $150,000 (small) and 75% of those greater than $150,000 (standard). Alternatively, the SBA Express program features a SBA turnaround time of 36 hours, a maximum loan amount of $350,000 during most of our sample period, and a maximum guarantee of 50%.[3] In exchange for a lower guarantee, loans made through the SBA Express program entail less documentation and fewer loan-vetting procedures compared to the Standard/Small 7(a) documentation.

Only SBA-certified lenders are eligible to make 7(a) loans. An experienced SBA lender can be granted Preferred status (referred to as "Preferred Lender Program" (PLP) in SBA documentation). A lender with Preferred status has the authority to generate SBA loans without SBA review. The SBA reviews the status of its Preferred lenders regularly and if a lender falls below certain standards, the SBA can choose not to renew the lender's status privileges. Using their Preferred status, these lenders can make loans through the subprograms including the Standard/Small 7(a) or SBA Express. Of the 15 programs in our sample, about one-third of the loans are Standard/Small 7(a) loans originated using Preferred Lender status and about half are through the SBA Express program. The remaining loans are generated by smaller programs with specific lending purposes or target particular geographies or demographics such as small rural populations or veterans.

Lenders that participate in the SBA are subject to certain fees which we describe in detail in Section I.B. These fees depend on loan size, maturity, and current SBA legislation. The SBA

the LIBOR rate (https://www.sba.gov/partners/lenders/7a-loan-program/terms-conditions-eligibility).

[3]The SBA temporarily increased this maximum to $1,000,000 in fiscal year 2011. In the post sample period, the SBA Express maximum loan amount is $1,000,000 in fiscal years 2020 and 2021 and $500,000 in fiscal years 2022, 2023, and 2024.

uses these fees to operate and fund its programs and administration. The SBA is required to report the amount of government funding it receives each year. The goal of the SBA is for its programs to generate adequate funds through fees and collateral repossession to break even on defaults and other organizational costs. The SBA 7(a) program has a deficit from 2010-2013 but had a "zero subsidy rate," meaning that it broke even, from 2014 to 2019. (Small Business Administration, 2022).

I.B SBA Fees

To participate in the program, lenders are required to pay fees to the SBA on all 7(a) loans. These fees include an upfront guarantee fee, an annual servicing fee, and a prepayment fee. It is important to note that lenders can pass these fees on to the borrower. The SBA revises these fees on an annual basis, releasing updates each October. Exact fee percentages by year can be found in Table A.3.

The guarantee fee is paid upfront to the SBA to cover potential defaults. It is generally deducted from the initial loan amount or added into the total cost of the loan and paid by the borrower. This fee ranges from 0-3.75% of the guaranteed portion of the initial loan amount. The exact percentage depends on loan size and loan maturity with smaller, shorter-term loans requiring lower fees. We use initial loan size, guarantee rate, loan maturity, and the SBA-released fee percentages to calculate the upfront guarantee fee for each loan.

SBA loans include a yearly servicing fee ranging from from 0-0.55% paid to the SBA on the guaranteed portion of the outstanding balance. This fee goes toward funding SBA operations. We assume that the ongoing servicing fee is paid every 12 months after the initial disbursement date on the guaranteed portion of the outstanding balance. We use the sum of these annual fees to generate the total ongoing servicing fee amount paid over the life of the loan.

The SBA requires a prepayment fee on all loans that have a maturity of more than 15 years that are paid in full within the first three years after disbursement. This fee is 5% of the prepayment amount if prepaid in the first year, 3% of the prepayment amount if prepaid in the second year, and 1% of the prepayment amount if prepaid in the third year. Borrower prepayment of loans that do not fulfill this criteria does not induce fees.

Since we are unable to observe the individual loan payments, we assume that all borrowers follow a traditional monthly payment schedule calculated using initial amount and interest rate. We assume that borrowers pay this calculated amount each month until the loan is either paid in full or charged off. If a loan is paid prior to its given maturity, we assume that the loan is paid following the normal schedule until the final month of payment in which we assume that the entirety of the remaining balance is paid. If a loan is classified as charged off, we assume that the loan is paid following the normal schedule until 90 days (three months) prior to the charge off date, after which we assume that the borrower stops paying the remaining balance.

I.C Lender Classification

We classify the SBA lenders into one of five mutually exclusive categories: online banks, big banks, traditional banks, credit unions, other lenders. The lender group of focus is online banks as they are rapidly gaining market share and their lending is not limited by geographic location. This group is comprised of deposit-taking institutions whose lending operations do not require any in-person interactions (Buchack, Matvos, Piskorski, and Seru, 2018). To identify whether a bank requires in-person interaction, we conservatively classify online banks as having less than ten physical branches and less than 10% of their loans coming from the state in which they are located. Big banks are deposit-taking institutions in the 99th percentile for size as measured by assets. Traditional banks are deposit-taking institutions that are not classified as online banks or big banks. Credit unions are lenders who are overseen by the National Credit Union Administration. The other lenders category comprises lenders that do not fit into one of the prior categories. This includes the group of "SBA supervised lenders" that are not deposit-taking institutions.

Online banks are responsible for 5.5% of the loans in our sample. The ten largest online banks by number of loans are listed in Table A.4. Of the other lenders, big banks provide 30.6% of loans, traditional banks provide 56.7%, credit unions provide 2.9%, and other lenders provide about 4.5%. While online banks provide 5.5% of the total loans on average, in Figure 1, we note that its market share is increasing over the period from about 1% in 2010 to about 9% in 2019. In terms of total loan amount, online bank market share grows from about 4% in 2010 to about 13% in 2019 in Figure 2.

Before 2023, going through online banks was the principal mechanism for new fintech lenders to enter the SBA 7(a) market. For non-depository institutions, the SBA had only 14 licenses delegated to "Small Business Lending Companies" (SBLCs), and have had a moratorium on creating new licenses since 1982. Under the Coronavirus Aid, Relief, and Economic Security Act (CARES) of 2020, the SBA allowed fintech nonbanks to provide loans to small businesses for PPP program (Erel and Liebersohn, 2022). This paved the way for fintech involvement in additional SBA programs. Effective May 11, 2023, the SBA removed its moratorium, allowing new nonbank entrants. Prior to this change, the other non-depository categorization, state-regulated lenders called "Non-Federally Regulated Lenders" (NFRLs), were largely restricted to lending within their respective state. So as opposed to other lending markets, the SBA 7(a) program enabled fintech activity through online banks. These banks either develop their own lending franchises or partner with fintech lenders. For example, all loans made prior to October 2020 by Kabbage, a major fintech small business lender, were issued by Celtic Bank, an online Utah-chartered Industrial Bank (Kabbage, 2022). Therefore, any SBA 7(a) loans originated by Kabbage would be reported by Celtic Bank. Gopal and Schnabl (2022) describe these partnerships between a fintech lender and a "funding bank." They explain that these fintech lenders attract borrowers online but that the funding bank is who makes the loan. These funding banks often immediately sell the loan to the fintech lender and are frequently located in areas with lighter regulation but make loans nationwide.

I.D Data

The primary source of data is the SBA 7(a) program. The SBA requires all its lenders to report any 7(a) loan applications. This data can be accessed publicly through the Freedom of Information Act (FOIA) on the SBA website. The overall sample contains all 545,751 SBA 7(a) loans made from 2010 to 2019 by 3,397 unique lenders. Because the SBA requires lenders to report all loan applications, there are loans in the sample that are canceled prior to disbursement. Since the reason for cancellation is not provided, we are unable to determine whether the cancellation was initiated by the lender, borrower, or the SBA. To account for this, we remove any loans with a status of canceled. This leaves us with 481,018 loans and 3,274 unique lenders. We remove observations that are missing key variables of analysis, giving us our sample of 459,725 loans and 3,218 unique lenders. The SBA 7(a) data contains information on the borrower, lender, and loan terms. This includes borrower name, location, and industry; lender name and location; and loan interest rate, amount, term in months, type, status, and the number of jobs supported.

We carefully match lenders with bank-level control variables from FDIC Summary of Deposits (SOD), Call Reports, and Statistics on Depository Institutions (SDI) data by bank name and location. Using SOD bank branch data, we generate the number of SBA bank branches in the borrower's zip code and the physical distance between each SBA borrower's zip code and the zip code of the nearest SBA bank branch. All FDIC-insured institutions are required to file quarterly updates on financial, demographic, and structural information. Because our sample consists of banks, credit unions, and nonbanks, not all lenders have these variables available. Over 90% of the loans in our sample come from FDIC-insured institutions therefore, the majority of observations are matched.

To allow for economic location analysis, we match borrower location by county and zip code with data from the US Census, the Bureau of Economic Analysis (BEA), County Business Patterns (CBP), and a major credit bureau. This economic data allows us to include location-specific characteristics such as income, employment rates, credit scores, rate of subprime borrowers, and poverty rates.

We additionally pull data from the USAspending.gov website which supplies a comprehensive report of US federal, state, and local government spending, including information on SBA guaranteed loans. This data provides business ownership information on the individual borrowers as firms self-identify under categories such as minority, woman, veteran, and disadvantaged owned. We assume that if a borrower is not classified into one of these categories that the owner is not a minority, woman, veteran, or disadvantaged. This is carefully merged with the original SBA data using a fuzzy merge on borrower name and location. The merged data contains 274,458 loans and 2,998 unique lenders.

From Table I, we see that the median loan size is \$125,000, median interest rate is 6%, and median term is seven years. About 30% of loans in the sample are a revolving line of credit. Looking at borrower business type, 88% of loans are made to corporations, 11% to individuals, and 2% to partnerships. The borrowers have a median business age of 2.5 years. The median borrower in our sample has six branches of SBA lenders in their zip code.

Lenders are required to regularly update the status of these loans, in our sample, 57% of the loans have been paid in full, 1% are undisbursed, 5% are charged off (deemed uncollectable by the lender), 37% are exempt (the loan has been disbursed but it has not yet been canceled, paid in full, or charged off). The average fees are about \$8,000 for the upfront guarantee fee, \$9,000 for the total ongoing servicing fee, and \$400 for the prepayment fee. From the BEA data, we see that our sample has an median county per capita income of \$47,970 and median county unemployment rate of 5.2%. Using SOD reports, we calculate our sample to have a median county scaled HHI of 0.039.

From the matched data, we report that 0.8% of the borrowers self-identify as a woman owned business while 0.6% self-identify as a minority owned business. We compare the matched sample to the overall sample in Table A.5 and find the samples to be similar in terms of loan attributes, borrower types, and loan outcomes.

II Specialization and SBA Loans

II.A Bank Specialization

We argue that online banks, given the nature of their business structure, will specialize in certain loan types rather than offering a broad set of products in a fixed geographic footprint. To establish whether online banks indeed specialize in this way, we run the following regression for lender b in year t:

$$\text{Specialization Measure}_{bt} = \beta_1 \text{Online Bank}_b + \beta_2 \text{Bank Controls}_{bt-1} + \gamma_t + \varepsilon_{bt}, \tag{1}$$

We include seven different specialization measures. From the bank's Call Report data, we include the Herfindahl-Hirschman Index (HHI) of asset types (*Assets HHI*), liability types (*Liabilities HHI*), income sources (*Income HHI*), and types of loans and leases *Loans HHI (CR)*. These are constructed by calculating the sum of the squared market shares of each of the categories on the balance sheet and income statement sections. Using Call Report total loans and leases, we construct *SBA to Total Loans* as the lender's total SBA lending divided by their total loans and leases. We assume a higher concentration in these measures indicates more specialization in the bank's business model. We also include two alternative measure of loan activities using the SDI data: an HHI measure and the number of distinct loan and lease categories for which the bank reports activity (*Loans HHI (SDI)* and *Loan Categories*). We include the bank's size, equity ratio, deposit ratio, and ROA as controls, along with year fixed effects.

Table II presents the results. We find that online banks have a more specialized balance sheets than other banks. The HHI of assets, liabilities, and income sources are all higher for online banks, controlling for other bank characteristics. These results are statistically significant at the 1% level for assets (column 1) and at the 10% level for liabilities and income sources (columns 2 and 3).

Turning to the type of loans that banks originate, we again find that online banks are more concentrated. Column 5 shows that online banks have significantly higher SBA lending relative to total loans. This indicates that these banks have a specific focus on SBA lending. This concentration also holds for both the HHI measures and the number of loan categories online banks report. The effects are economically meaningful: the difference between online banks and other lenders for *Loans HHI (CR)* is 75% of the sample standard deviation in this measure and statistically significant at the 1% level (column 4). The similar calculation for the alternative loan HHI measure (*Loans HHI (SDI)*) is about 50% of a sample standard deviation (column 6). As the average bank reports loans in 11 different categories, the fact that online banks on average have two fewer categories is also meaningful (column 7). Together, we take these findings as evidence that online banks are more specialized in their overall balance sheet assets and the types of lending they undertake, with specific emphasis on SBA lending.

II.B SBA Loans: Univariate Differences

As online banks are more specialized than other lenders, we next examine whether this affects the characteristics of their SBA loans using a simple univariate test. In Table III, we report the means and differences between online banks and all other lender groups. In Panel B, we find that online bank loans are larger in size and longer in term with online loans being $284,000 larger and three years longer on average than other lender loans. Interest rates appear similar on a univariate basis. Online banks loans have a higher SBA guarantee with the average online bank loan being 79% guaranteed compared to the average of other lender loans at 64% guaranteed. Given the difference in guarantee percents, it is unsurprising Panel A shows that 76% of online bank loans are Standard/Small 7(a) loans made with Preferred Lender Status (PLP) (which carries a 75% to 85% rate) while only 3% of online bank loans are SBA Express (which carries a 50% guarantee rate). This compares to other lenders with 30% PLP loans and 51% SBA Express loans.

Non-online bank lenders have significantly higher rates of being paid in full. This is expected as much of the online bank loans are concentrated in the later half of the data. What cannot be explained by an increasing market share is that online bank loans are associated with an increased rate and dollar amount of charge-offs. Online loans have an average charge-off to loan (the amount charged off divided by the total loan amount) of 7.3% compared to other lenders at 3.5%. Additionally, online loans have an average SBA loss to loan (the amount charged off times the SBA guarantee percent divided by the total loan amount) of 5.5% which is three percentage points higher than that of other lenders.

Looking at the differences in fees between online banks and other lenders, we see that online bank loans carry higher upfront, ongoing, and prepayment fees. Online bank loans have, on average, about $7,000 higher upfront guarantee fees, $8,000 higher ongoing servicing fees, and $400 higher prepayment fees than loans of other lenders. This is expected as these fees are determined by size and maturity and online banks loans are larger in size and longer in maturity on average.

