Where Do Small Firms Get Debt Financing?

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Abstract

We use detailed claim-level data from bankruptcy filings to study the types and sources of debt financing used by small firms. About half of firms in our data borrow from multiple lenders; 29% borrow from both bank and nonbank lenders. Only 29% of firms borrow exclusively from banks. We report detailed descriptive statistics on the types of debt used by small firms: credit cards, lines of credit, receivables financing, equipment financing, mortgages, and term loans. The smallest firms rely more on credit cards, receivables and equipment financing, while larger firms rely more on mortgages and lines of credit. Only half of the loans in our data are associated with UCC financing statements, calling for caution in using UCC filings as a proxy for small business lending. We examine the association between the structure of the local banking markets and the composition and sources of small business debt financing. Deposit concentration is associated with significantly lower share of bank debt, especially credit cards. Firms in counties with high deposit concentration appear to substitute to receivables financing and to mortgages from nonbank lenders. In counties with larger banks, small firms also substitute from bank to nonbank lenders. Finally, we investigate the presence of racial disparities in the utilization of different types and sources of debt financing. Black-owned firms rely significantly less on credit cards and receivables financing and more on mortgages. Asian-owned firms are significantly less likely to get their debt from banks than observably similar white-owned firms.

Keywords: small business lending, nonbank lending, bankruptcy, racial disparities in credit, UCC filings

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1 Introduction

Where do small firms get debt financing and how much of it comes from bank versus nonbank lenders? Answering these questions is surprisingly tricky due to the paucity of comprehensive data on small business lending. Most existing studies offer only partial glimpses into the sources of small business borrowing by studying specific lenders such as Business Development Companies (BDC),[1] SBA lending,[2] or lending by specific fintech firms or P2P platforms.[3] An influential paper by Gopal and Schnabl (2022) tries to get around these data limitations by using Uniform Commercial Code (UCC) filings as a proxy for small business lending. UCC filings allow Gopal and Schnabl (2022) to measure certain types of secured lending by bank and nonbank lenders and to track changes in lending over time. The main limitations of UCC filings are that they do not capture all small business lending and do not provide information on loan amounts or other terms. Thanks to their use of SEC filings, Chernenko, Erel, and Prilmeier (2022) observe all sources of lending to publicly-traded middle market firms in their sample and have detailed information on loan terms. The limitation of the data used by Chernenko, Erel, and Prilmeier (2022), however, is that publicly-traded middle market firms may not be representative of small business lending.

In this paper, we use detailed claim-level data from bankruptcy filings to provide new insights into small business lending. While the sample of firms that file for bankruptcy is obviously not random, the big advantage of using bankruptcy filings is that we have a complete and accurate picture of the sample firms' debt structure. Furthermore, to mitigate concerns that the debt structure of firms that file for bankruptcy may not be representative of all small firms, we focus on small business bankruptcies around the COVID pandemic — a large exogenous shock that firms and lenders did not anticipate when making their initial lending decisions. More generally, given the high failure rates of small firms — about a fifth fail within their first year of operation and about a half fail within the first five years[4] — small firms that file for bankruptcy are arguably representative of a large share of small firms in the economy. Finally, throughout the paper we discuss the potential effects of the sample selection bias and how they may affect the external validity of our results. Overall, despite their limitations, our data allow us to paint a rich picture of the debt structure of small firms.

We study the sample of small business bankruptcy filings in Florida during 2019–2021, excluding financial and real estate firms. We use Florida because it is a large state that on many dimensions is broadly representative of small businesses across the US and because the state's corporate records

[1] Davydiuk, Marchuk, and Rosen (2020, 2024); Chernenko, Ialenti, and Scharfstein (2024).

[2] Brown and Earle (2017).

[3] Mach, Carter, and Slattery (2014); Kim and Stähler (2020); Balyuk, Berger, and Hackney (2022).

[4] U.S. Bureau of Labor Statistics Establishment Age and Survival Data: https://www.bls.gov/bdm/bdmage.htm

and voter registration data allow us to identify the race of small business owners in our data.[5] Our sample is limited to incorporated firms and therefore excludes sole proprietors. While sole proprietors account for a large share of small businesses, their share of total employment is less than half. Furthermore, using bankruptcy filings of sole proprietors to study debt structure would be difficult due to the lack of separation between personal and business debt.

After summarizing our sample construction and discussing the representativeness of our data in Section 2, we start by describing in Section 3 the types of debt and lenders used by small firms. We classify debt into credit cards, equipment financing, lines of credit, mortgages, receivables financing, term loans, and other and tabulate the utilization of different types of debt by firms in our data. Term loans are the most common type of debt, but their share is still only 24%. Equipment financing is the next most common type of debt with 19% share, followed by other with 15% and credit cards with 14%. Lines of credit and receivables financing are less common with 7% and 9% shares. These averages mask significant variation in debt composition across firms of different size. Smaller firms rely more on credit cards and also on term loans than larger firms. The share of credit card debt, for example, is 19% for firms with less than $50 thousand in assets versus 9% for firms with $1–10 million in assets. Larger firms rely significantly more on mortgages. The share of mortgage debt increases monotonically from 4% for the smallest firms to 34% for the largest ones.

Section 3 also documents significant heterogeneity in who lends to small firms. Less than 30% of firms have banks as their sole lender type. This result casts doubt on the standard narrative that banks are uniquely positioned to extend credit to small firms. Almost 30% of firms in our sample borrow from both banks and nonbank lenders. Another 21% have nonbanks as their sole lender type. The fact that many small firms borrow from both banks and nonbanks is similar in spirit to the result in Haque, Stefanescu, and Mayer (2024) that banks and private debt lenders originate loans to the same middle-market firms. Our results suggest, however, that firms borrowing from both banks and nonbanks is a much broader phenomenon that is not limited to middle-market firms backed by private equity.

In addition to reporting descriptive statistics on the shares of different types of debt and lenders, Section 3 provides evidence of lender specialization. Not surprisingly, Merchant Cash Advance (MCA) lenders provide exclusively receivables financing, while equipment finance companies provide equipment financing. More surprising perhaps is our evidence on specialization by banks. Some large banks in our data specialize in credit cards. Other large banks specialize in equipment financing. Regional and local banks tend to be more diversified across different types of debt.

A unique aspect of our data is that it allows us to evaluate UCC financing statements as a measure of small business lending. UCC financing statements have been used by Gopal and Schnabl (2022) to study the growth in nonbank lending to small firms and by other papers to measure

[5] See Chernenko and Scharfstein (2024) for more details on using Florida corporate records and voter registration data to identify minority-owned firms.

borrowing relationships (Chernenko and Scharfstein, 2024; Balyuk, Prabhala, and Puri, 2021). We show in Section 4 that only about half of small business lending in our data is captured in UCC filings. Furthermore, there is significant heterogeneity in coverage across debt and lender types. Credit cards are almost never captured by UCC filing, yet are an important source of financing for the smallest firms. More surprising is that only 43% of equipment financing is captured in UCC filings. Similarly, less than 35% of mortgages have UCC filings.

Using our loan-level data, we estimate linear probability model regressions of whether a loan has a UCC financing statement. Controlling for debt type, larger loans and loans to larger firms are significantly more likely to have UCC filings. This means that UCC filings may be best at capturing lending to larger firms, in particular the ones with at least $1 million in assets. Loans from individuals are 14–40 percentage points less likely to have a UCC financing statement. This means that analyses using UCC filings are likely to significantly underestimate the importance of individuals in providing debt financing to small firms. Overall, the results in Section 4 suggest that UCC filings should be interpreted with caution as a proxy for small business lending.

We then turn to examining some of the determinants of debt structure. In Section 5 we study the association between the structure of the local banking markets and the types of debt and lenders that small firms borrow from. We use the Herfindahl-Hirschmann Index (HHI) of bank deposit concentration in a firm's county as a measure of bank competition. We also measure the average size of banks in the county, weighting each bank by its deposit share. Deposit concentration is associated with a significantly lower share of bank debt and a correspondingly higher share of nonbank debt. As a result, firms in counties with higher deposit concentration rely less on credit card debt and more on receivables financing, which tends to charge even higher interest rates. Deposit concentration is also associated with a shift in mortgage borrowing from banks to nonbanks. Consistent with the existing literature showing that large banks are less active in small business lending, we find that in counties with larger banks, small firms substitute from bank to nonbank financing. Interestingly, this effect appears to be driven by mortgage loans, which arguably rely less on soft information than other types of small business lending like term loans and lines of credit.

Finally, in Section 6, we take advantage of data on the racial and ethnic identity of firm owners to investigate racial disparities in small business lending. We find that compared to observably similar white-owned firms, Black-owned firms rely significantly less on credit cards (7.5 percentage points) and receivables financing (5.6 percentage points). Conversely, Black-owned firms have 13.7 percentage points higher share of mortgage debt than observably similar white-owned firms. We also document disparities in who firms borrow from conditional on utilizing a given type of debt. Asian-owned firms are 12.5 percentage points less likely to get the same type of loan from a bank than observably similar white-owned firms. We also find some evidence that conditional on getting a mortgage, Black-owned firms are 38–44 percentage points less likely to get it from a bank than observably similar white-owned firms.

Overall, our novel, hand-collected data paint a rich picture of the debt structure of small firms in terms of the types and sources of debt they utilize. Our paper thus contributes to a large literature on small business lending. Many papers in this literature rely either on survey data, which may be subject to response biases and which usually provides only a brush strokes picture of debt financing, or data covering a single type of lender such as banks, SBA, BDCs, or specific fintech lenders or P2P platforms. Although our data are subject to their own sample selection biases, it offers us a rare view into the debt structure of small firms.

Our paper also contributes to the literature on the changes in small business lending following the financial crisis (Chen, Hanson, and Stein, 2017; Bord, Ivashina, and Taliaferro, 2021; Cortés et al., 2020; Gopal and Schnabl, 2022). While our data are cross-sectional in nature, the results in Section 5 on the association between banking market structure and debt composition are broadly consistent with this literature. In particular, we find greater reliance on nonbank lenders in areas with stronger presence of large banks and in areas with larger deposit concentration, which may be a result of prior bank mergers.

Finally, our paper contributes to the literature studying racial disparities in access to credit. A number of papers in this literature study racial disparities in access to and pricing of home mortgages (Munnell et al., 1996; Ferguson and Peters, 1995; Ladd, 1998; Cheng, Lin, and Liu, 2015; Gerardi, Willen, and Zhang, 2023). Many of these papers take advantage of the confidential version of the Home Mortgage Disclosure Act (HMDA) data that includes measures of borrower creditworthiness along with their race. Research on disparities in access to credit among small businesses has had to rely on survey data (Fairlie, Robb, and Robinson, 2022; Fairlie and Robinson, 2023; Chernenko et al., 2024), which typically provides only a broad overview of debt types and lenders, or examines inequities in access to a single program or specific loan type (Howell et al., 2024; Chernenko and Scharfstein, 2024). Our paper contributes to this literature by documenting disparities in the types of debt and lenders used by observably similar white- and minority-owned firms.

2 Data

Our data cover small business bankruptcy filings in Florida during the 2019–2021 period. We start by using the Federal Judicial Center (FJC) bankruptcy database, available through WRDS, to identify 1,869 corporate bankruptcy filings under Chapters 7 and 11.[6] We then exclude cases that involve stockbrokers, clearing banks, commodity brokers, single-asset real estate, and railroads, as well as cases that are transferred to Florida or are non-lead cases.

Next, we search for each case in the Public Access To Court Electronic Records (PACER)

[6] We require the nature of debt (`ntrdbt` variable) to be "Business" and debtor type (`dbtrtyp`) to be corporation.

system and only keep cases that can be found in PACER system and have claims register.[7]

We then obtain self-reported industry information from case petitions. Because not all bankruptcy filings report debtor's industry, we supplement this by matching debtors to the Dun & Bradstreet (D&B) database and using industry classifications from D&B.[8] For a small fraction of cases that lack self-reported industry information, cannot be matched to D&B, or have missing industry information in D&B (including reporting industry as nonclassifiable establishments), but include a business description in the case management summary document, we ask ChatGPT to map the business description into 2-digit NAICS sectors.[9] We exclude financial, insurance, and real estate firms based on either 2-digit NAICS sectors 52 and 53 or SIC codes in the 6000–6799 range.[10] We also exclude a small number of non-profit firms by searching for debtors in Florida's corporate records[11].

