How Much Do Small Businesses Rely on Personal Credit?*

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March 2023

Abstract

This paper estimates the degree of substitution between personal and small business credit for U.S. entrepreneurs between 2009 and 2018 using a novel, individual-level dataset. We identify the effect of business credit supply shocks by exploiting geographic variation in the market share of large banks, which sharply reduced credit supply to small businesses after the 2008 financial crisis. This contraction decreased total business credit by $13,572 per firm in our sample, and we find that entrepreneurs on average were able to substitute for about 68% of this decline with personal credit, driven by mortgages. However, entrepreneurs with subprime credit scores, below-average income, and high credit utilization do not meaningfully substitute lost business credit with personal credit. Thus, we find that the personal financial characteristics of entrepreneurs play an economically important role in overall access to external finance for small businesses.

*We thank Manuel Adelino (discussant), Samuel Hanson (discussant), Adrien Matray, Ramana Nanda (discussant), Dejanir Silva, and participants at the AEA Annual Meeting, NBER Entrepreneurship Fall Meeting, Rome Junior Finance Conference, Indiana Junior Finance Conference, WEFI, and the CEPR Household Finance Seminar for helpful comments. We are grateful to Brian Chen, Samuel Hanson, and Jeremy Stein for sharing the data and code used to construct the county-level deposit share of Top 4 banks and to Manasa Gopal and Philipp Schnabl for sharing expertise on UCC loans. Peichen Li, Kunal Bagali, Peter Han, Yucheng Zhou, Hejia Liu, Matthew Boyd, and Kevin Tzeng provided valuable research assistance. We are grateful for support from the Alfred P. Sloan Foundation through the NBER Household Finance small grant program, the AWS Greg Gulick Honorary Award, and the Gies College of Business.

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1 Introduction

The aftermath of the Great Recession saw a large and persistent contraction in the supply of small business credit, especially by the largest U.S. banks (Chen, Hanson and Stein, 2017; Bord, Ivashina and Taliaferro, 2021). This contraction prompted widespread concern about the potential consequences for economic activity, as small and medium-sized enterprises (SMEs) create two out of every three new jobs in the United States and the health of these businesses depends on access to credit.[1]

In order to fully understand the implications of SME credit supply shocks for business dynamism and the macroeconomy, it is important to study the relationship between personal and business credit. Survey evidence shows that most small businesses rely on personal credit in some capacity to fund their activities, with 86 percent of small employer firms and 94 percent of non-employer firms reporting the use of personal credit scores to obtain financing (Small Business Credit Survey, 2019a,b).[2] While these findings are suggestive of economically important linkages between personal and small business credit, they do not quantify the intensity of this relationship.

In this paper, we quantify the degree of substitution between personal and business credit following a negative business credit supply shock and study how this substitution parameter varies with the personal financial characteristics of entrepreneurs. We do so by leveraging the fact that, following the 2008 financial crisis, the largest U.S. banks sharply contracted lending to small businesses (Chen, Hanson and Stein, 2017). Using a novel individual-level dataset, we confirm that large bank market share is associated with a reduction in SME credit. We then document that entrepreneurs are able to substitute for about 68% of this decline with personal credit on average, but only those with high personal creditworthiness

[1] See, for instance, Black and Strahan (2002), Cetorelli and Strahan (2006), Bertrand, Schoar and Thesmar (2007), and Kerr and Nanda (2009).

[2] Robb and Robinson (2014) also find that debt backed by the personal balance sheets of entrepreneurs is an important source of financing for firms in the Kauffman Firm Survey.

are able to meaningfully substitute.

The first stage of our estimation measures the decline in small business lending by the four largest banks across geographies in our data. We find that on average, entrepreneurs in counties with 100% Top 4 bank deposit share experience a $13,572 decline in business credit relative to those in counties with 0% Top 4 bank share. This result is consistent with prior work that finds that the largest US banks reduced their supply of small business credit after the Great Recession (Chen, Hanson and Stein, 2017; Cortés, Demyanyk, Li, Loutskina and Strahan, 2020; Bord, Ivashina and Taliaferro, 2021).

Next, we show that entrepreneurs turn to personal loans in response to the negative SME credit supply shock. An important concern for causal inference is that the market share of the four largest banks in a local area could directly affect the supply of personal credit as well as the supply of business credit. To alleviate this concern, we construct a matched sample of non-entrepreneurs residing in the same counties as the entrepreneurs and estimate the effect of large bank presence on the personal borrowing of entrepreneurs in a triple-differences setting. We provide evidence for the parallel trends assumption underlying this research design by showing that the personal credit outcomes of entrepreneurs and non-entrepreneurs evolved in close parallel prior to 2009.

We find that entrepreneurs increase their personal borrowing by $9,178 on average, driven by an increase in mortgage balances. This increase in personal borrowing persists throughout our sample period. By contrast, we find economically small negative changes in credit card balances, which are not significant at traditional levels. The increase in total personal credit accounts for 68% of the decline in business credit in our preferred specification, suggesting that entrepreneurs are able to meaningfully but not fully smooth business credit supply shocks by relying on personal credit. Our findings are robust to controlling for a range of local and individual characteristics and are not driven by the specifics of our matching procedure.

Turning to heterogeneity, we find that personal financial characteristics such as credit score, income, and credit card utilization are key determinants of the ability of entrepreneurs to smooth negative credit supply shocks by using personal credit. High-score, high-income, and low-utilization individuals are able to substitute essentially all of the decline in business credit with personal credit. In contrast, low-score, low-income, and high-utilization entrepreneurs do not substitute. We also examine the role of gender and find that the degree of substitution between personal and business credit does not vary meaningfully along this dimension. The heterogeneity we document along personal financial characteristics is not driven by observable firm-level measures of financial constraints.

While we cannot directly confirm that the increase in personal debt is used for SME investment, we provide supportive evidence for this interpretation. First, the increase in mortgage balances of entrepreneurs is driven by cash-out refinancing and not home-buying. Entrepreneurs experience no change in mortgage balances excluding balances that we identify as associated with refinancing activity. There is also no change in the number of open mortgage trades and no increase in the propensity of entrepreneurs to move following the negative business credit shock. Both of these patterns are consistent with refinancing and inconsistent with home-buying.

To support the interpretation that entrepreneurs are applying the funds obtained through increased personal borrowing toward their businesses instead of consumption or other uses, we rely on prior findings that a large negative shock to the supply of business credit leads to increased firm financial distress (e.g. Khwaja and Mian, 2008) and test whether entrepreneurs who substitute to personal credit are able to avoid distress. We show that prime entrepreneurs in our sample—who substitute approximately all of the declining business credit with personal credit—experience insignificant changes in firm financial distress. On the other hand, firms owned by subprime entrepreneurs experience significant increases in financial distress. These findings are consistent with the interpretation that personal credit is used by entrepreneurs to maintain business activity following negative business credit supply shocks.

Our findings have implications for how business and consumer credit markets interact to affect the aggregate economy and the role of personal financial characteristics in entrepreneurial success. In particular, we find that focusing only on business credit overstates the contraction in overall external finance experienced by the average small business after the Great Recession. However, the ability of entrepreneurs to find alternate sources of credit depends heavily on their personal credit scores. Thus, inequities in personal credit markets may have spillover effects on SME credit constraints and aggregate business dynamics.

This paper relates to several strands of literature. Previous work linking housing collateral to entrepreneurship includes Black, Meza and Jeffreys (1996); Adelino, Schoar and Severino (2015); Corradin and Popov (2015); Schmalz, Sraer and Thesmar (2017); Bracke, Hilber and Silva (2018); Jensen, Leth-Petersen and Nanda (2022) and Kerr, Kerr and Nanda (2022). While this literature generally examines the effect of geographic variation in housing equity on entry into entrepreneurship, we look at the intensive margin of substitution for existing businesses. Unique in this literature, we use a dataset that captures both business loans and all types of consumer loans at the individual level, which allows us to directly measure the use of mortgage debt to finance entrepreneurship and extend our analysis to other forms of personal credit. Furthermore, we show that the personal credit characteristics of entrepreneurs strongly mediate the ability to use housing collateral to finance small businesses, which has not been emphasized in most previous work.

Our results on substitution between business and personal credit contribute to the growing literature on the dynamics of credit supply since the global financial crisis of 2008, including Chen, Hanson and Stein (2017), Cortés, Demyanyk, Li, Loutskina and Strahan (2020), Gopal and Schnabl (2020), and Bord, Ivashina and Taliaferro (2021). In particular, Gopal and Schnabl (2020) examine substitution between the bank and nonbank business credit markets, which is related to our analysis of substitution between business and personal credit. Our measures of small business and personal credit include both banks and nonbanks. Our study also relates to that of Benetton, Buchak and Robles-Garcia (2022), who examine complementarities across household and corporate assets for bank profitability.

Another related literature studies the credit and liquidity constraints faced by entrepreneurs.[3] We focus on personal credit, an underexplored source of liquidity for entrepreneurs. While previous work has documented the use of personal loans and personal credit scores in financing entrepreneurship (e.g. Robb and Robinson, 2014; Berger, Cowan and Frame, 2011), we are able to quantify the importance of this channel and estimate the degree of substitution between these two sources of credit. Haughwout, Lee, Scally, Van der Klaauw et al. (2021) identify entrepreneurs in the New York Fed Consumer Credit Panel, and find that consistent with our results, entrepreneurs were more likely to take up mortgage forbearance during the COVID-19 pandemic. Recent work by Kim, Parker and Schoar (2020) and Kim (2022) explores a different aspect of the relationship between personal and business finances by analyzing the bank account transactions of entrepreneurs and focusing on consumption and cash flows instead of credit usage.

Finally, our findings relate to works that study how removing derogatory personal credit information affects self-employment (Bos, Breza and Liberman, 2018; Dobbie, Goldsmith-Pinkham, Mahoney and Song, 2020; Herkenhoff, Phillips and Ethan, 2021). While we share the common theme around how personal credit characteristics affect entrepreneurial activity, we focus on the degree of intensive-margin substitution between business credit and consumer loans instead of entry into self-employment.

The remainder of this paper is structured as follows. Section 2 describes the data we use

[3]Some key topics include relationship lending (Petersen and Rajan, 1994; Berger and Udell, 1995, 2002), banking deregulation (Black and Strahan, 2002; Cetorelli and Strahan, 2006; Zarutskie, 2006; Bertrand, Schoar and Thesmar, 2007; Kerr and Nanda, 2009; Chava, Oettl, Subramanian and Subramanian, 2013; Cornaggia, Mao, Tian and Wolfe, 2015; Hombert and Matray, 2016), and wealth (Hurst and Lusardi, 2004; Cagetti and De Nardi, 2006; Andersen and Nielsen, 2012; Bellon, Cookson, Gilje and Heimer, 2021).

in our analysis. Section 3 details the empirical strategy. Section 4 reports our main results. Section 5 explores heterogeneity by personal characteristics of entrepreneurs. Section 6 assesses the robustness of our results and Section 7 concludes.

2 Data

Our main dataset is the Gies Consumer and small business Credit Panel (GCCP), a novel panel dataset with credit bureau information on small businesses and consumers from Experian. Credit bureau data is typically a random anonymized sample drawn from the database of one of the three major national credit reporting agencies in the United States (Experian, TransUnion, and Equifax). While research on consumer credit using credit bureau data has grown dramatically since the 2000s, this is one of the first papers to use small business credit bureau data in the United States.[4]

The GCCP consists of a one percent random sample of individuals with a credit report (approximately 2 million individuals per year), which is linked to business credit records for individuals who own a business between 2009 and 2018 (approximately 300,000). On the consumer side, the data include the detailed credit attributes and tradelines of each individual including credit score and debt levels for all major forms of formal debt such as mortgages, student loans, and credit cards; as well as payment history, bankruptcies, and subprime borrowing history. In addition, it includes basic demographics such as zipcode of residency, age, gender, marital status, and employment status.[5] We use the zipcode information to merge in a zipcode-level house price index obtained from the Federal Housing

[4]See Avery, Calem, Canner and Bostic (2003) and Lee and Van der Klaauw (2010) for overviews of consumer credit bureau data, and Haughwout, Lee, Scally, Van der Klaauw et al. (2021), Brennecke, Siravyan and Witzen (2021), Bellon, Cookson, Gilje and Heimer (2021), and Benetton, Buchak and Robles-Garcia (2022) for other recent work incorporating small business variables.

[5]The GCCP also includes data on alternative credit products—such as payday loans—from Experian's alternative credit bureau, Clarity Services. For more information on that dimension of the GCCP, see Fonseca (2022).

Finance Agency.