II.C SBA Loans: Amounts, Interest Rates, and Guarantees

With a more specialized business model, online banks are expected to behave differently than traditional lenders and may target specific loan features and types. The univariate evidence shows that these banks favor the SBA loan programs that carry higher guarantee rates compared to other banks. It is less clear that these banks charge higher interest rates or make larger loans, controlling for the type of borrower, geographic location, and the year when the loan is made. To test this, we estimate the following equation using loan-level data:

$$\begin{aligned}\text{Loan Variable}_{lct} = &\beta_1 \text{Online Bank}_b + \beta_2 \text{Loan Controls}_{lt} + \beta_3 \text{Borrower Controls}_{ft} \\ &+ \beta_4 \text{Bank Controls}_{bt} + \alpha_{ct} + \tau_{nt} + \varepsilon_{lct},\end{aligned} \tag{2}$$

where l, f, n, b, c, and t represent loan, borrower, borrower industry, lender, county, and year, respectively. *Loan Variable* is either the *Log Loan Amount*, *Interest Rate*, or *SBA Guarantee Percent*. The independent variable of interest is *Online Bank*, which is an indicator equal to one if the lender is classified as an online bank and zero otherwise. Loan controls include *Loan Size Group*, which is loan size grouped into terciles; *Revolver Status*, which is an indicator equal to one if the loan is a revolving line and zero if it is a term loan; *Initial Interest Rate* which is the interest rate at the time of approval; and *Log Term in Months*, which is the log of the loan term length as measured in months. Borrower controls include business type, *Business is Corporation* and *Business is Individual* (*Business is Partnership* is the excluded category), and *Branches in Zip Code*, which is the number of branches of SBA lenders in the borrower's zip code. Bank controls include *Bank Log Assets*, *Bank Deposits to Assets*, *Bank Return on Assets*, and *Bank Equity to Assets*. We include county-year fixed effects (α_{ct}) and industry-year fixed effects (τ_{nt}) to control for time-variant county and borrower industry characteristics. Standard errors are clustered at both the lender and borrower level.

In Table IV, column 1, we consider loan size. We find that online banks do not give larger loans, when accounting for other loan characteristics, borrower characteristics, and fixed effects. This finding is in contrast to the univariate evidence, which shows larger average loan sizes for online banks. This difference suggests that online banks target borrowers and loan types with larger loan amounts, but offer similar loan amounts as other lenders for these borrowers.

Another dimension of the lending decision is the interest rate on these loans. While the SBA mandates maximum caps on the interest rate, a substantial fraction of loans are originated below these caps. Indeed, only about 5% of loans are originated at the maximum cap rate. The average loan is priced at about 67% of its maximum. In column 2, we test whether online banks differentially price their loans.

We find that online banks charge 0.5% higher interest rates than other banks. This difference is significant at the 1% level and is economically large, given the sample standard deviation of 1.5%. This further supports the idea that online banks are being strategic in pricing their loans and points to two factors. First, insofar as the borrower, county, industry, and other controls do not fully capture the creditworthiness of a borrower, these banks are likely making loans to the riskier borrowers. Second, these banks are receiving higher income streams from these loans prior to default.

In column 3, we look at differences in the SBA guarantee rates. Consistent with online banks utilizing programs with higher guarantees, we see that their loans have a 4.6% higher guarantee rate on average. This difference is significant at the 1% level. This supports our hypothesis that online banks target loans with high guarantees even after we control for the borrower's location, industry, and the other loan attributes.

A potential concern is that the guarantee rates are determined by differences in borrower demand across online and non-online lenders, and is not driven by bank targeting. We address this concern in two ways. First, we consider the bunching of SBA loans around guarantee thresholds. In the left panel of Figure 3, we show the percent of loans issued at different amounts relative to the total number of Standard/Small 7(a) loans approved using Preferred Lender status (PLP) by online and non-online lenders in the sample. These loans have a guarantee rate up to 85% for loans up to $150,000. After that threshold the guarantee rates decrease to 75%. While loan amounts tend to cluster in units of $50,000, we see evidence of a bunching at the loan size of $150,000, consistent with the findings of Bachas, Kim, and Yannelis (2021). However, we document that this bunching is most concentrated in online lenders: they originate about 40% of their loans at this threshold compared to only around 10% for non-online lenders. Further, while non-online banks similar amounts on either side of the threshold (e.g., $100,000 versus $200,000), online banks concentrate their lending on the smaller loans that carry the higher guarantee rate. In the right panel of Figure 3, we look at the percent of loans issued at different amounts relative to the total number of SBA Express loans, which features a constant guarantee rate. Here we do not find an abnormal concentration of lending at the $150,000 threshold. Taken together, these patterns suggest that online banks target certain loan characteristics to achieve a higher guarantee.

As a second approach to address the concern that borrower decisions drive the observed guarantees, we re-estimate the effect of online banks on guarantee rates but apply more stringent fixed effects. The results are presented in Appendix Table A.6. In column 1 we include county-year fixed effects and industry-year fixed effects similar to Table IV. In column 2, we apply borrower and industry-year fixed effects and in column 3, we apply borrower-year fixed effects. Columns 2 and 3 restrict identification to differences in loan guarantees for the same borrower and the same borrower-year, respectively, which remove any borrower-specific factor that would lead to higher guarantee rates. We find that across the various specifications, online loans are consistently associated with 4.5-6% higher guarantee rate on average, which is significant at the 1%.

To ensure that our results are not motivated by online banks lending to borrowers without local SBA lending options, in unreported results we include an additional independent variable, *Distance to SBA Lender*, and its interaction with the variable *Online Bank* in our specification. *Distance to SBA Lender* is the physical distance in miles between the borrower and the nearest branch of an SBA lender. When including this variable and interaction, our results still hold, suggesting that they are driven by online bank behavior rather than by some demand or borrower effect.

II.D SBA Loans: Charge-Offs and Losses

Online banks charge higher interest rates and utilize programs with higher guarantees. To confirm if their loans are indeed riskier, we estimate the following equation:

$$\begin{aligned}\text{Loss Variable}_{lct} = &\beta_1 \text{Online Bank}_b + \beta_2 \text{Loan Controls}_{lt} + \beta_3 \text{Borrower Controls}_{ft} \\ &+ \beta_4 \text{Bank Controls}_{bt} + \alpha_{ct} + \tau_{nt} + \varepsilon_{lct}, \qquad (3)\end{aligned}$$

where *Loss Variable* is either *Charge-Off Status*, *Charge-Off to Loan*, *SBA Loss to Loan*, or *SBA Profit to Loan*. *Charge-Off Status* is an indicator equal to one if the loan is deemed as uncollectable by the lender and zero otherwise. *Charge-Off to Loan* is the amount deemed as uncollectable divided by the total loan amount. *SBA Loss to Loan* is the amount deemed as uncollectable multiplied by the SBA guarantee percent, net of fees paid to the SBA, divided by the total loan amount. *SBA Profit to Loan* is the total sum of fees (upfront guarantee fee, ongoing servicing fee, and prepayment fee) net the guaranteed portion of the default amount (in the case of a default), divided by the total loan amount. As with Equation (2), we include the aforementioned loan controls, borrower controls, bank controls, county-year fixed effects (α_{ct}), and industry-year fixed effects (τ_{nt}).

The results of this equation can be found in Table IV, columns 4-7. In column 4, we find that loans from online banks are 6.1% more likely to be charged off. This estimate is statistically significant at the 1% level and economically large, as the average charge-off rate is 5.3%. Turning to charge-off amounts, we find the average charge-off is over 4.8% higher for online lenders as a fraction of their lending, and statistically significant at the 1% level.

A central aspect to the SBA program is the guarantees. In the case of non-guaranteed loans, a bank with a high level of defaults would be seen as a poor performer that does not price its loans appropriately. In the case of guaranteed loans, lenders take into account the decreased cost of default when pricing loans and may be willing to accept higher rates of default. The guarantees allow online lenders to offset high charge-offs as the SBA covers a major portion of the losses.

The results for SBA losses are presented in column 6. We find the coefficient on *Online Bank* to be 3.495 with significance at the 1% level. The results for SBA profits are presented in column 7. We find the coefficient on *Online Bank* to be -0.039 with significance at the 1% level. These results imply that much of the losses of online bank charge-offs are transferred to the SBA. Online banks loans cost the SBA more than loans of other lenders. Given the SBA has broken even during many of the years in our sample, we can view this transfer as coming from either the guarantee fees paid by other lenders, the borrower collateral that is recovered, or in some years, government funds.

II.E Expected Guarantee Subsidy

While SBA fees being independent of borrower risk combined with high guarantees and defaults of online bank loans imply cross-subsidization, we aim to test this in a more direct way. We follow the methodology of Bachas, Kim, and Yannelis (2021) to generate an expected guarantee subsidy (Γ_i). This variable is the expected amount that the SBA pays for each loan, net of fees that they collect.

This variable is generated using the following steps. First, we predict the expected charge-off probability for each loan ($\hat{\pi}_i$). Next, we generate total expected fees paid to the SBA as a percent of the initial loan amount. We use the SBA-provided fee percents in Table A.3 to calculate fee amounts and assume that borrowers pay a fixed monthly payment until the given loan term, regardless of whether the loan defaulted or was prepaid. We sum the expected guarantee fee and each year of the expected ongoing serving fee then divide by the initial loan amount to get σ_i, or the total expected fees as a percent of the initial loan amount. This allows us to calculate the expected guarantee subsidy as $\Gamma_i = \gamma_i \times \hat{\pi}_i - \sigma_i$ where γ_i is the SBA guarantee percent, $\hat{\pi}_i$ is the expected charge-off probability, and σ_i is the total fees to loan amount. Going forward, we will refer to Γ_i as *Expected Guarantee Subsidy*.

While Bachas, Kim, and Yannelis (2021) use loan amount to estimate charge-off probability for each loan ($\hat{\pi}_i$), we augment our charge-off prediction model with additional borrower and lender controls. In our setting, it is important to our hypothesis of cross-subsidization to have a more accurate expected charge-off probability across lenders. We employ the following logistic regression:

$$\text{Charge-off}_l = \beta_1 \text{Loan Controls}_l + \beta_2 \text{Lender Controls}_{bt} + \beta_3 \text{Location Controls}_{ct} + \varepsilon_l, \tag{4}$$

where l, b, c, and t represent loan, lender, county, and year, respectively. *Loan Controls* include log loan amount, term in months, initial interest rate, an indicator for whether the loan was securitized, and an indicator for whether the loan is a revolver. *Lender Controls* include assets, return on assets, and a measure of lender specialization in SBA lending. *Location Controls* include unemployment rate and log per capita income. Using these controls to obtain predictions for loan charge-offs, we find a significant correlation coefficient between the actual charge-off and the expected charge-off probability (0.468). This contrasts with a correlation of 0.0697 if we only use loan amount as a explanatory variable, suggesting that these additional variables improve the prediction substantially.

In Table I, we note that the average *Expected Guarantee Subsidy* is 0.05%. This seems reasonable given the SBA's goal of using the fees that it collects to break-even. Turning to Panel A of Table V, we report the univariate difference in the expected guarantee subsidy measure between online and non-online banks. We find the average expected guarantee subsidy of online bank loans to be 2% while the average for other lenders remains at about 0%. This suggests that online bank loans cost the SBA more, suggesting a transfer from other lenders and the government to these online banks.

In Figure 4 we present the distributions of the expected guarantee subsidies for both online and non-online banks. As mentioned above, the average expected guarantee subsidy is higher for online banks. It is of interest to note that the distribution is more dispersed, with a greater standard deviation observed for online banks.

II.F Lenders Internal Rate of Return

To analyze whether the loan characteristics that online banks target induce higher loan profitability for online lenders, we estimate the lender's internal rate of return (IRR) based on the initial loan amount and the estimated annual cash flows that lenders might receive throughout the life of the loan.

To calculate the lender IRR, we make various assumptions to estimate yearly cash flows using the loan terms provided by the SBA. We first calculate an estimated monthly payment using the initial loan amount, initial interest rate, and term in months. For loans with an exempt status (those that are disbursed but have not yet been paid in full or charged off), we assume that borrowers pay this payment monthly for the full term of the loan. For loans that are paid-in-full, we assume that borrowers pay the estimated monthly payment until the given paid-in-full date, where we assume the remaining balance of the loan is paid. For loans that are charged off, instead of paying the estimated monthly payment, we assume that borrowers only pay the difference between the initial loan amount and the reported default amount. Borrowers pay this difference in equal monthly payments from the disbursement date until three months before the charge-off date. Upon the date of default, we assume that lenders receive the guaranteed portion of the charge-off amount (the default amount times the SBA guarantee percent).

In Table I of summary statistics, we estimate a mean lender IRR of 4.8% and a standard deviation of 4.9%. In Panel B of Table V, we find the mean of the lender IRR for online lenders to be significantly higher, almost 5% versus 4.86% for other lenders. In the top panel of Figure 5, we show the distributions of the lender's IRR for online lenders and other lenders.

To further understand the importance of guarantees to the profitability of SBA lending, we develop a simple simulation exercise assuming a reduction in the loan guarantee rates that the SBA pays to online lenders only. In scenario one, the loans of online lenders with guarantee rates above or equal to 75% or higher we assume receive only a 50% guarantee instead. In scenario two, we assume only loans with guarantees rates above or equal to 85% are set to 50%.

In the third scenario, we assume that loans from online lenders with guarantee rates of 90% and above are set to 50%. Panel B of Table V presents the results of these simple simulations. For scenarios one and two, the average online lender IRR decreases between 70 and 80 basis points. However, online lenders still have a higher IRR for the third scenario. These results imply that online lenders target a higher volume of loans with guarantee rates between 75% and 85% and less volume of loans with guarantee rates of 90% or more.

III Credit Access

III.A County Credit Supply

To understand which markets online banks lend to, we plot the percent of loans made by online banks in a county by the average of various economic market variables in Figure 6. The economic measures include: *Per Capita Income*, which is the average per capita income in the county; *Unemployment Rate*, which is the county's percent of labor force that is unemployed; *Scaled Bank HHI*, which is the sum of squared shares of local branch deposits in the county scaled by 10,000; *Credit Score*, which is the average credit score at the zip code level; *Household Income*, which is the average household income at the zip code level; *Percent Subprime*, which is the percent of borrowers designated as having a subprime credit rating (below 640) at a zip code level; and *Poverty Rate*, which is the average poverty rate in a given zip code. For the purpose of the figure, we average the zip-code-based economic measures to the county level. We find that county market share of online banks is negatively correlated with average per capita income, average credit score, and average household income. County market share of online banks is positively correlated with average unemployment, average bank HHI, average percent subprime, and average poverty rate. This implies that the market share of online banks is greater in economically depressed and underserved areas.

These patterns suggest that targeting high guarantee rates may cause online banks to lend more in economically distressed areas. Indeed, in Figure 7, we plot the average SBA guarantee by the same economic market variables and notice similar patterns. The average SBA guarantee in a county is positively associated with unemployment rate, bank HHI, percent of subprime lenders, and poverty rate. It is negatively associated with per capita income, credit scores, and household income. Although guarantee rates are dictated by the specific SBA program used and not the borrower's location, the online banks lending activities drive the strong correlations documented in Figure 7.