To focus on small firms, we drop firms with total assets greater than $10 million based on the estimated assets information from the case petitions. After applying these screens, we have 760 small business bankruptcy filings.

For this sample of bankruptcy filings, we use the claims register data in PACER to manually collect and categorize claims into leases and money loaned versus all other types of claims: goods sold, services performed, unpaid taxes, and other. To economize on the costly manual data collection, we drop claims that account for less than 2.5% of the aggregate amount claimed in the case.[12] For equipment leases and money loaned claims, we collect the supporting documents. These typically include the Official Form 410 - Proof of Claim, original loan/lease contract(s), and/or UCC filing(s) if applicable.

We categorize lenders into banks, nonbank financial institutions, individuals, and government entities (primarily SBA). We search for each lender's name in Capital IQ and the National Information Center (NIC). A lender is identified as a bank if the creditor itself or its ultimate parent is a bank, credit union, or a bank holding company. Both individuals and named trusts are classified as individual lenders. We identify Merchant Cash Advance (MCA) lenders using a list of poten-

[7] We petitioned the three bankruptcy district courts in Florida through PACER for free access to the official court electronic document filing system.

[8] We first search D&B for the debtor's Employer Identification Number (EIN). If we cannot match based on the EIN, we try searching for the debtor's name. In cases of multiple matches in D&B where one is a parent and the other ones are subsidiaries or branches, we keep the parent.

[9] We ask ChapGPT to "Return the 2-digit NAICS sector that best fits each of the following business descriptions.

[10] SIC codes are from D&B.

[11] https://search.sunbiz.org/Inquiry/CorporationSearch/ByName

[12] In some cases, a single creditor may file multiple small claims that aggregate to a sizable share of total liabilities. An example would be a lender that financed multiple pieces of equipment and files separate claims for each piece of equipment. To account for such situations, we check whether each creditor's share is at least 2.5%.

tial MCA lender names obtained from claims that are classified as purchases of future receivables. Then, we manually search each lender in this list online to confirm whether it is a MCA lender.

The final sample consists of 637 cases. Table 1 summarizes the sample construction process and reports the number of cases filed in each of the three bankruptcy courts in Florida.

Table 1
Sample Construction

This table summarizes the steps in the sample construction process. The initial sample consists of Chapter 7 and 11 corporate bankruptcies in Florida filed during the 2019–2021 period.

Step	Middle	Northern	Southern	Total
0. Chapter 7 and 11 corporate bankruptcies	967	93	809	1,869
1. Exclude stockbroker, clearing bank, commodity broker, single asset real estate, and railroad cases	898	86	733	1,717
2. Exclude transferred cases and non-lead cases	812	81	605	1,498
3. Docket in PACER and has claims register	622	69	532	1,223
4. Exclude financial, real estate, and non-profit firms	419	45	323	788
5. Restrict to small firm cases	404	45	311	760
6. Exclude cases without loan/lease claims or with only government creditors	343	40	254	637

2.1 Owner's Race and Ethnicity

To examine racial disparities in small business lending, we follow Chernenko and Scharfstein (2024) in using the self-reported race from Florida voter registration data.[13] Specifically, we use their algorithm to match each firm's officers and directors (as reported in the corporate records data) to the voter registration data. We classify each firm based on the racial/ethnic identity of the first officer or director who we are able to match to the voter registration data. We are able to classify all but 40 cases or 6% of the sample.

2.2 Sample Characteristics

Table 2 reports descriptive statistics on the final sample of small business bankruptcies studied in the paper. Panel A reports the distribution of cases across the three bankruptcy districts in Florida: Northern, Middle, and Southern. Only 6% of all cases are filed in the Northern district. The Middle and Southern districts account for 54% and 40%.

Panel B reports the distribution of firms across bins of estimated assets: 0-50K, 50–100K, 100–500K, 500K–1M, and 1–10M. About 42% have less than $50 thousand in assets.

Panel C reports summary statistics on the firm's age. We measure each firm's age as the difference in years between the first filing in Florida corporate records and the bankruptcy filing

[13] https://dos.fl.gov/elections/data-statistics/voter-registration-statistics/voter-extract-request

Table 2
Sample Characteristics

The sample of small business bankruptcies in Florida during 2019–2021, excluding financial and real estate firms.

Panel A: Bankruptcy district ($N = 637$)

	Middle	Northern	Southern
N	343	40	254
%	54	6	40

Panel B: Estimated assets ($N = 637$)

	0–50K	50–100K	100–500K	500K–1M	1–10M
N	267	57	162	55	96
%	42	9	25	9	15

Panel C: Firm's age ($N = 637$)

Mean	SD	Min	25th	50th	75th	Max
11.39	10.14	0.23	4.30	8.62	15.26	89.00

Panel D: 2-digit NAICS industry ($N = 588$)

Industry	N	%
Agriculture, forestry, fishing and hunting	4	1
Mining, quarrying, and oil and gas extraction	2	0
Utilities	3	1
Construction	94	16
Manufacturing	41	7
Wholesale trade	72	12
Retail trade	58	10
Transportation and warehousing	37	6
Information	10	2
Professional, scientific and technical services	46	8
Management of companies and enterprises	2	0
Administrative and support and waste management and remediation services	23	4
Educational services	5	1
Health care and social assistance	58	10
Arts, entertainment, and recreation	29	5
Accommodation and food services	73	12
Other services	31	5

Panel E: Firm owner's race ($N = 597$)

	Asian	Black	Hispanic	White	Other
N	32	37	126	370	14
%	6	6	22	64	2

Panel F: Total debt in $ thousands ($N = 637$)

Mean	SD	Min	25th	50th	75th	Max
1,193	4,130	0	76	292	904	85,070

Panel G: Number of creditors ($N = 637$)

	1	2	3	4	5	6	7+
N	276	153	82	58	28	19	21
%	43	24	13	9	4	3	3

date. The mean (median) firm age is 11.39 (8.62) years. The interquartile range is 4.30–15.26 years. The youngest firm in our sample to file for bankruptcy is less than 3 months old.

Table 2 next reports the distribution of firms across 2-digit NAICS industries. The sample size is smaller because NAICS code is not classifiable for some firms.

Table 2 also reports the distribution of the firm's owner race. About 94% of firms in the sample have at least one officer matched with the Florida voting records. The distribution of race is 64% white, 22% Hispanic, 6% Black, 6% Asian, and 2% other.

Finally, Table 2 reports the distribution of firms across total debt and number of lenders. The median firm reports $292 thousand in total debt claims. The distribution of total debt is right-skewed: the mean is $1.193 million. Almost half of the sample (43%) have a single lender. About a quarter have two lenders. Ten percent of firms in our sample have five or more lenders. The maximum number of lenders is twelve.

Internet Appendix Figure IA1 and Table IA1 compare the characteristics of the companies filing for bankruptcy before COVID versus during COVID. Manufacturing sector (31–33) represents a significantly lower share during COVID than before COVID. Conversely, retail trade (44–45) and healthcare and social assistance (62) account for a higher share of bankruptcies during COVID than before COVID. These results make sense given that retail trade and healthcare firms were likely to be more affected by COVID. Otherwise, the industrial composition of the two subsamples is very similar. The subsamples are also comparable in terms of firm's age and owner's race. The main difference is that the pre-COVID subsample has a higher share of firms aged 11–15 years while the COVID subsample has a higher share of firms aged at least 16 years. Overall, the similarity between the two subsamples justifies analyzing the full sample of bankruptcies. Nevertheless, the Internet Appendix reports the robustness of our results to focusing on the COVID subsample.

2.3 Comparisons to the Population of Small Firms

How do the firms in our sample compare with the population of small firms in Florida and across the country? Figure 1 illustrates the distribution of firms in our sample, Florida and the whole country in terms of 2-digit NAICS industries, and Table 3 compares the distribution of firms in our sample, Florida, and the whole country in terms of firm's age and owner's racial and ethnic identity.

The data on the industry distributions for all small firms in Florida and the U.S. are from the Census Bureau's 2019 Statistics of U.S. Businesses (SUSB) Annual Data[14]. In calculating industry shares, we exclude firms in "Finance and Insurance" and "Real Estate and Rental and Leasing" from the denominator. We use the Small Business Administration's definition of small businesses

[14] https://www.census.gov/data/tables/2019/econ/susb/2019-susb-annual.html

Figure 1

Industry Composition of Sample versus All Small Firms in Florida and US

This figure compares the distribution of firms across 2-digit NAICS in our sample versus all small firms in Florida (subfigure a) and all small firms in the US (subfigure b). Data on the distribution of firms across industries is from the Census Bureau's 2019 Statistics of U.S. Businesses (SUSB) Annual Data.

(a) Florida **(b)** US

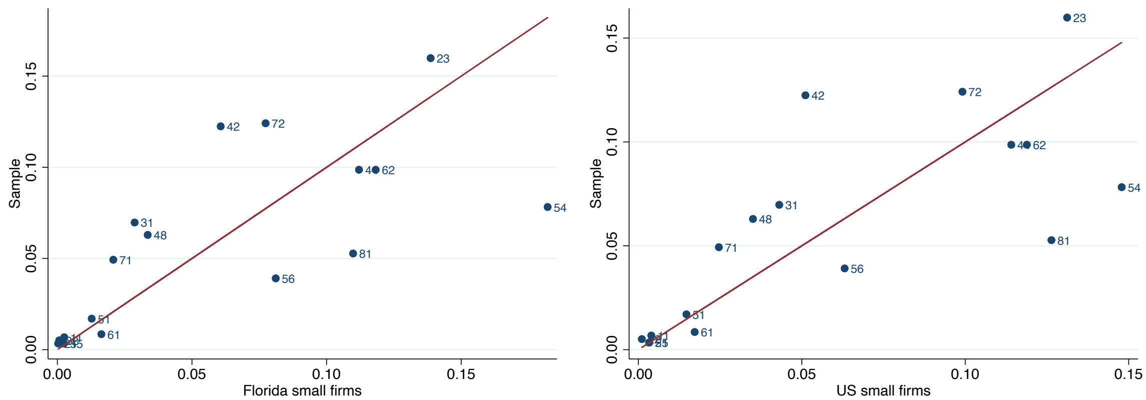

Table 3

Comparisons between Sample, Florida, and US Firms

This table compares the distributions of firm's age, and firm owner's race for sample firms versus all small firms in Florida and across the US. Data for small businesses in Florida and across the US are from the Census Bureau's 2019 Annual Business Survey (ABS). Because there is no consistent criterion that can be used to identify small firms in different data sets, different Panels use somewhat different criteria and some of the differences across samples are due to the variation in the criteria used. Panel A reports the distributions of firm's age (i.e., years in business). Panel B reports the distribution of firm owner's race. Percentages may not end up to hundred due to rounding.

Panel A: Age

	Sample	Florida	US
$<$ 2 years	6	17	15
2–3 years	17	14	12
4–5 years	14	11	10
6–10 years	23	18	16
11–15 years	17	14	14
$\geq$ 16 years	23	27	33

Panel B: Race

		Florida		US	
	Sample	Sales $<$ 1M	All	Sales $<$ 1M	All
Asian and Pacific Islander	6	6	6	10	10
Black, not Hispanic	6	3	3	2	2
Hispanic	22	17	16	6	6
White, not Hispanic	64	71	71	77	77
Other	2	3	5	4	5

as those with fewer than 500 employees. This definition does not perfectly match our sample's definition as firms with less than \$10 million in assets.

Figure 1 shows that our sample is broadly comparable to the population of small firms in Florida. The main difference is that the sample overweights "Wholesale Trade (42)" and "Accommodation and Food Services (72)" and underweights firms in the "Professional, Scientific, and Technical Services (54)", "Administrative and Support and Waste Management and Remediation Services (56)" and "Other Services (except Public Administration) (81)".

In Table 3, data for all small businesses in Florida and across the U.S. are from the Census Bureau's 2019 Annual Business Survey (ABS).[15] Panel A of Table 3 presents the distribution o firm's age, defined as years in business, within the ABS. Overall, the sample closely matches the distribution of firm's age in Florida, although it includes a smaller proportion of firms that are younger than 2 years.

