

How Much Do Small Businesses Rely on Personal Credit?*

Julia Fonseca

Jialan Wang

UIUC[†]

UIUC and NBER[‡]

November 2022

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 were able to substitute for about 68% of this decline with personal credit, driven by mortgages. Entrepreneurs with subprime credit scores, below-average income, and high credit utilization do not substitute lost business credit with personal credit. Thus, we find that the personal financial characteristics of entrepreneurs meaningfully affect 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, and WEFI 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.

[†]Gies College of Business, 1206 South 6th Street, Champaign IL, 61820. juliaf@illinois.edu

[‡]Gies College of Business, 1206 South 6th Street, Champaign, IL 61820. jialanw@illinois.edu

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

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

²Robb 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.³ 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

³For example, [DAcunto and Rossi \(2022\)](#) find that large banks disproportionately shifted mortgage originations away from conforming loans and toward jumbo loans during an overlapping time period.

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 experience distress. We show that prime entrepreneurs in our sample—who substitute approximately all of the declining business credit with personal credit—do not experience greater firm financial distress. On the other hand, firms owned by

subprime entrepreneurs, who do not substitute, do experience increased financial distress. These findings are consistent with entrepreneurs who substitute declining business credit with personal credit applying the additional liquidity toward their businesses.

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. This suggests that 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 examine the intensive margin of substitution between business and personal credit using data that captures both business loans and all types of consumer loans at the individual level, including but not restricted to mortgage credit. Furthermore, we show that the personal credit characteristics of entrepreneurs strongly mediate the ability to use housing collateral to finance small businesses.

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, while our measures of small business and personal credit include both banks and

nonbanks. Our study also relates to [Benetton, Buchak and Robles-Garcia \(2022\)](#), who examine complementarities between household and corporate assets for bank profitability.

We also contribute to the broader literature on the credit and liquidity constraints faced by entrepreneurs.⁴ We focus on personal credit, an underexplored source of liquidity for entrepreneurs that has important implications for the small business credit market. 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 quantify the importance of this channel and estimate the degree of substitution between these two sources of credit, which is made possible by the fact that we observe both personal and business credit balances of entrepreneurs. Our ability to observe the credit data used to generate both personal and business credit scores used by lenders also allows us to compare the information available in these two credit markets and shed light on the underlying reasons entrepreneurs rely so heavily on personal debt.

Finally, our findings also 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 also study the importance of personal credit characteristics for 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 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.

⁴Some 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](#)).

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.⁵

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 age, gender, marital status, and employment status.⁶

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 can

⁵See, for instance, [Avery, Calem, Canner and Bostic \(2003\)](#), [Lee and Van der Klaauw \(2010\)](#), [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 \(2022\)](#).

⁶The 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 \(2022\)](#).

be linked to the credit and demographic characteristics of entrepreneurs from the consumer side of GCCP through an anonymized consumer id provided by Experian.

Table 1 presents summary statistics of full sample of consumers in the GCCP and 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 sample in 2011 and 2014 and extend the full sample through 2022. We show summary statistics for the full sample and for the sample of entrepreneurs in Table 1.

In Figure 1, we show the geographical coverage of the full GCCP (panel A) and the small business component of the GCCP (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 firm size distribution in the GCCP broadly matches that of US businesses.⁷

One shortcoming of the GCCP and credit bureau data for small businesses in general is that 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 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 12 Federal Reserve Banks. Since our research question involves comparing changes in total business credit with consumer credit, which we believe is well-measured in the GCCP, we use the SBCS to

⁷We 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.

construct scaling factors that impute total business credit from observed business debt and firm characteristics in the GCCP.

Using the publicly available SBCS data appendices, we estimate that the total business debt reported in the SBCS is on average three times higher than the business debt reported in GCCP. Throughout the analysis, we report both the scaled and unscaled measures of total business debt for comparison. To construct the scaling factor used to estimate total business debt in the GCCP, we first obtain the estimates of total business debt for both employer and non-employer firms in the SBCS, which are reported in separate surveys, and for firms in the GCCP that either report nonzero or zero employees. We then further break down firms in both the GCCP and SBCS into 6 firm age bins for employer firms and 4 firm age bins for non-employer firms. Our scaling factor is the ratio of average business debt within each employer-status×firm-age-bin cell in the SBCS with the analogous levels in the GCCP.⁸

We then apply these scaling factors to observed business debt at the firm level in the GCCP to obtain estimates of total business debt. In particular, we estimate the total business debt in Equation (1) below with individual firm i , firm group g and year t .

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

In our baseline scaling procedure, g represents an employer-status×firm-age-bin cell and scaling factors are constructed using 2018 data and held fixed even if a firm i changes firm group g from one year to another. We report our baseline scaling factors in Table A.3. We also assess robustness to allowing scaling factors to vary over time as firm characteristics vary and to constructing alternative scaling factors based on all variables that are available across both datasets, including location, zipcode characteristics, firm size, industry composition,

⁸Since 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.

and owner gender.

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 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). We summarize the deposit share of Top 4 banks in the first row of Table 1.

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 $\text{Business Credit}_{i,c,t}$ 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.

Once we have estimated the effect of Top 4 bank presence on business loan balances, we

turn to personal borrowing in order to estimate the substitution effect between these two credit categories. We attempt to isolate the effect of the business credit supply shock on personal credit by employing a matched differences-in-differences specification, which allows us to compare entrepreneurs with otherwise similar individuals who do not own a business. Thus, our identification approach allows for the possibility that the Top 4 bank share may have direct or indirect effects on personal credit across geographies and over time, but relies on the assumption that these effects can be absorbed by differencing out the dynamics of personal credit in the matched group of non-entrepreneurs. 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 show that our results are robust to alternative matching procedures in Section 6.4.

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 matching procedure, such as credit scores, credit card balances, personal loans, and income. One dimension in which entrepreneurs and non-entrepreneurs 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 differences-in-differences specification in our matched sample:

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

where $\text{Consumer Credit}_{i,c,g,t}$ 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 this 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 correlate with the pre-2009 characteristics we match on. 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 trends across owners and non-owners, and a zipcode-level house price index (which we also interact 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 balance by the first-stage effect on business loan 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 and the reduced-form effect on consumer loan balances 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.

4 Main Results

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

We start by estimating the effect of the market share of Top 4 banks 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 baseline scaling factor constructed using Small Business Credit Survey (SBCS) data to estimate the total business credit of each business, 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 zero Top 4 bank presence, between year t and the baseline year (2009).

Panel A of Figure 3 shows that the decline in small business credit relative to 2009 peaks in 2015, and recovers slightly but persists until the end of our sample in 2018. Without taking into account the underreporting of small business credit, we find that an entrepreneur in a county with 100% Top 4 deposit share experiences an average decline of \$932.73, relative to an entrepreneur in a county with zero Top 4 presence (column 2 of Table 3).

Panel B of Figure 3 shows analogous results after applying the scaling factor described in Section 2 to small business credit. We again find that the average decline for an entrepreneur in a county with 100% Top 4 deposit share, relative to an entrepreneur in a county with zero Top 4 presence, peaks in 2015 and modestly recovers by 2018. The average entrepreneur experiences a decline in business credit of \$13,571.50 when scaling by employer status and firm age (columns 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.

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 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). By comparing entrepreneurs with otherwise similar individuals who do not own a business, we attempt to isolate the causal effect of business credit on personal credit as instrumented by Top 4 bank share while controlling for underlying trends in personal credit that affect both entrepreneurs and non-entrepreneurs.

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 these estimates 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 peaking after 2014 and stabilizing at a new higher level 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 calculate the degree to which consumer credit has been 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 lost business credit.