A central question is whether online banks focus their lending supply into these more depressed regions. After all, a primary purpose of the SBA is to extend credit to borrowers that would not receive it otherwise. If other lenders actively avoid these regions and these regions have lower credit demand, this combination could drive the observed market shares. To better understand the credit allocation across counties, we organize the data into bank-county-year observations and split the counties into terciles based on the county-level measures of *Per Capita Income*, *Unemployment Rate*, and *Scaled Bank HHI*. This allows us to see if more economically disadvantaged counties receive more credit supply from online banks.[4] We estimate the following equation:

$$\begin{aligned}\text{Log Loan Amount}_{bct} = &\beta_1 \text{Online Bank}_b \\ &+\beta_2 \text{Online Bank}_b \times \text{Bottom Tercile Economic Variable}_{ct} \\ &+\beta_3 \text{Online Bank}_b \times \text{Top Tercile Economic Variable}_{ct} \\ &+\beta_4 \text{Controls}_{bt} + \alpha_{ct} + \varepsilon_{bct}, \end{aligned} \tag{5}$$

where b, c, and t represent lender, county, and year, respectively, and *Log Loan Amount* is the log of a lender's total amount loaned in a county-year. The independent variable *Online Bank* is an indicator equal to one if the lender is classified as an online bank and zero otherwise. For

[4]A similar specification but using continuous versions of these economic variables is presented in Appendix Table A.7.

each economic variable, the middle tercile is the excluded category, meaning the estimates for the other terciles are relative to it.[5] We control for bank log assets (*Log Assets*), total bank deposits divided by total bank assets (*Deposits to Assets*), bank ROA (*Return on Assets*), total bank equity divided by total bank assets (*Equity to Assets*). We include α_{ct} as county-year fixed effects to address time-variant county characteristics. These fixed effects control for the level of credit demand in a county and allows us to interpret the regression coefficients as measures of credit supply (Khwaja and Mian, 2008). Standard errors are clustered at the bank level.

The results of this equation can be found in Table VI. Column 1 includes *Online Bank*, the interaction between *Online Bank* and *Bottom Tercile Per Cap Income*, and the interaction between *Online Bank* and *Top Tercile Per Cap Income*. We find that the coefficient on *Online Bank* $\times$ *Bottom Tercile Per Cap Income* is 0.289 and significant at the 1% level while the coefficient on *Online Bank* $\times$ *Top Tercile Per Cap Income* is insignificant. This estimate implies that for the counties with the lowest per capita income, online banks provide 34% more credit to these counties than the middle tercile counties.[6] Column 2 includes *Online Bank*, the interaction between *Online Bank* and *Bottom Tercile Unemployment*, and the interaction between *Online Bank* and *Top Tercile Unemployment*. We find that the coefficient on *Online Bank* $\times$ *Bottom Tercile Unemployment* is insignificant but the coefficient on *Online Bank* $\times$ *Top Tercile Unemployment* is 0.336 and significant at the 1% level. This estimate implies online banks provide about 40% more credit to the most unemployed counties compared to the middle tercile.[7] Taken together, these results show that online banks focus much of their lending in either the poorest or most economically-troubled counties, given they have about 30-40% more lending in these counties compared to the middle tercile counties. There is relatively little difference between the economically mid-level and strongest counties in terms of loan supply by these online banks.

Turning to bank competition, column 3 includes *Online Bank*, the interaction between *On-*

[5]The standalone versions of these tercile variables are absorbed by the county-year fixed effects.
[6]The calculation is $e^{.289} - 1 = .335$.
[7]The calculation is $e^{.336} - 1 = .399$.

line Bank and *Bottom Tercile HHI*, and the interaction between *Online Bank* and *Top Tercile HHI*. We find that the coefficient on *Online Bank* × *Bottom Tercile HHI* is -0.213 and is significant at the 1% level and the coefficient on *Online Bank* × *Top Tercile HHI* is 0.126 and is significant at the 1% level. Here the relationship is more linear—online banks provide more loan supply as counties have less local banking competition. Overall, the findings in Table VI suggest that online banks lend more in areas with lower income, higher unemployment, and lower bank competition and less in areas with higher bank competition.

III.B Minority Credit Supply

We find evidence that online banks supply more credit to economically-worse counties. This credit access is in line with the goals of the SBA. A second element of the SBA is to provide credit to groups who have traditionally been underserved, such as women-owned and minority-owned businesses. We therefore look at whether online bank behavior increases credit access for these groups. To test this we estimate the following equation using the matched loan-level data:

$$
\begin{aligned}
\text{Log Loan Amount}_{lct} = & \beta_1 \text{Online Bank}_b + \beta_2 \text{Online Bank}_b \times \text{Ownership}_f && (6) \\
& + \beta_3 \text{Ownership}_f + \beta_4 \text{Loan Controls}_{lt} + \beta_5 \text{Borrower Controls}_{ft} \\
& + \beta_6 \text{Bank Controls}_{bt} + \alpha_{ct} + \tau_{nt} + \varepsilon_{lct}, && (7)
\end{aligned}
$$

where l, f, n, b, c, and t represent loan, borrower, borrower industry, lender, county, and year, respectively, and *Log Loan Amount* is the log of the total loan amount. The key independent variables are *Online Bank*, an indicator equal to one if the lender is classified as an online bank and zero otherwise; *Ownership*, the self-identified ownership status of the borrower such as minority or woman owned; *Online Bank* × *Ownership*, the interaction between the two. In effort to separate the relationship, we include loan, borrower, and bank controls. Standard errors are clustered at both the bank and firm level.

In Table VII, we report the results for this equation. We find that the coefficients on *Woman Owned*, *Minority Owned*, and *Hispanic Owned* to be positive and significant while the coefficients on the interactions terms are negative and significant. Conditional on getting a loan, these groups of borrowers receive smaller loans from online banks than from other lenders. This suggests that online banks do not create an expansion in credit supply to minorities or women-owned businesses.[8]

For robustness, in Table A.10 we repeat our analysis using only observations that self-identify into at least one of the SBA business type categories to reduce the likelihood that our results are driven by a greater number of borrowers of online banks choosing not to self-identify. We find directionally similar results after dropping observations, although not statistically significant. Additionally, we collapse the business ownership variables at the bank-county-year level and repeat our analysis in Table A.11, regressing the log of total lender-county loan amount on the online bank indicator, the percent of loans made to minority groups, and their interactions. We find the interactions between online and the minority group percentages to be negative and insignificant. This suggests that our results are not driven by reduced demand or demand for lower loan amounts from minorities.

IV Loan Performance Across Different Areas

We have established that online banks make loans through the SBA with higher guarantees and higher interest rates. These loans also have higher charge-offs and SBA losses. We also find that much of the online banks' credit is supplied to areas with the lowest income, highest unemployment, and lower levels of banking competition. Given this concentration of lending,

[8]Tables A.8 and A.9 present the other loan variables (interest rate, guarantee rate, charge-off status, charge-off amount, SBA loss), allowing for differential effects for minority-owned and women-owned businesses, respectively. We note that overall, loans to minorities and women are less likely to default and are less costly to the SBA. Although, loans to minorities and women that are made by online banks are more likely to default and cost the SBA more.

a natural question is whether these specific loan performance results are concentrated in these markets. We therefore assess how these charge-offs and losses differ across economic markets. We estimate the following equation:

$$
\begin{aligned}
\text{Loan Perf. Variable}_{lct} = & \beta_1 \text{Online Bank}_b + \beta_2 \text{Online Bank}_b \times \text{Economic Variable}_{ZIPt} \\
& + \beta_3 \text{Economic Variable}_{ZIPt} + \beta_4 \text{Loan Controls}_{lt} \\
& + \beta_5 \text{Borrower Controls}_{ft} + \beta_6 \text{Bank Controls}_{bt} + \alpha_{ct} + \tau_{nt} + \varepsilon_{lct}, \qquad (8)
\end{aligned}
$$

where l, f, n, b, ZIP, c, and t represent loan, borrower, borrower industry, lender, zip code, county, and year, respectively. *Loan Performance Variable* is one of three variables: *Charge-Off Status*, *Charge-Off to Loan*, and *SBA Loss to Loan*. These variables are the same as used in Section II.D. In this analysis, we include zip code economic market measures *Log Credit Score*, *Log Income*, *Subprime*, and *Poverty Rate* and the interactions between *Online Bank* and these measures. The zip-code-level controls allow for a finer gradation of different areas. As with previous regressions, we include loan controls, borrower controls, and bank controls. To restrict the effect of time-variant local demand and industry characteristics, we incorporate county-year and industry-year fixed effects, α_{ct} and τ_{jt}. We report standard errors clustered at the lender and borrower level.

Panel A of Table VIII reports results for *Charge-Off Status*. Like in Table IV, we see a positive and significant relationship between online bank status and charge-off status. We note that, as expected, higher charge-offs are associated with economically depressed areas. It is of interest that the coefficients on the interaction terms between online bank status and the economic market measures are all near zero and insignificant. This suggests that online banks charge-off rates are affected in a similar manner by local economic conditions as other lenders. This implies that online banks target or attract a specific loan profile or demographic associated with higher charge-offs. This loan profile or demographic does not vary by region and is consistent with online banks' market not being defined geographically.

Next, in Panel B of Table VIII, we turn to *Charge-Off Amount*. We see a positive and significant relationship between online bank status and charge-off to loan. The percent of the loan charged off is positively associated with poorer areas. The coefficient on *Log Credit Score* in column 2 is -2.989 and is significant at the 1% level, the coefficient on *Log Income* in column 3 is -0.679 and is significant at the 1% level, and the coefficient on *Subprime* in column 4 is 0.012 and is significant at the 1% level. The coefficient on *Poverty Rate* in column 5 is positive but insignificant. Therefore, the other lenders experience higher losses in these zip codes compared to other zip codes within the same county. Turning to online banks, there is no significant relationship between the interaction terms and *Charge-Off to Loan*.

Finally, we consider *SBA Loss to Loan* in Panel C of Table VIII. We see a positive and significant relationship between online bank status and SBA losses, confirming that online banks loans cost more to the SBA than loans from other lenders. As expected, the SBA loss to loan is greater in economically-disadvantaged areas. The relationship between *SBA Loss to Loan* both *Log Credit Score* and *Log Income* is significant and negative while the relationship between *SBA Loss to Loan* and *Subprime* is positive and significant. With no significant relationship between the interaction terms and *SBA Loss to Loan*, we find that the online bank SBA losses evolve similarly to other lenders across geographies. Together, the charge-off and SBA loss results indicate that online banks target certain loan attributes or demographics as their loan outcomes do not vary according to expected location outcomes.

V Identification Strategy: Exogenous Shock to the Credit Supply of Online Lenders

V.A Institutional details

In this section, we provide some additional evidence that the effects of online lenders on credit access are causal. To achieve this, we test the effects on credit supply of a regulatory change that impacted the secondary market of SBA loans in October 2017. Lenders participating in the SBA loan guarantee program may opt to sell the guaranteed portion of their 7(a) loans. Assemblers subsequently pool the loans into SBA-guaranteed 7(a) pass-through securities and sell them to institutional investors in the secondary market.[9] Guaranteed portions typically trade at a considerable premium, making these loans attractive for securitization.

Lenders who opt to securitize the guaranteed portion of the 7(a) loans can generate liquidity to re-lend those dollars to other small businesses or to fund other lending activities. Those lenders give up long-term earnings for the up-front income (premium) and earn a servicing fee on the guaranteed portion. The secondary market assemblers form the SBA pools as a modified pass-through. The terms of pool loans can differ from the security's terms. This mismatch creates excess amortization at the pool level. Because the underlying loans often amortize at a faster rate than the pool's balance, the sum of current balances at the loan level is often less than the pool's trading balance. The SBA remits the excess of amortization to the pool holders. Before the 10/2017 SBA regulation change, the excess principal accumulated over time and was paid out when the last loan is paid off or the pool matured. After the regulation became effective, all excess principal held in pools created between 10/1/2004 and 9/1/2017 was reallocated to the unpaid loans in that pool on a pro-rata basis, regardless of its origin.

In addition, the SBA increased the minimum maturity ratio (MMR), the ratio between the shortest and longest remaining loan maturity in the pool, from 70% to 94%. The changes increased prepayment speeds on affected pools, according to industry research (Clark, 2018, 2019). Because prepayments can lead to yield volatility, making it challenging for investors to accurately predict the returns on their investments, investors would demand a higher premium to hold those securities. In principle, we should see a lower propensity to securitize SBA loans after the regulatory change.

Online lenders are more prone to securitize the guaranteed portion of the SBA loans. We document in Panel B of Table III that online lenders securitize 92% of their loans originated

[9] See `https://www.sba.gov/document/support--sba-secondary-market-program-securitizations-guide`.

in the sample while other lenders securitize only 23% of their originated loans. These simple statistics suggest that online lenders have a loan-originating model to sell and not hold these loans. We therefore exploit the regulatory change on the secondary market as a plausibly exogenous shock to the credit supply of online lenders because they are the banks with a model of originate to sell. In Figure 8, we plot the time-series variation in the ratio of loans that are securitized in our sample. During the sample period, online lenders have a higher ratio of securitization relative to the other lenders. However, after the year 2017 online lenders reduce their propensity to securitize the SBA loans.

V.B Empirical Design

We hypothesize that the SBA secondary market regulatory changes in October 2017 affected online lenders' incentives to originate SBA loans, particularly for long-term loans that are more likely to be included in the pools. We interpret the regulatory change as a negative shock to the credit supply of online lenders, and we test this hypothesis using a triple differences-in-differences approach. Specifically, we run the following regression specification:

$$
\begin{aligned}
\text{Credit Supply Variable}_{lct} = & \beta_1 \text{Online Bank}_b + \beta_2 \text{Online Bank} \times \text{Post}_{bt} \\
& + \beta_3 \text{Online Bank} \times \text{Treatment} \times \text{Post}_{lbt} + \beta_4 \text{Online Bank} \times \text{Treatment}_{lb} \\
& + \beta_5 \text{Treatment} \times \text{Post}_{lt} + \beta_6 \text{Treatment}_l + \beta_7 \text{Loan Controls}_{lt} \\
& + \beta_8 \text{Borrower Controls}_{ft} + \beta_9 \text{Bank Controls}_{bt} + \alpha_{ct} + \tau_{nt} + \varepsilon_{lct},
\end{aligned}
\tag{9}
$$

where l, f, n, b, c, and t represent loan, borrower, borrower industry, lender, county, and year, respectively. *Credit Supply Variable* includes the log of the gross loan amount and the initial interest rate as measures of loan credit supply. *Online* is an indicator equal to one is the lender is classified as an online bank and zero otherwise. *Treatment* equals one if the loan's term is greater than or equal to seven years and equals zero otherwise. Loans with longer maturities are those that are effected by the regulation change. *Post* indicates that the loan was made after the policy change in October 2017. Loan controls include *Loan Size Group*, *Revolver Status*, *Initial Interest Rate* and *Securitized*. Borrower controls include *Business is Corporation*, *Business is Individual*, and *Branches in Zip Code*. Bank controls include *Bank Log Assets*, *Bank Deposits to Assets*, *Bank Return on Assets*, *Bank Equity to Assets*, and *Percent Securitized*. We include county-year fixed effects (α_{ct}) and industry-year fixed effects (τ_{nt}) to control for time-variant county and borrower industry characteristics. Standard errors are clustered at both the lender and borrower level.

We repeat this specification at the bank-county-year level, modifying Equation (9) to fit the data format. *Credit Supply Variable* becomes the log of the total loan origination and the weighted average interest rate. The key independent variables *Online* and *Post* remain indicators of the lender being an online bank and the period being post-regulatory change, respectively. *Treatment* becomes the percent of loans with maturities of seven years or more. We do not include loan or borrower controls but do employ the same bank controls. We include county-year fixed effects (α_{ct}) to control for time-variant county characteristics. Standard errors are clustered at the lender level.