Panel B of Table 3 reports the distribution of firms according to the racial and ethnic identity of their owner(s). Because ABS classifies firms based on their sales, we define small firms as those with less than $1 million in sales. This is likely to be a stricter definition than $10 million in assets or less than 500 employees. Therefore, we include both the small firms and all firms in the comparisons in Panel B. Financial, real estate, and non-classifiable firms are not excluded in Panel B due to data limitations. To match the race categories in our sample and in the Census ABS, we use both ethnicity code and race code in the Census ABS data. Overall, our sample matches the firm owner's race distribution of Florida, though we have more Black- and Hispanic-owned firms.

3 Which Types of Debt and Lenders do Firms Utilize?

3.1 Types of Debt

We classify different types of debt into credit cards, equipment financing, lines of credit, mortgages, receivables financing, term loans, and other. Table 4 reports the average shares of different types of debt. We report the average shares for firms of different sizes in columns 1-5, and the overall average in the last column.

There are several interesting findings in Table 4. First, smaller firms rely significantly more on credit cards than do larger firms. Credit cards on average account for 14% of all debt. For firms with less than $50K in assets, credit cards account for 19% of all debt. The share of credit card debt is 16% and 12% for firms with $50–100K and $100–500K in assets. For firms with more than $1 million in assets, credit card share is about 9%. Greater reliance on credit cards by smaller firms could be due to these firms having few pledgeable assets to use as collateral for other types of debt. The shares of credit card debt for firms in our sample are significantly higher than the estimates in Luck and Santos (2023) and Gopal and Schnabl (2022). Using confidential FR Y-1Q data on the

[15] https://www.census.gov/programs-surveys/abs/data/tables.html

Table 4
Debt Composition by Firm Size

This table reports the average shares of different types of debt: credit card, equipment financing, lines of credit, mortgages, receivables financing, term loans, and other. Estimated asset size is from bankruptcy petitions. We also report the HHI of firm's loans.

	Estimated asset size					
	0–50K	50–100K	100–500K	500K–1M	1–10M	Total
	(1)	(2)	(3)	(4)	(5)	(6)
N	267	57	162	55	96	637
Debt type						
Credit card	19.0	16.1	12.4	4.7	8.7	14.3
Equipment financing	20.3	26.1	15.6	24.3	14.6	19.1
Line of credit	5.2	9.4	7.4	3.4	12.1	7.0
Mortgage	3.7	6.1	13.5	21.8	34.2	12.5
Receivables financing	9.7	3.8	9.0	14.3	4.9	8.6
Term loan	27.0	27.5	27.5	9.9	11.5	23.4
Other	15.2	11.0	14.6	21.6	13.9	15.0
Debt HHI	7,781.0	7,717.0	7,281.7	6,764.7	7,772.0	7,559.2

loan portfolios of large stress test banks, Luck and Santos (2023) estimate that less than 3.6% of C&I lending by stress tests banks to firms with less than $50 million in assets is unsecured. Gopal and Schnabl (2022) estimate that 5% of small business lending is unsecured. There are at least two potential alternative explanations for the difference in results. It could be that our sample has a higher share of smaller firms, which as Table 4 shows rely more heavily on credit card debt. Alternatively, the apparent higher reliance on credit card debt could be due to firms drawing down their credit card balances as they approach bankruptcy. Such draw-downs could help explain the high average share of credit card debt but not necessarily the decline in usage with firm size.

Term loans average about 23% of total debt. The share of term loans declines with firm size from 27% for the smallest firms with less than $50K in assets to less than 12% for the largest firms with more than $1 million in assets. The decline in term loans is more than offset by the increase in the share of mortgage debt from 3.7% for the smallest firms to 34.2% for the largest ones.

Equipment financing averages 19% of total debt; other accounts for about 15% of total debt; and lines of credit and receivables financing account for 7% and 9% of all debt. Although there is no clear monotonic pattern across size buckets for these types of debt, smaller firms seem to rely more on equipment financing but less on line of credit than larger firms.

In interpreting the results in Table 4, it is important to note that almost half of all firms have a single creditor and type of debt. Table 5 provides more insight into the composition of debt by reporting the fraction of firms that utilize each type of debt and the mean and percentiles of debt type shares conditional on utilizing a given type of debt. For example, about thirty percent of firms have credit card debt. Conditional on utilizing credit cards, the average share is 46.4% and the interquarterile range is 7.1–100.0%.

Table 5
Debt Composition

This table reports summary statistics on the conditional distributions of different types of debt. Panel A reports the probability of utilizing different types of debt as well as the mean, standard deviation, and percentiles of the conditional distribution. In each row of Panel B, we report the conditional means of different types of debt conditional on utilizing the type of debt indicated by the row. For example, conditional on having a mortgage, the average share of credit card debt is 2.0%. Probabilities of utilizing different types of debt and shares are percentages.

Panel A: Conditional Distributions

		Conditional on utilizing				
	P(Share > 0)	Mean	SD	25th	50th	75th
Credit card	30.8	46.4	41.4	7.1	28.0	100.0
Equipment financing	31.9	60.0	36.5	22.0	64.0	100.0
Line of credit	15.7	44.7	32.7	14.6	38.7	69.0
Mortgage	15.2	82.4	26.8	75.6	96.4	100.0
Receivables financing	17.7	48.7	35.1	17.1	38.6	83.5
Term loan	39.2	59.6	36.0	24.1	65.4	100.0
Other	25.7	58.4	39.8	16.9	69.5	100.0

Panel B: Debt Type Shares Conditional on Utilizing a Given Type

	N	CC	EF	LC	MTG	RF	TL	Other
Credit card (CC)	196	46.4	10.5	7.6	5.6	6.7	17.4	5.8
Equipment financing (EF)	203	5.0	60.0	5.1	4.6	6.6	12.3	6.3
Mortgage (MTG)	97	2.0	4.3	1.6	82.4	1.3	4.0	4.5
Line of credit (LC)	100	7.2	11.9	44.7	2.9	8.5	19.5	5.4
Receivables financing (RF)	113	4.3	13.3	6.3	3.6	48.7	17.4	6.5
Term loan (TL)	250	5.4	10.5	6.0	6.0	6.3	59.6	6.3
Other	164	4.6	8.9	6.5	7.6	2.8	11.3	58.4

There are a few takeaways from Panel A of Table 5. First, no single type of debt is utilized by more than 40% of all firms. Term loans are the most common at 39.2%, followed by equipment financing at 31.9% and credit cards at 30.8%. Second, mortgage debt is relatively rare (15.2%), but conditional on having mortgage debt, its average share is high at 82.4%. For most other types of debt, the conditional average is around fifty percent. Third, although credit card debt is fairly common, its conditional mean is 46.4%; its median is even lower at 28%. Lines of credit are less common than credit cards but have similar conditional moments.

In Panel B of Table 5, we examine the correlation between different types of debt. In each row on Panel B, we report the conditional means of different types of debt conditional on utilizing the type of debt indicated by the row. Conditional on having any type of debt, the average share of term loans is always the highest, and the average share for equipment financing follows after the term loans.

3.2 Types of Lenders

Table 6 reports the number and share of firms borrowing from different types of lenders. About half of firms borrow from a single lender type; 29% borrow from banks only, while 21% borrow from nonbanks only. Another half of firms borrow from multiple lenders: 29% borrow from both banks and nonbanks, another 15% borrow from both banks and individual or SBA or nonbanks and individual or SBA. The other categories account for a small share of firms. About 4% borrow from individuals only, while 7% borrow from nonbanks and individuals or SBA.

Table 6
Who Lends to Small Firms?

This table reports the number and share of firms borrowing from different types of lenders.

Lender types	*N*	%
Bank only	186	29.2
Nonbank only	133	20.9
Individual only	25	3.9
SBA only	14	2.2
Bank + Nonbank	184	28.9
Bank + Individual or SBA	49	7.7
Nonbank + Individual or SBA	45	7.1
Individual + SBA	1	0.2
Total	637	100.0

Table 7 decomposes the fraction of firms that utilize each type of lender. First, banks are still the most common type of lenders for small businesses in our sample. Almost two-thirds of firms borrow from banks. Conditional on having a bank lender, almost three-quarters of the firm's debt comes from banks.

Second, it is very common for firms to borrow from nonbanks: about 57% of firms borrow from nonbanks. Decomposing nonbanks into MCA companies, equipment finance companies, and other nonbanks, the average share conditional on utilizing for each category is smaller than the aggregate average nonbank share, indicating that if firms borrow from nonbanks, they are more likely to borrow from multiple types of nonbank lenders. In addition, MCAs and equipment finance companies serve more specialized or niche roles given their lower average utilization rates and high variability in share percentages.

Last, despite lower probabilities of utilizing, individuals and SBA play important roles for certain borrowers, covering substantial parts of their funding needs when utilized. For example, the average share conditional on utilizing individual lenders is over 60%, and the median share is over 60% as well.

3.3 Lender Specialization

Bank and nonbank lenders are likely to specialize in providing different types of financing. Banks, for example, are exclusive providers of credit card debt. Receivables financing, on the other hand, is provided almost exclusively by nonbank lenders. We report the number and share of each type of debt by different lender types in Table 8. Rows correspond to different types of debt, while

Table 7
Shares of Different Lender Types

This table reports summary statistics on the shares of different types of lenders: banks, merchant cash advance (MCA), captive finance companies, other nonbanks, individuals, and SBA. Probabilities of borrowing from different types of lenders and shares are in percentage form.

		Conditional on utilizing				
	P(Share > 0)	Mean	SD	25th	50th	75th
Bank	65.8	73.9	32.9	49.2	92.4	100.0
Nonbank	56.8	68.1	34.3	34.1	81.4	100.0
Equipment finance	17.4	48.5	35.9	13.2	36.7	89.2
MCA	10.4	46.7	35.2	14.7	35.0	82.2
Other nonbank	43.3	58.7	36.4	22.0	64.0	100.0
Individual	12.9	60.8	35.5	23.8	61.1	100.0
SBA	10.2	47.4	34.7	20.7	36.4	81.4

columns correspond to different types of lenders. Each row of Panel A reports the shares of different lender types in providing the type of debt specified in the row. Each column of Panel B reports the shares of different types of debt in total lending by the type of lender specified in the column.

Table 8
Specialization in Lending

Each row of Panel A reports the shares of different lender types in providing the type of debt specified in the row. Each column of Panel B reports the shares of different types of debt in total lending by the type of lender specified in the column.

		Nonbank				
	Bank	Equipment finance	MCA	Other	Individual	SBA
Panel A: Row %						
Credit card	100	0	0	0	0	0
Equipment financing	53	32	0	15	0	0
Line of credit	81	7	0	12	0	0
Mortgage	49	0	0	36	11	4
Receivables financing	1	1	55	44	1	0
Term loan	36	10	0	36	0	17
Other	29	0	0	25	45	0
Panel B: Column %						
Credit card	32	0	0	0	0	0
Equipment financing	30	81	0	21	1	1
Line of credit	10	4	0	3	0	0
Mortgage	7	0	0	13	12	9
Receivables financing	0	0	99	18	1	0
Term loan	13	15	0	30	0	89
Other	7	0	1	15	85	1

Credit card lending is done exclusively by banks and represents about 32% of all lending by banks. Similarly, most lines of credit are provided by banks; nonbank lenders account for 20% of all lines of credit. Banks and nonbanks account for roughly equal shares of equipment financing. Receivables financing is mainly provided by MCA companies, but other nonbank lenders also account for 44% of all receivables financing. Term loans are split among bank, other nonbanks, and SBA.

Mortgage loans are split roughly equally between banks and other lenders, with 11% provided by individuals.

Panel B of Table 8 reports the composition of financing provided by different types of lenders. Not surprisingly, MCA and equipment finance companies specialize in receivables and equipment financing. Almost all of SBA lending (89%) is term loans, with the rest being primarily mortgages. In the aggregate, banks are fairly diversified across different types of debt, except that they do not provide receivables financing.

While Table 8 provides evidence of specialization by different types of lenders, Table 9 reports descriptive statistics on the specialization of specific lenders. We report in Table 9 the composition of lending for the top 20 bank and nonbank lenders by number of loans. We focus on the largest lenders because they account for the bulk of lending — 72% for banks and 38% for nonbanks — and because smaller lenders extend too few loans to examine the composition of their lending.

