Seizing Opportunities: Small Businesses, Social Capital, and Banks*

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Abstract

Why do small businesses exploit business opportunities better in some areas than others? In a sample of 1.2 million consumer-facing establishments, stores differ significantly across neighborhoods and census tracts in the uptake of risk-free positive NPV forgivable loans to which they are entitled. Local social capital strongly predicts loan uptake after controlling for close-by bank branches, income, and education. Increasing our social capital measures by one standard deviation increases the loan uptake by 6.4 percent of the sample mean, accounting for 20 percent of the variation at the zip code level. The effect is higher than the effect of having a bank branch within 1000 yards. Large, low-growth stores in less-dynamic areas benefit more from strong social capital, while small, high-growth stores in more-dynamic areas benefit more from bank branches. Virtual connections act similarly to in-person social connections and have the greatest effect on loan uptake in already advantaged locations. Virtual connections within the county predict higher use of local banks over FinTech lenders, while out-of-county virtual connections predict increased use of FinTech lenders. Overall, we find that small businesses exploit opportunities better in areas with strong civic capital. Hence, it is civic capital that should be targeted by social planners.

JEL Classification: D91, G32, G41.

Keywords: Social Capital, Virtual Connections, Small Business, Local Banks, PPP, Business Dynamism, Reciprocity

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1 Introduction

Why do small businesses exploit business opportunities better in some locations than others? Are outcomes in a locality, such as growth and profitability, determined by the availability of investment opportunities and financial intermediation infrastructure, or are they also modified by the deeper characteristics of localities and the people who live there?

It is now well established that access to loans in specific locations depends on the characteristics of banks and the technology they use for the evaluation of soft and hard information about potential borrowers (e.g., Petersen and Rajan (1994, 2002), Berger and Udell (1995)), and many others.) Less is known about the locational characteristics of borrowers and how they access financial institutions. Guiso, Sapienza, and Zingales (2004), Glaeser, Kerr, and Kerr (2015) and Barrios, Hochberg, and Macciocchi (2021), among others argue that local culture shapes entrepreneurship. Dougal, Parsons, and Titman (2015, 2021) argue that public firms' locations predict their ability to create value. The relation between the local environment and value creation is increasingly important, given the recent debate on spatial economic polarization and differences in business dynamism.

A major challenge in addressing these questions is the extent to which new investment opportunities are themselves endogenous and may vary across localities. In this paper, we take advantage of a natural experiment by measuring the uptake of a virtually risk-free non-competitive investment project distributed by the U.S. federal government to small businesses across all locations in the United States. The scheme, the Payment Protection Plan (PPP), was a forgivable interest-free loan offered to small businesses from financial intermediaries without material underwriting requirements.

Intuitively, the PPP program can be viewed as a real-life analog of the famous "helicopter money" concept in Friedman (1969).[1] It is a "drop" of positive NPV loans subject to minimal financing frictions. Thus, the uptake of these positive NPV projects can be used to identify the predictors of small business dynamism across locations.

Our focus is on the interaction between the social capital in a location and the functioning of financial intermediaries. Putnam (2001) defines social capital as "connections among individuals – social connections and the norms of reciprocity and trustworthiness that arise from them" and argues that social capital is predictive of a range of social outcomes. In particular, civic capital, the community's adherence to the norms of reciprocity and propensity to form in-person connections,

[1] "Let us suppose now that one day a helicopter flies over this community and drops an additional $1,000 in bills from the sky, which is, of course, hastily collected by members of the community. Let us suppose further that everyone is convinced that this is a unique event which will never be repeated....." Friedman and numerous subsequent macro-economists used this mental experiment to analyze aggregate demand and the liquidity trap.

has been found to predict both entrepreneurial activities (Guiso, Sapienza, and Zingales (2004)) and the effectiveness of local governments (Knack (2002)). We compare the role of social capital with that of local and FinTech financial intermediaries, acting as motivated brokers incentivized with facilitating access to financing, controlling for (a) the immediate local neighborhood of an establishment (agglomeration, presence of other small independent businesses, level of foot traffic, number of brand vs. non-brand stores); (b) community demographics (income, education, diversity); and (c) more broadly, the virtual social ties between the community and other locations predict whether a store takes up a PPP loan.