Table IX shows the results for Equation (9). Column 1 shows a negative and statically significant coefficient for the triple interaction term Online Bank $\times$ Treatment $\times$ Post: the amount of originated loans of longer-term maturity of online banks decreased by 57% after 2017. The left plot of Figure 9 shows the event-time variation of the coefficient, excluding the year of the regulatory change. The year-by-year coefficient after 2017 is negative and significant, with a 95% confidence interval. Column 3 shows similar results after aggregating loan amounts at the bank-county-year. The magnitude and trend of the coefficient are similar to the loan-level results. Columns 2 and 4 show the regression analysis results using the initial interest rate as the outcome variable. The triple interaction coefficient is negative and significant for the interest rate, but once we dropped the year of the shock, the right panel of Figure 9 shows the coefficient is statistically close to zero. We find a similar conclusion if we use the bank-county level analysis (Figure 10).

VI Conclusion

Changes in the banking and lending space, such as regulation, consumer preferences, and technological innovation, have generated the entrance and expansion of a new class of non-traditional lender. While the literature has addressed much of the impact of shadow and nonbank fintech lenders, we focus on the behavior and effects of online banks who specialize in particular activities across broad geographic areas. These online banks are FDIC-insured institutions that perform all operations online. Unlike traditional banks, the application of technology allows them to make lending decisions using hard rather than soft information and lend at a distance. Therefore, they are not limited to borrowers in their immediate geography and can seek loans from any market.

In this paper, we examine the effect of these online banks in small business lending, using SBA 7(a) program data. We find that online banks specialize in SBA lending and are more concentrated in the types of products that they offer. Within the SBA market, online banks focus on a group of borrowers that are riskier and not ripe for cross-selling. This specialization causes online banks to target certain loan characteristics and to concentrate their lending in specific markets. We find that online banks lend more in areas that are economically disadvantaged and underserved by existing banks, suggesting an increase in credit access.

An important aspect of our paper is our setting of the SBA market. We find that online banks use features of the SBA program to target riskier loans while lowering the cost of default to them. Specifically, they target loans with high guarantees and charge higher interest rates on these loans. Online bank loans are associated with higher defaults and higher default amounts. Given the combination of higher guarantee percents and higher defaults, online banks loans cost more to the SBA than loans of other lenders. Since all lenders pay fees on SBA loans that are unrelated to likelihood of default, this results in a transfer of the fees of other lenders, and occasionally, funds from the government, to online banks.

The findings of our paper have become increasingly important as the SBA opens its programs to fintech nonbanks. Historically, nonbanks have only been granted limited access in SBA programs. As of May 2023, the SBA has removed lender restrictions, allowing nonbanks full participation. Therefore, understanding how lenders driven by technology and a more specialized business model behave and impact the SBA market is essential given the current policy changes.

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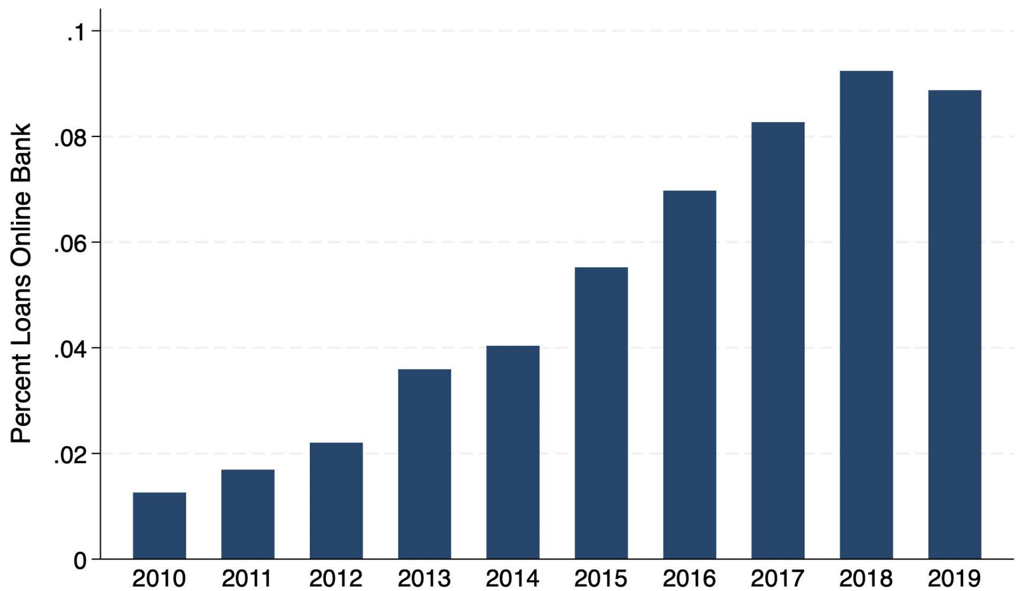

Figure 1: Online Bank Market Share by Number of Loans Over Time

This table displays the percent of loans in the SBA 7(a) program that are made by online banks each year from 2010 to 2019.

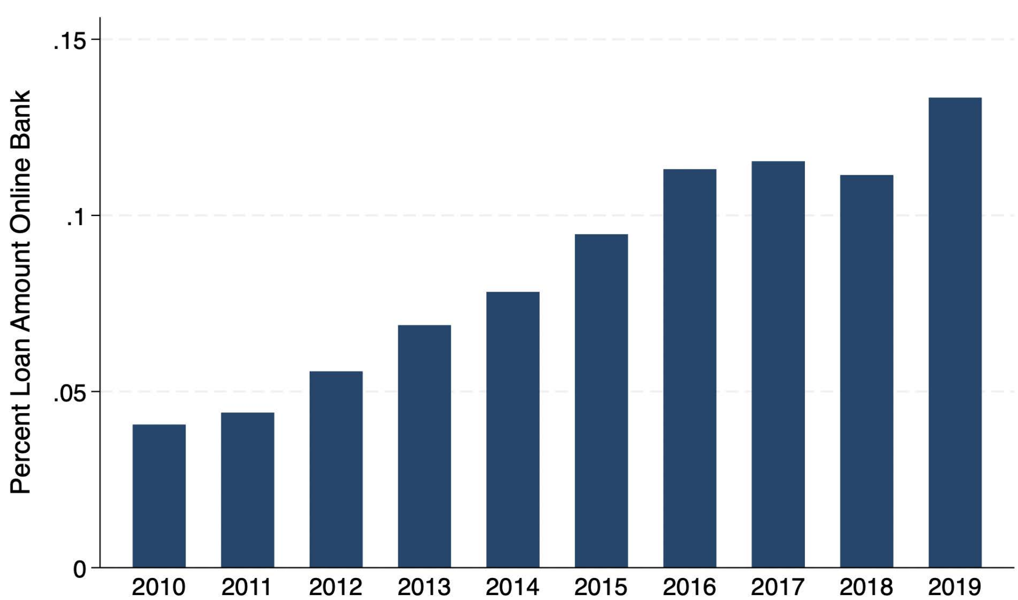

Figure 2: Online Bank Market Share by Loan Amount Over Time

This table displays the percent of total loan amount in the SBA 7(a) program that are made by online banks each year from 2010 to 2019.

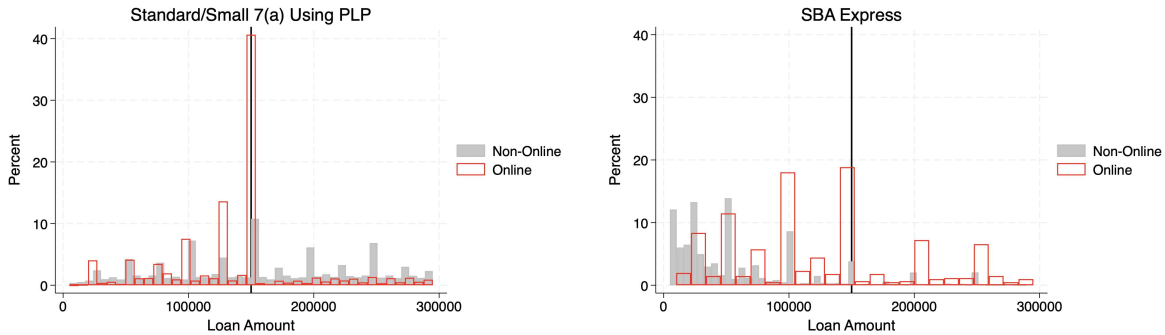

Figure 3: Percent of Loans in Program by Loan Amount

This figure displays the percent of total loans by loan amount of individual SBA programs for online banks and for non-online bank lenders. The graph on the left is restricted to Standard/Small loans made with Preferred status and the graph on the right is restricted to to loans in the SBA Express program. The vertical line marks $150,000 as the guarantee percent threshold for Standard/Small loan to visualize bunching at the threshold.

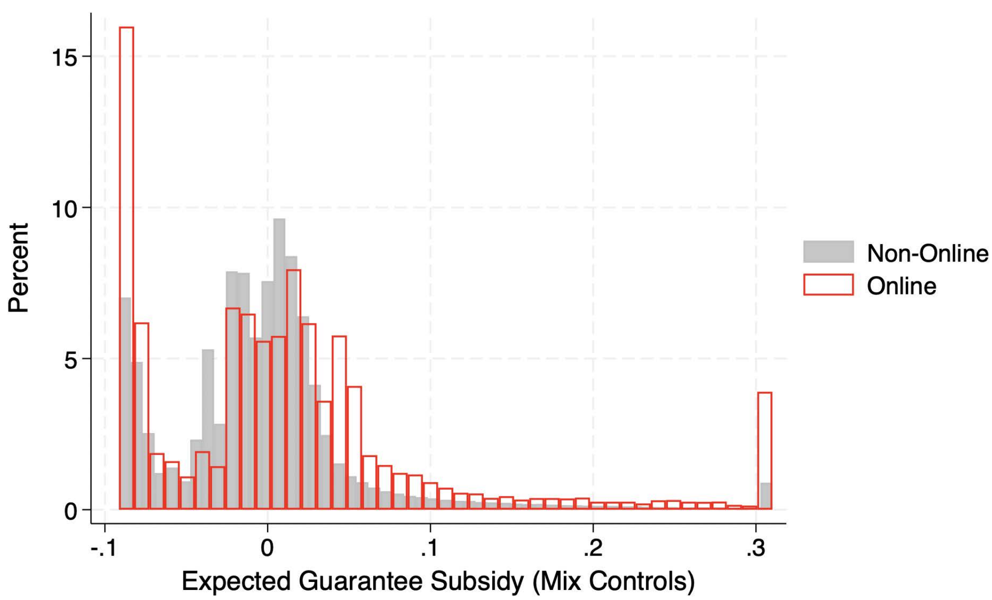

Figure 4: Percent of Loans by Expected Guarantee Subsidy

This figure displays the percent of total loans by expected guarantee subsidy calculated using loan, lender, and location controls for online banks and for non-online bank lenders.

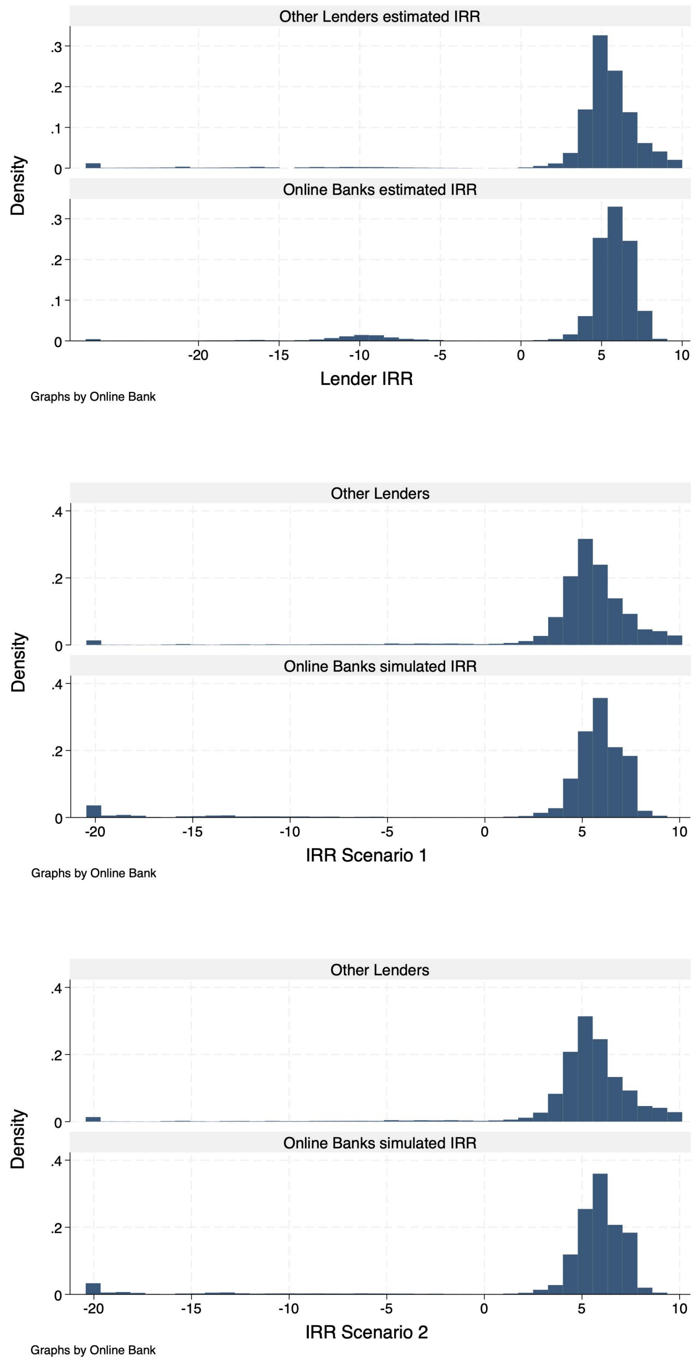

Figure 5: Estimated IRR and IRR Simulations

This figure shows in the top panel the histograms of the estimated lenders' Internal Rate of Return (IRR) based on the loan cash flows. The second panel shows the lenders' simulated IRR assuming a reduction of loan guarantees for online lenders from 75% or more to 50% (scenario 1). The third panel shows the lenders' simulated IRR assuming a reduction of loan guarantees for online lenders from 85% or more to 50% (scenario 2).