Table 9
Specialization of Top Bank and Nonbank Lenders

This table reports the identities and measures of specialization of the top 20 bank and nonbank lenders by number of loans. For each lender, we report its shares of the number (#) and value ($) of loans by that lender type. We also report the shares of different types of debt.

		Share		Debt type shares					
Lender	#	#	$	CC	EF	LOC	MTG	RF	TL
Banks									
American Express Company	152	14.4	5.7	88.8	0.0	0.0	0.0	0.0	10.5
Wells Fargo	97	9.2	4.9	49.5	23.7	4.1	5.2	0.0	5.2
Regions Financial	59	5.6	3.5	11.9	33.9	23.7	0.0	0.0	22.0
JPMorgan Chase & Co.	59	5.6	1.9	81.4	3.4	11.9	1.7	0.0	1.7
Bank of Montreal	58	5.5	4.3	0.0	98.3	0.0	0.0	0.0	0.0
Truist Financial	53	5.0	3.3	41.5	9.4	9.4	3.8	0.0	20.8
Ally Financial	44	4.2	1.7	0.0	100.0	0.0	0.0	0.0	0.0
PNC Financial Services Group	34	3.2	1.8	5.9	41.2	26.5	0.0	0.0	0.0
First Citizens BancShares	29	2.8	2.6	6.9	58.6	6.9	6.9	0.0	13.8
U.S. Bancorp	27	2.6	1.2	48.1	48.1	0.0	3.7	0.0	0.0
Capital One Financial	26	2.5	0.2	100.0	0.0	0.0	0.0	0.0	0.0
The Toronto-Dominion Bank	19	1.8	2.4	5.3	15.8	68.4	0.0	0.0	0.0
Synovus Financial Corp.	19	1.8	1.0	15.8	0.0	42.1	10.5	0.0	26.3
Huntington Bancshares	17	1.6	1.4	0.0	76.5	11.8	0.0	0.0	11.8
First Horizon	14	1.3	0.7	28.6	0.0	14.3	14.3	0.0	7.1
SouthState	13	1.2	1.8	0.0	0.0	15.4	46.2	0.0	23.1
Seacoast Banking	12	1.1	1.4	0.0	8.3	58.3	8.3	0.0	16.7

(Continued)

Table 9—*continued*

Lender	#	Share #	Share $	Debt type shares CC	EF	LOC	MTG	RF	TL
First Bancshares	10	0.9	0.3	0.0	10.0	0.0	20.0	0.0	70.0
Coöperatieve Rabobank U.A.	10	0.9	0.7	0.0	90.0	10.0	0.0	0.0	0.0
Heartland Financial USA	9	0.9	1.2	0.0	0.0	11.1	77.8	11.1	0.0
Nonbanks									
Enova International	47	6.0	1.8	0.0	0.0	19.1	0.0	17.0	63.8
Ford Motor Company	43	5.5	1.7	0.0	100.0	0.0	0.0	0.0	0.0
Deere & Company	36	4.6	6.2	0.0	100.0	0.0	0.0	0.0	0.0
PayPal Holdings	28	3.6	0.7	0.0	0.0	0.0	0.0	10.7	89.3
Complete Business Solutions	15	1.9	0.8	0.0	0.0	0.0	0.0	100.0	0.0
Caterpillar	12	1.5	1.5	0.0	100.0	0.0	0.0	0.0	0.0
Funding Circle Holdings plc	12	1.5	0.2	0.0	0.0	0.0	0.0	0.0	100.0
Chesswood Group	12	1.5	0.3	0.0	100.0	0.0	0.0	0.0	0.0
EBF Partners	11	1.4	0.5	0.0	0.0	0.0	0.0	100.0	0.0
Mitsubishi HC Capital	11	1.4	1.3	0.0	100.0	0.0	0.0	0.0	0.0
Forward Financing	9	1.1	0.2	0.0	0.0	0.0	0.0	100.0	0.0
Fundation Group	9	1.1	0.3	0.0	0.0	55.6	0.0	0.0	33.3
LG Funding Services	7	0.9	0.2	0.0	0.0	0.0	0.0	100.0	0.0
Marlin Capital Solutions	7	0.9	0.1	0.0	100.0	0.0	0.0	0.0	0.0
Funding Metrics	7	0.9	0.1	0.0	0.0	0.0	0.0	100.0	0.0
Expansion Capital Group	7	0.9	0.3	0.0	0.0	0.0	0.0	0.0	85.7
Commercial Credit	7	0.9	1.2	0.0	57.1	0.0	0.0	0.0	42.9
Tokyo Century	7	0.9	6.2	0.0	100.0	0.0	0.0	0.0	0.0
National Funding	7	0.9	0.1	0.0	0.0	0.0	0.0	0.0	100.0
Newtek Small Business Finance	6	0.8	1.5	0.0	16.7	0.0	16.7	0.0	66.7

There are a few noteworthy results in Table 9. Three of the top 20 banks — Capital One, American Express, and JPMorgan Chase — specialize in credit cards with at least 80% of their lending by number of loans being credit cards. Another three banks — Ally, Bank of Montreal, and Rabobank[16] — specialize in equipment financing. Huntington Bank, a regional bank headquartered in Columbus, Ohio, also has a high share, more than three-quarters, of equipment financing. But this probably does not accurately characterize its small business lending in areas where it has branches. Other regional banks such as First Citizens, PNC, US Bancorp, and Regions, also have high equipment finance shares between one-third to one-half. Smaller, more local banks on the other hand tend to have greater balance across different types of debt that is likely to be more

[16] Rabobank operates through De Lage Landen.

informationally-sensitive: term loans and lines of credit.

According to panel B of Table 9, nonbanks tend to exhibit greater specialization in debt type than banks. But this is partly because nonbank lenders in our data tend to be smaller. Nevertheless, a number of nonbank lenders clearly specialize in either equipment financing or receivables financing.

4 UCC Filings as a Measure of Small Business Lending

Given limited data on small business lending, a number of papers in the literature have used UCC filings to measure lending to small businesses and banking relationships (Gopal and Schnabl, 2022; Chernenko and Scharfstein, 2024; Balyuk, Prabhala, and Puri, 2021). Secured lenders file a UCC financing statement to perfect their claim and establish priority in the collateral that was pledged to them. Because the first lender to perfect its security interest is entitled to priority in collateral, lenders have a strong incentive to promptly file UCC financing statements.

UCC filings, however, have at least three important limitations as a measure of small business lending. First, UCC filings do not include unsecured lending or certain types of secured lending such as mortgages and car loans. Second, UCC filings do not provide any information on the size of the loan or any other terms. Third, there is only an imperfect association between UCC filings and lending activity. For example, if an existing lender extends a new loan backed by the same collateral, there generally will not be a new UCC filing. If a new lender lends against the same collateral as a previous lender, the new lender may become an assignee on an existing UCC financing statement rather than filing its own financing statement. The advantage of doing this is that if there is any dispute regarding who the collateral was pledged to, the new lender's priority will be determined by the date of the original UCC filing.

One unique advantage of using bankruptcy filings to study small business lending is that our data allow us to ask how well UCC filings characterize small business lending. To this end, Table 10 reports the share of all claims that have a UCC filing. In Panel A the unit of observation is a firm, and we report the share of all claims, in both equal- and value-weighted terms, with UCC filings. For the average firm, less than half of all borrowing has a UCC filing: the equal- and value-weighted averages are 44% and 50%. This result suggests that UCC filings must be interpreted with caution as a proxy for small business lending.

Panels B and C of Table 10 report loan-level statistics by debt and lender type. Panel B reports UCC coverage for different types of debt. Because credit cards are not secured, they almost never have an associated UCC filing.[17] Almost two-thirds of mortgages and a bit more than three-

[17] A handful of credit card claims in the data are classified as having UCC filings. These cases involve lenders extending multiple types of debt to the same firm and filing a UCC financing statement to perfect their security interest in a blank first priority lien on all of the debtor's property.

Table 10
UCC Filings as a Measure of Small Business Lending

This table reports the share of small business lending that is captured by UCC filings. In Panel A the unit of observation is a firm. In Panels B and C, the unit of observation is a loan.

Panel A: Firm-Level ($N = 637$)

	Mean	SD	Median	Min	Max
Share-weighted	0.50	0.44	0.58	0	1
Equal-weighted	0.45	0.41	0.46	0	1

Panel B: Loan-Level by Debt Type ($N = 1,985$)

	No UCC		UCC	
	N	%	N	%
Credit card	318	98.1	6	1.9
Equipment financing	333	56.4	257	43.6
Line of credit	50	40.0	75	60.0
Mortgage	98	63.6	56	36.4
Receivables financing	12	6.7	167	93.3
Term loan	93	26.2	262	73.8
Other	199	77.1	59	22.9

Panel C: Loan-Level by Lender Type ($N = 1,985$)

	No UCC		UCC	
	N	%	N	%
Bank	663	65.2	354	34.8
Equipment finance	126	54.3	106	45.7
MCA	2	2.0	97	98.0
Other nonbank	191	44.3	240	55.7
Individual	113	83.1	23	16.9
SBA	8	11.4	62	88.6

quarters of other debt do not have UCC filings. Receivables financing on the other hand almost always involves a UCC filing: less than 7% of receivables financing cases do not have a UCC filing indicated in the claim supporting documents.[18] A bit more than half of all equipment financing does not have a UCC filing. Most of these are car loans, for which security interest is perfected through title.

Panel C of Table 10 reports UCC coverage for different lender types. Much of the cross lender variation is driven by lenders specializing in different types of debt. For example, almost all receivables financing loans by MCA lenders have a UCC filing. UCC filings on the other hand capture only 35% of bank lending. This result is due to banks being the sole provider of credit cards, which are not secured and do not have UCC filings.

To get further insights into which loans are more likely to be captured in the UCC filings data, Table 11 estimates linear probability model regressions of whether a loan has an associated UCC financing statement on debt and lender type indicators, loan size, firm age and size, and 2-digit NAICS industry indicators. We report equal-weighted regressions in columns 1–2 and share-

[18] It is possible that these loans do have UCC filings but that these were not submitted to the bankruptcy court along with the claim.

weighted regressions in columns 3–4. The omitted categories are term loans for debt type, banks for lender type, $0–50K for asset size, and 11 for 2-digit NAICS.

Table 11
Which Loans Have UCC Financing Statements?

This table reports the results of linear probability model regressions of whether a given loan has a UCC financing statement. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Equal-weighted		Share-weighted	
	(1)	(2)	(3)	(4)
Ln(Loan amount)	0.051***	0.053***	0.049***	0.052***
	(0.006)	(0.007)	(0.011)	(0.012)
Firm size				
50-100K	0.010	0.003	0.099**	0.081*
	(0.034)	(0.035)	(0.047)	(0.046)
100-500K	−0.004	−0.002	0.031	0.013
	(0.022)	(0.023)	(0.036)	(0.037)
500K-1M	0.021	0.000	0.089	0.075
	(0.033)	(0.034)	(0.055)	(0.058)
1-10M	0.076**	0.061*	0.021	0.027
	(0.031)	(0.032)	(0.051)	(0.055)
Ln(Age)	0.003	−0.008	0.008	−0.000
	(0.010)	(0.011)	(0.016)	(0.018)
Debt type				
Credit card	−0.602***	−0.595***	−0.658***	−0.646***
	(0.033)	(0.035)	(0.052)	(0.052)
Equipment financing	−0.238***	−0.224***	−0.207***	−0.192***
	(0.035)	(0.038)	(0.053)	(0.056)
Line of credit	−0.127**	−0.124**	−0.150**	−0.155**
	(0.050)	(0.053)	(0.071)	(0.071)
Mortgage	−0.423***	−0.404***	−0.377***	−0.362***
	(0.048)	(0.051)	(0.062)	(0.066)
Receivables financing	0.195***	0.183***	0.304***	0.305***
	(0.050)	(0.055)	(0.059)	(0.065)
Other	−0.373***	−0.385***	−0.262***	−0.260***
	(0.044)	(0.046)	(0.074)	(0.076)
Lender type				
Equipment finance	−0.028	−0.029	−0.097	−0.030
	(0.037)	(0.037)	(0.062)	(0.061)
MCA	0.101*	0.109*	−0.064	−0.049

(Continued)

Table 11—*continued*

	Equal-weighted		Share-weighted	
	(1)	(2)	(3)	(4)
	(0.053)	(0.057)	(0.063)	(0.069)
Other nonbank	−0.042	−0.033	−0.170***	−0.157***
	(0.033)	(0.033)	(0.048)	(0.050)
Individual	−0.191***	−0.228***	−0.391***	−0.418***
	(0.046)	(0.046)	(0.075)	(0.075)
SBA	0.195***	0.192***	0.187***	0.202***
	(0.042)	(0.045)	(0.044)	(0.049)
N	1,985	1,871	1,985	1,871
Adjusted R^2	0.344	0.376	0.347	0.380

Controlling for debt and lender type, as well as firm characteristics, larger loans are significantly more likely to have a UCC financing statement. The effect is both statistically and economically significant. A doubling in loan size is associated with about 3.5 percentage points higher probability of having a UCC financing statement. We also find that controlling for loan size, loans to larger firms are more likely to have a UCC financing statement. The pattern however is somewhat different between equal- and share-weighted regressions. In the equal-weighted regressions, it is primarily loans to the largest firms that are significantly more likely to have UCC financing statements. In the share-weighted regressions, we have less statistical power, the pattern is non-monotonic, and the biggest difference appears to be between the smallest firms and everyone else.