Since mortgages are the key channel through which entrepreneurs increase their personal borrowing, we provide evidence that these higher balances are driven by cash-out refinancing and *not* by home-buying or moving, which would be inconsistent with our interpretation of these results as entrepreneurs substituting for declining business credit with personal credit. We do so in three different ways.

First, we leverage the fact that consumer data is also available at the loan level to identify refinancing activity. We define a new mortgage loan as refinancing if it was opened within a

30-day window of an existing mortgage loan being paid off and closed.⁹ 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 a channel other than refinancing. Second, we look at total open mortgage trades as an additional test of whether this behavior is driven by first-time home purchases. Finally, we look at the propensity to move zipcodes to rule out that higher mortgage balances are driven by an entrepreneur-specific moving shock that correlates 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 became 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 entrepreneurs do not take out additional mortgages relative to non-entrepreneurs. This is inconsistent with mortgage-financed first time home-buying, which would cause the number of mortgage loans to increase from zero to one.¹⁰ Finally, the dependent variable in column 4 is an indicator for the individual residing in a different zipcode than in the previous year. If anything, we find that entrepreneurs are slightly less likely to move than non-entrepreneur following the business credit shock, which is also inconsistent with higher mortgage balances being driven by new home purchases.

⁹Since 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.

¹⁰No change in the number of mortgages is consistent with refinancing, where typically one mortgage is closed and another is opened, leading to no change in the overall number of loans.

5 Heterogeneity by Entrepreneur Characteristics

In Section 4, we show 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 affect their ability to smooth business credit supply shocks and thus the firm’s overall access to external finance. Our primary focus is on the personal credit characteristics of entrepreneurs, such as credit scores, but we also explore the effect 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 subprime entrepreneurs to substitute more if they have smaller businesses that require less capital and face a smaller absolute decline in business credit that is more easily compensated by personal credit. On the other hand, subprime 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.

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, but might not reflect patterns of substitution to personal credit for existing female-owned businesses.

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 the highest 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 business loan balance (Panel A) and total personal credit (Panel B) as dependent variables, and report pooled estimates in Panel A Table 5. We find that 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 and superprime entrepreneurs replace all of the lost business credit with personal credit, with an implied substitution factor of 108% (column 6 of Table 5).

This result suggests that personal credit characteristics of entrepreneurs are key determinants of the degree of substitution between business and personal credit, and thus important determinants of a firm's overall access to external finance.

5.2 Income

Next, we conduct an analogous exercise sorting of entrepreneurs into high- and low-income bins based on whether their pre-2009 average income is above or is below the median, respectively. We show results of this exercise in Figure 7 and Panel B of Table 5. We find that high-income individuals borrow substantially more following a negative business credit supply shock, with an estimated increase of \$17,924.44 (column 5 of Table 5), representing 94% of the decline in small business credit experienced by these entrepreneurs (column 6 of Table 5). By comparison, we estimate a small decline of -\$623.68 in the personal borrowing of low-income individuals (column 2 of Table 5), which is not statistically significant. Consistent with results by credit score, we find that high-income individuals are able to substitute nearly all of the decline in business credit with personal credit, while low-income individuals do not substitute.

While income may not be the most important personal characteristic for some types of 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 (see, e.g. [DeFusco and Mondragon \(2020\)](#)).

5.3 Credit card utilization

The next source of heterogeneity we consider is credit card utilization, which is also a key metric observed by lenders and thus an important personal financial characteristic of entrepreneurs. 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 [Panel C Table 5](#). Consistent with the results presented so far, entrepreneurs with high credit card utilization substitute virtually none of the decline in small business credit with personal credit. We estimate an increase of \$173.02 is the overall personal borrowing of high-utilization entrepreneurs (column 2 of [Table 5](#)), corresponding to just 1% of the decline in small business credit (column 3 of [Table 5](#)), which is not statistically significant. In contrast, entrepreneurs with low credit card utilization replace all of the lost business credit with personal credit (columns 4 and 5 of [Table 5](#)).

Taken together, the findings presented in this section suggest that the remedy of personal borrowing following an aggregate business supply shock is only available to individuals with high incomes, high credit scores, and low credit card utilization. This occurs despite the observation that subprime, low-income, and high-utilization entrepreneurs have smaller absolute declines in business credit that would need to be substituted.

These findings shed light on which entrepreneurs can tap into personal credit to make up

for shortfalls in small business credit, and point to the importance of personal financial characteristics of entrepreneurs in determining the overall access to external finance of small businesses. While a determination of whether these substitution patterns are 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, and it is possible that personal creditworthiness is not perfectly correlated with expected business returns. If the reliance on personal credit is in part driven by differences in information asymmetry between the personal and business credit markets, there may be more scope for potential inefficiency and innovation to 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 receive similar business credit supply shocks and 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 sample.

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.2 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. We leave further disentangling the potential explanations for these patterns for future work.

6 Additional Results and Robustness

6.1 The effect on firm financial distress

In Section 4, we show 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 business. 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 of 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 declining business credit with personal credit, 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 to 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 not for prime entrepreneurs (column 3). Columns 4 to 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 entrepreneurs and not prime entrepreneurs. These results are consistent with the hypothesis that entrepreneurs who substitute declining business credit with personal credit apply the additional liquidity provided by their personal credit lines toward their businesses.

6.2 Personal financial characteristics vs. firm-level measures

In Section 5, we argue that personal financial characteristics of entrepreneurs are key determinants of the substitution between personal and business credit that we document in this paper. This suggests that these individual characteristics affect the overall access to external finance of small businesses and are an important determinant of the financial constraints faced by these businesses.

However, one might worry that the personal financial characteristics of entrepreneurs are correlated with other characteristics of the business that determine 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 findings that small and young firms are financially constrained (Hadlock and Pierce, 2010).

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

of the type

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

where Personal_i is an indicator variable for one of the personal financial characteristics cuts of Section 5—whether the entrepreneur has a prime/superprime credit score, has above-median income, or has below-median credit card utilization— and Firm_i is an indicator variable for a measure of firm-level financial constraints. The measures available in the GCCP include firm size (measured as being an employer or 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 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, with results by credit score reported in Panel A, by income in Panel B, and by credit card utilization in Panel C. We indicate which firm-level measures of financial constraints are included in the horse race in the bottom rows of Table 7. Across all personal characteristic cuts, we find that point estimates are stable to the inclusion of analogous cuts by firm characteristics. These results are evidence that the relationship we document between personal financial characteristics of entrepreneurs and access to external finance of small businesses is not driven by common 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 procedures to impute total business credit from observed business debt and firm characteristics in the GCCP. We construct alternative scaling factors based on the additional 5 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, 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 further break down employer and non-employer firms 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 6 alternative firm characteristic groups, we compute 4 versions of our scaling factors.¹¹ We compute both a time-invariant version, in which the 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 using 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 by 2018, so we caution against strong conclusions

¹¹The 6 alternative firm characteristic groups are employer status, employer status \times firm size, employer status \times census division, employer status \times rural-urban zipcode, employer status \times sector, employer status \times owner gender.

based on the rebound effect.

6.4 Robustness to alternative matching procedures

In Table A.4, we report our main reduced form estimates under alternative procedures for obtaining a matched sample of control non-entrepreneurs.¹² In column 1 of Table A.4, 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 2 closest controls among 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 2 to either 1 (column 5) or 3 (column 6). We find consistent results across this range of alternative matching procedures.

6.5 Robustness to additional controls

Finally, we assess robustness to controlling for a range of other local and individual characteristics and report results in Table A.5. In column 1 of Table A.5, we report the effect on total consumer balances without controls and, in column 2, controlling for a zipcode house-price index (our baseline estimate). In subsequent columns, we control for the state-level unemployment rate and pre-2009 averages of credit scores, income, total consumer balances, and mortgage balances. Given that we show that Top 4 bank presence affects the personal

¹²Note that our first stage estimates are obtained using a sample of entrepreneurs and not a matched sample, and are thus not affected by this matching procedure.

borrowing of entrepreneurs, we control for the pre-reform 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.