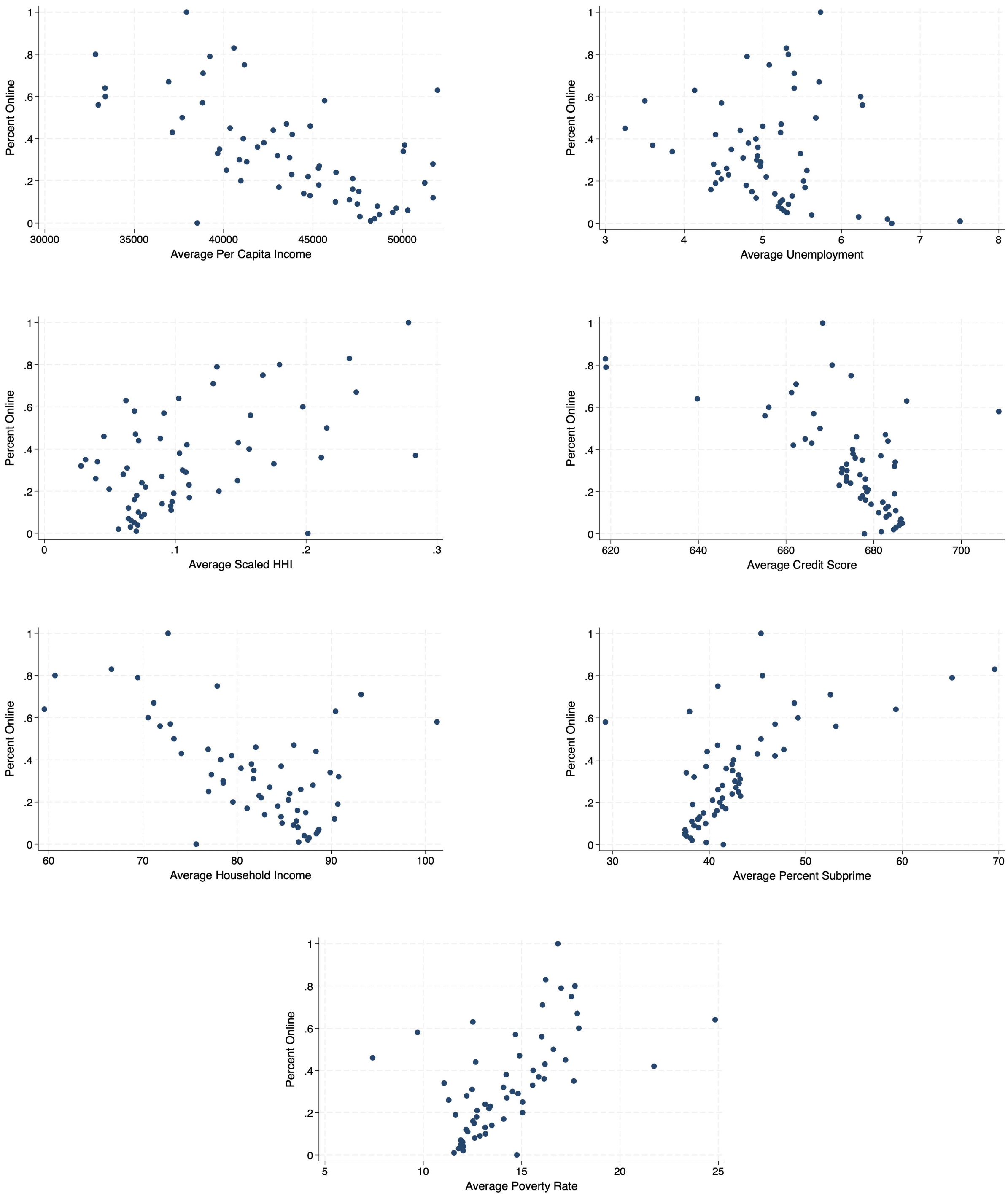

Figure 6: Percent Online by Average Economic Measures

Employing county-level data, these figures present the average of various economic measures by the percent of loans that are made by online banks. The measures used are the per capita income, unemployment rate, bank concentration (scaled HHI), credit score, household income, percent of borrowers that are classified as subprime, and poverty rate.

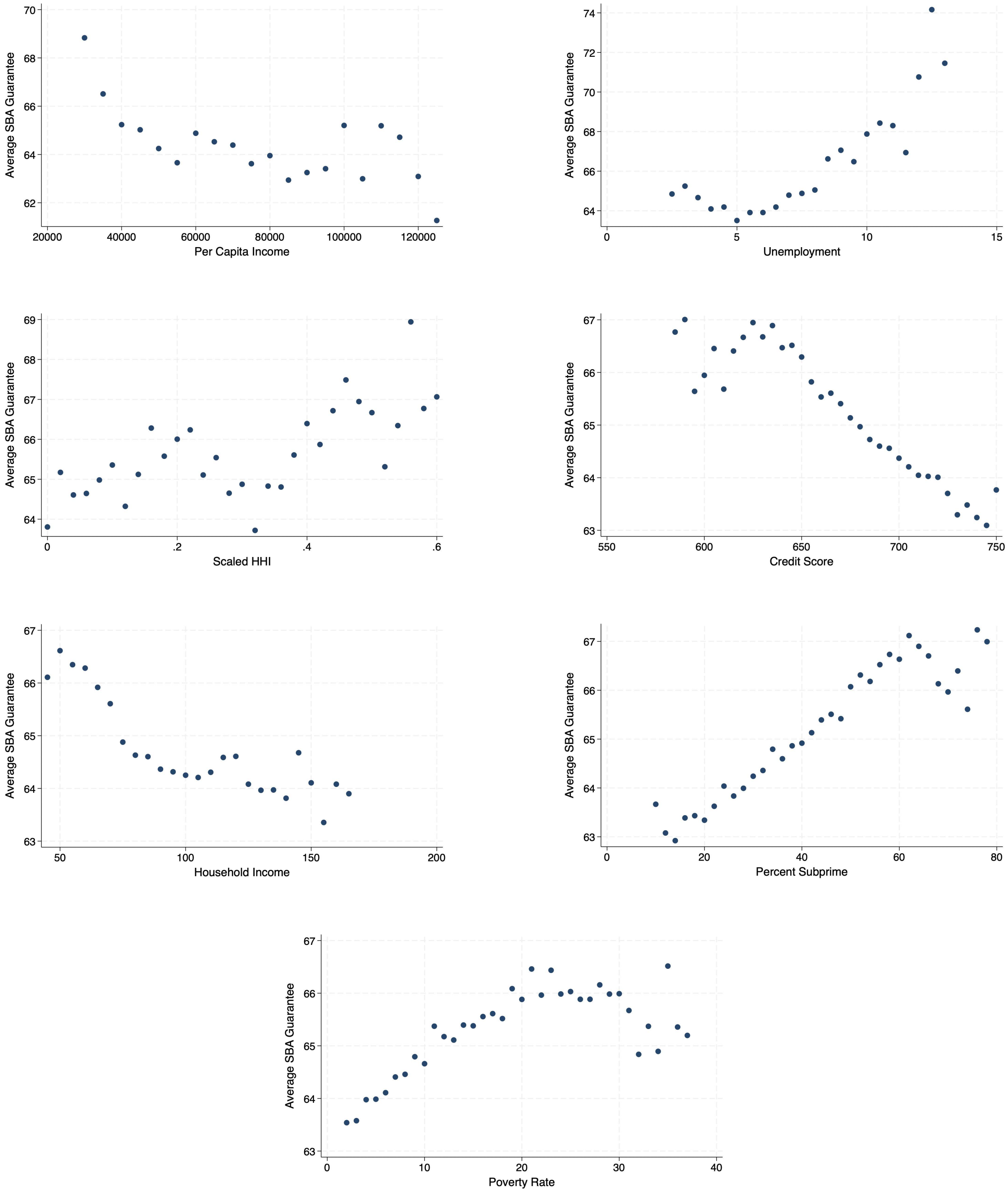

Figure 7: Average SBA Guarantee by Economic Variables

Employing county-level data, these figures display the average percent guaranteed on SBA loans by the various local economic measures. The measures used are the per capita income, unemployment rate, bank concentration (scaled HHI), credit score, household income, percent of borrowers that are classified as subprime, and poverty rate.

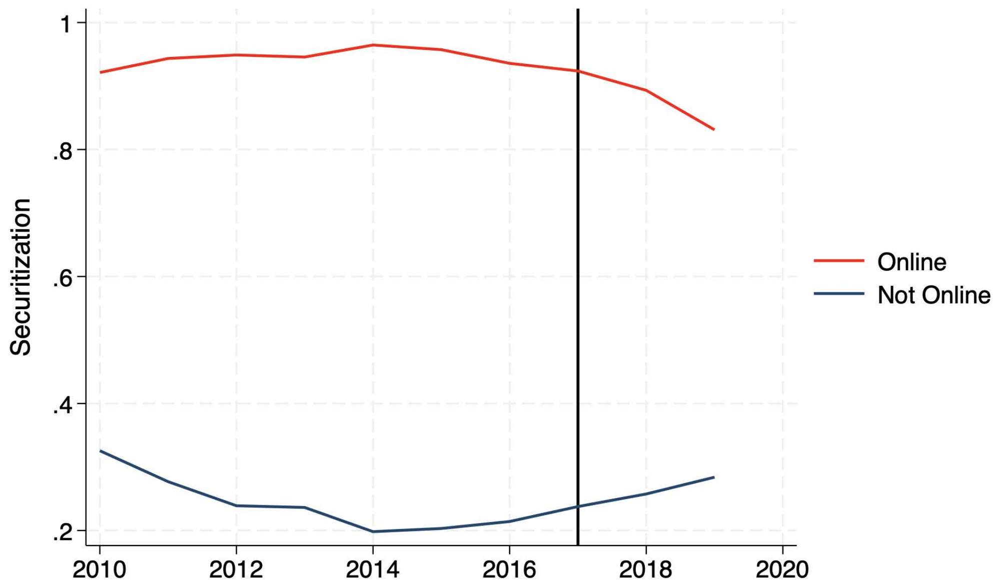

Figure 8: Percent of Loans Securitized Over Time

This figure examines the percent of loans that are sold on the secondary market by online and non-online lenders from 2010 to 2019. The vertical line characterizes the cutoff between the pre- (2010-2017) and the post- (2018-2019) periods.

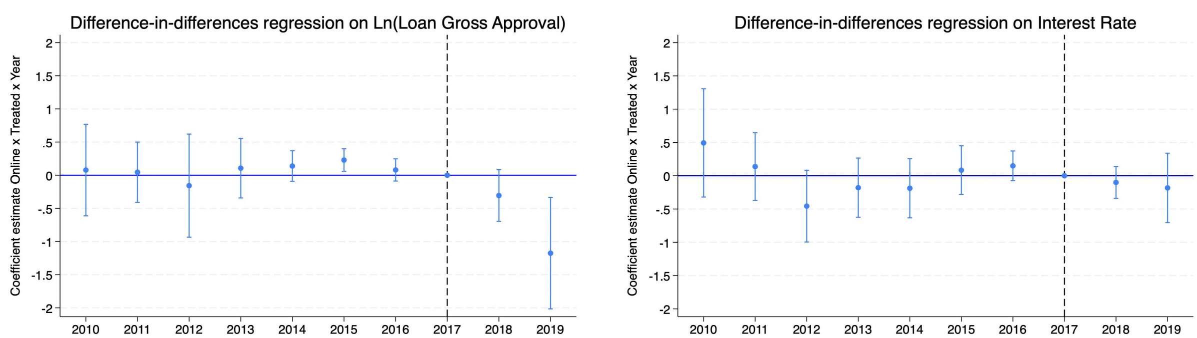

Figure 9: Difference-in-Differences Regression: Loan Level

This figure shows the Online × Treatment × Post coefficient estimates and 95% confidence intervals over the sample period where observations are at the loan level. The left plot displays coefficients with the dependent variable being the log of the gross loan amount, while the right plot displays coefficients with the dependent variable being the loan's interest rate. The vertical line distinguishes between the pre-regulatory change period (2010-2017) and the post-regulatory change period (2018-2019).

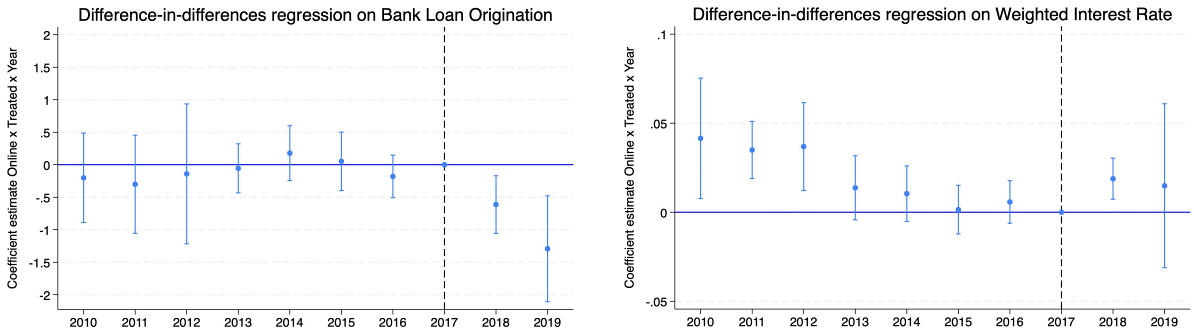

Figure 10: Difference-in-Differences Regression: Bank-County Level

This figure shows the Online $\times$ Treatment $\times$ Post coefficient estimates and 95% confidence intervals over the sample period where observations are at the bank-county level. The left plot displays coefficients with the dependent variable being the log of the total bank loan origination, while the right plot displays coefficients with the dependent variable being the weighted average interest rate. The vertical line distinguishes between the pre-regulatory change period (2010-2017) and the post-regulatory change period (2018-2019).

Table I: Summary Statistics

This table reports summary statistics of the main analysis variables. Our sample is from 2010-2019. The columns report the mean, standard deviation, 25th percentile, median, 75th percentile, and number of observations, respectively. *Loan Variables* consist of SBA 7(a) loan observations, excluding loans with a cancelled status and those missing primary variables. *Bank Variables* are reported at the year level for each lender. *County Variables* are constructed at the county-year level. *Zip Code Variables* are constructed at the zip-code-year level. *Minority-Matched Loan Variables* are reported at the loan level for each of the matched loan observations. For variable descriptions, see Appendix Table A.1.