On the small business side, the data include credit attributes of each business, including proprietary credit scores used by lenders to assess delinquency and failure risk; debt levels across different categories including term loans, credit lines, credit cards, and leases; and payment history, bankruptcies, liens, UCC filings, and other public records. In addition, it includes the zipcode of each business and information such as firm age, ownership structure, number of employees, annual revenues, and industry classification. These firm attributes are linked to the credit and demographic characteristics of entrepreneurs from the consumer side of the GCCP through an anonymized consumer id provided by Experian.

Table 1 presents summary statistics for the full sample of consumers in the GCCP and the business owner sample. While consumer data are available for every year from 2004 to 2018 (archived as of March 31st of each year), small business data are only available starting in 2009. Furthermore, due to budget limitations we only collected small business credit data in 2009, 2010, 2012, 2013, and 2015 through 2020, archived on the same date as the consumer data in each year. We only include the years 2004 through 2018 for our analysis sample since the consumer data ends in 2018. In ongoing work, we will fill in the small business data in 2011 and 2014 and extend the full sample through 2022.

As illustrated in Table 1, the full sample in the GCCP is representative by design of consumers in the United States. The average credit score in the full sample is 667, and the average loan balance is $50,533, more than $40,000 of which is mortgage debt. Eight percent of the full sample is entrepreneurs. As one would expect, the entrepreneur sample looks significantly different than a random sample of consumers. The average credit score of the entrepreneur sample is 713, and holds more than twice as much overall debt and mortgage debt compared to the average consumer. Entrepreneurs are also somewhat older than typical consumers (53 vs. 48 years of age) and less likely to be female (37% vs. 48%). The average firm owned by entrepreneurs is about 11 years old, with 79% being non-employers and having an average of 2.6 employees. Hence, the majority of the sample consists of non-employers and micro-businesses (Bartlett III and Morse, 2020), and our results should primarily be interpreted as pertaining to these types of firms and entrepreneurs.

In Figure 1, we show the geographical coverage of the full GCCP (panel A) and the entrepreneur sample (panel B) in 2018, illustrating that the GCCP has national coverage of both consumers and entrepreneurs. In panel A of Figure 2, we compare the firm size distribution measured by number of employees in the GCCP with Census business counts in 2018 and find that the the GCCP broadly matches the overall distribution of all U.S. businesses.[6]

One shortcoming of the GCCP and small business credit bureau data in general in the United States is that loan-level coverage is incomplete relative to that of consumer credit (Brennecke, Siravyan and Witzen, 2021). We illustrate this issue in panel B of Figure 2, which plots the share of firms across debt balance categories in 2018 in both the GCCP and the Small Business Credit Survey (SBCS), an annual survey of firms with fewer than 500 employees conducted by the twelve Federal Reserve Banks. As shown in the figure and consistent with discussions with the data provider, firms in the GCCP have significantly less debt compared with the SBCS, which we take as the most representative sample available for our time period. Since our research question involves comparing changes in total business credit and total consumer credit, we use the SBCS to construct scaling factors that impute total business credit from observed business debt and firm characteristics in the GCCP.

We construct our scaling factor by breaking down firms in both the GCCP and SBCS into cells based on employer status and firm age, and calculate the ratio of average debt levels in the SBCS (which we take as the "true" debt level) and average debt levels in the GCCP (which we take as the "observed" debt level that could be subject to under-reporting) within each cell. Specifically, we categorize employer firms in both the GCCP and SBCS into six firm

[6]We obtain the number of non-employer firms from the 2018 Non-Employer Statistics and the number of employer firms by number of employees from the 2018 County Business Patterns.

age bins and categorize non-employer firms into four firm age bins, based on the categories available and populated in both datasets. Since exact debt levels are not reported in the SBCS, we use the mid-points of the ranges provided. For the top debt range, which is > $1 million, we use $1 million as the average level of debt.

We then apply these scaling factors to observed business debt for each observation in the GCCP to obtain estimates of total business debt at the firm level. To be precise, we estimate total business debt for firm i in firm group g for year t using equation (1) below.

$$\text{TotalBus}_{igt}^{GCCP} = \frac{\overline{\text{TotalBus}}_{gt}^{SBCS}}{\overline{\text{ObsBus}}_{gt}^{GCCP}} \times \text{ObsBus}_{igt}^{GCCP} \tag{1}$$

In our baseline scaling procedure, g represents an employer status×firm age cell and scaling factors are constructed using 2018 data and held fixed even if firm i changes its group g from one year to another. We report our baseline scaling factors in Table A.4. We also assess the robustness of our results to allowing scaling factors to vary over time as firm characteristics change and to alternative scaling factors based on all variables that are available across both datasets, including location, zipcode characteristics, firm size, industry composition, and owner gender in Section 6.3 and Figure A.1.

3 Empirical Strategy

Our empirical strategy exploits county-level differences in the presence of Top 4 banks, which sharply contracted lending to small businesses after the 2008 financial crisis likely due to a reassessment of their comparative advantage in small business lending and changes in financial regulation (Chen, Hanson and Stein, 2017). We construct the county-level deposit share of the Top 4 using the 2005 Summary of Deposits Survey by the Federal Deposit Insurance Corporation (FDIC) adjusted for mergers as in Chen, Hanson and Stein (2017). The first row of Table 1 summarizes the Top 4 deposit share in our sample.

We estimate the effect of Top 4 bank presence on business credit balances for our sample of individuals who owned a business at any point during 2009 and 2018 in the following specification:

$$\text{Business Credit}_{i,c,t} = \sum_{\tau=2009}^{2018} \beta_\tau \text{ Top 4 Share}_c \times \mathbb{I}_{t=\tau} + X_{i,c,t} + \alpha_i + \gamma_c + \theta_t + \varepsilon_{i,c,t}, \quad (2)$$

where Business $\text{Credit}_{i,c,t}$ is the business loan balance of entrepreneur i in county c and year t. The β coefficients represent the effect of Top 4 bank presence on the volume of business credit in each year τ for each firm. By including separate β_τ terms for each year, we are able to account for the moderate recovery in large bank credit supply during our sample period, although we also report pooled estimates replacing indicator variables for each year with a variable that equals 1 after 2009 and 0 before. We control for firm, county, and time fixed effects as well as zipcode-level house prices in our baseline specification and for additional firm, entrepreneur, and local characteristics in robustness checks. We cluster standard errors at the county level.

Next, we estimate the effect of Top 4 bank presence on personal borrowing. We isolate the effect of the business credit supply shock on personal credit by employing a triple-differences specification, which allows us to compare entrepreneurs with otherwise similar individuals who do not own a business. We select a control group of non-entrepreneurs by matching with replacement on the level of total consumer credit between 2004 and 2008 and use a nearest neighbor algorithm to select the two closest controls among non-entrepreneurs residing in the same county. We opt for this parsimonious procedure as our baseline, but show that our results are robust to alternative matching procedures in Section 6.4, including the addition of credit score, income, and gender as matching variables and varying the number of controls per entrepreneur.

We present pre-2009 summary statistics for the matched sample, broken down by treatment (entrepreneurs) and control (non-entrepreneurs) in Table 2. We find that entrepreneurs and non-entrepreneurs are similar across a wide range of characteristics, including those not targeted in our baseline matching procedure, such as credit scores, credit card balances, personal loans, and income. One dimension along which entrepreneurs and non-entrepreneurs differ in the matched sample is gender, with only 37% of entrepreneurs being women compared to over 50% of non-entrepreneurs. However, we show that our results are robust to exact matching on gender—so that all entrepreneurs are of the same gender as control non-entrepreneurs—in Section 6.4.

We estimate the following specification in the matched sample:

$$\begin{aligned}\text{Consumer Credit}_{i,c,g,t} = &\sum_{\tau=2004}^{2018} \delta_\tau \text{Top 4 Share}_c \times \mathbb{I}_{t=\tau} \times \text{Entrepreneur}_i \\ &+ X_{i,c,t} + \alpha_i + \gamma_{gt} + \theta_{ct} + \varepsilon_{i,c,t}\end{aligned} \tag{3}$$

where Consumer $\text{Credit}_{i,c,g,t}$ is a consumer credit outcome such as total consumer credit, mortgage balances, or credit card balances for an individual i in county c and year t, in matched treated-control group g. Entrepreneur_i is a dummy that equals one if the individual matches as a beneficial owner of a business in the commercial credit database at any point between 2009 and 2018. As with equation (2), we also report pooled estimates replacing indicator variables for each year with a variable that equals 1 after 2009 and 0 before.

We saturate the specification with fixed effects, controlling for individual, match-year, and county-year fixed effects. Adding match-year fixed effects controls for time-varying unobserved heterogeneity across groups, and filters out potential unobserved shocks that affect both entrepreneurs and observably-similar non-entrepreneurs. County-year fixed effects allow us to control for unobserved time-varying heterogeneity across counties. We also include owner-year fixed effects to account for different nationwide trends between entrepreneurs and non-entrepreneurs, and a zipcode-level house price index and its interaction with the

Entrepreneur$_i$ dummy. Standard errors are clustered at county level.

We scale the reduced-form effect of the Top 4 bank share on consumer credit balances by the first-stage effect on business credit balances to compute an estimate of the dollar elasticity of substitution between business and personal credit following a negative business credit shock. To do so, we jointly estimate the first-stage effect of Top 4 bank presence on business loan balances (equation 2) and the reduced-form effect on consumer loan balances (equation 3) using seemingly unrelated regression (SUR). We then compute the ratio of the reduced-form and first-stage coefficients, and compute standard errors for this ratio using the delta method.

Our triple-difference research design allows for the possibility that the Top 4 bank share could directly or indirectly affect the supply of personal credit. An example of this concern is that large banks disproportionately shifted mortgage originations away from conforming loans and toward jumbo loans during an overlapping time period, which is a shock to personal credit that is correlated with the instrument we use for small business credit (D'Acunto and Rossi, 2022). Our approach addresses this type of concern under the assumption that the personal credit utilization of entrepreneurs and matched non-entrepreneurs would have evolved in parallel in the absence of the Top 4 bank shock to small business credit.

This assumption might be violated if, for example, lenders treat entrepreneurs differently when providing personal credit because of entrepreneurship itself or unobserved characteristics associated with entrepreneurship, conditional on other observables. However, this differential treatment would have to both be correlated with Top 4 bank share and evolve over time in a way that's consistent with the negative small business credit supply shock in order to violate our exclusion restriction. We think such a violation is unlikely to drive our results, and we are not aware of evidence that entrepreneurship status plays a first-order role in consumer credit decisions or that lenders systematically collect this information when underwriting major forms of consumer credit.[7]

4 Main Results

4.1 First stage: The decline in small business lending by large banks

We start by estimating the effect of Top 4 bank market share on business credit. We estimate equation (2) and plot coefficients and 95% confidence intervals in Figure 3. Panel A reports the effect on unscaled business credit, while panel B reports results using our scaled measure of total business credit as described in Section 2. In both panels, the coefficient on year t can be interpreted as the average change in business loan balances for an entrepreneur in a county with 100% Top 4 deposit share relative to an entrepreneur in county with no Top 4 bank presence between year t and the baseline year (2009).

Table 3 presents regression estimates for both unscaled and scaled business credit that pool the post-2009 effects into a single *Post* variable interacted with the Top 4 share, which we use as our baseline results. Columns (2) and (4) present results from our baseline specification including borrower, county, and year fixed effects and zipcode-level house prices, and columns (1) and (3) present these results with only fixed effects and not house prices for comparison.

Panel A of Figure 3 shows that the decline in small business credit relative to 2009 grows in magnitude until 2015, and recovers slightly but persists until the end of our sample in 2018. Without taking into account the under-reporting of small business credit, we find that

[7]For example, the CFPB website lists credit score, home location, home price and loan amount, down payment, loan term, interest rate type, and loan type as the seven key factors that affect mortgage interest rates, and lists name, income, Social Security number, property address, estimated value of property, and desired loan amount as the six pieces of information consumers need to provide to obtain loan estimates. See https://www.consumerfinance.gov/about-us/blog/7-factors-determine-your-mortgage-interest-rate/ and https://www.consumerfinance.gov/ask-cfpb/what-information-do-i-have-to-provide-a-lender-in-order-to-receive-a-loan-estimate-en-1987/

an entrepreneur in a county with 100% Top 4 deposit share experiences an average decline of $932.73 in observed balances between 2010 and 2018, relative to an entrepreneur in a county with zero Top 4 presence (column 2 of Table 3). Panel B shows the analogous results for scaled total business credit. We observe a similar time series pattern in the estimated coefficients, with the effect of Top 4 bank presence growing in magnitude until 2015 and recovering modestly from 2015 to 2018. Our preferred estimate of the average decline in total business credit as a result of exposure to Top 4 banks is $13,571.50 (column 4 of Table 3).

Overall, our findings are consistent with an economically meaningful, statistically significant, and persistent decline in business credit for entrepreneurs in counties with a large initial presence of Top 4 banks. As shown in Table 3, the inclusion of a house price control does not significantly change the magnitude or precision of our results, suggesting that mortgage-market factors are not likely to confound our identification approach.