References

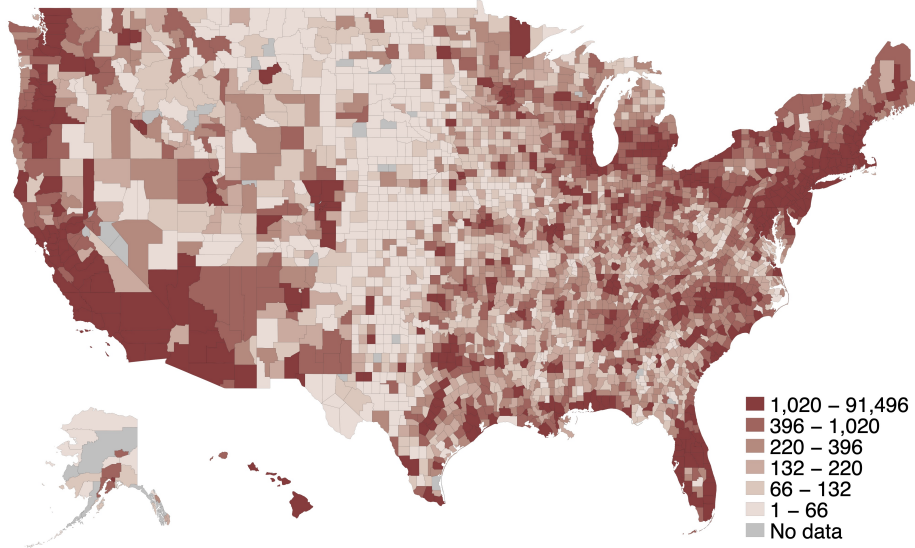
- Adelino, Manuel, Antoinette Schoar, and Felipe Severino**, “House prices, collateral, and self-employment,” *Journal of Financial Economics*, 2015, 117 (2), 288–306.
- Andersen, Steffen and Kasper Meisner Nielsen**, “Ability or Finances as Constraints on Entrepreneurship? Evidence from Survival Rates in a Natural Experiment,” *The Review of Financial Studies*, 12 2012, 25 (12), 3684–3710.
- Avery, Robert B, Paul S Calem, Glenn B Canner, and Raphael W Bostic**, “An overview of consumer data and credit reporting,” *Fed. Res. Bull.*, 2003, 89, 47.
- Bellon, Aymeric, J Anthony Cookson, Erik P Gilje, and Rawley Z Heimer**, “Personal wealth, self-employment, and business ownership,” *The Review of Financial Studies*, 2021, 34 (8), 3935–3975.
- Benetton, Matteo, Greg Buchak, and Claudia Robles-Garcia**, “Wide or Narrow? Competition and Scope in Financial Intermediation,” 2022. Working Paper.
- Berger, Allen N, Adrian M Cowan, and W Scott Frame**, “The surprising use of credit scoring in small business lending by community banks and the attendant effects on credit availability, risk, and profitability,” *Journal of Financial Services Research*, 2011, 39 (1-2), 1–17.
- Berger, Allen N. and Gregory F. Udell**, “Relationship Lending and Lines of Credit in Small Firm Finance,” *The Journal of Business*, 1995, 68 (3), 351–381.
- and –, “Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure,” *The Economic Journal*, 03 2002, 112 (477), F32–F53.
- Bertrand, Marianne, Antoinette Schoar, and David Thesmar**, “Banking deregulation and industry structure: Evidence from the French banking reforms of 1985,” *The Journal of Finance*, 2007, 62 (2), 597–628.
- Black, Jane, David de Meza, and David Jeffreys**, “House Prices, The Supply of Collateral and the Enterprise Economy,” *The Economic Journal*, 01 1996, 106 (434), 60–75.
- Black, Sandra E and Philip E Strahan**, “Entrepreneurship and bank credit availability,” *The Journal of Finance*, 2002, 57 (6), 2807–2833.
- Bord, Vitaly M, Victoria Ivashina, and Ryan D Taliaferro**, “Large banks and small firm lending,” *Journal of Financial Intermediation*, 2021, 48, 100924.
- Bos, Marieke, Emily Breza, and Andres Liberman**, “The Labor Market Effects of Credit Market Information,” *The Review of Financial Studies*, 01 2018, 31 (6), 2005–2037.
- Bracke, Philippe, Christian A.L. Hilber, and Olmo Silva**, “Mortgage debt and entrepreneurship,” *Journal of Urban Economics*, 2018, 103, 52–66.

- Brennecke, Claire, Gohar Siravyan, and B Heath Witzten**, “Commercial Credit on Consumer Credit Reports,” *Consumer Financial Protection Bureau Office of Research Reports Series*, 2021, (21-7).
- Cagetti, Marco and Mariacristina De Nardi**, “Entrepreneurship, Frictions, and Wealth,” *Journal of Political Economy*, 2006, *114* (5), 835–870.
- Cetorelli, Nicola and Philip E Strahan**, “Finance as a barrier to entry: Bank competition and industry structure in local US markets,” *The Journal of Finance*, 2006, *61* (1), 437–461.
- Chava, Sudheer, Alexander Oettl, Ajay Subramanian, and Krishnamurthy V. Subramanian**, “Banking deregulation and innovation,” *Journal of Financial Economics*, 2013, *109* (3), 759–774.
- Chen, Brian S, Samuel G Hanson, and Jeremy C Stein**, “The decline of big-bank lending to small business: Dynamic impacts on local credit and labor markets,” Technical Report, National Bureau of Economic Research 2017.
- Cole, Rebel A, Hamid Mehran, and Germana Giombini**, “Gender and the availability of credit to privately held firms: evidence from the surveys of small business finances,” *FRB of New York Staff Report*, 2018, (383).
- Cornaggia, Jess, Yifei Mao, Xuan Tian, and Brian Wolfe**, “Does banking competition affect innovation?,” *Journal of Financial Economics*, 2015, *115* (1), 189–209.
- Corradin, Stefano and Alexander Popov**, “House prices, home equity borrowing, and entrepreneurship,” *The Review of Financial Studies*, 2015, *28* (8), 2399–2428.
- Cortés, Kristle R, Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip E Strahan**, “Stress tests and small business lending,” *Journal of Financial Economics*, 2020, *136* (1), 260–279.
- DeFusco, Anthony A and John Mondragon**, “No job, no money, no refi: Frictions to refinancing in a recession,” *The Journal of Finance*, 2020, *75* (5), 2327–2376.
- Dobbie, Will, Paul Goldsmith-Pinkham, Neale Mahoney, and Jae Song**, “Bad Credit, No Problem? Credit and Labor Market Consequences of Bad Credit Reports,” *The Journal of Finance*, 2020, *75* (5), 2377–2419.
- DAcunto, Francesco and Alberto G Rossi**, “Regressive mortgage credit redistribution in the post-crisis era,” *The Review of Financial Studies*, 2022, *35* (1), 482–525.
- Farrell, Diana, Chris Wheat, and Chi Mac**, “Small business financial outcomes during the onset of COVID-19,” *JP Morgan Chase Institute*, 2020.
- Fonseca, Julia**, “Less Mainstream Credit, More Payday Borrowing? Evidence from Debt Collection Restrictions,” *Journal of Finance*, 2022. Forthcoming.
- Gopal, Manasa and Philipp Schnabl**, “The rise of finance companies and FinTech lenders in small business lending,” *NYU Stern School of Business*, 2020.