Our analysis is focused on consumer-facing sectors in the U.S.[2] Retail is of significant social and economic significance, and independently owned retail establishments are ubiquitous across the country. The skills required to run such establishments are widely dispersed. In addition, highly granular geographic and performance data on over 1.2 million establishments is available during our sample period.

We find a great deal of heterogeneity in the uptake of PPP at the county and zip code levels, as well as the very granular census block group and the 200-yard immediate neighborhood levels. Figure 1 below shows that conditional on industry fixed effects (based on 4-digit NAICS), the marginal increase in the R-square from adding county and zip code fixed effects is 2.28%. In contrast, conditional on industry and zip code fixed effects, the census tract fixed effects increase the R-square by 3.88%, and adding census block group (CBG) fixed effects provides an additional 5.72% increase in R-square.

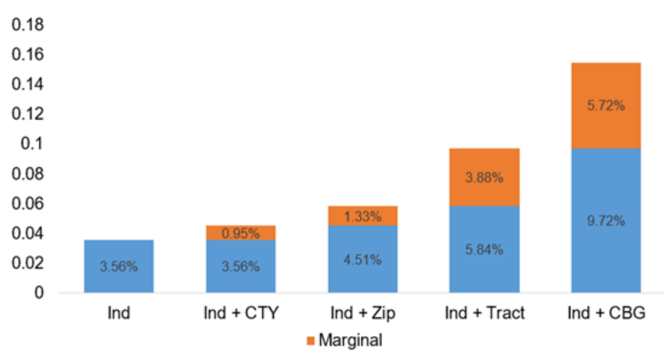

Figure 1: **Variance Decomposition.** The figure presents the R-square from regressing the indicator of receiving a PPP loan at the store level on various fixed effects. We first regress the PPP indicator on industry fixed effects and incrementally add county, zip code, census tract, and census block group fixed effects. The orange bars show the incremental increase in R-square when an additional set of fixed effects is added.

[2]For brevity, we refer to these sectors as "retail" and establishments in these sectors as "stores." We describe the industries in the Data Section.

We have four main findings. First, we find that social capital in a locality increases the uptake of PPP. We consider two main measures of social capital, including civic capital and social connections. As Figure 2 illustrates, both measures are positively related to PPP uptake at the zip-code level after controlling for county-industry fixed effects. but civic capital has a more substantial effect. The take-up rate on PPP is higher in communities with higher civic capital. Loan uptake is also higher when a large percentage of residents participate in associations (civic, business, sports, etc.) and are socially connected. Virtual connections on Facebook extend in-person social connections and predict PPP uptake. In particular, virtual connections within the county are associated with large increases in PPP uptake. Interestingly, virtual connections do not affect the relation between in-person social capital and PPP uptake.

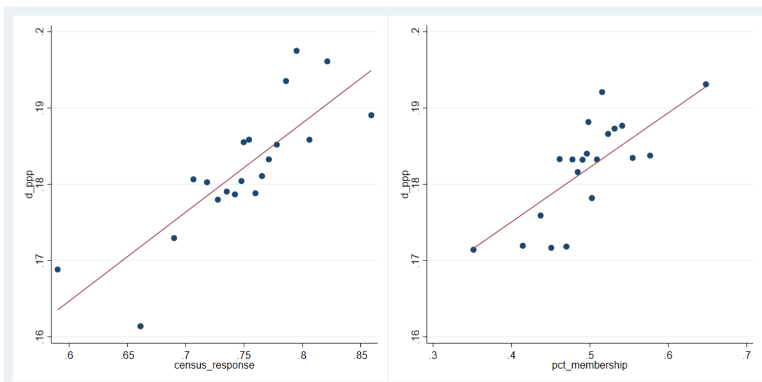

Figure 2: **Correlation between Social Capital Measures and the PPP Uptake.** This figure shows the bin-scatter plots of the PPP percentage and our social capital measures at the zip code level, controlling for county x industry fixed effects. We use the Census response rate to measure civic capital (left) and the percentage of club membership to measure social connections (right).