Turning to lender types, the results suggest that equipment finance and individual lenders are less likely to file UCC financing statements, while SBA is more likely to have UCC financing statements. The result for equipment finance is likely driven by car loans not being covered in UCC. The result for individuals may be due to individuals being less sophisticated and failing to file UCC financing statements.

Overall, Table 10 and Table 11 suggest that UCC filings should be interpreted with caution as a proxy for small business lending. UCC filings capture only half of all debt raised by the average firm in our data. And because of variation in the types of debt raised by firms of different size and in different industries, UCC filings may paint an inaccurate picture of the relative importance of banks versus nonbank in lending to small firms.

How might our use of bankrupt firms affect the external validity of the results in Tables 10 and 11? While bankrupt firms may be different from other firms in terms of the composition of their debt, sample selection is less likely to affect the results on which types of debt are covered in the UCC filings data. As for the firm-level results in Panel A of Table 10, sample selection could affect the results in either direction. On the one hand, lenders may not want to extend unsecured credit to firms approaching bankruptcy. If healthier firms rely more on unsecured debt, then our results may overstate the share of small business lending that is captured by the UCC filings. On the other hand, firms may draw down their credit cards and lines of credit as they approach default. In this case, our results may understate the share of small business lending that is captured by the UCC filings. Either way, our results call for caution in using UCC filings as a measure of small business lending and in interpreting any cross-sectional results, which may be driven by variation across firms in how well UCC filings capture total lending.

5 Banking Market Structure

How do bank competition and the structure of the local banking market affect who small firms borrow from and the type of debt that they raise? Lack of bank competition may incentivize entry by nonbank lenders and may be associated with a higher share of debt being raised from nonbank lenders. As these lenders may not be local, they may primarily extend receivable or equipment financing loans that rely primarily on hard information. On the other hand, lack of competition may allow banks to invest in the production of soft information about local businesses and may be associated with more bank lending to small businesses (Petersen and Rajan, 1995). Furthermore, this lending may take the form of term loans and lines of credit that rely more on soft information.

Variation in the size of local banks may also be associated with differences in lender and debt types. Small banks may have a comparative advantage in generating soft information about potential borrowers and lending based on such soft information (Berger et al., 2005). This means that if a firm's local market is dominated by large banks, which rely primarily on hard information, the firm may be more likely to turn to nonbank lenders. If the firm does borrow from banks, it may borrow through the types of debt that rely on hard information and that large banks tend to specialize in: credit cards and equipment financing.

To examine the association between local banking market structure and small business borrowing, Table 12 estimates regressions of the shares of different types of debt and lenders on the characteristics of the local banking market in which the firm is located. We define local banking markets as counties and measure their characteristics as of 2018, the last year before our sample period. Given that county-level banking market structure is highly persistent, the choice of the specific year has little effect on our results. Because bank concentration and average bank size may be correlated with market size, we control for logs of county population and personal per capita income. Standard errors are adjusted for clustering by county.

Panel A of Table 12 reports the results of regressions of the share of different types of lenders on the characteristics of the local banking market. Firms in larger markets, as measured by county population, rely more on receivables financing from MCA. A one unit increase in log population is associated with 1.04–1.72 percentage points higher share of MCA lenders. This is about 21–34% of

Table 12
Banking Market Structure and Debt Composition

This table reports the results of regressions of the shares of different types of lenders and debt on local banking market structure variables. Firm-level controls are i) log of firm age, ii) indicators for the estimate asset size: less than \$50K, \$50–100K, \$100–500K, \$500K–1M, and \$1–10M, and iii) indicators for 2-digit NAICS sectors. The number of observations is 637 without controls (odd-numbered columns) and 588 with controls (even-numbered columns). Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: Lender Type

			Nonbank									
	Bank		All		Equip finance		MCA		Individual		SBA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Population)	0.09	−0.96	0.50	1.40	−2.36*	−1.13	1.04*	1.72***	0.42	1.04	−1.01	−1.48
	(1.90)	(1.96)	(1.83)	(1.94)	(1.31)	(1.20)	(0.53)	(0.49)	(1.16)	(1.28)	(1.25)	(1.42)
Ln(Per capita income)	−15.11**	−17.36**	1.04	0.08	0.67	−0.42	2.50	3.11	8.86**	11.61**	5.21	5.67
	(6.10)	(6.67)	(4.76)	(5.02)	(5.13)	(3.86)	(2.04)	(2.52)	(4.14)	(4.51)	(5.49)	(6.29)
Deposit HHI	−89.79***	−100.52***	78.70***	106.23***	20.53	21.81**	28.86***	35.16***	15.55	2.14	−4.45	−7.85
	(15.72)	(18.74)	(15.69)	(14.39)	(12.82)	(9.44)	(6.69)	(7.39)	(12.51)	(13.48)	(9.44)	(10.39)
Ln(Average bank size)	−4.65**	−5.14**	7.28***	9.32***	1.58	0.54	0.78	1.44	−2.15	−4.03*	−0.48	−0.16
	(2.09)	(2.42)	(2.27)	(2.58)	(1.86)	(1.61)	(1.02)	(0.98)	(1.83)	(2.09)	(1.21)	(1.31)
Adjusted R^2	0.011	0.036	0.008	0.031	0.007	0.007	0.004	0.060	0.003	0.039	0.001	−0.008
μ_y	48.61	48.10	38.72	38.58	8.44	8.58	4.84	5.06	7.83	8.08	4.84	5.24
Controls		✓		✓		✓		✓		✓		✓

Panel B: Debt Type

	Credit card		Equipment financing		Line of credit		Mortgage		Receivables financing		Term loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Population)	2.64**	0.81	−4.14**	−2.16	0.97	1.28	−0.90	−2.03	2.21***	2.69***	−2.33	−2.61
	(1.24)	(1.26)	(1.74)	(1.47)	(0.89)	(0.78)	(1.77)	(1.54)	(0.67)	(0.74)	(2.17)	(2.10)
Ln(Per capita income)	−0.22	1.78	−16.41**	−17.67**	0.29	−0.42	−5.70	−10.43**	3.71	5.91	9.70	8.53
	(5.05)	(4.42)	(7.13)	(7.20)	(2.88)	(3.28)	(5.61)	(4.74)	(2.93)	(3.69)	(8.85)	(8.64)
Deposit HHI	−36.14**	−22.96*	−7.39	−7.88	2.01	1.06	14.00	−2.53	24.70***	34.70***	−16.88	−12.25
	(16.04)	(12.85)	(13.55)	(13.43)	(8.86)	(9.31)	(25.28)	(21.22)	(6.93)	(8.75)	(24.12)	(17.64)
Ln(Average bank size)	−3.13*	−0.39	3.71*	1.95	−0.98	−1.35	−0.37	0.18	0.02	0.75	−1.41	−1.47
	(1.67)	(1.62)	(2.01)	(1.79)	(1.50)	(1.56)	(2.70)	(2.55)	(1.04)	(1.23)	(2.91)	(2.50)
Adjusted R^2	0.006	0.047	0.013	0.090	−0.005	0.008	−0.000	0.148	0.002	0.037	0.002	0.044
μ_y	14.27	14.05	19.13	18.58	7.01	7.24	12.55	12.48	8.64	8.78	23.37	23.40
Controls		✓		✓		✓		✓		✓		✓

the average share of MCA lenders. Higher per capita income is associated with significantly smaller bank share and significantly larger share of individual lenders. A one standard deviation increase in the log of per capita income of around 0.225 is associated with 3.2–3.7 percentage points smaller bank share and 2.0–2.6 percentage points higher share of individual lenders. While the decline in bank share represents less than 10% of the average bank share, the increase in individual lenders share is large at about 26–32% of the unconditional mean.

Higher deposit HHI, and thus weaker bank competition, is associated with significantly smaller bank share. A one standard deviation increase in deposit HHI of about 0.075 is associated with 6.5–7.3 percentage points smaller bank share. Nonbank share on the other hand is significantly higher. We also find that in counties with larger banks, the share of bank lenders is smaller while the share of nonbank lenders is higher. The effect is again sizable. A one standard deviation increase in the log of average bank size of around 0.600 is associated with 2.8–3.1 percentage points smaller share of bank debt.

Panel B of Table 12 estimates similar regressions but using the shares of different types of debt as the dependent variable. Mirroring the results in Panel A, county population is associated with greater reliance on receivables financing. Per capita income is associated with significantly smaller share of equipment financing. A one standard deviation increase in the log of per capita income of around 0.225 is associated with about 3.7–4.0 percentage points lower share of equipment financing. This may be because individual lenders, who provide more debt financing in these counties, are unlikely to provide equipment financing.

Deposit concentration is associated with a significantly smaller share of credit card debt and a higher share of receivables financing. It appears that credit cards and receivables financing may act as substitutes. We also find some suggestive evidence that deposit concentration is associated with a lower share of term loans, though the estimated coefficients are not statistically significant. Finally, there is no clear pattern of the effect of bank size on the shares of different types of debt.

The results in Table 12 on the negative correlation between average bank size and the share of debt raised from banks are consistent with the findings in the recent literature (Bord, Ivashina, and Taliaferro, 2021; Cortés et al., 2020; Chen, Hanson, and Stein, 2017; Gopal and Schnabl, 2022). These papers provide evidence of large banks pulling back from small business lending following the financial crisis and subsequent regulatory changes, including stress tests of large banks. Having said that, our results do not speak to changes over time in bank versus nonbank shares.

We next look more closely at how banking market structure may affect the interaction between lender and debt type. In Table 13 we use loan-level data to estimate linear probability model regressions of whether the loan is of a particular type, while restricting the sample to either bank lenders in Panel A or nonbank lenders in Panel B. These regressions ask whether conditional on borrowing from a given lender type, banking market structure is associated with differences in the type of debt raised.