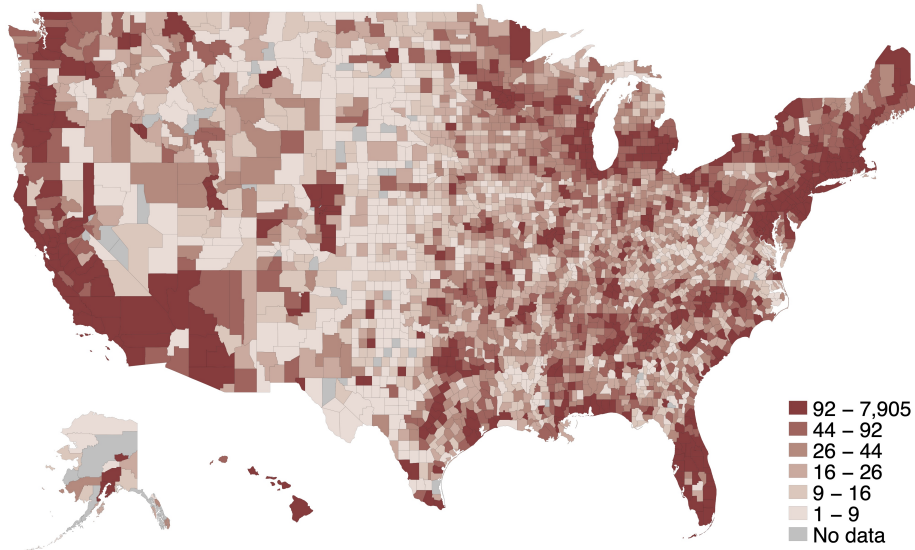
- Hadlock, Charles J and Joshua R Pierce**, “New evidence on measuring financial constraints: Moving beyond the KZ index,” *The Review of Financial Studies*, 2010, *23* (5), 1909–1940.
- Haughwout, Andrew F, Donghoon Lee, Joelle Scally, Wilbert Van der Klaauw et al.**, “Small Business Owners Turn to Personal Credit,” Technical Report, Federal Reserve Bank of New York 2021.
- Herkenhoff, Kyle, Gordon Phillips, and Cohen-Colem Ethan**, “The Impact of Consumer Credit Access on Self-Employment and Entrepreneurship,” *Journal of Financial Economics*, 2021, *141* (1), 345–371.
- Hombert, Johan and Adrien Matray**, “The Real Effects of Lending Relationships on Innovative Firms and Inventor Mobility,” *The Review of Financial Studies*, 10 2016, *30* (7), 2413–2445.
- Hurst, Erik and Annamaria Lusardi**, “Liquidity constraints, household wealth, and entrepreneurship,” *Journal of political Economy*, 2004, *112* (2), 319–347.
- Hwang, Victor, Sameeksha Desai, and Ross Baird**, “Access to capital for entrepreneurs: Removing barriers,” *Available at SSRN 3389924*, 2019.
- Jensen, Thais Laerkholm, Søren Leth-Petersen, and Ramana Nanda**, “Financing constraints, home equity and selection into entrepreneurship,” *Journal of Financial Economics*, 2022, *145* (2, Part A), 318–337.
- Kerr, Sari Pekkala, William R Kerr, and Ramana Nanda**, “House Prices, Home Equity and Entrepreneurship: Evidence from U.S. Census Micro Data,” *Journal of Monetary Economics*, 2022. Forthcoming.
- Kerr, William R and Ramana Nanda**, “Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship,” *Journal of Financial Economics*, 2009, *94* (1), 124–149.
- Khwaja, Asim Ijaz and Atif Mian**, “Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market,” *American Economic Review*, September 2008, *98* (4), 1413–42.
- Krause, Alex and Emily Fetsch**, “Labor after labor,” *Kauffman Foundation Research Series on Entrepreneurship and Motherhood Report*, 2016, *1*.
- Lee, Donghoon and Wilbert Van der Klaauw**, “An introduction to the FRBNY consumer credit panel,” *FRB of New York Staff Report*, 2010, (479).
- Petersen, Mitchell A and Raghuram G Rajan**, “The benefits of lending relationships: Evidence from small business data,” *The journal of finance*, 1994, *49* (1), 3–37.
- Robb, Alicia M and David T Robinson**, “The capital structure decisions of new firms,” *The Review of Financial Studies*, 2014, *27* (1), 153–179.
- Robb, Alicia, Susan Coleman, and Dane Stangler**, “Sources of economic hope: Women’s entrepreneurship,” *Available at SSRN 2529094*, 2014.

- Schmalz, Martin C, David A Sraer, and David Thesmar**, “Housing collateral and entrepreneurship,” *The Journal of Finance*, 2017, 72 (1), 99–132.
- Shaheen, J**, “Tackling the gender gap: What women entrepreneurs need to thrive,” *US Senate Committee on Small Business & Entrepreneurship*, 2017.
- Small Business Credit Survey**, “Report on Employer Firms, 2019,” Technical Report, Federal Reserve Banks 2019. Available at <https://www.fedsmallbusiness.org/medialibrary/fedsmallbusiness/files/2019/sbcs-employer-firms-report.pdf>.
- , “Report on Nonemployer Firms, 2019,” Technical Report, Federal Reserve Banks 2019. Available at <https://www.fedsmallbusiness.org/medialibrary/fedsmallbusiness/files/2019/sbcs-nonemployer-firms-report-19.pdf>.
- Zarutskie, Rebecca**, “Evidence on the effects of bank competition on firm borrowing and investment,” *Journal of Financial Economics*, 2006, 81 (3), 503–537.