4.2 Reduced form: The effect of business credit supply on consumer loans

Next, we ask whether entrepreneurs use personal credit to smooth the negative shock to business credit supply described in the previous section. To shed light on this question, we estimate equation (3) with personal credit outcomes as dependent variables. This specification uses matched non-entrepreneurs as a control group to alleviate concerns that Top 4 bank presence directly affects the supply of personal credit as well as the supply of business credit or is correlated with unobserved factors that affect both forms of credit (i.e. violates the exclusion restriction).

We plot coefficient estimates and 95% confidence intervals from equation (3) with total personal credit balances as the dependent variable in Figure 4 and report estimates pooling the post period in Table 4. Since data on personal credit is available from 2004 onward, we are able to test for pre-trends between entrepreneurs (treatment) and matched non-entrepreneurs (control) prior to the shock to business credit starting in 2009. We find no consistent trend in total personal credit prior to 2009, with annual coefficients ranging from -$1,796 to $2,751 that are statistically indistinguishable from zero, providing evidence in favor of the parallel trends assumption.

In the years after 2009, we find that the personal balances of entrepreneurs in counties with high Top 4 bank presence increase relative to the balances of matched non-entrepreneurs in the same counties. Consistent with these results being driven by a shock to business credit supply, the dynamics of personal credit mirror those of small business credit, with the effect increasing up to 2015 and stabilizing thereafter. The average entrepreneur increases personal borrowing by $9,178.30 relative to matched non-entrepreneurs who reside in the same county and have similar characteristics prior to 2009 (column 2 of Table 4). Since credit bureau records capture the substantial majority of consumer credit relative to small business credit and provide the most complete measurements available of consumer credit levels, we do not rescale the consumer credit estimates.

By comparing our first stage and reduced form estimates, we are able to quantify the degree to which consumer credit is used as a substitute for business credit. The increase in personal borrowing of $9,178.30 corresponds to 68% of the average decline in business credit (column 6 of Table 4). This suggests that entrepreneurs are able to meaningfully but not fully smooth business credit supply shocks by relying on personal credit. Next, we estimate equation (3) for different categories of personal credit in order to understand what types of personal loans entrepreneurs rely on. In Figure 5, we report coefficient estimates and 95% confidence intervals of equation (3) with mortgage balances (panel A) and credit card balances (panel B) as dependent variables. We find that the increase in personal balances is entirely driven by mortgages, which rise by $10,303.56 (column 3 of Table 4).

Despite the prevalence of both business and consumer credit cards as a source of liquidity for entrepreneurs, we find no significant effect on personal revolving and credit card borrowing (columns 4 and 5 of Table 4). Possible explanations are that entrepreneurs prefer to access cheaper credit by tapping into home equity or that credit card borrowing is not a large enough source to meaningfully substitute for the lost business credit due to the shock we focus on. It could also be the case that credit cards are used for short-term liquidity and not the types of investments affected by the shock we analyze, or that credit cards are more important for startup capital relative to ongoing financing for existing small firms. These are interesting dimensions for future research.

To support our interpretation that entrepreneurs use their additional mortgage credit for business purposes, we next provide evidence that the higher mortgage balances are driven by cash-out refinancing and *not* by home-buying or moving. We do so in three different ways.

First, we leverage the loan-level data in the GCCP to identify refinancing activity. We define a new mortgage loan as a refinancing if it was opened within a 30-day window of an existing mortgage loan being paid off and closed. Since the average time to close on a house exceeds 30 days, we think it's unlikely that paying off a mortgage and opening a new one within 30 days represents a new home purchase. However, we also complement this analysis by showing that entrepreneurs are not more likely to move across zipcodes. We then aggregate balances associated with refinancing to the consumer-year level and subtract them from overall mortgage balances. This allows us to test whether entrepreneurs increase mortgage balances through refinancing versus other channels such as purchasing additional homes or taking out home equity loans. Second, we look at total open mortgage trades as an additional test of whether are results are driven by new home purchases. Third, we look at the propensity to move zipcodes to rule out that higher mortgage balances are driven by entrepreneur-specific moving shocks that correlate with the presence of Top 4 banks.

We report results of this exercise in Table A.1. In column 1, we reproduce our baseline result on the increase in mortgage balances, which matches column 3 of Table 4. In column 2, the dependent variable is mortgage balances excluding balances associated with refinancing. Excluding balances associated with refinancing causes estimates to drop from over $10,000 (column 1) to below $200 (column 2) and become statistically indistinguishable from zero. We take this as strong evidence that higher mortgage balances are driven by cash-out refinancing and not by home purchases. In column 3, we show that there is no significant difference in the total number of open mortgage trades for entrepreneurs and non-entrepreneurs. This is also consistent with the refinancing channel, whereby one mortgage trade is closed and another opened in quick succession, and inconsistent with mortgage-financed additional homebuying, which would cause the number of mortgage loans to increase. Finally, the dependent variable in column 4 is an indicator for the individual changing their zipcode of residence compared with the previous year. If anything, we find that entrepreneurs are slightly less likely to move than non-entrepreneurs following the business credit shock, which is also consistent refinancing being the primary driver of higher mortgage balances rather than homebuying.

Finally, we show that our results are driven by areas with high growth in house prices, where available home equity was likely to have increased the most. To do that, we split entrepreneurs into those that experienced high or low local house-price growth between 2004 and 2018 based on a zipcode-level index and run our analysis separately for each group. We define low house-price growth as the first quartile of the house-price growth distribution and high growth as the second through fourth quartiles.[8] As we report in Table A.2, entrepreneurs that experienced high and low house price growth saw similar declines in business credit (columns 1 and 4). However, we only estimate a statistically significant increase in personal borrowing for those who experienced high price growth. This evidence further supports the interpretation that higher personal borrowing by entrepreneurs is driven

[8]The 25th percentile of the house-price growth distribution between 2004 and 2018 is 10.76%. Results are qualitatively identical if we define low growth as negative growth.

by equity extraction.

5 Heterogeneity by Entrepreneur Characteristics

In Section 4, we showed that entrepreneurs turn to personal credit when faced with a negative shock to business credit supply. In this section, we explore how the personal characteristics of entrepreneurs mediate the substitution parameter we estimate and thus affect their firms' overall access to external finance. Our primary focus is on the personal financial characteristics of entrepreneurs such as income and credit scores, but we also explore the role of gender. We sort matched treated-control groups into bins according to characteristics of the treated entrepreneur within each group and estimate the response of personal credit (equation 3) for each bin separately.

On the one hand, we might expect entrepreneurs with lower income and credit scores to substitute more if they have smaller businesses that require less capital and face a smaller absolute decline in business credit that can be more easily compensated by personal credit. On the other hand, less creditworthy entrepreneurs might have less home equity or less ability to access it in the post-crisis period, which would limit their ability to substitute declining business credit with personal credit. Our empirical results help to disentangle which of these possibilities dominate in practice.

In terms of gender, we might expect lower substitution by female entrepreneurs since prior research has found that they are less likely to apply for loans and have less start-up capital (e.g. Hwang, Desai and Baird 2019; Krause and Fetsch 2016; Robb, Coleman and Stangler 2014; Cole, Mehran and Giombini 2018; Shaheen 2017). However, these prior results reflect disparities in access to business credit on the extensive margin, and might not reflect patterns of substitution to personal credit for existing female-owned businesses in response to the specific shock we study. We contribute to the literature on gender and entrepreneurship by studying this intensive margin of substitution.

5.1 Credit score

We start by documenting that the ability to tap into personal credit when faced with business credit supply shocks is limited to entrepreneurs with higher personal credit scores. In this exercise, we classify entrepreneurs as subprime or nonprime if their average pre-2009 credit score is lower than 700, and as prime or superprime if their average score exceeds 700. We then estimate equation (3) separately for subprime/nonprime borrowers and for prime/superprime borrowers.

We show results of this exercise in Figure 6 with total business loan balance (panel A) and total personal credit (panel B) as dependent variables, and report pooled estimates in panel A of Table 5. As expected, subprime entrepreneurs experience a significantly smaller absolute decline in business credit during the post-crisis period. However, subprime entrepreneurs actually reduce their personal borrowing while the supply of business credit contracts, although the effect on personal credit is economically small and our estimated substitution factor is noisily estimated and statistically indistinguishable from zero (column 3 of Table 5). In contrast, prime entrepreneurs replace all of the lost business credit with personal credit, with an estimated substitution factor of 108% (column 6 of Table 5).

Our results show that even though both subprime and prime entrepreneurs suffer a negative business credit supply shock driven by the Top 4 bank share, their personal credit responses to this shock are dramatically different. Only prime entrepreneurs are able to substitute any of their lost business credit by using personal credit.

5.2 Income

Next, we conduct an analogous exercise sorting entrepreneurs into high- and low-income bins based on whether their pre-2009 average income is above or below the sample median. We show the results of this exercise in Figure 7 and report pooled regression estimates in panel B of Table 5. Our findings when splitting entrepreneurs by income are very similar to those when splitting by credit score.

Like subprime entrepreneurs, low-income entrepreneurs experience a smaller absolute decline in business credit, and demonstrate no substitution to personal credit, resulting in an estimated substitution parameter of 7% (column 3 of Table 5). High-income entrepreneurs substitute almost fully, with a substitution parameter of 94% (column 6 of Table 5).

While income may not be the most important personal characteristic for all consumer credit supply decisions, income may be particularly important for mortgage refinances, which drive our results. The heterogeneous substitution by income is consistent with the idea that income-based underwriting policies during the post-crisis period significantly affected credit supply in the mortgage market (DeFusco and Mondragon, 2020).

5.3 Credit card utilization

The next source of heterogeneity we consider is credit card utilization, which is another key metric used for credit underwriting. We sort individuals into high- and low-utilization bins based on whether their average pre-2009 credit card utilization—defined as total credit card balance divided by total credit card limit—is above or below the median, and estimate equation (3) separately for each bin.

We show results of this exercise in Figure 8 and report pooled regression estimates in panel C Table 5. In contrast to the sample splits by credit score and income, where the negative business credit supply shocks experienced by subprime and lower-income entrepreneurs were less than half the size of those experienced by prime and higher-income entrepreneurs, high- and low-utilization entrepreneurs experience business credit supply shocks of more comparable magnitude (\$-12,317.55 vs. \$-16,836.65). However, consistent with our other measures of personal credit constraints, entrepreneurs with high levels of credit card utilization are unable to substitute to personal credit, with an estimated substitution parameter of 1% (column 3 of Table 5) compared with 111% for low-utilization entrepreneurs (column 6 of

Table 5).

Taken together, the findings presented in this section suggest that only entrepreneurs with high incomes, high credit scores, and low credit card utilization are able to leverage personal borrowing to finance their small businesses following an aggregate business credit supply shock. This occurs despite the finding that subprime, low-income, and high-utilization entrepreneurs have smaller absolute declines in business credit that would need to be substituted.

While a determination of whether these substitution patterns are economically efficient is beyond the scope of our paper, the answer likely hinges on the extent to which personal financial characteristics are correlated with the investment opportunities available to entrepreneurs. It is plausible that entrepreneurs with lower personal creditworthiness have disproportionately worse investment opportunities in a downturn, but this remains an open empirical question. It is also possible that personal creditworthiness is not perfectly correlated with expected business returns. If the reliance on personal characteristics for entrepreneurial financing is in part driven by differences in information asymmetry between the the consumer and small business credit markets, these asymmetries may both cause inefficiency and motivate innovations that could expand credit supply and build more accurate credit models for small firms.

5.4 Gender

In the last exercise of this section, we investigate whether conditional on entrepreneurship, women face barriers to smoothing business credit shocks with personal credit. To do so, we estimate equation (3) separately for male and female entrepreneurs, and show results in Figure 9 and panel D of Table 5. We find that male and female entrepreneurs experience similar business credit supply shocks and that their personal borrowing responses are comparable.

This result contrasts with prior work finding that female entrepreneurs are less likely to apply for loans and have less start-up capital (e.g. Hwang, Desai and Baird 2019; Krause and Fetsch 2016; Robb, Coleman and Stangler 2014; Cole, Mehran and Giombini 2018; and Shaheen 2017) and that female-owned businesses experience lower revenue growth (e.g. Farrell, Wheat and Mac 2020; Robb, Coleman and Stangler 2014). Our findings suggest that despite these disparities, there is no intensive-margin effect of gender on the degree of substitution between personal and business loans in our setting.