Second, variations in civic capital are as economically important as the presence of bank branches. Increasing the civic capital by one standard deviation increases loan uptake by 5 percent of the sample mean, controlling for store and neighborhood characteristics and bank access. The effect of civic capital is higher than having a bank branch within 1000 yards of the store. Collectively, the two components of social capital explain about 20 percent of the variation of PPP uptake at the zip-code level.

Third, nearby bank branches and high social capital operate through different channels. We find evidence of a substitution effect between social connections and the presence of a nearby local bank branch (within 1000 yards). Connections through local associations, clubs, and networks can partially substitute banks' information functions. Similar to in-person connections, online virtual connections also have a substitution effect for banks. On the other hand, civic capital and local banks have a complementary effect– local banks' effect on PPP uptake is higher in areas of moderate civic capital.

Last, local bank access and social capital benefit different communities. Proximity to bank branches of non-community banks is particularly beneficial to small businesses in high-density and high-growth locations with high business turnover. By contrast, community bank branches are associated with higher PPP uptake in less educated and less business-dense areas. Different components of social capital interact differently with local characteristics in predicting the uptake of PPP. Civic capital has a more significant association with PPP uptake in highly educated neighborhoods with many stable stores and low business turnover. It also has a bigger effect on areas with a higher percentage of minorities. By contrast, the prevalence of local associations has a greater association with PPP in less store-dense neighborhoods with a lower percentage of minorities. Virtual connections are associated with higher takeup of PPP in already relatively advantaged areas, with effects being highest for larger stores in more affluent, educated, and faster-growing locations.

We also track the uptake of PPP from FinTech lenders as well as banks. We find that all measures of social capital and virtual connections strongly predict uptake from a local bank branch over FinTech. The presence of local bank branches, in contrast, predicts higher PPP rates from both banks and FinTech lenders. These results suggest that virtual connections are unlikely to be a substitute for in-person social capital or physical bank branches in underserved areas.

We find similar positive effects using alternative measures of social capital used in the literature by Barrios, Benmelech, Hochberg, Sapienza, and Zingales (2020), Chetty, Hendren, Kline, and Saez (2014), and others.[3] In addition, we find a smaller independent effect of pride in the local community.[4] We also find that local distrust of banks, specifically, reduces stores' uptake of PPP. Collectively, these four social capital measures explain 25 percent of the variation of PPP uptake at the zip code level.

Our results on social capital can be contrasted to Knack (2002), who finds that civic capital predicts local government efficiency in the US, but that connectedness does not. In our setting, civic capital is also the most important social capital component, but the other components are also positively related to taking up loans. This difference can be rationalized by the fact that community investment in government quality is a pure public good, whereas PPP loans are a private good. Thus, while a culture of reciprocity may facilitate optimal PPP uptake, weaker ties, such as simple information sharing through connectedness and local pride, may also do so for some groups.

[3] See Guiso, Sapienza, and Zingales (2011) for a discussion of social capital metrics used in the literature.

[4] See Chuluun and Graham (2016) for evidence of the positive relation between local satisfaction and firm investment, and Bernstein, Mcquade, and Townsend (2021) who show that risk of personal financial distress reduces innovation at work.

In summary, we find that small businesses across localities in the US significantly differ in the uptake of net present value risk-free projects, even in the absence of project risk, financial constraints, information asymmetries, or credit risk. Predictors of economically thriving communities - education, income, dynamism, non-minority population - and social capital have significant explanatory power. This finding implies that the solutions for frictions observed in local financial markets may not stem only from subtle imperfections of the financial infrastructure, such as how information is processed within banks, but may reflect differences in economic fundamentals across locations. We also find that a portion of the social capital, such as social connections, can, to some extent, substitute for the information function of banks. However, strong civic capital also helps small businesses better exploit opportunities, an effect that cannot be easily substituted by financial intermediaries. Thus, policies and entrepreneurship research on geographic and economic polarization need to address granular differences in social capital on the demand side and the distribution and informational efficiency of financial intermediaries on the supply side.