Figure 1: Geographical Coverage in 2018



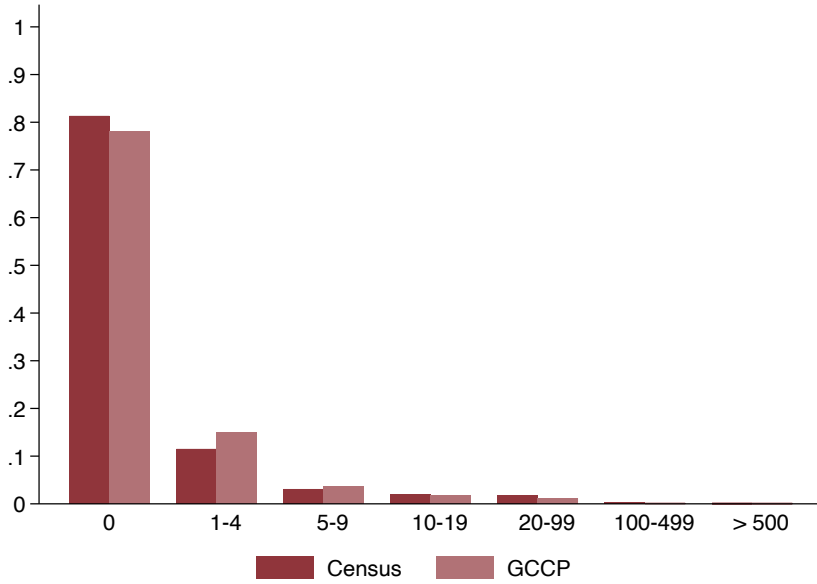
(a) Full sample



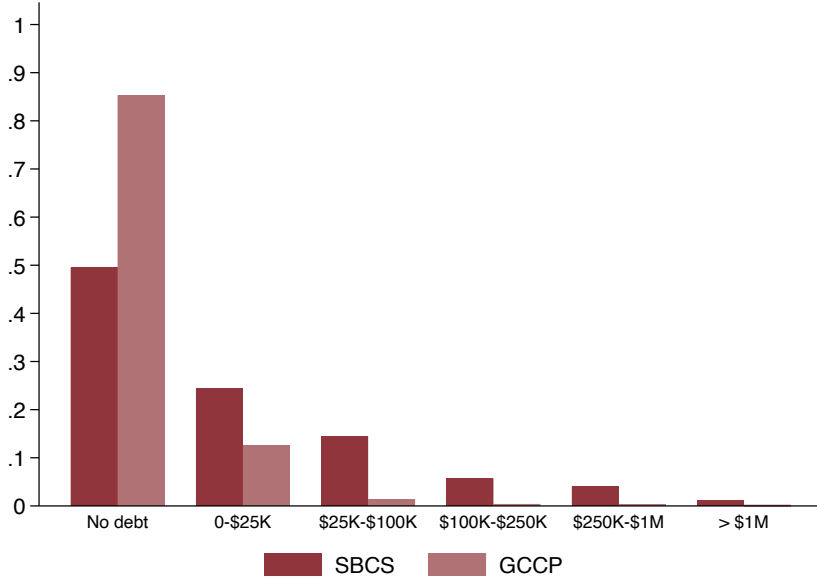
(b) Entrepreneurs

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



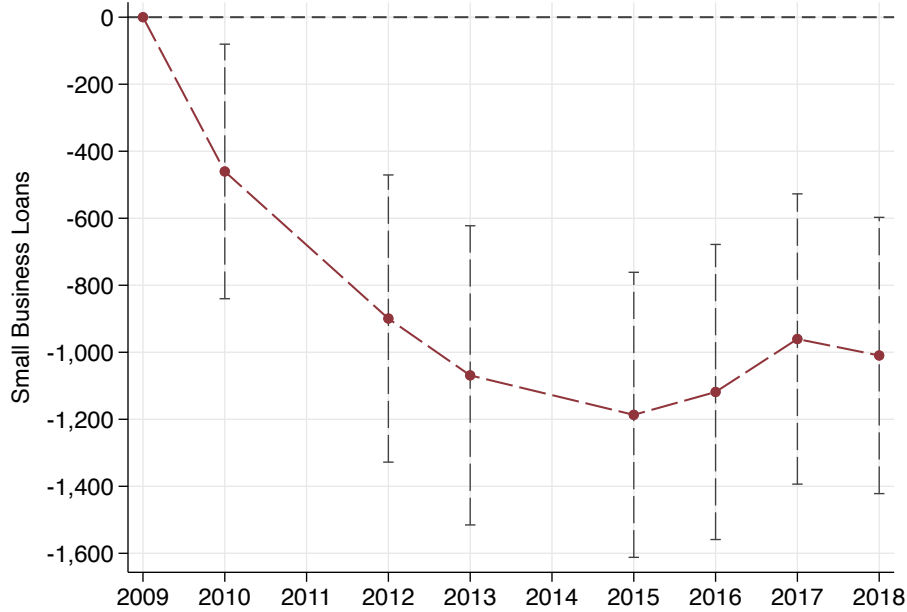
(a) Number of Employees



(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



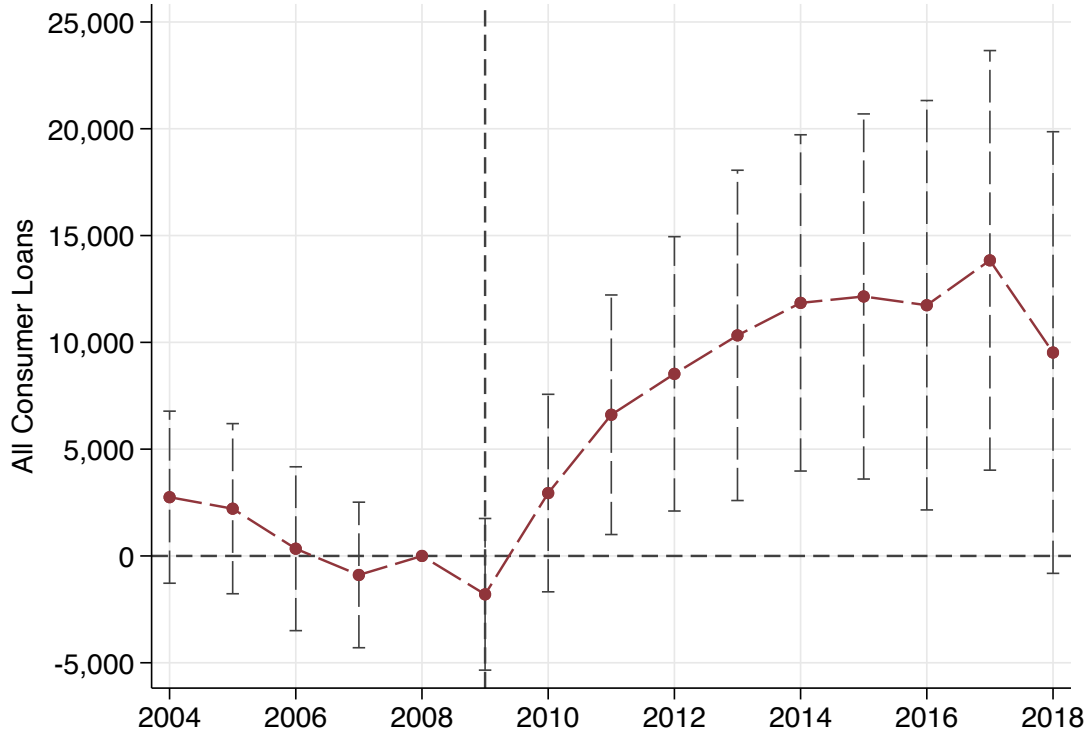
(a) Unscaled Business Loan Balance



(b) Scaled Business Loan Balance

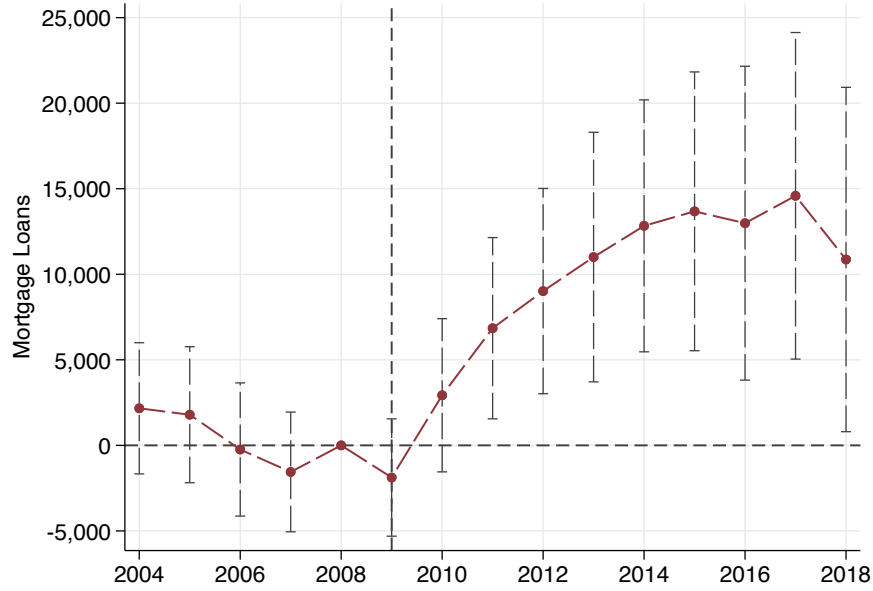
This figure plots coefficient estimates and 95% confidence intervals from equation (2), which models the effect of Top 4 bank presence on total business loan balances. Panel A shows unscaled estimates of observed loan balances in the GCCP, and panel B shows results when we scale business loans in the 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: Differences-in-differences 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 consumer loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same county. 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. Standard errors are clustered at the county level.