	Mean	Std Dev	25th Pctile	Median	75th Pctile	# Obs.
Loan Variables						
Online Lender	.0548	.23	0	0	0	458,938
Loan Amount ($ thousands)	378	672	40	125	361	458,938
Initial Interest Rate (%)	6.54	1.5	5.5	6	7.4	458,938
SBA Guarantee (%)	64.9	15	50	75	75	458,938
Charge Off	.0514	.22	0	0	0	458,938
Charge Off Amount ($)	6,451	61,237	0	0	0	458,938
Charge Off to Loan (%)	3.75	17	0	0	0	458,938
Securitized	.28	.45	0	0	1	366,779
SBA Loss to Loan (%)	2.29	10	0	0	0	458,938
SBA Profit to Loan (%)	.00012	.12	.0023	.019	.039	458,938
Lender IRR (%)	4.81	4.8	5	5	6	458,911
Exp. Guarantee Subsidy (%)	.0464	7.3	-3.5	-0.33	1.9	342,466
Revolver Status	.311	.46	0	0	1	458,938
Term in Months	122	79	84	84	120	458,938
Business is Corporation	.875	.33	1	1	1	458,938
Business is Individual	.107	.31	0	0	0	458,938
Business is Partnership	.0187	.14	0	0	0	458,938
Business Age	2.12	1.4	.5	2.5	2.5	61,001
Branches in Zip Code	6.64	5.2	3	6	10	400,452
Distance to SBA Lender	.481	1.8	0	0	0	405,717
Total Fees (%)	2.47	2.3	.52	1.9	3.9	458,938
Guarantee Fee (%)	1.14	1.1	0	1	2.3	458,938
Ongoing Fee (%)	1.29	1.5	.24	.88	1.7	458,938
Prepayment Fee (%)	.0355	.3	0	0	0	458,938

Table I: Summary Statistics - *Continued*

	Mean	Std Dev	25th Pctile	Median	75th Pctile	# Obs.
Lender Variables						
Log Assets	13.1	1.5	12	13	13.8	13,677
Deposits to Assets	.833	.057	.8	.84	0.88	13,677
Return on Assets	.94	.72	.62	.95	1.30	13,677
Equity to Assets	.105	.023	.089	.1	0.12	13,677
Balance Sheet Asset HHI	1,326	502	992	1,186	1500.6	13,677
Balance Sheet Liabilities HHI	6,137	1,105	5,373	6,108	6876.1	13,677
Income HHI	3,051	1,139	2,241	2,849	3581.7	13,677
Loans HHI (CR)	2,056	780	1,545	1,841	2293.0	13,677
Loans HHI (SDI)	2,838	1,008	2,136	2,610	3226.9	13,677
SBA to Total Loans	.0227	.096	.0014	.0043	.014	13,677
Loan Categories (SDI)	10.9	2	10	11	12	13,677
County Variables						
County Per Cap Income ($)	40,757	11,975	33,566	38,527	45059	21,190
County Unemployment (%)	6.29	2.7	4.2	5.7	7.90	21,190
County Scaled HHI	.174	.16	.068	.13	0.23	21,190
County Per Cap Establishments	.0231	.0082	.018	.022	0.026	21,190
Zip Code Variables						
Zip Code Credit Score	681	41	654	685	710.8	114,737
Zip Code Income	84.9	26	67	80	98.0	114,737
Zip Code Subprime Rate	39.8	17	28	38	50.5	114,737
Zip Code Poverty Rate	12.6	7.8	6.7	11	16.7	114,737
Minority-Matched Loan Variables						
Online Lender	.0588	.24	0	0	0	274,463
Woman Owned	.00829	.091	0	0	0	274,463
Minority Owned	.00674	.082	0	0	0	274,463
Black Owned	.0018	.042	0	0	0	274,463
Hispanic Owned	.00222	.047	0	0	0	274,463

Table II: Online Banks and Specialization

The table uses data at the bank-year level from 2010-2019. The dependent variables are all measures of specialization and are balance sheet assets HHI, balance sheet liabilities HHI, Income HHI, Loans HHI (CR), Loans HHI (SDI), Loan Categories (SDI), and SBA to Total Loans (CR). The primary independent variable of interest is online bank, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise. We control for bank characteristics: lag log assets, lag deposits to assets, lag return on assets, and lag equity to assets. We include year fixed effects. Standard errors are clustered at the bank level.

Specialization Measure	Assets HHI	Liabilities HHI	Income HHI	Loans HHI (CR)	SBA to Total Loans	Loans HHI (SDI)	Loan Categories
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Online Bank	344.173***	503.918*	452.093*	584.661***	0.122***	490.408*	-2.036***
	(122.419)	(283.064)	(258.039)	(198.514)	(0.024)	(252.190)	(0.475)
Log Assets	-68.504***	-189.712***	-133.839***	-91.964***	-0.007***	-95.126***	0.634***
	(8.034)	(16.952)	(17.972)	(13.554)	(0.001)	(17.390)	(0.028)
Deposits to Assets	-1816.804***	7288.362***	-672.005	-2591.345***	0.012	-2381.506***	4.437***
	(270.991)	(361.679)	(485.831)	(411.950)	(0.015)	(495.873)	(0.797)
Return on Assets	-15.981	-10.544	-122.809***	-68.000***	0.001	-178.868***	0.396***
	(14.769)	(26.504)	(34.886)	(22.614)	(0.002)	(29.576)	(0.050)
Equity to Assets	1456.126**	6989.766***	7997.789***	2834.012***	0.116**	5025.317***	-5.070**
	(593.343)	(1028.301)	(1230.097)	(951.124)	(0.046)	(1193.813)	(1.988)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,917	9,917	9,917	9,917	9,917	9,917	9,917
Adjusted R^2	0.090	0.286	0.074	0.081	0.156	0.068	0.261

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table III: Online Versus Other Lenders

This table reports univariate differences between online banks and all other lender types at the loan level from 2010 to 2019. The columns report the mean of online bank lenders, mean of all other lenders, difference between the means, and number of observations, respectively. Panel A features the various loan programs and Panel B provides loan characteristics and outcomes.

Panel A: Loan Programs				
	Online Banks	Other Lenders	Online Banks - Other Lenders	
	(1)	(2)	(1-2)	
Mean	Mean	Diff.	Obs.	
Standard/Small With Preferred Status	0.76	0.30	0.46***	459,722
SBA Express	0.03	0.51	-0.48***	459,722
Other 7(a) Loan	0.06	0.09	-0.03***	459,722
Small Loan Advantage	0.14	0.05	0.09***	459,722
All Other Programs	0.01	0.06	-0.05***	459,722
Panel B: Loan Characteristics and Outcomes				
	Online Banks	Other Lenders	Online Banks - Other Lenders	
	(1)	(2)	(1-2)	
Mean	Mean	Diff.	Obs.	
Initial Interest Rate (%)	6.49	6.53	-.0422***	357,018
Term in Months	159	125	34.5***	357,018
Loan Amount ($ thousands)	661	377	284***	357,018
SBA Guarantee (%)	78.9	63.8	15.2***	357,018
Business is Corporation	.899	.877	.0215***	357,018
Business is Individual	.0878	.104	-.0161***	357,018
Business is Partnership	.0136	.019	-.00543***	357,018
Branches in Zip Code	6.85	6.61	.237***	357,018
Distance to SBA Lender	.446	.413	.0328***	357,018
Paid in Full	.416	.593	-.176***	357,018
Charge Off	.0926	.0478	.0448***	357,018
Charge Off to Loan (%)	7.31	3.48	3.83***	357,018
Securitized	.916	.229	.687***	357,018
SBA Loss to Loan (%)	5.47	2.05	3.42***	357,018
SBA Profit to Loan (%)	-.028	.00294	-.0309***	357,018
Lender IRR (%)	4.76	4.89	-.127***	357,018
Total Fees (%)	3.33	2.48	.843***	357,018
Guarantee Fee (%)	1.5	1.13	.367***	357,018
Ongoing Fee (%)	1.77	1.32	.455***	357,018
Prepayment Fee (%)	.0552	.0341	.0211***	357,018

Table IV: Online Bank Lending Behavior and SBA Losses

The table uses data at the loan level from 2010-2019. The dependent variables are log loan amount, interest rate, SBA guarantee percent, charge-off status, charge-off to loan, and SBA loss to loan, and SBA profit to loan. Charge-off status is equal to 1 if the loan is deemed uncollectable and 0 otherwise, charge-off to loan is the charge-off amount divided by the total loan, SBA loss to loan is the guaranteed portion of the charge-off amount minus fees paid to the SBA divided by the total loan if the loan defaults and 0 otherwise, and SBA profit to loan is the total fees paid to the SBA net of any SBA charge-off payments. The independent variable is online bank, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise. We include loan controls: loan size, revolver status, initial interest rate, and log term in months. We include business type (corporate or individual excluding partnership) and the number of SBA lender branches in the borrower's zip code as borrower controls. We control for bank characteristics: log assets, deposits to assets, ROA, and equity to assets. We include county-year and industry-year fixed effects. Standard errors are clustered at both the lender and borrower level.

	Log Loan Amount	Interest Rate	Guarantee Percent	Charged Off Status	Charge Off to Loan	SBA Loss to Loan	SBA Profit to Loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Online Bank	0.171	0.495***	4.629**	0.061***	4.814***	3.495***	-0.039***
	(0.204)	(0.084)	(1.915)	(0.018)	(1.581)	(1.223)	(0.014)
Loan Size Group		-0.810***	4.935***	0.032***	1.842***	1.030***	-0.000
		(0.130)	(0.425)	(0.005)	(0.392)	(0.235)	(0.003)
Revolver Status	-0.714***	0.441***	-10.156***	-0.033***	-1.491**	-1.206***	0.007*
	(0.116)	(0.162)	(1.204)	(0.007)	(0.593)	(0.400)	(0.004)
Initial Interest Rate	-0.389***		-0.260	0.016***	1.259***	0.676***	-0.007***
	(0.045)		(0.177)	(0.001)	(0.121)	(0.067)	(0.001)
Log Term in Months	0.702***	0.102***	2.697***	-0.127***	-8.492***	-4.830***	0.064***
	(0.049)	(0.030)	(0.367)	(0.011)	(0.794)	(0.378)	(0.004)
Business is Corporation	0.008	0.050	-0.182	0.007	0.544	0.387**	-0.005***
	(0.016)	(0.032)	(0.198)	(0.005)	(0.346)	(0.194)	(0.001)
Business is Individual	-0.492***	0.213***	-0.577**	0.019***	1.377***	0.749***	-0.008***
	(0.029)	(0.058)	(0.236)	(0.004)	(0.297)	(0.168)	(0.001)
Branches in Zip Code	0.005***	-0.001**	0.019***	-0.001***	-0.041***	-0.022***	0.000***
	(0.001)	(0.001)	(0.005)	(0.000)	(0.007)	(0.004)	(0.000)
Bank Log Assets	-0.050***	0.101***	-0.681**	0.001	0.085	-0.000	0.000
	(0.015)	(0.009)	(0.268)	(0.002)	(0.147)	(0.103)	(0.001)
Bank Deposits to Assets	-0.267	0.813	12.448	0.053	3.516	1.824	-0.009
	(0.373)	(0.510)	(7.921)	(0.054)	(4.618)	(3.124)	(0.031)
Bank Return on Equity	-0.008**	-0.002	0.125**	0.001**	0.088**	0.066**	-0.001*
	(0.004)	(0.004)	(0.051)	(0.000)	(0.042)	(0.031)	(0.000)
Bank Equity to Assets	-0.234	2.684**	31.382**	0.169	16.036	14.046	-0.158*
	(1.164)	(1.175)	(14.986)	(0.139)	(11.932)	(8.786)	(0.092)
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	371,695	371,695	371,695	371,695	371,695	371,695	371,695
Adjusted R^2	0.597	0.492	0.579	0.126	0.097	0.094	0.167

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table V: Online Versus Other Lenders: Subsidy and IRR

This table reports univariate differences between online banks and all other lender types at the loan level from 2010 to 2019. The columns report the mean of online bank lenders, mean of all other lenders, difference between the means, and number of observations, respectively. Panel A reports the *Expected Guarantee Subsidy*, which is the expected amount that the SBA pays for each loan, net of fees that they collect. Panel B reports on the lender IRR and IRR simulations. *Lender IRR* is the estimated internal rate of return using the initial loan amount and the estimated annual cash flows of the loan. *IRR Scenario 1* assumes a reduction of the loan guarantee rates of online lenders from 75% and above to 50%. *IRR Scenario 2* assumes a reduction of the loan guarantee rates for online lenders from 85% and above to 50%. *IRR Scenario 3* assumes a reduction of the loan guarantee rates for online lenders from 90% and above to 50%.

Panel A: Expected Guarantee Subsidy

	Online Banks (1) Mean	Other Lenders (2) Mean	Online Banks - Other Lenders (1-2) Diff.	Obs.
Expected Guarantee Subsidy (%)	2.03	-0.08	2.12***	342,466

Panel B: Internal Rate of Return

	Online Banks (1) Mean	Other Lenders (2) Mean	Online Banks - Other Lenders (1-2) Diff.	Obs.
Lender IRR (%)	4.97	4.86	0.11***	459,696
IRR Scenario 1	4.14	4.85	-0.71***	459,696
IRR Scenario 2	4.23	4.85	-0.62***	459,696
IRR Scenario 3	4.92	4.86	0.06**	459,696

Table VI: Credit Access Using Loan Amount and County Market Groups

The table uses data at the bank-county-year level from 2010 to 2019. The dependent variable, log loan amount, measures the log of the total sum of loan amounts originated by a lender in a county-year. The independent variables of interest include online, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise, and county economic measures broken into terciles interacted with online. We leave out the middle tercile of each county market variable. These market measures are bottom tercile per capita income, top tercile per capita income, bottom tercile unemployment, top tercile unemployment, bottom tercile lagged HHI scaled by 10,000, and top tercile lagged HHI scaled by 10,000. We include the following bank controls; log assets, deposits to assets, return on assets, and equity to assets. We include county-year fixed effects. Standard errors are clustered at the lender level.

	Log Total Loan Amount		
	(1)	(2)	(3)
Online Bank	-0.149	-0.170	-0.086
	(0.238)	(0.241)	(0.255)
Online Bank × Bottom Tercile Per Cap Income	0.289***		
	(0.078)		
Online Bank × Top Tercile Per Cap Income	-0.064		
	(0.070)		
Online Bank × Bottom Tercile Unemployment		-0.023	
		(0.113)	
Online Bank × Top Tercile Unemployment		0.336***	
		(0.106)	
Online Bank × Bottom Tercile HHI			-0.201**
			(0.094)
Online Bank × Top Tercile HHI			0.135***
			(0.043)
Log Assets	-0.013	-0.013	-0.010
	(0.016)	(0.017)	(0.017)
Deposits to Assets	1.359**	1.364**	1.439**
	(0.564)	(0.568)	(0.624)
Return on Assets	0.025	0.026	0.024
	(0.034)	(0.034)	(0.037)
Equity to Assets	-3.324*	-3.196*	-3.191*
	(1.708)	(1.714)	(1.714)
County × Year FE	Yes	Yes	Yes
Observations	111,815	111,815	101,190
Adjusted R^2	0.174	0.174	0.173

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table VII: Credit Access to Minorities

The table uses matched data at the loan level from 2010-2019. The dependent variable is *Log Loan Amount*. The independent variables of interest include *Online Bank*, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise, borrower ownership indicators including *Woman Owned*, *Minority Owned*, *Black Owned*, and *Hispanic Owned*, and the ownership indicators interacted with *Online Bank*. *Additional Controls* include the loan controls, borrower controls and bank controls. Standard errors are clustered at both the lender and borrower level.

	Log Loan Amount				
	(1)	(2)	(3)	(4)	(5)
Online Bank	0.146	0.148	0.148	0.147	0.147
	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)
Online Bank × Woman Owned		-0.512***			
		(0.063)			
Online Bank × Minority Owned			-0.616***		
			(0.135)		
Online Bank × Black Owned				-0.426***	
				(0.106)	
Online Bank × Hispanic Owned					-1.072***
					(0.254)
Woman Owned		0.178***			
		(0.029)			
Minority Owned			0.200***		
			(0.036)		
Black Owned				0.029	
				(0.064)	
Hispanic Owned					0.244***
					(0.047)
Additional Controls	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	219,360	219,360	219,360	219,360	219,360
Adjusted R^2	0.663	0.663	0.663	0.663	0.663

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table VIII: Loan Performance and Zip Code Market Measures

The table uses data at the loan level from 2010-2019. For Panel A, the dependent variable is the charge-off status which is an indicator equal to 1 if the loan is deemed uncollectable by the lender and 0 otherwise. For Panel B, the dependent variable is the charge-off to loan which is the charge-off amount divided by the total loan amount. For Panel C, the dependent variable, SBA loss to loan, is the charge-off amount times the SBA guarantee percent divided by the loan amount. The independent variables of interest include online, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise, zip code economic variables, and zip code economic variables interacted with online. The zip code economic variables are log credit score, log household income, percent subprime, and poverty rate. *Additional Controls* include the loan controls, borrower controls and bank controls. Standard errors are clustered at both the lender and borrower level.