Table 13

Banking Market Structure and Choice of Debt Type Conditional on Lender Type

This table reports the results of linear probability model regressions of whether a given loan is of a particular type: credit card, equipment financing, line of credit, mortgage, receivables financing, term loan, and other. We estimate these regressions separately for bank lenders in Panel A and nonbank lenders in Panel B. Dependent variables are expressed in percentage form. Firm-level controls are i) log of firm age, ii) indicators for the estimate asset size: less than \$50K, \$50–100K, \$100–500K, \$500K–1M, and \$1–10M, and iii) indicators for 2-digit NAICS sectors. Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	CC (1)	EF (2)	LOC (3)	MTG (4)	RF (5)	TL (6)	Other (7)
Panel A: Bank Lender ($N = 954$)							
Ln(Population)	0.05	0.27	2.64**	−1.09	−0.29	−2.69	1.11
	(2.05)	(2.51)	(1.20)	(1.06)	(0.28)	(1.60)	(1.25)
Ln(Per capita income)	12.90**	8.13	−6.64	−11.58***	−0.61	−2.53	0.33
	(5.93)	(7.28)	(5.76)	(4.16)	(0.64)	(4.49)	(2.96)
Deposit HHI	5.95	−0.22	4.85	−40.99***	−0.97	7.69	23.69***
	(19.31)	(27.67)	(17.55)	(13.73)	(1.05)	(17.53)	(8.27)
Ln(Average bank size)	0.96	−0.79	−0.84	−5.38***	0.16	3.34	2.55*
	(3.25)	(3.28)	(2.50)	(1.26)	(0.16)	(2.17)	(1.30)
Adjusted R^2	0.097	0.204	0.003	0.115	−0.012	0.046	0.010
μ_y	32.60	29.66	10.27	7.55	0.10	12.37	7.44
Controls	✓	✓	✓	✓	✓	✓	✓
Panel B: Nonbank Lender ($N = 720$)							
Ln(Population)		−1.72	0.40	0.81	−0.06	−1.03	1.59
		(2.97)	(0.58)	(1.59)	(2.31)	(2.49)	(2.36)
Ln(Per capita income)		−43.25***	3.11	−4.58	18.11*	23.52**	3.08
		(9.19)	(1.89)	(4.78)	(9.96)	(10.39)	(4.92)
Deposit HHI		−68.53**	0.31	64.05**	−8.40	4.48	8.10
		(29.58)	(5.01)	(24.69)	(24.38)	(19.76)	(15.81)
Ln(Average bank size)		−2.98	0.32	7.93***	−3.88	−3.85**	2.47
		(3.81)	(0.78)	(2.64)	(2.36)	(1.69)	(2.04)
Adjusted R^2		0.139	−0.006	0.134	0.020	0.037	0.033
μ_y		37.36	3.06	6.67	23.06	21.25	8.61
Controls		✓	✓	✓	✓	✓	✓

The main result that stands out is that conditional on borrowing from a bank, per capita income, deposit concentration, and average bank size in the county are all strongly negatively correlated with the loan being a mortgage. Panel B shows that conditional on borrowing from a nonbank, deposit concentration and average bank size are positively correlated with the loan being a mortgage. Thus it appears that in counties with less bank competition and with larger banks, small firms shift their mortgage borrowing from banks to nonbanks.[19]

We also find that conditional on borrowing from a nonbank lender, higher per capita income and deposit concentration are associated with lower probability of the loan being equipment finance.

[19] Using HMDA data, Buchak et al. (2018) find that the concentration of mortgage lending across lenders is negatively correlated with the market share of shadow banks and positively with the market share of fintech lenders. Our results are different in that we are using deposit concentration among banks and looking at mortgage borrowing by small businesses rather than households.

Per capita personal income is on the other hand positively correlated with the probability of a loan being receivables financing or term loan.

6 Racial Disparities

In the wake of incidents of police brutality against Black individuals, there has been renewed interest in understanding the causes of racial disparities in access to credit (Fairlie, Robb, and Robinson, 2022; Howell et al., 2024; Chernenko and Scharfstein, 2024; Chernenko et al., 2024, see for example). Many of the papers in this literature either rely on survey data, which generally paints a very coarse picture of the types of debt and lenders, or study disparities in access to a single program or type of loan. In this section, we contribute to this literature by asking whether there are disparities in the types of debt utilized by minority-owned firms. While our data are not well-suited to explore the causes of racial disparities, their unique advantage is the ability to characterize the composition of debt across white- versus minority-owned firms.

Panel A of Table 14 reports the results of regressions of the shares of different types of debt on minority indicators. Odd-numbered columns report unconditional disparities, while even-numbered columns report estimates of conditional disparities that control for firm age and size and industry fixed effects.

Columns 1–2 of Table 14 show that Black-owned firms have 7.1–7.4 percentage points lower share of credit card debt. This result is consistent with Fairlie, Robb, and Robinson (2022) who find that 30% of white- versus 15% of Black-owned businesses use business credit cards in their first year in business. Our results suggest that disparities in reliance on credit cards persist for many years after founding. It is also worth noting that the conditional disparity in the reliance on credit cards is actually larger in magnitude than the unconditional one: 7.4pp versus 7.1pp.

Columns 9–10 of Table 14 show that Black-owned firms also rely less on receivables financing. The effect is especially large relative to the average share of receivables financing being around 8.5%.

Black-owned firms on the other hand are significantly more likely to rely on mortgages. The coefficient is 8.381 in the unconditional regression in column 7 and 13.746 in the conditional regression in column 8. This is very large relative to the average share of mortgage debt of around 11%.

In contrast to Black-owned firms, we do not find evidence of statistically significant disparities for Asian- or Hispanic-owned firms, except for weak evidence that Asian-owned firms may have lower share of term loans. Lack of results for Asian and Hispanic-owned firms may be due to weak statistical power: our estimates for Asian-owned firms are especially noisy.

Table 14

Racial Disparities in Small Business Lending

Panel A uses firm-level data to estimate regressions of the shares of different types of debt on the racial and ethnic identity of the firm's owner(s). Panel B uses loan-level data to estimate linear probability model regressions of whether the lender is a bank on the racial and ethnic identity of the firm's owner(s) while controlling for debt type. The sample in Panel B is limited to loans from banks and NBFIs. Columns 1–2 of Panel B include all types of debt and control for debt type indicators; columns 3–8 limit the sample to different types of debt: equipment financing, mortgages, and term loans. Firm-level controls are i) log of firm age, ii) indicators for the estimate asset size: less than \$50K, \$50–100K, \$100–500K, \$500K–1M, and \$1–10M, and iii) indicators for 2-digit NAICS sectors. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: Racial Disparities in Debt Type

	Credit card		Equipment financing		Line of credit		Mortgage		Receivables financing		Term loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Asian	1.316	0.411	−4.018	0.618	5.109	4.151	7.377	5.887	−1.726	0.104	−9.478	−14.264**
	(6.374)	(6.352)	(6.425)	(6.404)	(5.889)	(5.985)	(6.565)	(6.422)	(4.438)	(4.472)	(6.157)	(6.495)
Black	−7.095**	−7.350*	−5.060	−5.556	2.986	3.355	8.381	13.746**	−5.423***	−5.639***	6.574	2.480
	(3.392)	(3.935)	(5.442)	(5.339)	(4.337)	(4.910)	(6.327)	(5.872)	(1.938)	(1.609)	(7.090)	(7.424)
Hispanic	5.103	1.883	−3.935	−3.611	−2.699	−1.963	0.617	5.310*	3.705	3.751	−1.705	−5.601
	(3.732)	(3.747)	(3.520)	(3.710)	(1.871)	(2.230)	(2.984)	(3.065)	(2.906)	(3.192)	(3.822)	(4.015)
N	579	539	579	539	579	539	579	539	579	539	579	539
Adjusted R^2	0.004	0.043	−0.001	0.087	0.002	0.012	0.012	0.145	0.004	0.015	−0.001	0.042
μ_y	14.527	14.623	19.480	18.591	7.675	7.858	11.276	11.644	8.512	8.503	23.573	23.601
Controls		✓		✓		✓		✓		✓		✓

Panel B: Racial Disparities in Lender Type

	All		Equipment		Mortgage		Term Loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asian	−12.725**	−12.892**	−32.405***	−33.776**	−22.857	−25.936	−28.346**	−38.753**
	(4.966)	(5.198)	(10.677)	(13.191)	(16.919)	(19.717)	(13.829)	(15.332)
Black	7.037*	9.076**	18.183	22.728**	−37.857	−44.099**	9.220	7.797
	(4.111)	(4.390)	(11.384)	(10.333)	(22.930)	(20.964)	(10.357)	(10.966)
Hispanic	2.015	2.634	4.738	3.470	−2.857	−23.196	7.368	12.417
	(2.701)	(2.850)	(5.097)	(5.666)	(12.672)	(14.067)	(8.274)	(9.180)
N	1,676	1,581	559	524	111	104	277	257
Adjusted R^2	0.301	0.325	0.011	0.102	−0.002	0.202	0.002	0.094
μ_y	57.757	57.685	53.309	51.718	58.559	60.577	43.682	43.191
Controls		✓		✓		✓		✓

In Panel B of Table 14 we look at racial disparities in lender type conditional on debt type. We use loan-level data to estimate linear probability model regressions of whether the lender is a bank. The sample of loans is limited to loans from banks and nonbank lenders, loans from individuals and SBA are excluded.

Columns 1 and 2 use all debt types and control for debt type indicators. Controlling for debt type, Asian-owned firms are 12.5–12.7 percentage points less likely to get their loans from a bank. The point estimates for Black- and Hispanic-owned firms are positive, suggesting if anything greater reliance on banks.

In columns 3–8, we limit the sample to equipment financing loans (columns 3–4), mortgages (columns 5–6), and term loans (7–8). We do not separately look at credit cards, lines of credit, receivables financing, or other loans because these categories are either dominated by a single lender type or are small. In columns 3–4, we find that compared to white-owned firms, Asian-owned firms are 32.4–33.8 percentage points less likely to get their equipment financing loans from banks. The estimated coefficients for Black are positive 18.2–22.7 but only statistically significant at 5% in column 4 once we control for firm characteristics.

In columns 5–6, the sample consists of mortgage loans. We find large negative coefficients on Asian and Black, but only the latter is statistically significant at 5% in column 5 regressions that do not control for firm characteristics. Finally, when we look at terms loans in columns 7–8, we find large negative and statistically significant coefficients for Asian.

Overall, the results in Panel B of Table 14 suggest that, controlling for debt type, Asian-owned firms are significantly less likely to use banks. There is some evidence that when they get mortgages, Black-owned firms are less likely to use banks and more likely to use NBFIs.

7 Conclusion

We take advantage of granular loan-level data from bankruptcy filings to paint a detailed picture of where small firms get their debt financing and how their debt structure may be affected by local banking market conditions. To alleviate concerns about sample selection, we focus on bankruptcies around COVID, a large exogenous shock that tipped many otherwise healthy firms into bankruptcy. Given that we have limited data on the debt structure of small firms, the results in this paper should serve as valuable stylized facts to inform and motivate future research.

Although banks are still the primary source of small business lending, nonbank lenders also play a critical role in providing credit to small business. Less than 30% of firms in our data rely solely on banks, whereas 21% use only nonbank lenders. About 30% use both banks and nonbanks.

Our data call for caution in using UCC financing statements as a proxy for small business lending as only half of the loans in our data are captured in UCC filings. Furthermore, the ability of UCC filings to proxy for small business lending varies in the cross section with firm size and across industries.

Additionally, we show that the structure of local banking markets is associated with larger differences in the types of lenders and debt utilized by small firms. In counties with high bank deposit concentration, small firms tend to use a lower proportion of bank loans and a higher proportion of mortgages, suggesting that they substitute bank loans with nonbank mortgages. It is crucial to understand such disparities in access to finance for small firms in different regions when designing policies to improve financial inclusion and equality.

Finally, we document the existence of racial disparities for minority-owned firms in utilizing different types of debt. Minority-owned firms may have difficulty in accessing unsecured credit and have to rely more on secured loans such as mortgages. Compared to white-owned firms, Black-owned firms rely less on credit card debt and receivables financing but rely more on mortgages. Asian-owned firms are significantly more likely to borrow from nonbanks than observably similar white-owned firms.

Overall, our results provide insights into recent trends in small business lending and highlight the need for policymakers to consider these findings when developing policies to support small business financing.

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Internet Appendix

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Where Do Small Firms Get Debt Financing?

Figure IA1 and Table IA1 show that firms filing for bankruptcy before COVID are similar on observable characteristics to firms filing for bankruptcy during COVID.

Tables IA2–IA12 replicate the analyses in the paper restricting the sample to those bankruptcy filed between March 11, 2020 and December 31, 2021.

Figure IA1

Industry Composition of the Pre-COVID versus COVID Subsamples

This figure compares the distribution of firms across 2-digit NAICS sectors in the pre-COVID versus COVID subsamples. The pre-COVID period is Jan 1, 2019 to March 10, 2021. The COVID period is March 11, 2020 to December 31, 2021.