2 Discussion and Literature Review

2.1 The Payment Protection Plan

The Payment Protection Plan was a program instituted by the U.S. Federal government to stabilize the economy following the onset of the 2020 Covid pandemic.[5] Specifically, the PPP was intended to facilitate the support of businesses and employees whose normal function was disrupted by the pandemic, the subsequent stay-at-home orders, and the associated production declines. Another goal was to keep workers attached to employers through the pandemic, thereby mitigating organizational capital destruction from mass layoffs.

The PPP enabled small businesses (500 or fewer employees) to take out forgivable loans administered through the federal Small Business Administration (SBA). These loans were guaranteed by the federal government to equal up to 2.5 months of average payroll in the prior year, 2019. To qualify for loan forgiveness, at least 75% of the loan had to be used on the payroll. Up to 25% could be used on mortgage interest, rent, and utilities. Originally, borrowers had eight weeks to use the money. Loans not meeting forgiveness criteria had to be repaid at a 1% interest rate. Over time, Congress created additional forgivable expenses, and the covered period was extended to up to 24 weeks. The original appropriation, in early April 2020, was for $350 billion and was increased

[5] The next two paragraphs rely heavily on Faulkender, Jackman, and Miran (2021), and Faulkender (2021), which contain further discussion of the institutional framework.

to \$650 billion later that month. The loans were administered through the banking system, with additional non-bank lenders such as FinTech firms. Borrowers were not quantity constrained: when the enrollment period into PPP ended, \$6 billion still remained available. It is noteworthy that in the end, almost all small loans were forgiven without routine audits.

To apply to the program, businesses had to complete a two-page application. Businesses also had to provide payroll information for 2019 in the form of either 2019 tax filings or payroll documentation. In addition, borrowers had to provide enough information so that the commercial lenders could comply with the Banks Secrecy Act and Anti-Money-Laundering requirements. Since the Federal Government guaranteed the loans, lenders did not have to make any decisions based on the perceived creditworthiness of the applicant, as would be the case with standard commercial loans.

The PPP provides positive net value projects for borrowers. Any business that planned to keep employees on the payroll (up to 2019 levels) could get these employees fully paid for by the Federal Government and use the additional 25% of this amount to pay for rent, utilities, etc. Thus, even if the Covid pandemic reduced demand for a firm's output leading to fewer required workers, the firm should still find it profitable to keep all of its workers and apply for a PPP loan to fund its payroll and other expenses.

Alternatively, it may be optimal for such businesses to lay off some, especially low-wage employees who can benefit more from the unemployment benefit and at the same time to retain high-wage employees, perhaps granting them temporarily higher "hazard" pay during the pandemic to maintain the value of the total payroll at 2019 levels.[6] In this case, in addition to the direct benefit to the business, there would also be an additional financial benefit to employees: higher pay to the employees who remained with the business and an attractive level of federal government unemployment support for those who were furloughed or let go.

In either case, applying for a PPP loan is a positive NPV strategy for qualifying businesses. The fact that PPP a loan is a non-rivalrous positive NPV opportunity where the dominant strategy for the business is to obtain a loan eliminates the need to model competitive interactions across firms in predicting PPP uptake.[7] However, whether a firm takes advantage of the loan depends on the firm and location characteristics which we investigate.[8]

[6] PPP requires borrowers to maintain a certain payroll level. To do so, the firm could also replace its existing workers with new workers. The Federal component of unemployment benefits during the pandemic paid \$600 per week. We discuss this further and provide supporting estimates below.

[7] Early in the program there were issues of access to loans as banks organized to process applications(Faulkender et al. (2021)). However, by the time the application period ended, these issues had been eliminated, and surplus funds remained unallocated.