Panel A: Charge-Off Status

	Charge-Off Status				
	(1)	(2)	(3)	(4)	(5)
Online Bank	0.060***	0.061***	0.061***	0.061***	0.060***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Online Bank × Log Credit Score		0.000			
		(0.038)			
Online Bank × Log Income			-0.002		
			(0.009)		
Online Bank × Percent Subprime				-0.000	
				(0.000)	
Online Bank × Poverty Rate					-0.001
					(0.001)
Log Credit Score		-0.043***			
		(0.011)			
Log Income			-0.010***		
			(0.002)		
Subprime				0.000***	
				(0.000)	
Poverty Rate					0.000
					(0.000)
Additional Controls	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	369,049	369,049	369,049	369,049	369,049
Adjusted R^2	0.119	0.119	0.119	0.119	0.119

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table VIII: Loan Performance and Zip Code Market Measures—*Continued*

Panel B: Charge-Off to Loan					
	Charge-Off to Loan				
	(1)	(2)	(3)	(4)	(5)
Online Bank	4.649***	4.669***	4.677***	4.668***	4.609***
	(1.478)	(1.471)	(1.455)	(1.472)	(1.451)
Online Bank × Log Credit Score		-0.282			
		(2.864)			
Online Bank × Log Income			-0.090		
			(0.651)		
Online Bank × Percent Subprime				-0.001	
				(0.010)	
Online Bank × Poverty Rate					-0.048
					(0.044)
Log Credit Score		-2.989***			
		(0.881)			
Log Income			-0.679***		
			(0.196)		
Subprime				0.012***	
				(0.003)	
Poverty Rate					0.003
					(0.005)
Additional Controls	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	369,049	369,049	369,049	369,049	369,049
Adjusted R^2	0.091	0.091	0.091	0.091	0.091

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table VIII: Loan Performance and Zip Code Market Measures—*Continued*

Panel C: SBA Loss to Loan (Net Fees)					
	SBA Loss to Loan (Net Fees)				
	(1)	(2)	(3)	(4)	(5)
Online Bank	2.882***	2.901***	2.902***	2.900***	2.853***
	(1.083)	(1.074)	(1.065)	(1.075)	(1.063)
Online Bank × Log Credit Score		-2.211			
		(2.194)			
Online Bank × Log Income			-0.203		
			(0.506)		
Online Bank × Percent Subprime				0.006	
				(0.008)	
Online Bank × Poverty Rate					-0.031
					(0.032)
Log Credit Score		-1.125**			
		(0.493)			
Log Income			-0.272***		
			(0.105)		
Subprime				0.005**	
				(0.002)	
Poverty Rate					-0.001
					(0.003)
Additional Controls	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	369,049	369,049	369,049	369,049	369,049
Adjusted R^2	0.094	0.094	0.094	0.094	0.094

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table IX: Shock to Credit Supply

The table uses data from 2010-2019. In columns (1) and (2), the data is at the loan level and and in columns (3) and (4), the data is at the bank-county-year level. The independent variables of interest include online, treatment, post, and their interactions. Online is an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise. Treatment is an indicator equal to 1 for loans with maturities of greater than 7 years and 0 otherwise. Post is an indicator equal to 1 for observations in 2018-2019 and 0 for observation in 2010-2017. *Loan Controls* include loan size group, revolver status, initial interest rate, and securitized. *Borrower Controls* include business is corporation, business is individual, and branches in zip code. *Lender Controls* include log assets, deposits to assets, return on assets, deposits to assets, and equity to assets. The bank-level regressions of columns (3) and (4) have lagged controls and include an additional control of lagged bank securitization. Standard errors are clustered at the lender and borrower level in columns (1) and (2) and at the lender level in columns (3) and (4).

	Loan Level		Bank-County Level	
	Log Loan Amount	Interest Rate	Log Bank Origination	Weighted Interest Rate
	(1)	(2)	(3)	(4)
Online Bank	0.192	0.438***	-0.405**	0.021***
	(0.129)	(0.114)	(0.165)	(0.005)
Online Bank × Post	0.394	0.347**	0.464	-0.015*
	(0.361)	(0.150)	(0.345)	(0.008)
Online Bank × Treatment × Post	-0.549**	-0.293**	-0.534*	0.006
	(0.275)	(0.129)	(0.301)	(0.011)
Online Bank × Treatment	-0.161	-0.139	0.150	-0.026***
	(0.188)	(0.091)	(0.223)	(0.004)
Treatment × Post	0.350***	0.091	0.189*	-0.014***
	(0.112)	(0.133)	(0.115)	(0.003)
Treatment	0.619***	0.245***	0.725***	0.014***
	(0.071)	(0.070)	(0.068)	(0.002)
Loan Controls	Yes	Yes	No	No
Borrower Controls	Yes	Yes	No	No
Lender Controls	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	No	No
Observations	329,442	329,442	92,088	92,088
Adjusted R^2	0.598	0.524	0.224	0.153

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

A Appendix

Table A.1: Variable Definitions

Variable	Description
Bank Deposits to Assets	The total deposits of the FDIC reporting institution divided by its total assets
Bank Equity to Assets	The financial institution's reported equity divided by its assets
Bank Log Assets	The log total assets of the financial institution as reported by the FDIC
Bank Returns on Assets	The return on assets as reported by the FDIC
Branches in Zip Code	The number of branches of SBA lenders within the borrower's zip code.
Business is Corporation	Indicator variable that equals 1 if the borrower business type is corporation and 0 otherwise
Business is Individual	Indicator variable that equals 1 if the borrower business type is individual and 0 otherwise
Business is Partnership	Indicator variable that equals 1 if the borrower business type is partnership and 0 otherwise
Charge-Off Loan Status	Indicator variable that equals 1 if the loan has been deemed uncollectable by the lender and 0 otherwise
Charge-Off to Loan	The gross charge-off amount divided by the total loan amount
County Per Cap Income	Total personal income, as defined by the Bureau of Economic Analysis (BEA), divided by the total population
County Scaled Bank HHI	The sum of squared share of local bank branch deposits of the banks in the county scaled by 10,000
County Unemployment Rate	The number of individuals in the labor force that are unemployed divided by the total labor force
Distance to SBA Lender	The distance in miles between the borrower's zip code to the zip code of the nearest SBA lender branch.
Expected Guarantee Subsidy	The expected amount that the SBA pays for each loan minus fees that they are expected to collect where defaults are predicted using various loan, lender, and location controls.

Table A.1: Variable Definitions—*Continued*

Variable	Description
Fee: Guarantee Fee	The upfront fee amount required by the SBA that range from 0-3.75% of the guaranteed portion of the initial loan amount
Fee: Ongoing Fee	The total amount that SBA borrowers pay toward the annual servicing fee over the life of the loan which ranges from 0-0.55% of the guaranteed outstanding portion of the loan each year
Fee: Prepayment Fee	The amount that SBA borrowers are required to pay on loans with a maturity of above 15 years that are prepaid within the first 3 years
Initial Interest Rate	The interest rate on the loan at the time of approval. SBA 7(a) loans may come with fixed or variable rates
Lender IRR	The internal rate of return using the initial loan amount and cash flows calculated using initial interest rate, term in months, and payment and default information
Log Loan Amount	The log of the dollar loan amount as provided by the SBA
Minority: Woman Owned	Indicator variable that equals 1 if the borrower self-identifies her business as Woman Owned Business in the System for Award Management (SAM) Entity Registration Records, and 0 otherwise
Minority: Minority Owned	Indicator variable that equals 1 if the borrower self-identifies under business code 23: Minority Owned Business in the System for Award Management (SAM) Entity Registration Records, and 0 otherwise
Minority: Black Owned	Indicator variable that equals 1 if the borrower self-identifies under business code OY: Black American Owned Business in the System for Award Management (SAM) Entity Registration Records, and 0 otherwise
Minority: Hispanic Owned	Indicator variable that equals 1 if the borrower self-identifies under business code PI: Hispanic American Owned Business in the SAM Entity Registration Records and 0 otherwise
Online Bank	Indicator variable that equals 1 when a lender is classified as an online bank, meaning it has less than 10 physical locations and less than 10% of its loans made in the state in which it is located, and 0 otherwise
Post	An indicator that equals one for loans made after October 2017 and zero otherwise

Table A.1: Variable Definitions—*Continued*

Variable	Description
Revolver Status	Indicator variable that equals 1 if the loan is a revolving line of credit and 0 if a term loan
SBA Guarantee Percent	The amount of the loan guaranteed by the SBA divided by the total loan amount
SBA Loss to Loan	The gross charge-off amount, net of fees, multiplied by the SBA guarantee percent, divided by the total loan amount
SBA Profit to Loan	The sum of fees paid to the SBA minus the guaranteed portion of the default amount in the case of a charge-off, divided by the total loan amount
Specialization: Assets HHI	The sum of a lender's annual squared share of balance sheet asset categories and sub-categories using bank call reports
Specialization: Income HHI	The sum of a lender's squared annual share of income statement categories using bank call reports
Specialization: Liabilities HHI	The sum of a lender's annual squared share of balance sheet liability categories and sub-categories using bank call reports
Specialization: Loan Categories (SDI)	The number of loan and lease categories a lender utilized each year using Summary of Deposit data from the Statistics on Depository Institutions
Specialization: Loans HHI (CR)	The sum of a lender's annual squared share of loans and leases categories using bank call reports
Specialization: Loans HHI (SDI)	The sum of a lender's squared share of loans and leases categories using Summary of Deposit data from the Statistics on Depository Institutions
Specialization: SBA to Total Loans	The sum of the lender's loan originations in the SBA program divided by total loans and leases on their call reports
Term in Months	The length of loan term as measured in months
Treatment	An indicator that equals one for loans with maturities of seven years or more and zero otherwise
Weighted Average Interest Rate	The sum of the initial interest rates times the loan amounts divided by the total sum of loan amounts
Zip Code Credit Score	The average credit score of borrowers in a given ZIP Code
Zip Code Income	The average estimated household income in a given ZIP code
Zip Code Subprime Rate	The average ratio of borrowers with a subprime credit score (below 640)
Zip Code Poverty Rate	Average poverty rate based on U.S Census in a given ZIP code

Table A.2: SBA 7(a) Loan Delivery Methods

Using information from the SBA, this table provides a brief description of the primary 7(a) programs with their respective guarantee rates and year active in the sample.

Program	Description	Guarantee	Years Active in Sample
Community Advantage	Community-based focus on local small businesses in underserved markets. Max loan amount of $350,000.	Up to 85% for loans up to $150,000 and 75% for loans greater than $150,000	2011-2019
Community Express	Focus on underserved communities that qualify for CRA. Max loan amount of $250,000.	Up to 85% for loans up to $150,000 and 75% for loans greater than $150,000	2010-2011
Certified Lender	Made by SBA certified lenders who receive expedited processing of loan applications.	Up to 85% for loans up to $150,000 and 75% for loans greater than $150,000	2010-2017
Other 7(a) Loan	The SBA's category for all other loan delivery methods.	Variable guarantees	2010-2019
Patriot Express	Focuses on veteran-owned small businesses. Max loan amount of $500,000.	Up to 85% for loans up to $150,000 and 75% for loans greater than $150,000	2010-2014
Standard/Small With Preferred Lender Status	Standard/Small 7(a) loans made by SBA preferred lenders who have more authority to process, close, service, and liquidate SBA-guaranteed loans.	Up to 85% for loans up to $150,000 and 75% for loans greater than $150,000	2010-2019
SBA Express	Accelerated turnaround time for SBA review (within 36 hours). Maximum loan amount of $350,000 during the most of the sample period.	50%	2010-2019
Small Loan Advantage	Focuses on small loans with a max loan amount of $350,000 and a streamlined application process with the goal to expand credit to underserved markets.	Up to 85% for loans up to $150,000 and 75% for loans greater than $150,000	2011-2017
All Other Programs	Consists of all loan programs where the sample is below 1% for both online and other lenders. This includes dealer floor plan, export working capital, export express, gulf opportunity, international trade, and rural lender advantage.	75% to 90%	2010-2019

Table A.3: SBA 7(a) Fees

This table lists the various fees associated with SBA 7(a) loans and their percentages for each fiscal year during the sample.

	FY 2010	FY 2011	FY 2012	FY 2013	FY 2014	FY 2015	FY 2016	FY 2017	FY 2018	FY 2019
Guarantee fee - upfront fee on the guaranteed portion of loan										
Short term : $125,000 or less	N.A.*	0.25%	0.25%	0.25%	0.00%	0.00%	0.00%	0.00%	0.25%	0.25%
Short term : $125,001 to $150,000	N.A.*	0.25%	0.25%	0.25%	0.00%	0.00%	0.00%	0.00%	0.25%	0.25%
Short term : $150,001 to $700,000	N.A.*	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%
Short term : $700,001 to $5,000,000	N.A.*	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%
Long term : $125,000 or less	N.A.*	2.00%	2.00%	2.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.00%
Long term : $125,001 to $150,000	N.A.*	2.00%	2.00%	2.00%	0.00%	0.00%	0.00%	0.00%	2.00%	2.00%
Long term : $150,001 to $700,000	N.A.*	3.00%	3.00%	3.00%	3.00%	3.00%	3.00%	3.00%	3.00%	3.00%
Long term : $700,001 to $5,000,000	N.A.*	3.50%	3.50% on up to $1 million plus 3.75% on amount over $1 million	3.50% on up to $1 million plus 3.75% on amount over $1 million	3.50% on up to $1 million plus 3.75% on amount over $1 million	3.50% on up to $1 million plus 3.75% on amount over $1 million	3.50% on up to $1 million plus 3.75% on amount over $1 million	3.50% on up to $1 million plus 3.75% on amount over $1 million	3.50% on up to $1 million plus 3.75% on amount over $1 million	3.50% on up to $1 million plus 3.75% on amount over $1 million
Ongoing servicing fee - yearly fee on the guaranteed portion of the outstanding loan balance										
Short term : $150,000 or less	0.55%	0.55%	0.55%	0.55%	0.00%	0.00%	0.00%	0.546%	0.546%	0.55%
Short term : more than $150,000	0.55%	0.55%	0.55%	0.55%	0.52%	0.519%	0.473%	0.546%	0.546%	0.55%
Long term : $150,000 or less	0.55%	0.55%	0.55%	0.55%	0.00%	0.00%	0.00%	0.546%	0.546%	0.55%
Long term : $150,001 to $700,000	0.55%	0.55%	0.55%	0.55%	0.52%	0.519%	0.473%	0.546%	0.546%	0.55%
Long term : $700,001 to $5,000,000	0.55%	0.55%	0.55%	0.55%	0.52%	0.519%	0.473%	0.546%	0.546%	0.55%
Prepayment fee - only applicable to loans with maturity of 15 years or more that prepay within the first 3 years										
5% if prepaid in the first year, 3% if prepaid in the second year, and 1% if prepaid in the third year										

*The Small Business Job Creation and Access to Capital Act of 2009 waived all SBA guarantee fees to encourage financial recovery.