One potential explanation for this finding is that conditional on entrepreneurship, female and male entrepreneurs have similar personal credit characteristics. As we show in Table 1, women are underrepresented among entrepreneurs, making up 50% of the full sample but only 36% of entrepreneurs. However, we show in Table A.3 that conditional on owning a business in our sample, men and women have similar credit scores, personal loan balances, and income, although female entrepreneurs have substantially smaller business loan balances. Thus, female entrepreneurs do experience a larger relative business credit supply shock compared with their average level of business credit, and may suffer disproportionately negative consequences for that reason. However, male and female entrepreneurs do not differ ex ante on key measures of personal creditworthiness such as income and credit score that drive the differences in the substitution parameter that we uncover in this section. We leave it to future work to disentangle the potential explanations behind these patterns.

6 Additional Results and Robustness

6.1 The effect on firm financial distress

In Section 4, we showed that entrepreneurs respond to a decline in small business credit by increasing their personal borrowing, driven by higher mortgages balances. While the evidence is consistent with cash-out refinancing and not with home-buying or moving, one potential remaining concern is that entrepreneurs are consuming or saving these additional funds rather than applying them toward their businesses. These uses of personal credit would not be consistent with our interpretation of substitution for lost business credit.

Since we do not directly observe firm investment, we instead analyze the effect of Top 4 bank presence on measures of firm financial distress. Intuitively, a large negative shock to the supply of business credit would lead to increased firm distress for entrepreneurs who were not able to substitute to personal credit (e.g. Khwaja and Mian, 2008). If entrepreneurs were using personal credit for consumption or other purposes, we would expect no relationship between substitution to personal credit and firm distress. Based on the results of Section 5, we would therefore expect firms owned by subprime entrepreneurs, who do not substitute for declining business credit with personal credit when exposed to the Top 4 bank shock, to experience greater financial distress after 2009. Since prime entrepreneurs substitute on average all of their lost business credit with personal credit, we expect their levels of firm financial distress to remain roughly unchanged after 2009.

In Table 6, we report estimates of equation (2) with measures of firm financial distress as dependent variables. In columns 1 through 3, we show that Top 4 bank presence leads to a three percentage point increase in the probability of having a delinquent business trade for subprime entrepreneurs (column 2), but a small and insignificant change for prime entrepreneurs (column 3). Columns 4 through 6 report analogous results with a proprietary firm risk score as the dependent variable, and again show that Top 4 bank presence leads to firm financial distress for subprime and not prime entrepreneurs. The risk score we use is a scale from 1 to 100 provided by the data vendor, where 100 represents the lowest-risk score and 1 represents the highest-risk score. These results are consistent with the hypothesis that entrepreneurs who substitute declining business credit with personal credit apply the additional liquidity from mortgage refinancing toward their businesses, allowing their firms to mitigate financial distress.

6.2 Personal financial characteristics vs. firm-level measures

In Section 5, we argued that the personal financial characteristics of entrepreneurs are key determinants of their ability to substitute between personal and business credit in the setting we analyze. However, one might worry that these personal financial characteristics are correlated with business characteristics that determine investment opportunities or access to finance. For instance, if prime entrepreneurs own firms that are larger and older, our results could be driven by the same mechanisms as prior work showing that small and young firms are more likely to be financially constrained (Hadlock and Pierce, 2010).

To alleviate these concerns, we run horse races between the personal financial characteristics explored in Section 5 and measures of firm-level financial constraints. Specifically, we run regressions of the type

$$
\begin{aligned}
\text{Consumer Credit}_{i,c,g,t} = {} & \delta \text{Top 4 Share}_c \times \text{Post}_t \times \text{Entrepreneur}_i \times \text{Personal}_i \\
& + \sum_f \rho_f \text{Top 4 Share}_c \times \text{Post}_t \times \text{Entrepreneur}_i \times \text{Firm}_i^f \\
& + \lambda \text{Top 4 Share}_c \times \text{Post}_t \times \text{Entrepreneur}_i \\
& + X_{i,c,t} + \alpha_i + \gamma_{gt} + \theta_{ct} + \varepsilon_{i,c,t},
\end{aligned}
\tag{4}
$$

where Personal_i is an indicator variable for having high levels of personal creditworthiness as measured by prime/superprime credit score, above-median income, or below-median credit card utilization, and Firm_i^f are indicators for one or more proxies for firm-level financial constraints. The measures available in the GCCP include firm size (measured as being an employer vs. non-employer firm), firm age (above or below the median age), and a proprietary firm risk score (above or below the median score). We construct these firm-level indicator variables using the first year of available business credit data, which is 2009.

We report results of this exercise in Table 7, which shows results for the personal credit score interaction in panel A, the personal income interaction in panel B, and the credit card utilization interaction in panel C. We indicate which measures of firm-level financial constraints are included in the horse race in the bottom rows of Table 7. Column 1 has no interactions with firm characteristics; columns 2 through 4 include a interactions with firm size, firm age, and firm risk score; and column 5 includes interactions with all three firm-level measures. Across all three panels, we find that the point estimates are stable to the inclusion of interaction terms with firm characteristics. These results are evidence that the relationship we document between the personal financial characteristics of entrepreneurs and their ability to subtitute for lost business credit is driven by their personal creditworthiness and not by observable measures of firm-level financial constraints.

6.3 Robustness to alternative scaling factors

Next we assess the robustness of our first stage estimates to alternative ways of imputing total business credit from a combination of observed business credit and firm characteristics in the GCCP and total business credit in the SBCS. Our baseline methodology splits firms in both datasets into cells based on employer status and firm age to construct the scaling factor. We construct alternative scaling factors based on the five additional variables that are available across both datasets: firm size in number of employees, the census division of the firm, whether the firm is in an urban or rural zipcode, firm sector, and owner gender. Since the SBCS reports data for employer and non-employer firms separately and not as part of a pooled representative sample, each of these variables is used to break down employer and non-employer firms separately into cells as in our baseline procedure described in Section 2. We also consider a scaling factor based solely on employer status, meaning it is simply the ratio of average business debt for employer and non-employer firms in the SBCS with the analogous levels in the GCCP.

For each of these six cell groupings, we compute four versions of our scaling factors.[9] We

[9]The six cell groups are employer status, employer status×firm size, employer status×census division, employer status×rural-urban zipcode, employer status×sector, employer status×owner gender.

compute both a time-invariant version in which the scaling factor is computed based on 2018 characteristics and a time-varying version that allows the factor to change as the relevant firm characteristics change. We also assess robustness to using \$2 million as the average level of debt for the top debt range reported in the SBCS (> \$1 million) in addition to our baseline of \$1 million.

We report estimates of equation (2) with business credit scaled according to each of these 24 alternative scaling factors in Figure A.1. We plot our baseline estimates in red and estimates under alternative scaling procedures in grey. Overall, we obtain similar results under alternative scaling factors, and nearly every estimate falls within our 95% confidence intervals. This exercise does suggest that our baseline procedure potentially overstates the extent to which business credit supply rebounded between 2015 and 2018, so we caution against strong conclusions based on this rebound effect.

6.4 Robustness to alternative matching procedures

In Table A.5, we report our main reduced form estimates under alternative procedures for obtaining a matched sample of control non-entrepreneurs.[10] In column 1 of Table A.5, we report results from our baseline procedure, which consists of matching with replacement on the level of total consumer loans before 2009 using a nearest neighbor algorithm and selecting the 2 closest controls among non-entrepreneurs residing in the same county, as described in Section 3.

In the next two columns, we report results obtained from nearest-neighbor matching on total consumer loans in addition to average pre-2009 credit scores (column 2) and average pre-2009 income (column 3). In column 4, we match on the level of total consumer loans before 2009 using a nearest neighbor algorithm and select the two closest controls among

[10]Note that our first stage estimates are obtained using only entrepreneurs and not a matched sample, and are thus not affected by this matching procedure.

non-entrepreneurs residing in the same county *and* of the same gender. In the final two columns, we vary the number of neighbors we select from our baseline of two to either one (column 5) or three (column 6). We find consistent results across this range of alternative matching procedures.

6.5 Robustness to additional controls

Finally, we assess the robustness of our results to controlling for a range of other local and individual characteristics and report results in Table A.6. In column 1 of Table A.6, we report the effect of Top 4 bank share on total consumer balances without controls and in column 2, we report the effect controlling for a zipcode-level house price index (our baseline estimate). In subsequent columns, we include additional controls. In column 3, we control for the state-level unemployment rate, interacted with the Entrepreneur dummy, to help alleviate the concern that our results might be driven by the fact that entrepreneurs are differentially exposed to economic conditions. In subsequent columns, we include pre-2009 averages of credit scores, income, total consumer balances, and mortgage balances. This helps address the concern that our results might be driven by differences in borrower characteristics that remain after our matching procedure. Given that we show that Top 4 bank presence affects the personal borrowing of entrepreneurs, we control for the pre-2009 value of these personal characteristics interacted with year fixed effects. We find that our estimates are quantitatively very similar across all these specifications.

7 Conclusion

This paper estimates the degree of substitution between personal and small business credit for U.S. entrepreneurs between 2009 and 2018 using a novel, individual-level dataset. We identify the effect of business credit supply shocks by exploiting geographic variation in the market share of large banks, which sharply reduced credit supply to small businesses relative to other banks after the 2008 financial crisis. While this contraction decreased total business credit by $13,571 per firm in our sample, we find that entrepreneurs were able to substitute about 68% of this decline with personal credit, driven by mortgages. However, this channel is not used by all entrepreneurs, and those with subprime credit scores, below-average income, and high credit card utilization do not make up for lost business credit with personal credit. These findings suggest that taking into account the personal finances and financial characteristics of entrepreneurs is crucial for understanding the overall access to external finance of small businesses.

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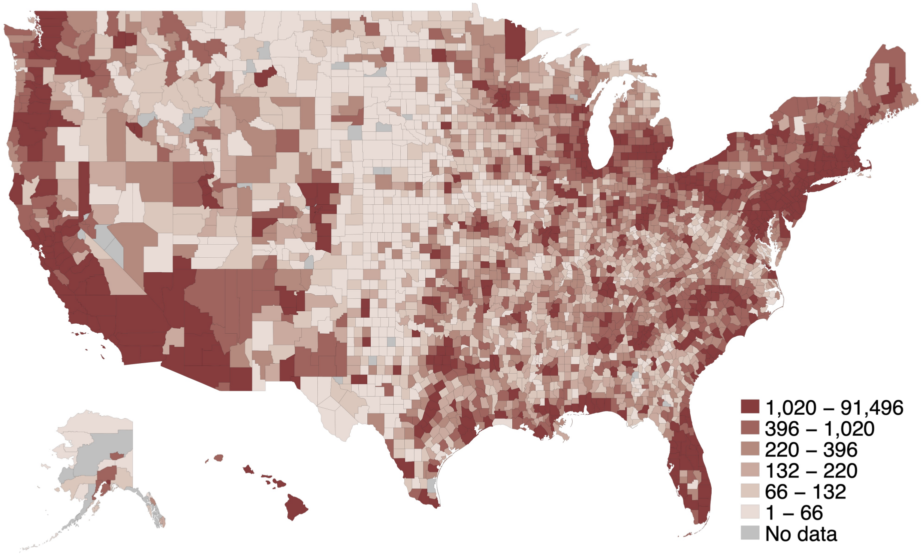
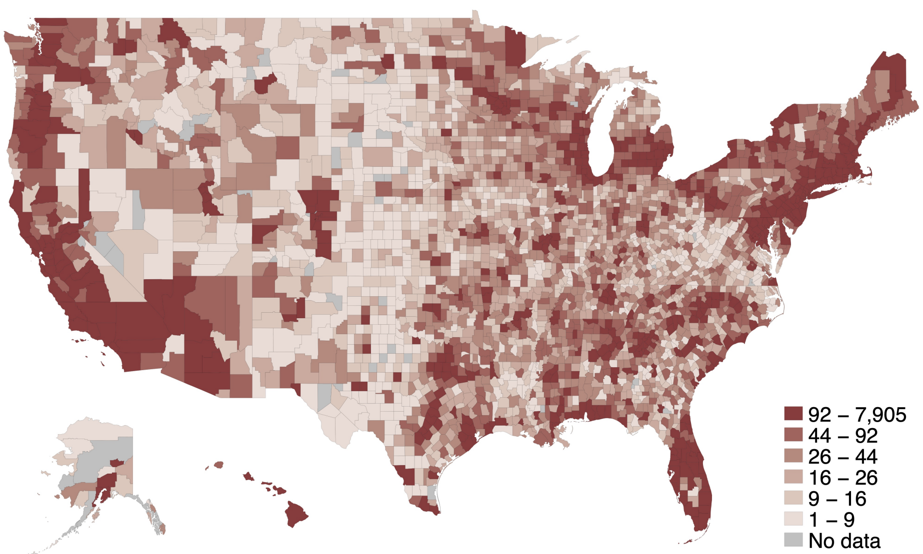
Figure 1: Geographical Coverage in 2018