Figure 5: Differences-in-differences effect by consumer loan category



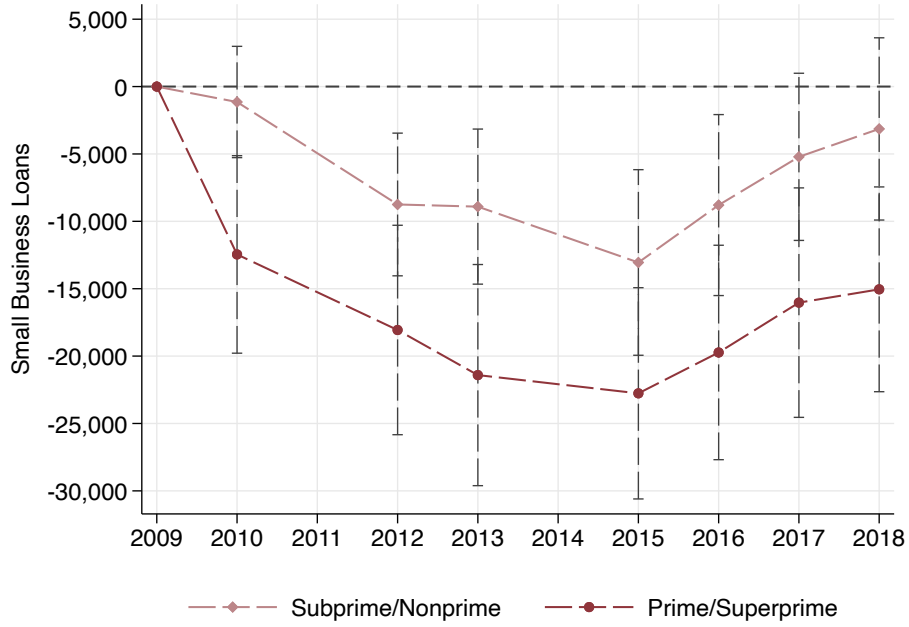
(a) Mortgage loan balance



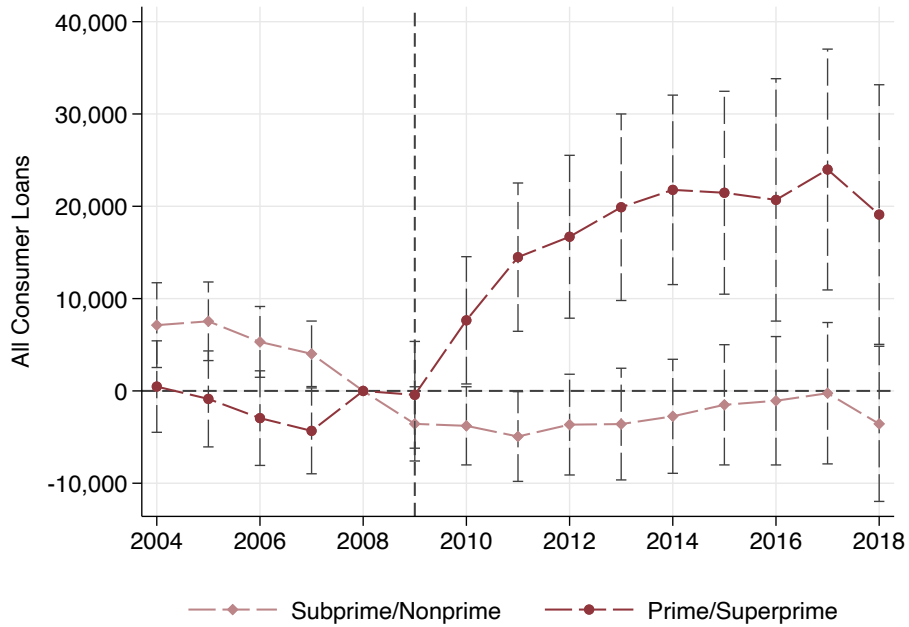
(b) Credit card balance

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 county. 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. Standard errors are clustered at the county level.

Figure 6: Heterogeneity by credit score



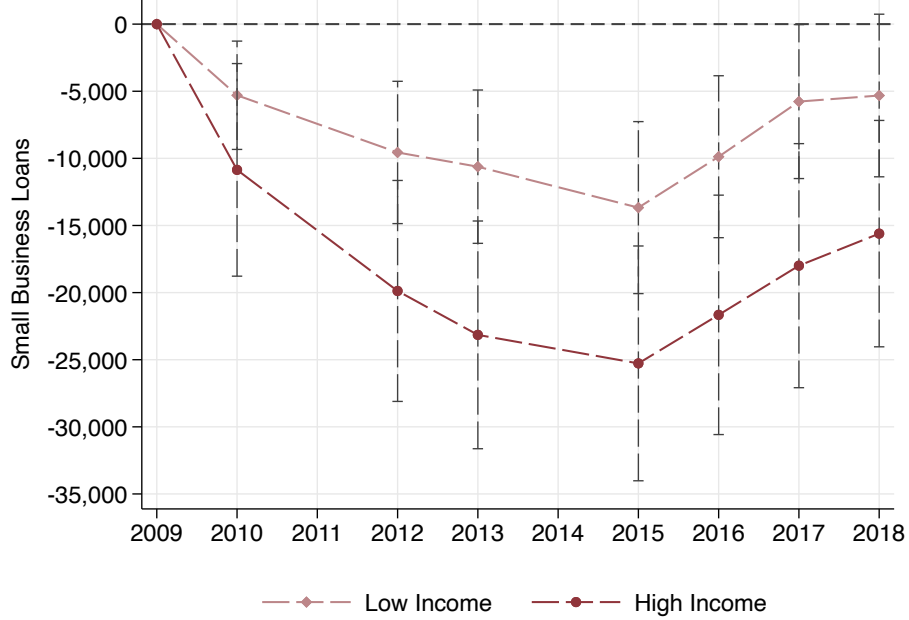
(a) Scaled business loan balance



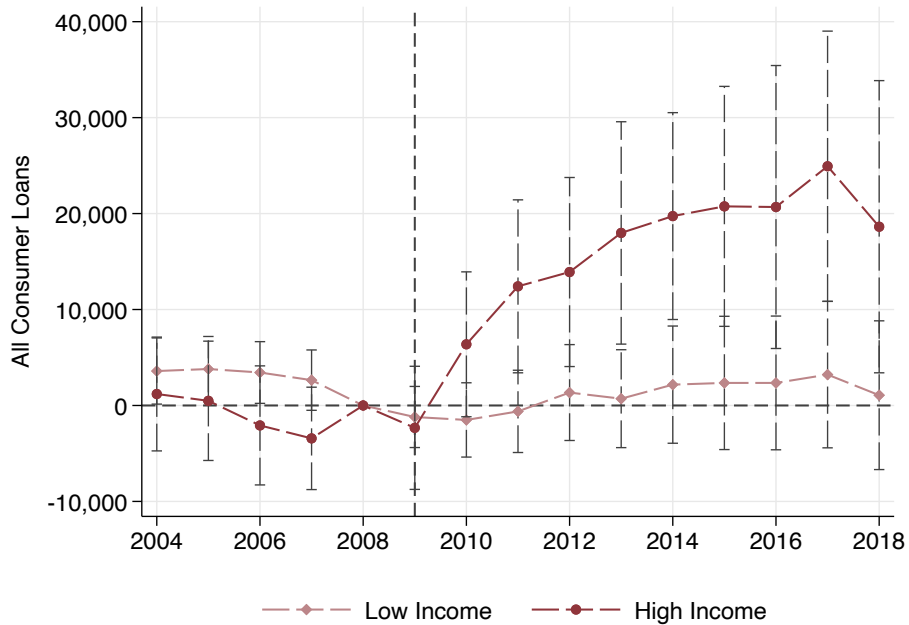
(b) Total personal loan balance

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. Standard errors are clustered at the county level.