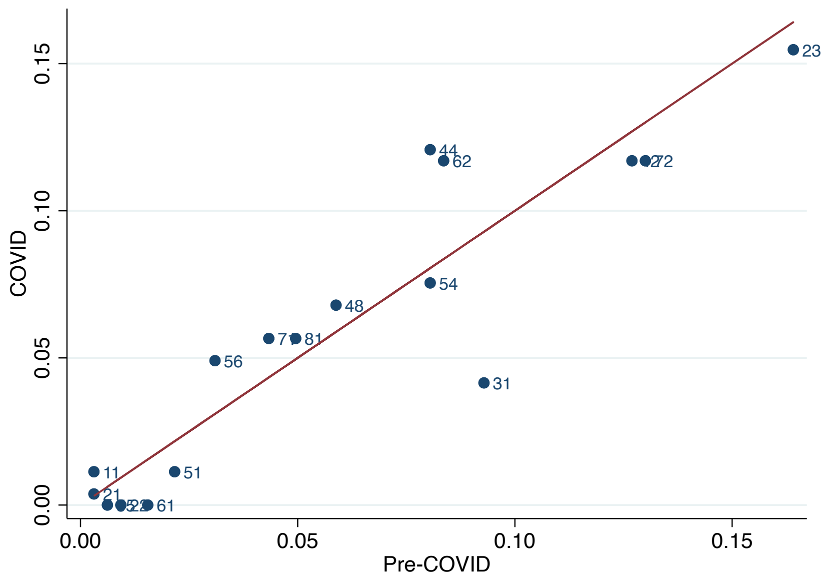

Table IA1

Comparisons between Pre-COVID, COVID, and All Sample

This table compares the distributions of firm's age and firm owner's race in the pre-COVID versus COVID subsamples. The pre-COVID period is Jan 1, 2019 to March 10, 2021. The COVID period is March 11, 2020 to December 31, 2021. Panel A reports the distribution of firm age. Panel B reports the distribution of firm owner's race.

Panel A: Firm Age (%)

	Pre-COVID	COVID	All
$<$ 2 years	7	5	6
2–3 years	16	18	17
4–5 years	15	13	14
6–10 years	22	24	23
11–15 years	20	15	17
$\geq$ 16 years	20	25	23

Panel B: Race (%)

	Pre-COVID	COVID	All
Asian and Pacific Islander	5	6	6
Black, not Hispanic	6	6	6
Hispanic	23	21	22
White, not Hispanic	64	64	64
Other	2	3	2

Table IA2
Sample Characteristics

Sample period is from March 11, 2020 to December 31, 2021.

Panel A: Bankruptcy district ($N = 346$)

	Middle	Northern	Southern
N	179	20	147
%	52	6	42

Panel B: Estimated assets ($N = 346$)

	0–50K	50–100K	100–500K	500K–1M	1–10M
N	132	33	91	32	58
%	38	10	26	9	17

Panel C: Firm's age ($N = 346$)

Mean	SD	Min	25th	50th	75th	Max
11.68	10.29	0.44	4.23	8.75	16.10	89.00

Panel D: 2-digit NAICS industry ($N = 323$)

Industry	N	%
Agriculture, forestry, fishing and hunting	1	0
Mining, quarrying, and oil and gas extraction	1	0
Utilities	3	1
Construction	53	16
Manufacturing	30	9
Wholesale trade	41	13
Retail trade	26	8
Transportation and warehousing	19	6
Information	7	2
Professional, scientific and technical services	26	8
Management of companies and enterprises	2	1
Administrative and support and waste management and remediation services	10	3
Educational services	5	2
Health care and social assistance	27	8
Arts, entertainment, and recreation	14	4
Accommodation and food services	42	13
Other services	16	5

Panel E: Firm owner's race ($N = 313$)

	Asian	Black	Hispanic	White	Other
N	20	20	65	199	9
%	6	6	21	64	3

Panel F: Total debt, $ thousands ($N = 346$)

Mean	SD	Min	25th	50th	75th	Max
1,369	5,239	0	78	291	904	85,070

Panel G: Number of creditors ($N = 346$)

	1	2	3	4	5	6	7+
N	149	87	47	29	15	12	7
%	43	25	14	8	4	3	2

Table IA3

Debt Composition by Firm Size

This table reports average shares of different types of debt: credit card, equipment financing, lines of credit, mortgages, receivables financing, term loans, and other. Sample period is from March 11, 2020 to December 31, 2021.

	Estimated asset size					
	0–50K	50–100K	100–500K	500K–1M	1–10M	Total
	(1)	(2)	(3)	(4)	(5)	(6)
N	132	33	91	32	58	346
Debt type						
Credit card	18.8	11.9	13.4	6.7	8.2	13.8
Equipment financing	21.6	35.0	16.0	24.4	14.2	20.4
Line of credit	4.8	10.9	4.7	3.8	6.7	5.6
Mortgage	3.2	2.0	13.0	19.3	35.4	12.6
Receivables financing	7.5	1.4	7.8	6.7	6.1	6.7
Term loan	30.6	28.8	28.6	11.6	12.8	25.2
Other	13.4	10.0	16.5	27.6	16.7	15.7
Debt HHI	7,970.8	7,942.7	7,197.8	7,509.5	7,575.5	7,655.9

Table IA4

Debt Composition

This table reports summary statistics on the conditional distributions of different types of debt. Panel A reports the probability of utilizing different types of debt as well as the mean, standard deviation, and percentiles of the conditional distribution. In each row on Panel B, we report the conditional means of different types of debt conditional on utilizing the type of debt indicated by the row. For example, conditional on having a mortgage, the average share of credit card debt is 0.8%. Probabilities of utilizing different types of debt and shares are percentages. Sample period is from March 11, 2020 to December 31, 2021.

Panel A: Conditional Distributions

		Conditional on utilizing				
	P(Share > 0)	Mean	SD	25th	50th	75th
Credit card	29.2	47.4	41.4	7.7	29.7	100.0
Equipment financing	33.8	60.4	36.3	22.7	62.5	100.0
Line of credit	13.6	41.1	31.5	13.0	38.3	67.6
Mortgage	15.6	80.5	25.7	66.2	95.4	100.0
Receivables financing	14.5	46.4	35.4	15.0	33.0	84.5
Term loan	40.5	62.2	34.9	27.0	68.1	100.0
Other	27.7	56.7	38.7	15.9	52.0	100.0

Panel B: Debt Type Shares Conditional on Utilizing a Given Type

	N	CC	EF	LC	MTG	RF	TL	Other
Credit card (CC)	101	47.4	12.6	6.7	4.3	3.6	17.6	7.8
Equipment financing (EF)	117	5.2	60.4	5.2	5.5	4.3	13.6	5.7
Mortgage (MTG)	54	0.8	5.9	0.8	80.5	0.7	6.3	4.9
Line of credit (LC)	47	5.9	17.3	41.1	3.5	6.3	19.5	6.4
Receivables financing (RF)	50	4.2	15.3	6.4	2.6	46.4	19.0	6.1
Term loan (TL)	140	4.6	10.2	4.4	7.2	3.8	62.2	7.5
Other	96	5.7	9.7	4.8	7.2	2.1	13.8	56.7

Table IA5

Who Lends to Small Firms?

This table reports the number and share of firms borrowing from different types of lenders. Sample period is from March 11, 2020 to December 31, 2021.

Lender types	N	%
Bank only	96	27.7
Nonbank only	68	19.7
Individual only	15	4.3
SBA only	12	3.5
Bank + Nonbank	88	25.4
Bank + Individual or SBA	31	9.0
Nonbank + Individual or SBA	35	10.1
Individual + SBA	1	0.3
Total	346	100.0

Table IA6

Shares of Different Lender Types

This table reports summary statistics on the conditional distributions of different types of lenders. Panel A reports the probability of utilizing different types of lenders as well as the mean, standard deviation, and percentiles of the conditional distribution. In each row on Panel B, we report the conditional means of different types of lenders conditional on utilizing the type of debt indicated by the row. For example, conditional on having an equipment finance lender, the average share of bank debt is 28.3%. Probabilities of utilizing different types of lenders and shares are percentages. Sample period is from March 11, 2020 to December 31, 2021.

Panel A: Conditional Distributions

		Conditional on utilizing				
	P(Share > 0)	Mean	SD	25th	50th	75th
Bank	62.1	73.7	32.4	49.2	91.8	100.0
Nonbank	55.2	68.4	34.2	34.8	83.6	100.0
Equipment finance	17.6	49.5	35.6	17.3	44.6	89.2
MCA	7.8	44.0	35.1	15.2	31.5	82.5
Other nonbank	42.2	60.7	36.6	22.7	71.9	100.0
Individual	13.6	61.7	34.7	25.0	57.9	100.0
SBA	17.1	47.4	34.5	20.7	37.5	81.4

Panel B: Lender Type Shares Conditional on Utilizing a Given Type

	N	BK	NB	EF	MCA	Other NB	Indiv	SBA
Bank (BK)	215	73.7	17.7	4.5	1.4	11.7	3.6	5.0
Nonbank (NB)	191	22.4	68.4	15.8	6.2	46.4	4.5	4.7
Equipment Finance (EF)	61	28.2	64.6	49.5	3.8	11.2	2.9	4.3
MCA	27	20.6	72.9	7.5	44.0	21.4	1.9	4.6
Other nonbank (Other NB)	146	20.4	69.7	6.6	2.5	60.7	4.8	5.0
Individual (Indiv)	47	14.2	23.1	4.6	0.5	17.9	61.7	1.1
SBA	59	24.5	26.0	6.7	2.5	16.8	2.2	47.4

Table IA7
Specialization in Lending

Each row of Panel A reports the shares of different lender types in providing the type of debt specified in the row. Each column of Panel B reports the shares of different types of debt in total lending by the type of lender specified in the column. Sample period is from March 11, 2020 to December 31, 2021.

		Nonbank				
	Bank	Equipment finance	MCA	Other	Individual	SBA
Panel A: Row %						
Credit card	100	0	0	0	0	0
Equipment financing	56	29	0	15	0	0
Line of credit	82	9	0	9	0	0
Mortgage	44	0	0	37	17	2
Receivables financing	0	0	49	51	0	0
Term loan	30	10	0	30	0	30
Other	29	0	1	29	40	1
Panel B: Column %						
Credit card	31	0	0	0	0	0
Equipment financing	34	79	0	21	1	0
Line of credit	9	4	0	2	0	0
Mortgage	8	0	0	15	21	3
Receivables financing	0	0	97	17	0	0
Term loan	11	17	0	26	0	95
Other	8	0	3	18	77	2

Table IA8

UCC Filings as a Measure of Small Business Lending

This table reports summary statistics on the share of small business lending that is captured by UCC filings. In Panel A the unit of observation is a firm. In Panels B and C, the unit of observation is a loan. Sample period is from March 11, 2020 to December 31, 2021.

Panel A: Firm-Level ($N = 346$)

	Mean	SD	Median	Min	Max
Share-weighted	0.50	0.44	0.57	0	1
Equal-weighted	0.45	0.41	0.50	0	1

Panel B: Loan-Level by Debt Type ($N = 1,021$)

	No UCC		UCC	
	N	%	N	%
Credit card	153	97.5	4	2.5
Equipment financing	175	56.8	133	43.2
Line of credit	25	45.5	30	54.5
Mortgage	57	63.3	33	36.7
Receivables financing	6	7.8	71	92.2
Term loan	49	25.1	146	74.9
Other	107	77.0	32	23.0

Panel C: Loan-Level by Lender Type ($N = 1,021$)

	No UCC		UCC	
	N	%	N	%
Bank	329	64.0	185	36.0
Equipment finance	72	64.3	40	35.7
MCA	1	2.6	38	97.4
Other nonbank	109	48.9	114	51.1
Individual	57	80.3	14	19.7
SBA	4	6.5	58	93.5

Table IA9

Which Loans Have UCC Financing Statements?