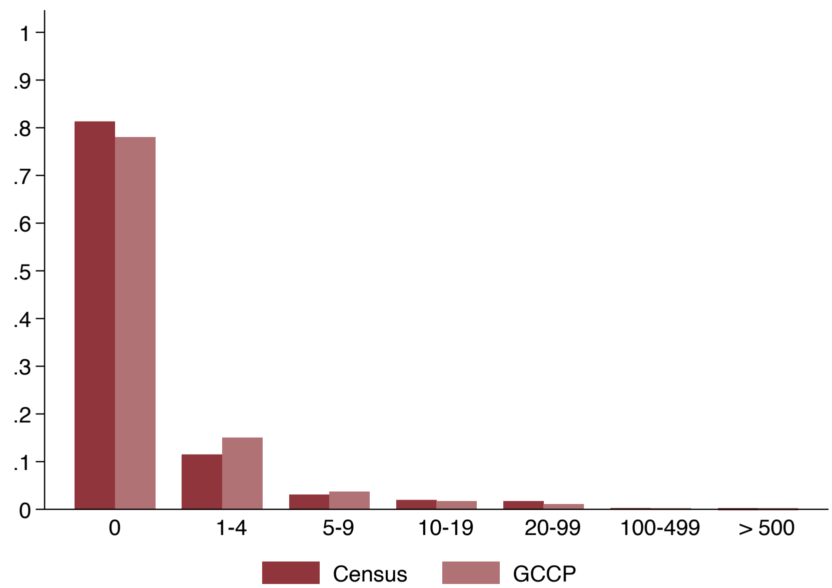
(a) Full sample



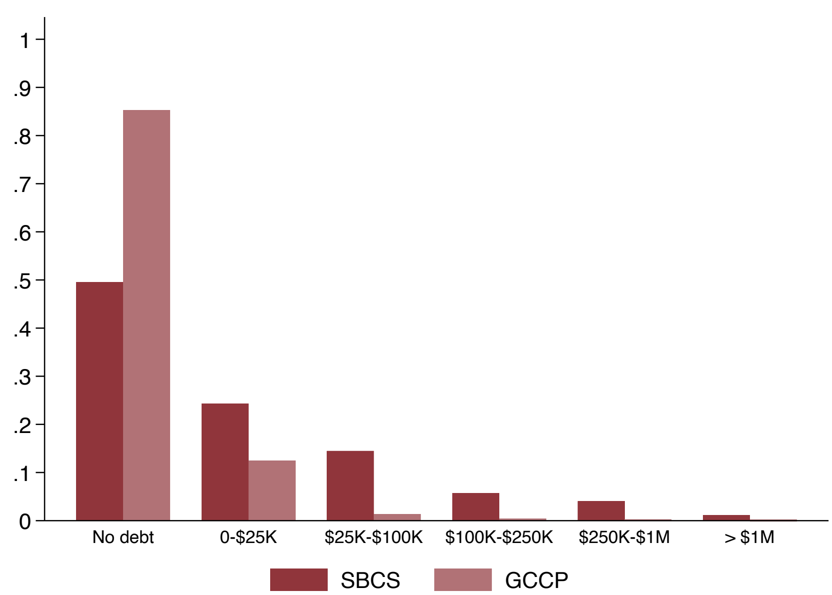
(b) Entrepreneurs

This figure shows the geographical coverage of our dataset in 2018 by plotting the number of individuals (panel A) and entrepreneurs (panel B) in our sample by county. Entrepreneurs are individuals who match to a business in the commercial credit database at any point between 2009 and 2018.

Figure 2: Firm Size and Total Debt Distribution in 2018



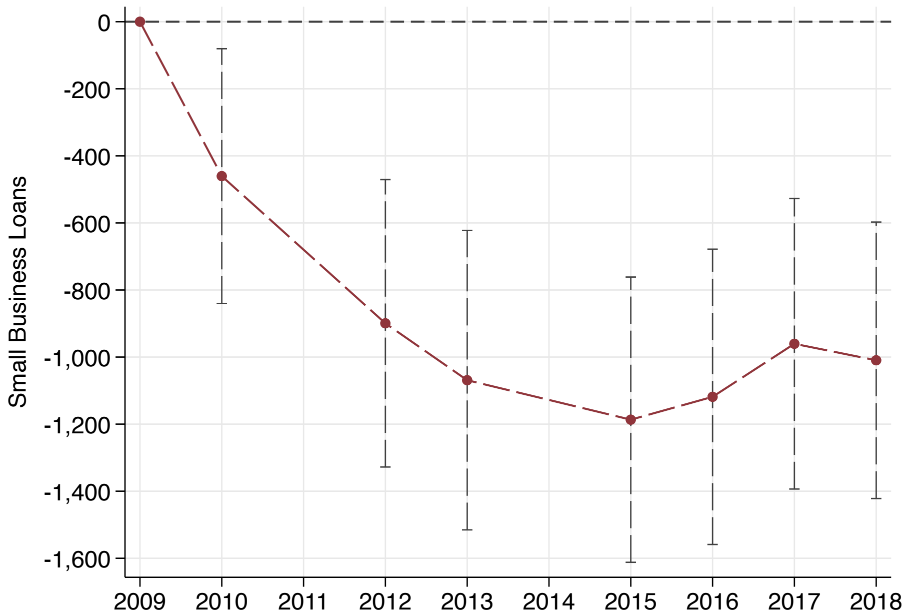
(a) Number of Employees



(b) Total Business Debt

This figure shows the distribution of firms in across firm size and debt categories in 2018. In panel A, we plot the share of firms in each firm size bin, measured as number of employees, in both the GCCP and Census data. In panel B, we plot the share of firms in each total business debt bin in both the GCCP and the Small Business Credit Survey. Entrepreneurs are individuals who match to a business in the commercial credit database at any point between 2009 and 2018.

Figure 3: Effect of Top 4 Bank Deposit Share on Small Business Lending

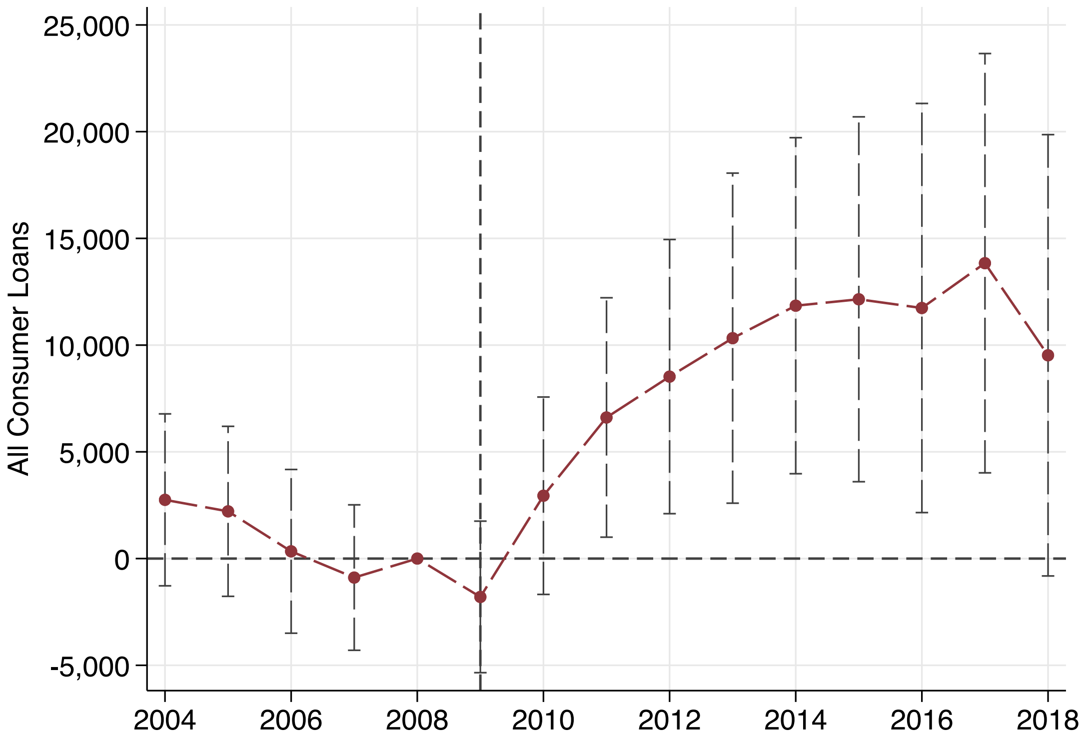


(a) Unscaled Business Loan Balance

(b) Scaled Business Loan Balance

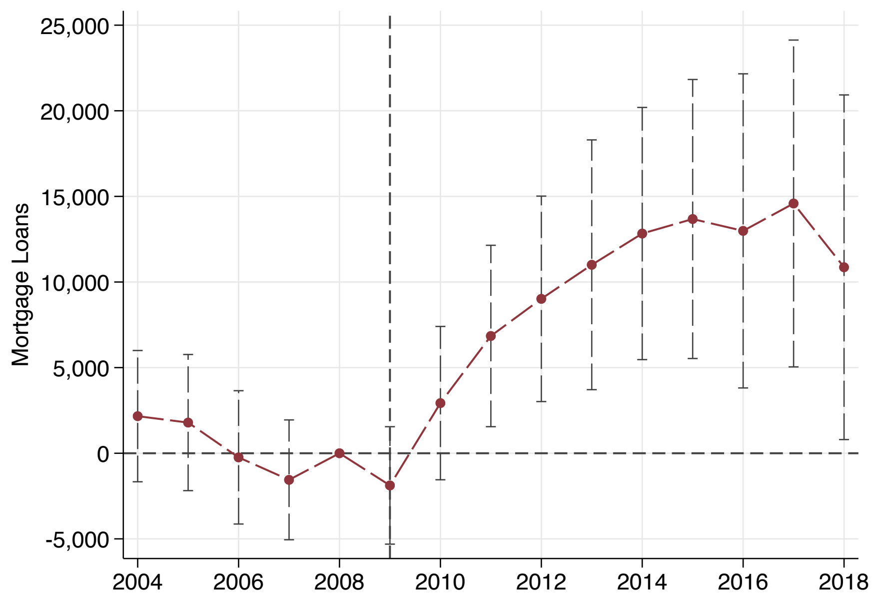
This figure plots coefficient estimates and 95% confidence intervals from equation (2), which models the effect of Top 4 bank presence on total business loan balances. Panel A shows unscaled estimates of observed loan balances in the GCCP, and panel B shows results when we scale business loans in the GCCP by factors constructed with 2018 SBCS data as estimates of total business debt. The scaling factor is based on total business debt in the SBCS for firms matched by employer status and firm size categories. See text for details. Controls include borrower, year, and county fixed effects, as well as a zipcode-level house price index. Standard errors are clustered at the county level.

Figure 4: Effect on total consumer loan balance



This figure plots coefficient estimates and 95% confidence intervals of the differences-in-differences specification from equation (3), which models the effect of Top 4 bank presence on the consumer loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same counties. Total personal loan balance is the sum of all personal loan balances for a given individual in a given year. Controls include borrower, match-year, owner-year, and county-year fixed effects, as well as a zipcode-level house price index and its interaction with the Entrepreneur_i dummy. Standard errors are clustered at the county level.