Figure 7: Heterogeneity by income



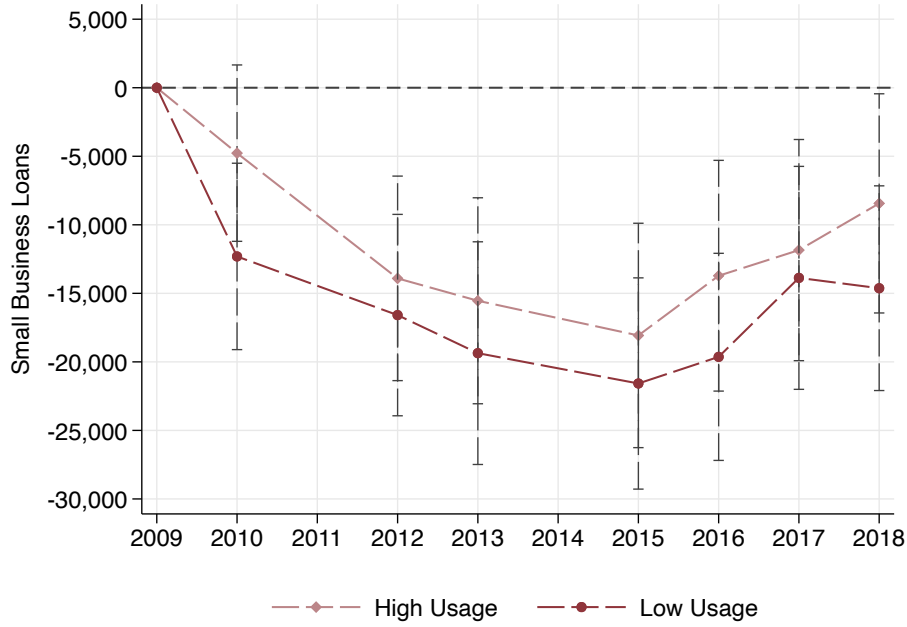
(a) Scaled business loan balance



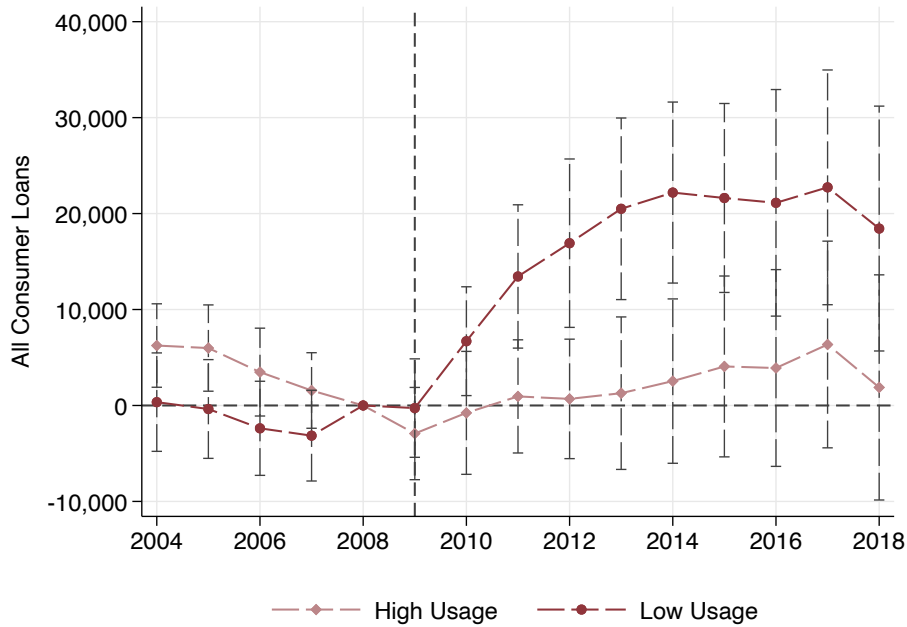
(b) Total personal loan balance

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. Standard errors are clustered at the county level.

Figure 8: Heterogeneity by credit card utilization



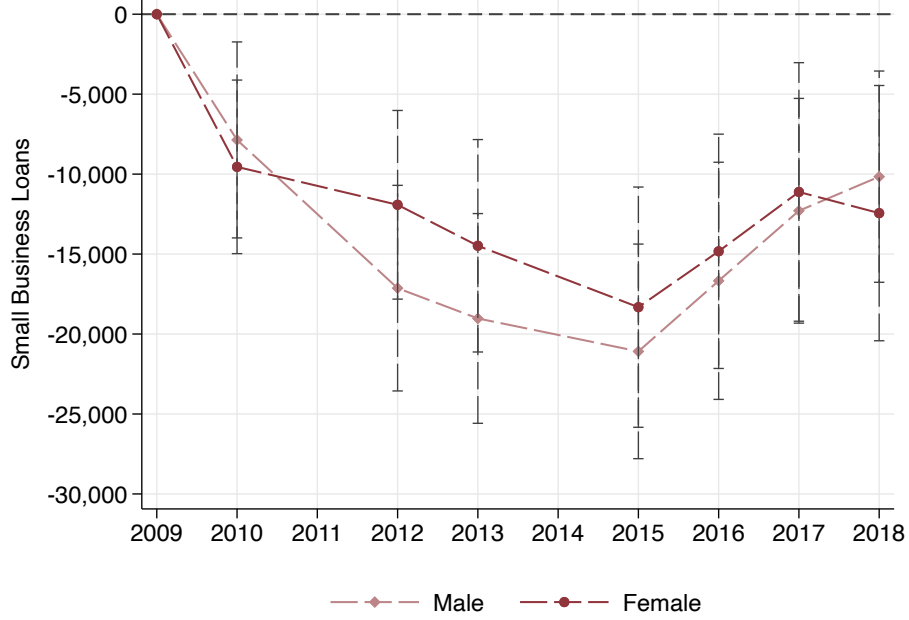
(a) Scaled business loan balance



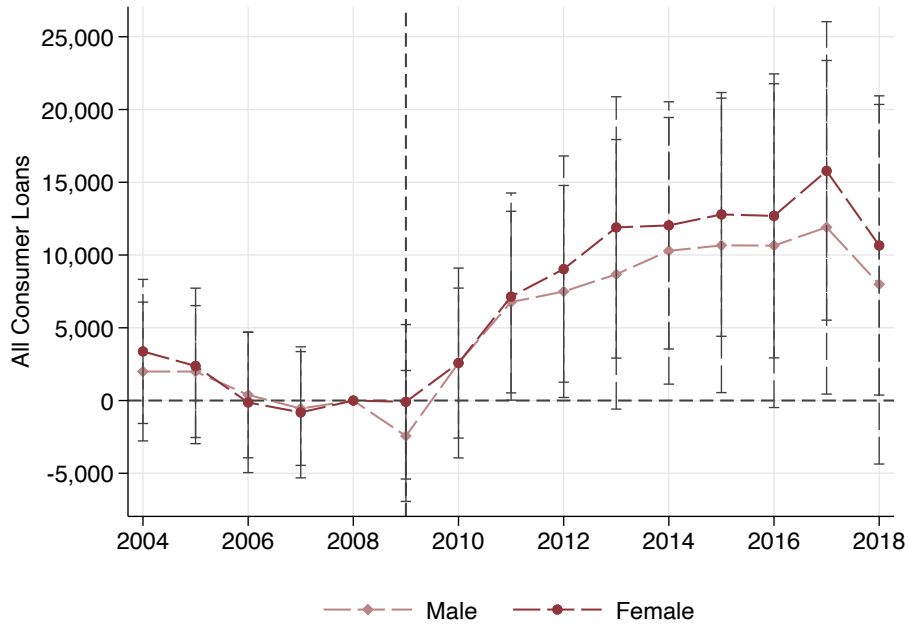
(b) Total personal loan balance

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. 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. 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 our sample of entrepreneurs and for our full sample. Entrepreneurs 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 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 county. 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			
	Unscaled		Scaled	
Scaling:	(1)	(2)	(3)	(4)
Top 4 Share\timesPost	-847.68*** (204.91)	-932.73*** (202.91)	-12,543.26*** (2,874.84)	-13,571.58*** (2,947.39)
Borrower FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	1,428,776	1,288,420	1,428,737	1,288,387