Table A.4: Largest Online Banks by Lending Volume

This table lists the identities, loan amounts, and locations of the ten largest online banks in our sample period of 2010-2019.

Bank Name	No. of Loans	Overall Loan Amount	State Located
Celtic Bank Corporation	6,593	$2,469,248,200	UT
Live Oak Banking Company	6,367	$7,811,133,000	NC
Stearns Bank National Association	3,853	$1,435,446,600	MN
Independence Bank	3,257	$456,019,200	RI
United Midwest Savings Bank, National Association	1,660	$676,273,300	OH
The Bancorp Bank	750	$559,078,600	DE
LendingClub Bank, National Association*	501	$390,020,400	UT
Coastal States Bank	362	$328,938,400	SC
FinWise Bank	300	$224,446,100	UT
West Town Bank And Trust	286	$360,663,700	IL

*Previously known as Radius Bank until 2021 when it was acquired by LendingClub.

Table A.5: Matched Versus Total Sample

This table reports univariate differences between the matched and total sample. The columns report the mean of matched loan observations, mean of total sample loan observations, difference between the means, and t-statistic, respectively.

	Matched (1)	Total (2)	Matched - Total (1-2)	
	Mean	Mean	Diff.	t-stat
Initial Interest Rate (%)	6.67	6.53	.144***	35.51
Term in Months	128	122	6.11***	29.26
Loan Amount ($ thousands)	375	371	3.98*	2.30
SBA Guarantee (%)	64.3	64.1	.201***	5.21
Business is Corporation	.859	.876	-.0164***	-18.83
Business is Individual	.121	.106	.0151***	18.60
Business is Partnership	.02	.0187	.00127***	3.58
Branches in Zip Code	6.68	6.64	.0372**	2.76
Distance to SBA Lender	.408	.414	-.00609	-1.39
Preferred Lender Program (%)	.317	.31	.00706***	5.90
SBA Express Program (%)	.501	.507	-.00646***	-5.00
Paid in Full	.609	.621	-.0124***	-9.90
Charge Off	.0521	.0516	.00051	0.89
Charge Off to Loan (%)	3.91	3.83	.0756	1.68
SBA Loss to Loan (%)	2.38	2.31	.0656*	2.38
SBA Profit to Loan (%)	-.001	-.001	.0000	0.13
Lender IRR (%)	4.88	4.74	.136***	10.46
Total Fees (%)	2.48	2.41	.0703***	11.60
Guarantee Fee (%)	1.11	1.12	-.00731**	-2.65
Ongoing Fee (%)	1.33	1.25	.0733***	18.20
Prepayment Fee (%)	.0401	.0359	.00426***	5.32

* p<.10, ** p<.05, *** p<.01

Table A.6: Online Banks and SBA Guarantee Percent

The table uses data at the loan level from 2010-2019. The dependent variable is SBA guarantee percent. The independent variable is online bank, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise. We include loan controls: loan size, revolver status, initial interest rate, and log term in months. We include business type, corporate or individual excluding partnership, as a borrower control. We control for bank characteristics: log assets, deposits to assets, ROA, and equity to assets. We include a variety of fixed effects. Column 1 includes county-year and industry-year fixed effects, column 2 includes borrower and industry-year fixed effects, and column 3 includes borrower-year fixed effects. Standard errors are clustered at both the lender and borrower level.

	Guarantee Percent		
	(1)	(2)	(3)
Online Bank	4.540***	5.786***	5.934***
	(1.739)	(1.273)	(2.206)
Loan Size Group	4.786***	5.295***	6.305***
	(0.415)	(0.420)	(0.397)
Revolver Status	-10.571***	-10.455***	-10.303***
	(1.193)	(0.840)	(0.836)
Initial Interest Rate	-0.257	-0.042	0.085
	(0.175)	(0.317)	(0.381)
Log Term in Months	2.555***	2.832***	3.171***
	(0.360)	(0.374)	(0.428)
Business is Corporation	-0.127	-1.677	-2.027
	(0.192)	(1.589)	(3.066)
Business is Individual	-0.485**	-2.195	-0.895
	(0.231)	(2.132)	(3.433)
Bank Log Assets	-0.766***	-0.959***	-0.798***
	(0.265)	(0.185)	(0.301)
Bank Deposits to Assets	9.647	-0.107	6.636
	(7.651)	(4.839)	(13.751)
Bank Return on Equity	0.119***	0.011	0.213***
	(0.045)	(0.030)	(0.077)
Bank Equity to Assets	32.186**	32.728***	42.126*
	(14.273)	(8.638)	(25.070)
Borrower FE	No	Yes	No
Borrower × Year FE	No	No	Yes
County × Year FE	Yes	No	No
Industry × Year FE	Yes	Yes	No
Observations	421,334	92,032	59,654
Adjusted R^2	0.580	0.609	0.594

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table A.7: Credit Access Using Loan Amount and County Market Measures

The table uses data at the bank-county-year level from 2010 to 2019. The dependent variable, log loan amount, measures the log of the total sum of loan amounts originated by a lender in a county-year. The independent variables of interest include online, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise, and county economic variables interacted with online. These economic variables are log per capita income, unemployment rate, and HHI scaled by 10,000. We include the following bank controls; log assets, deposits to assets, return on assets, and equity to assets. We include county-year fixed effects. Standard errors are clustered at the bank level.

	Log Total Loan Amount			
	(1)	(2)	(3)	(4)
Online Bank	-0.110	-0.082	-0.060	-0.099
	(0.247)	(0.244)	(0.233)	(0.246)
Online Bank $\times$ Log Per Cap Income		-0.427**		
		(0.191)		
Online Bank $\times$ Unemployment Rate			0.069*	
			(0.036)	
Online Bank $\times$ Scaled HHI				0.740***
				(0.182)
Log Assets	-0.014	-0.013	-0.013	-0.014
	(0.016)	(0.016)	(0.017)	(0.016)
Deposits to Assets	1.347**	1.358**	1.366**	1.348**
	(0.564)	(0.564)	(0.567)	(0.563)
Return on Assets	0.028	0.026	0.025	0.028
	(0.036)	(0.035)	(0.034)	(0.036)
Equity to Assets	-3.435**	-3.348*	-3.164*	-3.442**
	(1.727)	(1.714)	(1.713)	(1.728)
County $\times$ Year FE	Yes	Yes	Yes	Yes
Observations	111,815	111,815	111,815	111,815
Adjusted R^2	0.173	0.174	0.174	0.174

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table A.8: Online Bank and Minority Borrowers

The table uses data at the loan level from 2010-2019. The dependent variables are interest rate, SBA guarantee percent, charge-off status, charge-off to loan, and SBA loss to loan. The independent variables of interest include *Online Bank*, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise, and *Minority Owned*, a borrower ownership indicator. Standard errors are clustered at both the lender and borrower level.

	Guarantee Percent	Interest Rate	Charge-Off Status	Charge-Off to Loan	SBA Loss to Loan Net Fees
	(1)	(2)	(3)	(4)	(5)
Online Bank	4.194**	0.526***	0.051***	3.896***	2.939**
	(1.661)	(0.085)	(0.016)	(1.471)	(1.144)
Minority Owned	0.425	-0.136***	-0.006	-0.325	-0.136
	(0.498)	(0.040)	(0.007)	(0.551)	(0.359)
Online Bank $\times$ Minority Owned	3.075**	0.069	0.096***	7.761***	6.437***
	(1.363)	(0.131)	(0.018)	(1.394)	(1.058)
Loan Size Group	4.037***	-0.922***	0.038***	2.301***	1.266***
	(0.438)	(0.122)	(0.005)	(0.420)	(0.246)
Revolver Status	-10.386***	0.542***	-0.039***	-2.075***	-1.568***
	(1.494)	(0.204)	(0.009)	(0.691)	(0.462)
Initial Interest Rate	-0.355**		0.015***	1.177***	0.630***
	(0.170)		(0.002)	(0.134)	(0.074)
Log Term in Months	3.266***	0.089**	-0.141***	-9.571***	-5.504***
	(0.377)	(0.036)	(0.012)	(0.858)	(0.409)
Business is Corporation	-0.109	0.052	0.006	0.387	0.290
	(0.228)	(0.042)	(0.007)	(0.504)	(0.293)
Business is Individual	-0.778***	0.166***	0.008	0.434	0.203
	(0.276)	(0.057)	(0.008)	(0.583)	(0.332)
Branches in Zip Code	0.013***	-0.001**	-0.000***	-0.036***	-0.018***
	(0.005)	(0.001)	(0.000)	(0.009)	(0.005)
Bank Log Assets	-0.636**	0.096***	0.001	0.068	-0.012
	(0.295)	(0.009)	(0.002)	(0.148)	(0.106)
Bank Deposits to Assets	16.521**	0.764	0.080	5.704	3.189
	(8.239)	(0.609)	(0.055)	(4.722)	(3.138)
Bank Return on Assets	1.275***	-0.031	0.011**	0.978**	0.767***
	(0.443)	(0.033)	(0.004)	(0.396)	(0.297)
Bank Equity to Assets	19.436	2.536*	0.124	11.549	9.794
	(16.233)	(1.416)	(0.143)	(12.182)	(9.031)
County $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Observations	219,360	219,360	219,360	219,360	219,360
Adjusted R^2	0.623	0.540	0.130	0.099	0.098

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table A.9: Online Banks and Women Borrowers

The table uses data at the loan level from 2010-2019. The dependent variables are interest rate, SBA guarantee percent, charge-off status, charge-off to loan, and SBA loss to loan. The independent variables of interest include *Online Bank*, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise, and *Woman Owned*, a borrower ownership indicator. Standard errors are clustered at both the lender and borrower level.

	Guarantee Percent	Interest Rate	Charge-Off Status	Charge-Off to Loan	SBA Loss to Loan Net Fees
	(1)	(2)	(3)	(4)	(5)
Online Bank	4.192**	0.526***	0.051***	3.904***	2.947**
	(1.658)	(0.085)	(0.017)	(1.477)	(1.149)
Women Owned	-0.012	-0.143***	-0.016***	-1.369***	-0.849***
	(0.346)	(0.042)	(0.005)	(0.362)	(0.213)
Online Bank × Women Owned	3.142***	-0.039	0.044**	3.875**	2.695**
	(0.610)	(0.076)	(0.021)	(1.761)	(1.315)
Loan Size Group	4.038***	-0.922***	0.038***	2.303***	1.267***
	(0.438)	(0.122)	(0.005)	(0.420)	(0.246)
Revolver Status	-10.385***	0.542***	-0.039***	-2.072***	-1.566***
	(1.493)	(0.204)	(0.009)	(0.692)	(0.462)
Initial Interest Rate	-0.356**		0.015***	1.176***	0.629***
	(0.170)		(0.002)	(0.134)	(0.074)
Log Term in Months	3.265***	0.089**	-0.141***	-9.575***	-5.507***
	(0.378)	(0.036)	(0.012)	(0.858)	(0.409)
Business is Corporation	-0.107	0.052	0.006	0.393	0.295
	(0.228)	(0.042)	(0.007)	(0.504)	(0.294)
Business is Individual	-0.778***	0.166***	0.008	0.431	0.201
	(0.276)	(0.057)	(0.008)	(0.583)	(0.332)
Branches in Zip Code	0.013***	-0.001**	-0.000***	-0.036***	-0.019***
	(0.005)	(0.001)	(0.000)	(0.009)	(0.005)
Bank Log Assets	-0.636**	0.096***	0.001	0.067	-0.012
	(0.295)	(0.009)	(0.002)	(0.148)	(0.106)
Bank Deposits to Assets	16.519**	0.764	0.080	5.690	3.179
	(8.239)	(0.609)	(0.055)	(4.723)	(3.140)
Bank Return on Assets	1.275***	-0.031	0.011**	0.979**	0.768**
	(0.443)	(0.033)	(0.004)	(0.397)	(0.298)
Bank Equity to Assets	19.448	2.537*	0.125	11.579	9.815
	(16.234)	(1.416)	(0.143)	(12.200)	(9.049)
County × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	219,360	219,360	219,360	219,360	219,360
Adjusted R^2	0.623	0.540	0.130	0.099	0.098

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table A.10: Credit Access to Minorities, Reporting-Only Sample

The table uses matched data at the loan level from 2010-2019. Here we restrict the sample to only those borrowers that self-identify into one of the SBA business-type categories (e.g., veteran, disadvantaged, woman, minority). The dependent variable is *Log Loan Amount*. The independent variables of interest include *Online Bank*, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise, borrower ownership indicators including *Woman Owned*, *Minority Owned*, *Black Owned*, and *Hispanic Owned*, and the ownership indicators interacted with *Online Bank*. *Additional Controls* include the loan controls, borrower controls and bank controls. Standard errors are clustered at both the lender and borrower level.

	Log Loan Amount				
	(1)	(2)	(3)	(4)	(5)
Online Bank	0.025	0.079	0.094	0.026	0.054
	(0.238)	(0.270)	(0.246)	(0.239)	(0.241)
Online Bank × Woman Owned		-0.257			
		(0.231)			
Online Bank × Minority Owned			-0.264		
			(0.199)		
Online Bank × Black Owned				0.059	
				(0.188)	
Online Bank × Hispanic Owned					-0.570**
					(0.264)
Woman Owned		-0.160***			
		(0.039)			
Minority Owned			-0.095**		
			(0.045)		
Black Owned				-0.309***	
				(0.094)	
Hispanic Owned					-0.021
					(0.075)
Additional Controls	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	5,780	5,780	5,780	5,780	5,780
Adjusted R^2	0.528	0.531	0.529	0.530	0.528

Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01

Table A.11: Credit Access to Minorities, County-Level Sample

The table uses data at the bank-county-year level from 2010 to 2019. The dependent variable, *Log Total Loan Amount*, measures the log of the total sum of loan amounts originated by a lender in a county-year. The independent variables of interest include online, an indicator equal to 1 if a lender is classified as an online bank and 0 otherwise, and county economic variables interacted with online. County-level variables include *Percent Women*, *Percent Minority*, *Percent Black*, and *Percent Hispanic*. *Additional Controls* include *Log Assets*, *Deposits to Assets*, *Return on Assets*, and *Equity to Assets*. Standard errors are clustered at the bank level.

	Log Total Loan Amount			
	(1)	(2)	(3)	(4)
Online Bank	-0.123	-0.124	-0.124	-0.125
	(0.233)	(0.233)	(0.232)	(0.233)
Online Bank × Percent Women	-0.370			
	(0.225)			
Online Bank × Percent Minority		-0.268		
		(0.378)		
Online Bank × Percent Black			-0.397	
			(0.377)	
Online Bank × Percent Hispanic				-0.415
				(0.449)
Percent Women	-0.033			
	(0.091)			
Percent Minority		0.066		
		(0.129)		
Percent Black			-0.432**	
			(0.202)	
Percent Hispanic				-0.212
				(0.210)
Additional Controls	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Observations	84,585	84,585	84,585	84,585
Adjusted R^2	0.188	0.188	0.188	0.188