Figure 5: Effect by consumer loan category

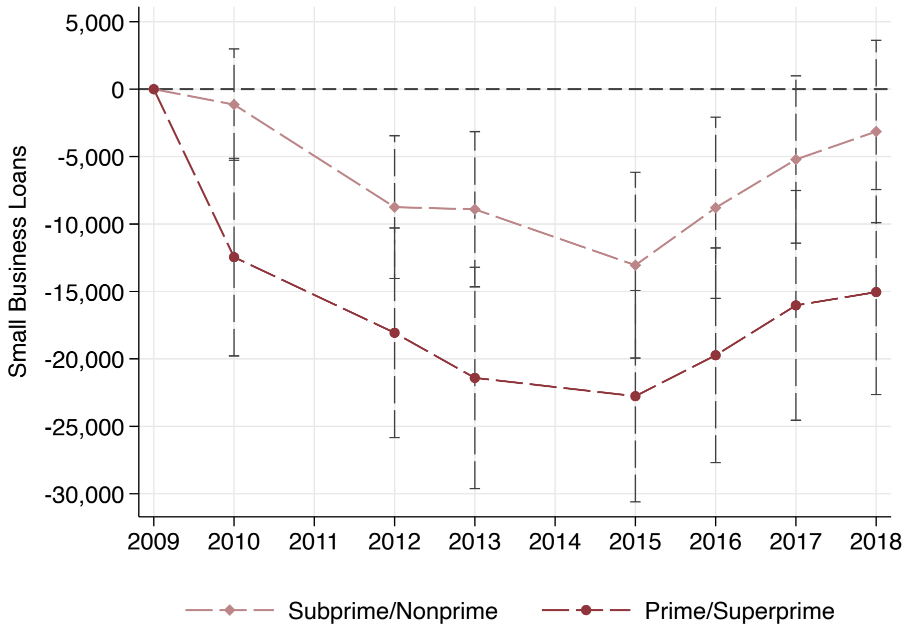


(a) Mortgage loan balance

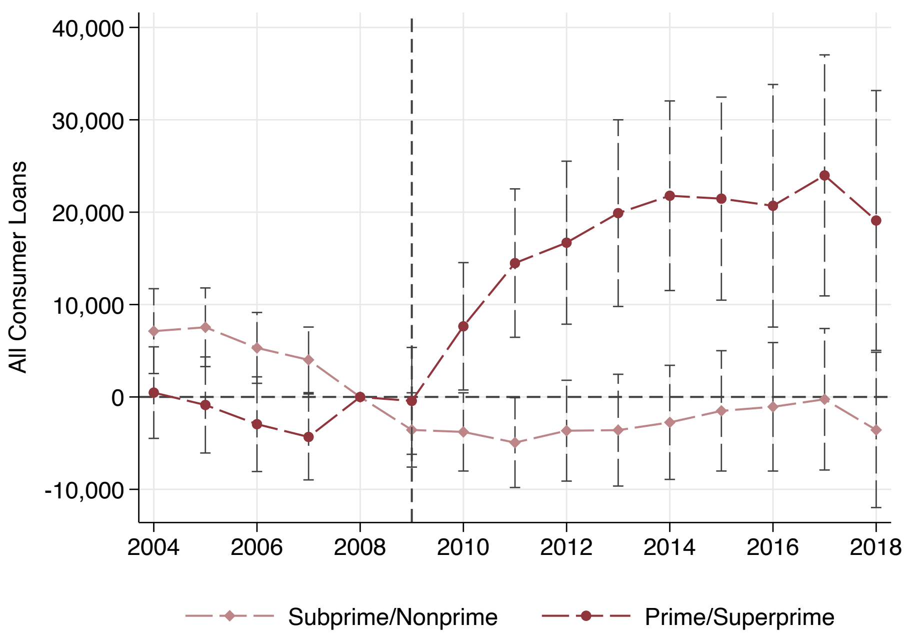
(b) Credit card balance

This figure plots coefficient estimates and 95% confidence intervals of the differences-in-differences equation (3), which estimates the effect of Top 4 bank presence on consumer loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same counties. Mortgage loan balances is the sum of all mortgage loans for a given individual in a given year and credit card balance is the sum of all credit card balances. Controls include borrower, match-year, owner-year, and county-year fixed effects, as well as a zipcode-level house price index and its interaction with the Entrepreneur$_i$ dummy. Standard errors are clustered at the county level.

Figure 6: Heterogeneity by credit score



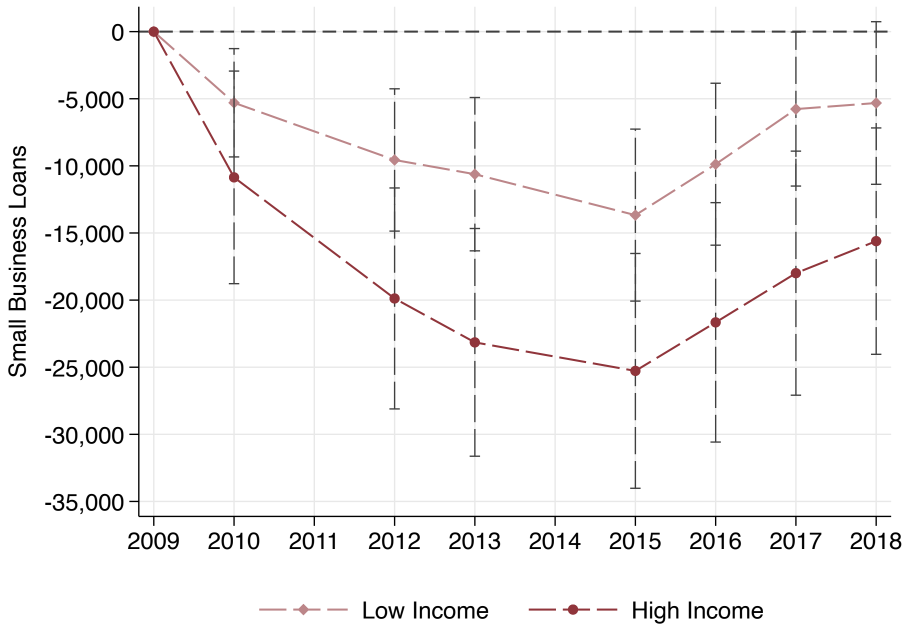
(a) Scaled business loan balance



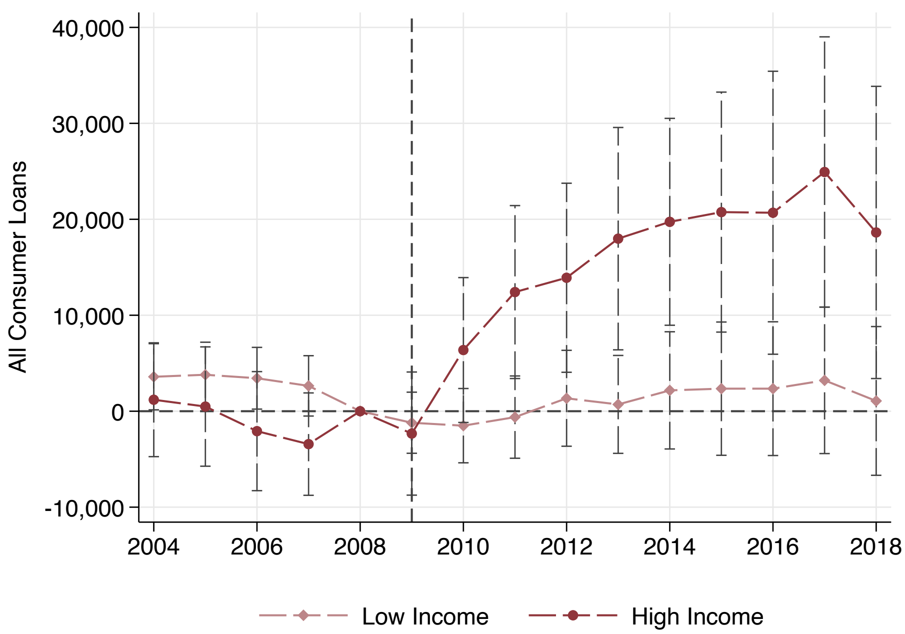
(b) Total personal loan balance

This figure plots coefficients and 95% confidence intervals of equation (3) estimated separately for entrepreneurs with credit scores below 700 (Subprime/Nonprime) and above it (Prime/Superprime). Scaled business loan balance is the total balance on business loans scaled by employer status and firm age. Controls include borrower, match-year, owner-year, and county-year fixed effects, as well as a zipcode-level house price index and its interaction with the Entrepreneur_i dummy. Standard errors are clustered at the county level.

Figure 7: Heterogeneity by income



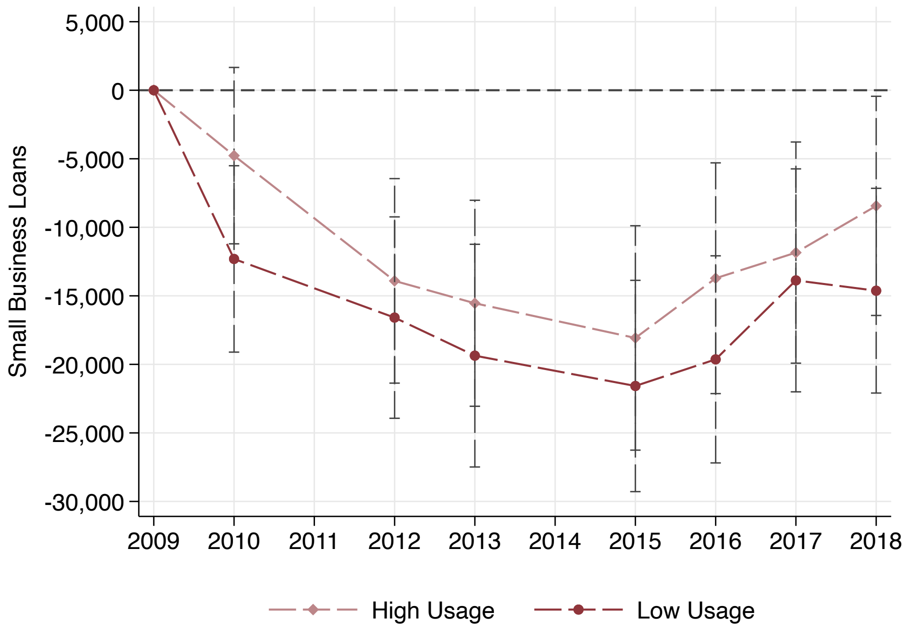
(a) Scaled business loan balance



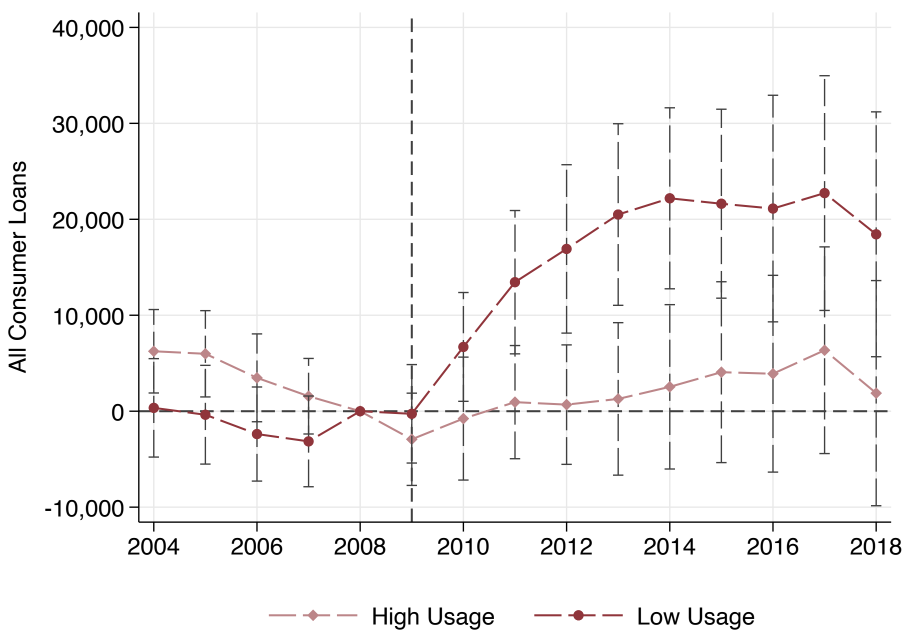
(b) Total personal loan balance

This figure plots coefficients and 95% confidence intervals of equation (3) estimated separately for entrepreneurs with average pre-2009 income above (High Income) the median and below it (Low Income). Scaled business loan balance is the total balance on business loans scaled by employer status and firm age. Controls include borrower, match-year, owner-year, and county-year fixed effects, as well as a zipcode-level house price index and its interaction with the Entrepreneur$_i$ dummy. Standard errors are clustered at the county level.