Notes: This table shows estimates of Equation (2), which estimates the effect of Top 4 bank presence on business loan balances. Columns (1)-(2) show unscaled estimates and columns (3)-(4) show estimates scaled by a factor that takes into account employer status and firm size categories constructed using 2018 SBCS data. 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 4: Effect of Top 4 Bank Share on Consumer Credit and Substitution

Variable:	Business loans		Consumer Loan Balance			Substitution Factor
Loan type:		Total	Mortgage	Revolving	Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)
Top 4 Share×Post×Entrepreneur	-13,571.58*** (2,947.39)	9,178.30** (3,929.86)	10,303.56*** (3,755.40)	536.18 (457.10)	112.45 (168.80)	-0.68** (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 personal loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same county. 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*** (2,475.66)	-5,729.07** (2,674.19)	0.81 (0.50)	-17,935.27*** (3,788.12)	19,397.62*** (4,954.80)	-1.08*** (0.38)
Panel B: By income						
Group :	Low Income			High Income		
Top 4 Share×Post×Entrepreneur	-8,728.64*** (2,441.32)	-623.68 (2,686.57)	0.07 (0.30)	-19,096.25*** (4,033.65)	17,924.44*** (5,535.97)	-0.94** (0.37)
Panel C: By credit card utilization						
Group :	High Usage			Low Usage		
Top 4 Share×Post×Entrepreneur	-12,317.55*** (3,483.55)	173.02 (3,975.11)	-0.01 (0.32)	-16,836.65*** (3,607.30)	18,770.69*** (4,669.98)	-1.11*** (0.39)
Panel D: By gender						
Group :	Male			Female		
Top 4 Share×Post×Entrepreneur	-15,036.73*** (3,076.50)	8,231.76* (4,470.91)	-0.55* (0.32)	-13,128.39*** (3,138.44)	9,603.13** (4,049.15)	-0.73** (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		
	All	Subprime	Prime	All	Subprime	Prime
Group :	(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 estimates of Equation (2) with measures of firm risk as dependent variables. 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)
<u>Panel A: Credit score interaction</u>					
Top 4 Share×Post×Entr.×Prime	25,113.34*** (4,021.95)	25,411.32*** (3,988.63)	29,022.62*** (4,020.00)	24,456.94*** (3,996.46)	27,961.28*** (4,005.36)
<u>Panel B: Income interaction</u>					
Top 4 Share×Post×Entr.×High Inc.	18,534.53*** (5,114.16)	19,327.37*** (5,015.15)	23,804.37*** (5,068.02)	17,481.03*** (5,053.11)	22,517.22*** (4,950.55)
<u>Panel C: Credit card utilization interaction</u>					
Top 4 Share×Post×Entr.×Low Usage	18,651.576*** (3230.646)	18,587.228*** (3222.159)	21,179.868*** (3278.649)	17,737.792*** (3251.819)	20,068.140*** (3317.987)
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
<i>Horse-Race Variable</i>					
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

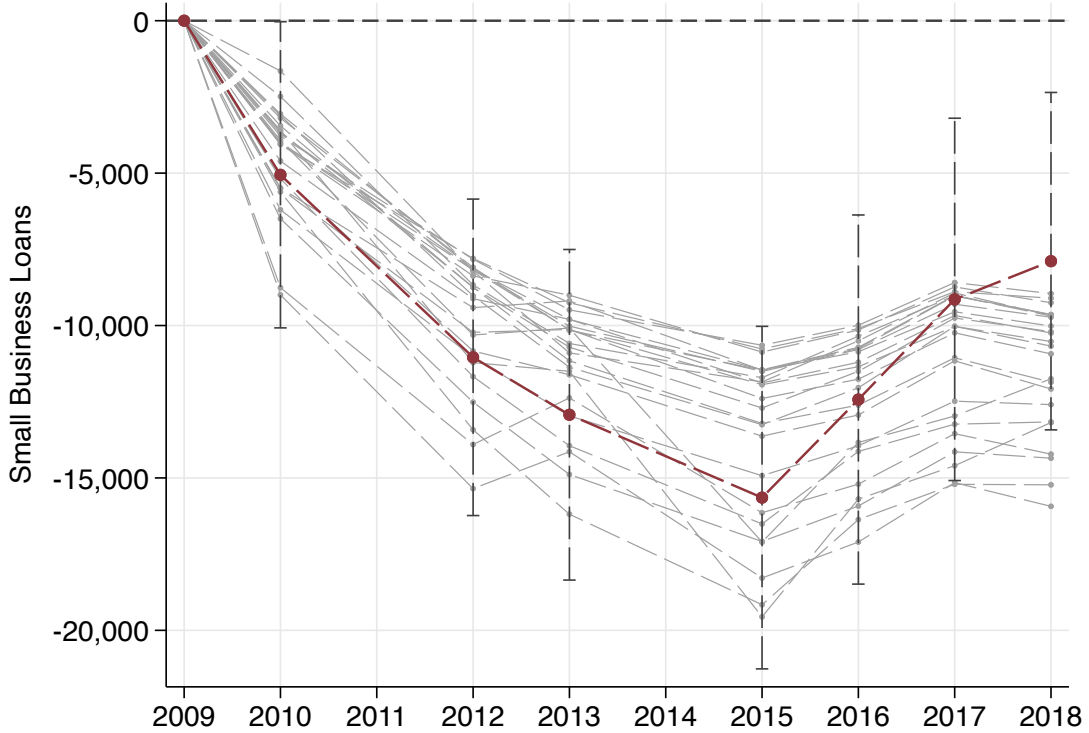
Notes: This table reports the effect of Top 4 bank presence on total consumer loan balances of entrepreneurs, relative to a matched sample of otherwise similar non-entrepreneurs residing in the same county. We further interact the $\text{Top 4 Share}_c \times \text{Post}_t \times \text{Entrepreneur}_i$ 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*** (3,755.40)	194.05 (699.51)	0.00 (0.02)	-0.01*** (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. Standard errors are clustered at the county level.

Table A.2: 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.3: Scaling Factors for Imputing Total Business Credit

Firm Categories	Employer	Debt Categories					
		\$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.4: Robustness to Alternative Matching Procedures

Dependent Variable:	Consumer Loan Balance					
	Baseline	Credit Score	Income	Gender	1 Neighbor	3 Neighbors
Matching Procedure:	(1)	(2)	(3)	(4)	(5)	(6)
Top 4 Share×Post×Entrepreneur	9,178.30** (3,929.86)	7,263.94** (3,161.70)	6,901.21*** (2,583.54)	8,672.60*** (3,175.60)	9,694.48** (4,908.92)	8,527.30** (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 county 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 4, 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.5: 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** (3,994.98)	9,178.30** (3,929.86)	9,422.03** (4,198.59)	9,033.28** (3,979.10)	9,260.49** (4,004.38)	9,711.63** (4,177.14)	10,425.21** (4,233.73)	10,306.44** (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
<i>Controls</i>								
House Price Index	No	Yes	No	No	No	No	No	Yes
Unemployment Rate	No	No	Yes	No	No	No	No	Yes
Credit Score _{pre}	No	No	No	Yes	No	No	No	Yes
Income _{pre}	No	No	No	No	Yes	No	No	Yes
Personal Balance _{pre}	No	No	No	No	No	Yes	No	Yes
Mortgage Balance _{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 county 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.