This table reports the results of linear probability model regressions of whether a given loan has a UCC financing statement on debt and lender type dummies, firm size and age, and SIC1 industry dummies. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Equal-weighted		Share-weighted	
	(1)	(2)	(3)	(4)
Ln(Loan amount)	0.057***	0.059***	0.047***	0.057***
	(0.009)	(0.010)	(0.015)	(0.017)
Firm size				
50-100K	0.014	0.007	0.088	0.108
	(0.052)	(0.054)	(0.066)	(0.067)
100-500K	−0.014	−0.001	0.030	0.046
	(0.031)	(0.032)	(0.050)	(0.053)
500K-1M	0.053	0.076	0.152**	0.193**
	(0.046)	(0.049)	(0.076)	(0.079)

(Continued)

Table IA9—*continued*

	Equal-weighted		Share-weighted	
	(1)	(2)	(3)	(4)
1-10M	0.034	0.040	0.003	0.027
	(0.043)	(0.046)	(0.068)	(0.074)
Ln(Age)	−0.021	−0.015	−0.019	−0.011
	(0.014)	(0.014)	(0.022)	(0.023)
Debt type				
Credit card	−0.585***	−0.579***	−0.710***	−0.681***
	(0.051)	(0.054)	(0.071)	(0.072)
Equipment financing	−0.196***	−0.185***	−0.182**	−0.193**
	(0.052)	(0.056)	(0.072)	(0.076)
Line of credit	−0.152**	−0.141*	−0.266***	−0.232**
	(0.077)	(0.081)	(0.100)	(0.098)
Mortgage	−0.389***	−0.382***	−0.355***	−0.346***
	(0.066)	(0.068)	(0.088)	(0.089)
Receivables financing	0.240***	0.257***	0.327***	0.364***
	(0.076)	(0.079)	(0.087)	(0.099)
Other	−0.394***	−0.394***	−0.299***	−0.310***
	(0.059)	(0.062)	(0.094)	(0.097)
Lender type				
Equipment finance	−0.166***	−0.188***	−0.245***	−0.158*
	(0.051)	(0.053)	(0.083)	(0.084)
MCA	0.058	0.035	−0.121	−0.115
	(0.083)	(0.087)	(0.090)	(0.103)
Other nonbank	−0.093**	−0.103**	−0.243***	−0.234***
	(0.046)	(0.046)	(0.065)	(0.065)
Individual	−0.144**	−0.242***	−0.356***	−0.409***
	(0.062)	(0.057)	(0.094)	(0.090)
SBA	0.225***	0.220***	0.146**	0.173***
	(0.054)	(0.057)	(0.059)	(0.065)
N	1,021	962	1,021	962
Adjusted R^2	0.338	0.378	0.362	0.407

Table IA10
Banking Market Structure and Debt Composition

This table reports the results of regressions of the shares of different types of lenders and debt on local banking market structure variables. Sample period is from March 11, 2020 to December 31, 2021. Firm-level controls are i) log of firm age, ii) indicators for the estimate asset size: less than \$50K, \$50–100K, \$100–500K, \$500K–1M, and \$1–10M, and iii) indicators for 2-digit NAICS sectors. The number of observations is 346 without controls (odd-numbered columns) and 323 with controls (even-numbered columns). Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: Lender Type

			Nonbank									
	Bank		All		Equip finance		MCA		Individual		SBA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Population)	3.19	1.92	−0.64	1.58	−1.30	0.67	1.50**	2.46***	−0.78	−0.18	−1.77	−3.32
	(2.91)	(2.92)	(2.45)	(2.65)	(1.46)	(1.51)	(0.56)	(0.76)	(1.84)	(1.77)	(2.16)	(2.60)
Ln(Per capita income)	−13.30	−7.17	−1.51	−11.12	3.79	−0.05	−1.12	−2.01	7.82	10.33	6.99	7.95
	(10.51)	(11.27)	(11.18)	(10.88)	(7.78)	(7.26)	(2.29)	(3.10)	(7.33)	(7.67)	(8.73)	(10.87)
Deposit HHI	−62.58**	−55.59	48.76**	79.33***	−17.12	−14.53	26.62**	36.63***	25.29	0.95	−11.48	−24.69
	(28.15)	(35.10)	(22.72)	(26.68)	(15.93)	(13.99)	(12.69)	(11.97)	(17.55)	(20.71)	(16.09)	(19.95)
Ln(Average bank size)	−2.44	−1.33	4.19	4.27	−2.04	−3.30*	−0.82	−0.52	−1.43	−3.45	−0.33	0.51
	(3.01)	(3.01)	(2.94)	(3.03)	(2.18)	(1.83)	(1.51)	(1.54)	(2.75)	(3.05)	(1.75)	(2.22)
Adjusted R^2	0.005	0.027	−0.006	0.033	−0.004	−0.013	0.008	0.016	0.004	0.095	−0.001	−0.009
μ_y	45.78	45.20	37.76	37.91	8.73	8.73	3.43	3.45	8.38	8.24	8.08	8.65
Controls		✓		✓		✓		✓		✓		✓

Panel B: Debt Type

	Credit card		Equipment financing		Line of credit		Mortgage		Receivables financing		Term loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Population)	3.73**	1.28	−3.13	1.00	0.57	0.88	0.03	−1.86	2.04*	3.25***	−3.55	−4.95
	(1.73)	(1.84)	(2.66)	(2.08)	(1.08)	(1.08)	(2.01)	(1.80)	(1.07)	(1.17)	(3.14)	(3.20)
Ln(Per capita income)	−0.52	3.70	−15.30*	−17.32**	−0.10	−1.72	−9.81	−14.15**	3.89	3.46	12.58	12.28
	(5.43)	(5.51)	(8.34)	(7.15)	(3.84)	(4.08)	(6.77)	(6.33)	(3.02)	(3.58)	(14.87)	(15.27)
Deposit HHI	−2.05	7.45	−45.76**	−13.70	−4.86	−2.93	22.13	−6.11	32.04**	42.71**	−28.20	−41.72*
	(21.70)	(20.21)	(20.10)	(17.52)	(11.54)	(16.11)	(36.53)	(29.01)	(14.90)	(17.07)	(35.45)	(24.74)
Ln(Average bank size)	−1.86	2.13	−0.26	−2.11	−0.02	−0.34	−0.95	0.35	−1.09	−1.40	−0.73	−0.98
	(1.92)	(2.21)	(3.01)	(2.39)	(1.34)	(1.94)	(3.43)	(3.31)	(1.71)	(1.62)	(3.88)	(3.42)
Adjusted R^2	−0.002	0.037	0.003	0.113	−0.010	−0.026	0.001	0.146	0.001	0.009	0.003	0.057
μ_y	13.83	13.50	20.44	19.16	5.59	5.75	12.56	12.98	6.70	6.96	25.16	25.96
Controls		✓		✓		✓		✓		✓		✓

Table IA11

Banking Market Structure and Choice of Debt Type Conditional on Lender Type

This table reports the results of linear probability model regressions of whether a given loan is of a particular type: credit card, equipment financing, line of credit, mortgage, receivables financing, term loan, and other. We estimate these regressions separately for bank lenders in Panel A and nonbank lenders in Panel B. Dependent variables are expressed in percentage form. Firm-level controls are i) log of firm age, ii) indicators for the estimate asset size: less than $50K, $50–100K, $100–500K, $500K–1M, and $1–10M, and iii) indicators for 2-digit NAICS sectors. Sample period is from March 11, 2020 to December 31, 2021. Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	CC	EF	LOC	MTG	RF	TL	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Bank Lender ($N = 479$)							
Ln(Population)	−1.12	2.82	−0.65	−0.59		−2.04	1.57
	(2.41)	(3.38)	(1.54)	(1.57)		(2.29)	(2.28)
Ln(Per capita income)	6.19	15.58	−5.99	−16.03*		−2.93	3.18
	(11.08)	(14.06)	(7.49)	(8.60)		(9.12)	(7.10)
Deposit HHI	48.63*	71.06*	−14.36	−84.68***		−28.16	7.51
	(25.52)	(39.43)	(15.97)	(24.10)		(29.01)	(12.16)
Ln(Average bank size)	3.90	−0.28	0.55	−5.60***		−0.44	1.87
	(3.19)	(3.72)	(1.75)	(1.89)		(2.85)	(2.29)
Adjusted R^2	0.117	0.176	−0.018	0.131		0.032	0.019
μ_y	31.32	31.73	9.19	8.35		11.48	7.93
Controls	✓	✓	✓	✓		✓	✓
Panel B: Nonbank Lender ($N = 359$)							
Ln(Population)		5.07	0.12	1.37	2.11	−9.19***	0.52
		(3.14)	(1.08)	(1.99)	(3.02)	(3.01)	(3.16)
Ln(Per capita income)		−19.54	1.84	−19.55*	8.48	29.91**	−1.15
		(12.13)	(5.44)	(9.66)	(11.31)	(14.69)	(8.51)
Deposit HHI		−93.77**	−14.09	71.38*	38.79	−22.22	19.91
		(39.05)	(12.03)	(37.77)	(47.38)	(29.13)	(25.09)
Ln(Average bank size)		−11.32***	0.38	10.49**	−5.07	2.33	3.19
		(3.87)	(1.08)	(3.86)	(3.08)	(2.15)	(2.91)
Adjusted R^2		0.168	−0.004	0.144	−0.004	0.090	0.079
μ_y		36.49	2.51	8.36	20.89	20.89	10.86
Controls		✓	✓	✓	✓	✓	✓

Table IA12
Racial Disparities in Small Business Lending

Panel A uses firm-level data to estimate regressions of the shares of different types of debt on the racial and ethnic identity of the firm's owner(s). Panel B uses loan-level data to estimate linear probability model regressions of whether the lender is a bank on the racial and ethnic identity of the firm's owner(s) while controlling for debt type. The sample in Panel B is limited to loans from banks and NBFIs. Columns 1–2 of Panel B include all types of debt and control for debt type indicators; columns 3–8 limit the sample to different types of debt: equipment financing, mortgages, and term loans. Firm-level controls are i) log of firm age, ii) indicators for the estimate asset size: less than \$50K, \$50–100K, \$100–500K, \$500K–1M, and \$1–10M, and iii) indicators for 2-digit NAICS sectors. Sample period is from March 11, 2020 to December 31, 2021. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: Racial Disparities in Debt Type												
	Credit card		Equipment financing		Line of credit		Mortgage		Receivables financing		Term loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Asian	0.920	−0.703	−2.362	2.051	−1.983	−3.693	12.927	13.870	−7.959***	−7.487***	−6.663	−13.850
	(7.801)	(8.287)	(8.441)	(7.599)	(5.124)	(5.719)	(9.078)	(9.401)	(1.547)	(2.420)	(8.376)	(8.769)
Black	−3.345	−6.132	3.376	1.056	2.439	2.831	5.159	13.391*	−7.959***	−7.118***	−8.354	−11.311
	(5.678)	(7.175)	(8.795)	(8.400)	(5.681)	(6.524)	(8.003)	(6.837)	(1.547)	(2.218)	(8.013)	(8.869)
Hispanic	7.493	2.744	−2.205	0.174	−4.052**	−5.319**	3.604	7.683*	0.232	0.372	0.433	−4.885
	(5.285)	(5.057)	(5.026)	(5.406)	(1.880)	(2.330)	(4.451)	(4.516)	(3.638)	(4.090)	(5.543)	(5.760)
N	313	293	313	293	313	293	313	293	313	293	313	293
Adjusted R^2	−0.001	0.036	−0.009	0.108	−0.004	−0.018	0.009	0.143	0.003	−0.016	−0.006	0.028
μ_y	14.532	14.757	20.624	19.019	6.127	6.292	11.783	12.066	7.032	7.265	24.239	25.145
Controls		✓		✓		✓		✓		✓		✓
Panel B: Racial Disparities in Lender Type												
	All		Equipment		Mortgage		Term Loan					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)				
Asian	−12.654	−16.897**	−25.729*	−18.840	−25.490	−53.673**	−24.510	−43.007**				
	(7.736)	(7.713)	(15.056)	(17.981)	(18.432)	(22.919)	(16.459)	(17.305)				
Black	6.947	7.615	15.699	16.241			8.824	19.291				
	(5.899)	(6.104)	(12.703)	(11.972)			(17.035)	(20.086)				
Hispanic	2.815	1.454	7.285	−4.691	−5.490	−54.824**	3.268	18.952				
	(3.827)	(4.099)	(6.749)	(8.119)	(15.914)	(21.347)	(13.139)	(13.843)				
N	836	790	295	271	63	60	124	119				
Adjusted R^2	0.287	0.327	0.005	0.132	−0.018	0.238	−0.018	0.194				
μ_y	58.732	58.101	57.627	54.982	53.968	56.667	41.129	40.336				
Controls		✓		✓		✓		✓				