Figure 8: Heterogeneity by credit card utilization



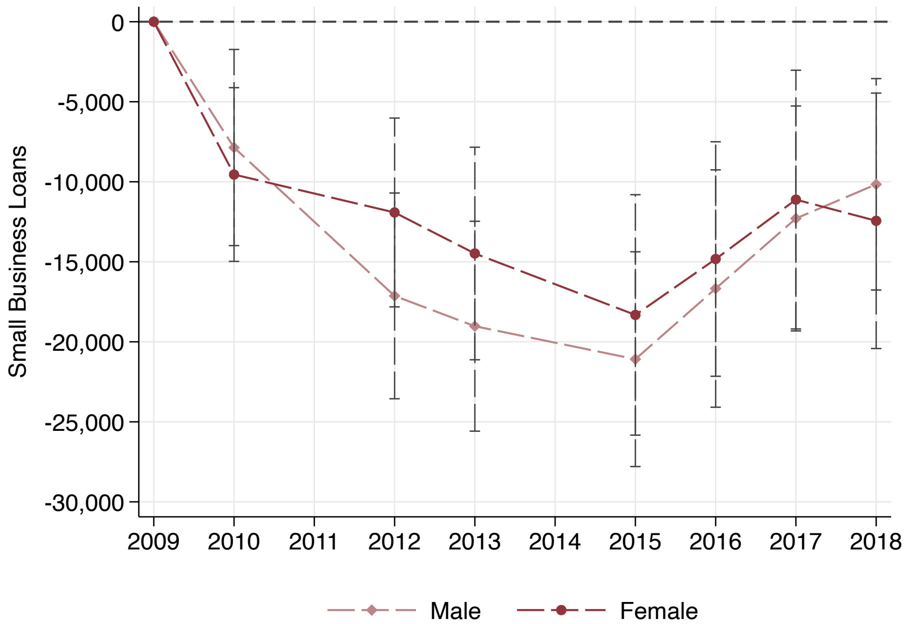
(a) Scaled business loan balance



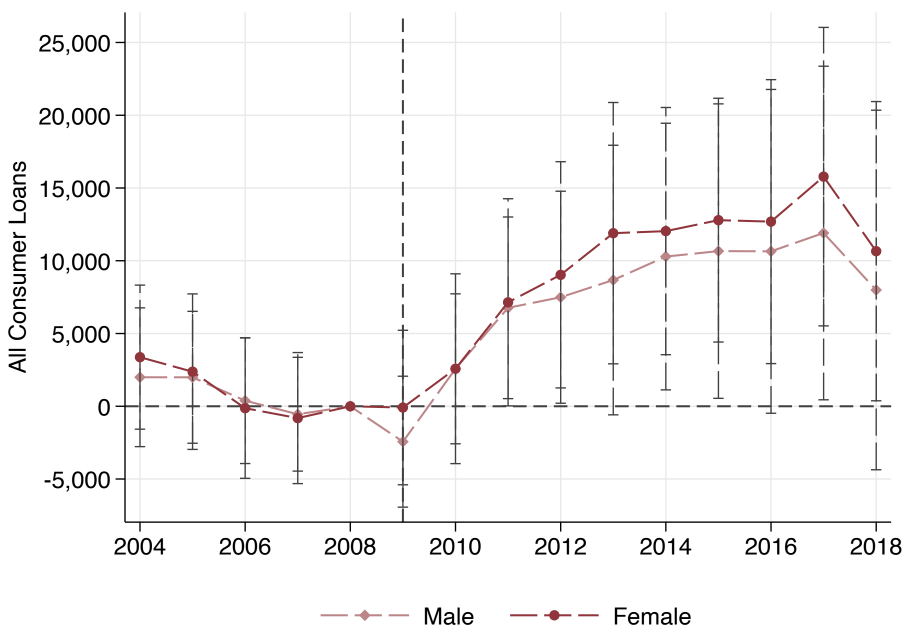
(b) Total personal loan balance

This figure plots coefficients and 95% confidence intervals of equation (3) estimated separately for entrepreneurs with average pre-2009 credit card utilization above (High Usage) the median and below it (Low Usage). Scaled business loan balance is the total balance on business loans scaled by employer status and firm age. Controls include borrower, match-year, owner-year, and county-year fixed effects, as well as a zipcode-level house price index and its interaction with the Entrepreneur$_i$ dummy. Standard errors are clustered at the county level.

Figure 9: Heterogeneity by gender



(a) Scaled business loan balance



(b) Total personal loan balance

This figure plots coefficients and 95% confidence intervals of equation (3) estimated separately for male and female entrepreneurs. Scaled business loan balance is the total balance on business loans scaled by employer status and firm age. Controls include borrower, match-year, owner-year, and county-year fixed effects, as well as a zipcode-level house price index and its interaction with the Entrepreneur$_i$ dummy. Standard errors are clustered at the county level.

Table 1: Summary Statistics

	Entrepreneurs			Full Sample		
	Mean	Med.	St. Dev.	Mean	Med.	St. Dev.
Top 4 Bank Share	0.29	0.25	0.23	0.31	0.29	0.23
Credit Score	712.53	731.00	97.88	666.73	661.00	102.82
All Consumer Loans	111,641.28	38,135.00	153,614.55	50,532.67	1,037.00	107,099.18
Mortgage Loans	91,644.90	0.00	143,436.04	40,715.17	0.00	98,624.43
Credit Card Loans	5,722.44	1,722.00	9,092.65	2,845.85	0.00	6,516.80
Personal Loans	133.14	0.00	714.01	63.68	0.00	492.27
Income	107,140.25	82,000.00	82,791.68	73,039.84	62,000.00	56,888.21
Age	53.24	54.00	14.40	48.33	47.00	17.50
Female	0.37	0.00	0.48	0.50	1.00	0.50
Entrepreneur	1.00	1.00	0.00	0.08	0.00	0.26
Small Business Loans	1,658.30	0.00	8,288.60	52.94	0.00	1,509.35
Small Business Loans (Scaled)	19,250.78	0.00	131,727.74	614.53	0.00	23,777.68
Firm Age	10.71	9.00	7.60			
Firm Risk Score	42.03	35.00	23.24			
Non-employer	0.79	1.00	0.41			
Employees	2.60	0.00	75.80			

Notes: This table shows descriptive statistics for the sample of entrepreneurs in the GCCP and for the full sample of consumers. Entrepreneurs are individuals who owned a business at any point between 2009 and 2018. Small business loans are the balances of loans observed in the small business portion of the GCCP. Scaled small business loans are observed small business loans in the GCCP scaled by total loan balances in the Small Business Credit Survey matched on employer status and firm age. See Section 2 for details on our scaling procedure.

Table 2: Summary Statistics of Matched Sample (2004–2009)

	Entrepreneurs			Matched Sample of Non-Entrepreneurs		
	Mean	Med.	St. Dev.	Mean	Med.	St. Dev.
Top 4 Bank Share	0.29	0.25	0.23	0.29	0.26	0.23
Credit Score	703.08	720.00	93.88	698.07	711.00	92.91
All Consumer Loans	112,869.70	46,406.00	150,269.98	110,758.42	47,472.00	146,256.29
Mortgage Loans	92,595.76	8,088.00	140,501.39	92,938.48	19,868.00	137,328.77
Credit Card Loans	6,095.02	2,003.00	9,304.99	5,445.00	1,629.00	8,680.53
Personal Loans	147.09	0.00	748.61	138.31	0.00	726.50
Income	96,249.74	76,000.00	74,506.90	85,996.26	71,000.00	62,615.58
Female	0.37	0.00	0.48	0.53	1.00	0.50
N	1,091,663			2,096,245		

Notes: This table shows descriptive statistics for our matched sample of entrepreneurs and non-entrepreneurs between 2004 and 2009. We select a control group of non-entrepreneurs by matching with replacement on total consumer balances between 2004 and 2008. We use a nearest neighbor algorithm to select the two closest controls among non-entrepreneurs residing in the same counties. Summary statistics for entrepreneurs differ from those of Table 1 because that table summarizes data between 2004 and 2018.

Table 3: First Stage: Effect of Top 4 Bank Share on Business Credit

Dependent Variable:	Business Loan Balance			
Scaling:	Unscaled		Scaled	
	(1)	(2)	(3)	(4)
Top 4 Share×Post	-847.68***	-932.73***	-12,543.26***	-13,571.58***
	(204.91)	(202.91)	(2,874.84)	(2,947.39)
Borrower FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
House price index	No	Yes	No	Yes
Observations	1,428,776	1,288,420	1,428,737	1,288,387

Notes: This table shows pooled estimates of the effect of Top 4 bank presence on business loan balances. Columns (1)-(2) show unscaled business loan balances and columns (3)-(4) show total business loan balances based on a scaling factor that takes into account employer status and firm size categories constructed using the 2018 SBCS. See Section 2 for details on our scaling procedure. Borrower, year, and county fixed effects are included in all regressions, and a zipcode-level house price index is included in columns (2) and (4). Standard errors are clustered at the county level.

Table 4: Effect of Top 4 Bank Share on Consumer Credit and Substitution

Variable:	Business loan Balance		Consumer Loan Balance			Substitution Factor
Loan type:	Scaled	Total	Mortgage	Revolving	Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)
Top 4 Share×Post×Entrepreneur	-13,571.58***	9,178.30**	10,303.56***	536.18	112.45	-0.68**
	(2,947.39)	(3,929.86)	(3,755.40)	(457.10)	(168.80)	(0.33)
County FE	Yes					
Year FE	Yes					
Borrower FE	Yes	Yes	Yes	Yes	Yes	
Match-Year FE		Yes	Yes	Yes	Yes	
Owner-Year FE		Yes	Yes	Yes	Yes	
County-Year FE		Yes	Yes	Yes	Yes	
Observations	1,288,387	8,554,413	8,554,413	8,554,413	8,554,413	

Notes: This table reports reduced form estimates, our preferred first stage estimates, and a substitution coefficient computed as the ratio of the reduced form to the first stage. Column (1) reports our preferred first stage estimate, which corresponds to column (4) of Table 3. Columns (2) - (5) show results of the differences-in-differences equation (3), which estimates the effect of Top 4 bank presence on the personal loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same counties. Column (6) reports a substitution factor computed as the coefficient in column (2) divided by the coefficient in column (1). Standard errors for the substitution factor of column (6) are obtained using the delta method after jointly estimating the first stage and reduced form using SUR. Standard errors are clustered at the county level.

Table 5: Effect of Top 4 Bank Share on Consumer Credit: Heterogeneity

Variable:	Business	Consumer	Substitution	Business	Consumer	Substitution
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: By credit score			
Group :	Subprime/Nonprime			Prime/Superprime		
Top 4 Share×Post×Entrepreneur	-7,042.98***	-5,729.07**	0.81	-17,935.27***	19,397.62***	-1.08***
	(2,475.66)	(2,674.19)	(0.50)	(3,788.12)	(4,954.80)	(0.38)
			Panel B: By income			
Group :	Low Income			High Income		
Top 4 Share×Post×Entrepreneur	-8,728.64***	-623.68	0.07	-19,096.25***	17,924.44***	-0.94**
	(2,441.32)	(2,686.57)	(0.30)	(4,033.65)	(5,535.97)	(0.37)
			Panel C: By credit card utilization			
Group :	High Usage			Low Usage		
Top 4 Share×Post×Entrepreneur	-12,317.55***	173.02	-0.01	-16,836.65***	18,770.69***	-1.11***
	(3,483.55)	(3,975.11)	(0.32)	(3,607.30)	(4,669.98)	(0.39)
			Panel D: By gender			
Group :	Male			Female		
Top 4 Share×Post×Entrepreneur	-15,036.73***	8,231.76*	-0.55*	-13,128.39***	9,603.13**	-0.73**
	(3,076.50)	(4,470.91)	(0.32)	(3,138.44)	(4,049.15)	(0.37)
County FE	Yes			Yes		
Year FE	Yes			Yes		
Borrower FE	Yes	Yes		Yes	Yes	
Match-Year FE		Yes			Yes	
Owner-Year FE		Yes			Yes	
County-Year FE		Yes			Yes	
Controls	Yes	Yes		Yes	Yes	

Notes: This table reports reduced form estimates, our preferred first stage estimates, and a substitution coefficient computed as the ratio of the reduced form to the first stage, broken down by entrepreneur credit score (panel A), income (panel B), credit card utilization (panel C), and gender (panel D). Columns (1) and (4) reports our preferred first stage estimate. Columns (2) and (5) show estimates of (3) for total personal loans. Columns (3) and (6) report a substitution factor computed as the reduced-form coefficient on total personal loans divided by the first-stage coefficient on business loans. Standard errors for the substitution factor of columns (3) and (6) are obtained using the delta method after jointly estimating the first stage and reduced form using SUR. Standard errors are clustered at the county level.

Table 6: Effect of Top 4 Bank Share on Firm Financial Distress

Dependent Variable:	Business Delinquency			Firm Risk Score		
Group :	All	Subprime	Prime	All	Subprime	Prime
	(1)	(2)	(3)	(4)	(5)	(6)
Top 4 Share×Post	0.02*	0.03*	0.01	0.38	-1.78**	1.53***
	(0.01)	(0.02)	(0.01)	(0.42)	(0.71)	(0.51)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,288,420	495,388	743,665	848,344	316,020	496,756

Notes: This table shows pooled estimates of the effect of Top 4 bank presence on measures of firm financial distress. The dependent variable is an indicator variable for a firm having delinquent trades in columns (1)-(3) and a proprietary firm risk score in columns (3)-(6). Controls include borrower, year, and county fixed effects, as well as a zipcode-level house price index. Standard errors are clustered at the county level.

Table 7: Horse Race Between Personal and Firm Characteristics

Dependent Variable:	Consumer Loan Balance				
	(1)	(2)	(3)	(4)	(5)
	Panel A: Credit score interaction				
Top 4 Share×Post×Entr.×Prime	25,126.68***	25,425.15***	29,026.78***	24,467.40***	27,962.98***
	(4,005.80)	(3,971.18)	(4,007.84)	(3,980.56)	(3,992.69)
	Panel B: Income interaction				
Top 4 Share×Post×Entr.×High Inc.	18,548.11***	19,339.09***	23,808.83***	17,491.84***	22,520.26***
	(5,041.70)	(4,942.74)	(5,002.48)	(4,980.38)	(4,885.31)
	Panel C: Credit card utilization interaction				
Top 4 Share×Post×Entr.×Low Usage	18,597.68***	18,535.39***	21,124.19***	17,683.93***	20,013.93***
	(3,215.72)	(3,207.74)	(3,264.65)	(3,235.75)	(3,303.33)
Borrower FE	Yes	Yes	Yes	Yes	Yes
Match-Year FE	Yes	Yes	Yes	Yes	Yes
Owner-Year FE	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
Horce-Race Variable					
Firm Size	No	Yes	No	No	Yes
Firm Age	No	No	Yes	No	Yes
Firm Risk Score	No	No	No	Yes	Yes
Observations	7,981,048	7,965,629	7,981,048	7,981,048	7,965,629

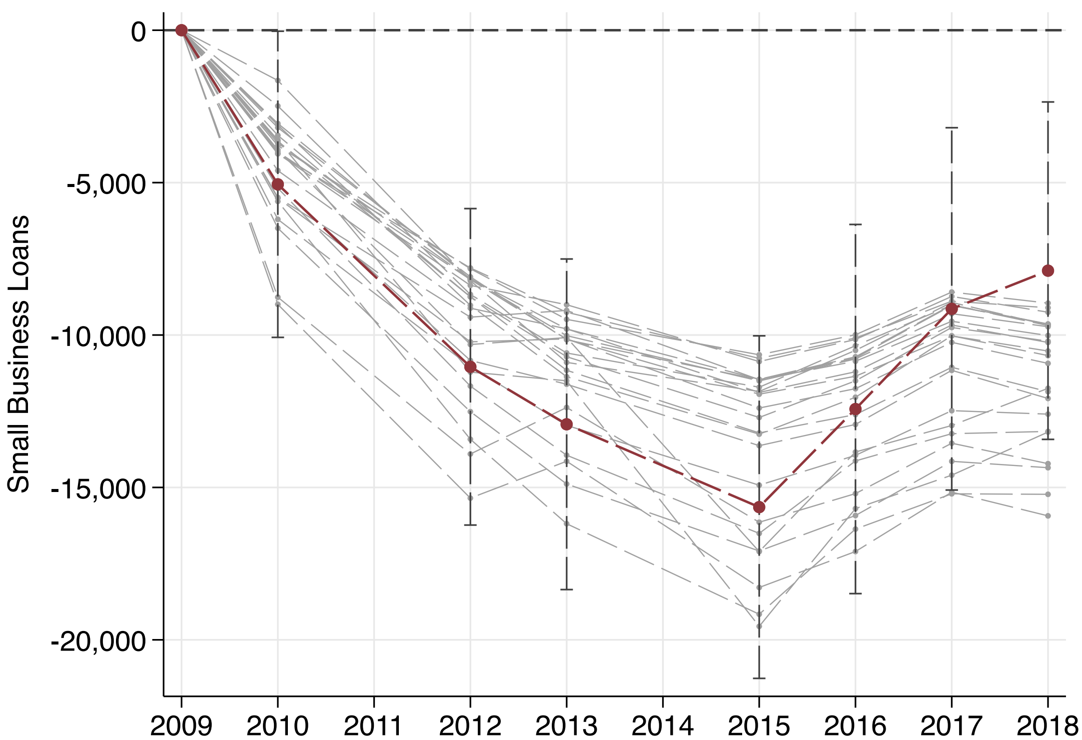
Notes: This table reports the effect of Top 4 bank presence on total consumer loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same counties. We further interact the Top 4 $\text{Share}_c \times Post_t \times \text{Entrepreneur}_i$ variable with indicators of the entrepreneur having a prime/superprime credit score (panel A), above-median income (panel B), or below-median credit card utilization (panel C). We horse-race these interactions with analogous interactions with indicators for the firm being a non-employer firm, being younger than the median firm, and having a below-median risk score. Standard errors are clustered at the county level.

Online Appendix for

"How Much Do Small Businesses Rely on Personal Credit?"

A Additional Figures and Tables

Figure A.1: Robustness to alternative scaling procedures



This figure plots coefficient estimates and 95% confidence intervals of equation (2), which estimates the effect of Top 4 bank presence on business loan balances using alternative procedures to scale business loans using factors constructed with 2018 SBCS data. Alternative scaling factors take into account combinations of employer status, industry code, firm age census division, whether firm is located in an urban or rural zipcode, and the gender of the owner. We consider versions of the scaling procedure that either fix scaling factors based on 2018 firm characteristics or allow factors to vary as firm characteristics change over time. Controls include borrower, year, and county fixed effects, as well as a zipcode-level house price index. Standard errors are clustered at the county level.

Table A.1: Effect on Mortgage Balances, Trades, and Propensity to Move

Dependent Variable:	Mortgage Balance	Excl. Refinancing	Mortgage Trades	Moved
	(1)	(2)	(3)	(4)
Top 4 Share×Post×Entrepreneur	10,303.56***	194.05	0.00	-0.01***
	(3,755.40)	(699.51)	(0.02)	(0.00)
Borrower FE	Yes	Yes	Yes	Yes
Match-Year FE	Yes	Yes	Yes	Yes
Owner-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	8,554,413	8,554,413	8,554,413	8,554,413

Notes: This table shows estimates of equation (3) with variables relating to mortgage balances and the propensity to move as dependent variables. In column 1, the dependent variable is total mortgage balances, which matches the estimate in Table 4. Column 2 shows estimates of mortgage balances excluding balances associated with refinancing. The dependent variable is total open mortgage trades in column 3 and an indicator variable for moving zipcode relative to the prior year in column 4. Controls include borrower, year, and county fixed effects, as well as a zipcode-level house price index and its interaction with the Entrepreneur_i dummy. Standard errors are clustered at the county level.

Table A.2: Effect of Top 4 Bank Share by House Price growth

Variable:	Business	Consumer	Substitution	Business	Consumer	Substitution
	(1)	(2)	(3)	(4)	(5)	(6)
Group :	Low growth			High growth		
Top 4 Share×Post×Entrepreneur	-14,065.00***	3,807.99	-0.27	-14,111.58***	9,898.44**	-0.70*
	(4,214.39)	(4,114.42)	(0.30)	(3,336.17)	(4,403.19)	(0.36)
County FE	Yes			Yes		
Year FE	Yes			Yes		
Borrower FE	Yes	Yes		Yes	Yes	
Match-Year FE		Yes			Yes	
Owner-Year FE		Yes			Yes	
County-Year FE		Yes			Yes	
Controls	Yes	Yes		Yes	Yes	
Observations	273,460	1,884,003		872,429	6,670,410	

Notes: This table reports reduced form estimates, our preferred first stage estimates, and a substitution coefficient computed as the ratio of the reduced form to the first stage, broken down by zipcode-level house price growth between 2004 and 2018. Low growth is defined as the first quartile of the house price growth distribution. Columns (1) and (4) reports our preferred first stage estimate. Columns (2) and (5) show estimates of (3) for total personal loans. Columns (3) and (6) report a substitution factor computed as the reduced-form coefficient on total personal loans divided by the first-stage coefficient on business loans. Standard errors for the substitution factor of columns (3) and (6) are obtained using the delta method after jointly estimating the first stage and reduced form using SUR. Standard errors are clustered at the county level.

Table A.3: Summary Statistics by Gender

	Male			Female		
	Mean	Med.	St. Dev.	Mean	Med.	St. Dev.
Top 4 Bank Share	0.28	0.23	0.23	0.29	0.25	0.23
Credit Score	722.30	748.00	98.02	718.14	742.00	100.92
All Consumer Loans	113,514.23	39,169.00	155,995.50	105,129.63	33,407.00	148,963.92
Mortgage Loans	92,045.45	0.00	144,835.50	85,719.28	0.00	139,611.82
Credit Card Loans	5,603.10	1,576.00	9,084.37	6,094.95	1,974.00	9,371.88
Personal Loans	148.20	0.00	755.46	139.53	0.00	727.15
Income	119,104.70	91,000.00	89,818.44	110,058.14	87,000.00	79,976.36
Age	55.30	56.00	14.17	55.61	56.00	13.53
Female	0.00	0.00	0.00	1.00	1.00	0.00
Entrepreneur	1.00	1.00	0.00	1.00	1.00	0.00
Small Business Loans	1,871.10	0.00	8,766.83	994.38	0.00	6,316.91
Small Business Loans (Scaled)	21,772.02	0.00	141,999.37	12,260.01	0.00	99,880.88
Firm Age	10.90	10.00	7.79	9.88	9.00	6.96
Firm Risk Score	42.21	35.00	23.76	40.43	33.00	21.58
Non-employer	0.77	1.00	0.42	0.83	1.00	0.38
Employees	2.99	0.00	85.26	1.56	0.00	55.71

Notes: This table shows descriptive statistics for our sample of entrepreneurs broken down by gender. Small business owners are individuals who owned a business at any point between 2009 and 2018. Scaled business loan balance is the total balance on business loans scaled by employer status and firm age.

Table A.4: Scaling Factors for Imputing Total Business Credit

		Debt Categories					
Firm Categories	Employer	\$0	\$1-\$25K	\$26K-\$100K	\$101K-\$250K	\$251K-\$1M	>\$1M
All	1	30%	17%	21%	13%	13%	6%
Firm Age							
0-2 Years	1	33%	21%	22%	13%	10%	2%
3-5 Years	1	25%	21%	22%	15%	13%	4%
6-10 Years	1	28%	17%	25%	13%	14%	4%
11-15 Years	1	27%	19%	20%	13%	14%	6%
16-20 Years	1	31%	16%	20%	14%	12%	7%
> 21 Years	1	34%	13%	16%	12%	15%	10%
All	0	54%	26%	13%	4%	2%	0%
Firm Age							
0-2 Years	0	59%	26%	10%	2%	1%	0%
3-4 Years	0	52%	28%	13%	4%	2%	0%
5-12 Years	0	51%	26%	15%	4%	3%	0%
>13 Years	0	50%	27%	14%	5%	4%	1%

Notes: this table reports the scaling factors that are used to estimate the total business debt for both employer and non-employer firms in the SBCS. These factors are essentially distributions of firms of different categories in the SBCS, and can be obtained from the publicly available SBCS data appendices.

Table A.5: Robustness to Alternative Matching Procedures

Dependent Variable:	Consumer Loan Balance					
Matching Procedure:	Baseline	Credit Score	Income	Gender	1 Neighbor	3 Neighbors
	(1)	(2)	(3)	(4)	(5)	(6)
Top 4 Share×Post×Entrepreneur	9,178.30**	7,263.94**	6,901.21***	8,672.60***	9,694.48**	8,527.30**
	(3,929.86)	(3,161.70)	(2,583.54)	(3,175.60)	(4,908.92)	(3,339.03)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Match-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Owner-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,554,413	8,626,285	8,606,466	7,768,559	5,780,537	11,324,755

Notes: This table reports the effect of Top 4 bank presence on total consumer loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same counties under different matching procedures. Column 1 reports our baseline estimate obtained by nearest neighbor matching on the level of total consumer loan balances prior to 2009 and selecting the two closest controls. In Column 2, we match on average pre-2009 credit scores in addition to balances. In Column 3, we match on average pre-2009 income in addition to balances. In Column 3, we exact match on gender in addition to nearest neighbor matching on balances. In Column 5, we select one nearest neighbor instead of two. In Column 6, we select three nearest neighbors instead of two. Standard errors are clustered at the county level.

Table A.6: Robustness to Additional Controls

Dependent Variable:	Consumer Loan Balance							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 4 Share×Post×Entrepreneur	9,156.53**	9,178.30**	9,422.03**	9,033.28**	9,260.49**	9,711.63**	10,425.21**	10,306.44**
	(3,994.98)	(3,929.86)	(4,198.59)	(3,979.10)	(4,004.38)	(4,177.14)	(4,233.73)	(4,317.39)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Owner-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls								
House Price Index	No	Yes	No	No	No	No	No	Yes
Unemployment Rate	No	No	Yes	No	No	No	No	Yes
Credit Score$_{\text{pre}}$	No	No	No	Yes	No	No	No	Yes
Income$_{\text{pre}}$	No	No	No	No	Yes	No	No	Yes
Personal Balance$_{\text{pre}}$	No	No	No	No	No	Yes	No	Yes
Mortgage Balance$_{\text{pre}}$	No	No	No	No	No	No	Yes	Yes
Observations	8,554,413	8,554,413	8,552,194	8,554,413	8,554,413	7,969,061	7,969,061	7,966,940

Notes: This table reports the effect of Top 4 bank presence on total consumer loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same counties with additional controls. Controls include borrower, match-year, owner-year, and county-year fixed effects, as well as a zipcode-level house price index, the state-level unemployment rate, and pre-2009 averages of credit scores, income, total consumer loan balances, and mortgage balances. We interact pre-2009 averages with time fixed effects. Standard errors are clustered at the county level.