[8] Analogously, Bernstein, Colonnelli, Iverson, and Hoffman (2022) show that the lack of knowledge of bankruptcy

Our identification strategy depends on two assumptions. First, the same project is presented to firms in all locations. We argue below that PPP's contractual features, together with granular spatial fixed effects, satisfy that requirement. Second, we make the plausible assumption that Covid and PPP shocks were not expected when establishments chose their locations. We use civic capital measures and other locational measures that predate both. It is possible that our estimates may be subject to omitted variable bias - for example, a bank office is located in an area where it is easier for its potential customers to access financial information. The effect of endogenous bank location, if any, is unclear and might depend on the specifics of the banks' location decisions.[9] To mitigate this potential bias, we employ granular fixed effects at the industry x location levels and obtain consistent results at different levels of aggregation - county, zip code, census tract, or census block group.

2.2 Social Capital

The concept of social capital is elaborated by Sander (2015) as "the collective value of all social networks (who people know), and the inclinations that arise from these networks to do things for each other (norms of reciprocity)." As a result, social capital creates "specific benefits that flow from the trust, reciprocity, information, and cooperation associated with social networks...[and] creates value for the people who are connected, and for bystanders as well."

Several studies have found a relation between social capital and economic and financial development, among the first being Guiso, Sapienza, and Zingales (2004) and Knack (2002), and more generally, that local culture predicts entrepreneurship (Barrios et al. (2021)). Our work builds on this earlier literature and argues that locations with high social capital have higher levels of small business dynamism, with small businesses taking advantage of business opportunities at a higher rate. Specifically, we measure high levels of business dynamism by the uptake rate of PPP across localities.

In our context, there are two main channels through which social capital might, in principle, affect business dynamism across locations. Generalized reciprocity, or civic capital, which Guiso, Sapienza, and Zingales (2011) define as the "set of values and beliefs that help a group overcome the free-rider problem in the pursuit of socially valuable activities", facilitates the directed flow of advice and information and efficient contracting that lead to fast exploitation of investment

laws, addressable by the provision of educational materials, lead some firms to fail to take advantage of the provisions of the bankruptcy code.

[9] See, for example, Oberfield, Rossi-Hansberg, Sarte, and Trachter (2020) for the complex trade-offs involved in the location of establishments.

opportunities. Following Knack (2002), we measure civic capital by the rate of completion of the 2010 Census form by the population in the location.[10] Filling out the Census form is a public good for the community because it informs long-term decision-making and may increase the flow of federal resources to community members. However, at this same time, it is also subject to the free-rider problem in that it does not offer a direct marginal benefit to individuals. This measure is particularly well suited for our purposes since completing a Census form and completing a PPP application are very similar activities, the former producing a public good, and the latter a clear private benefit.[11]

A second channel by which social capital facilitates business is information flows across the community through informal associations and connections, even when such associations do not develop civic capital. The commonly used social capital indicators based on Rupasingha, Goetz, and Freshwater (2006) contain several metrics of connectedness and have been used by Chetty et al. (2014) and Barrios et al. (2020), including participation in local associations. We also consider virtual social connections. Virtual connections, such as Facebook connections, extend interactions from in-person to online and are also likely to transmit information. In addition, we consider a more "formal" channel of financial information from local bank branches, which are incentivized to provide information and support to potential clients in their localities. The informational channel of social connections is likely to assume differential importance depending on the granular aggregation. We predict that all information channels, nearby banks, local social connections, and virtual connections will likely have substantive effects. How these information channels affect different types of stores is an open question that we address below. Similarly, information is more likely to flow between stores that are co-located in the same micro-environment.[12]

In addition, we consider two other variables related to the above measures of social capital. First, we assess the extent to which inhabitants of a locality express pride in the locality. Prior work suggests that satisfaction with one's locality is associated with better business outcomes (Chuluun and Graham (2016)). In our context, local pride is related to social capital in that we expect that it is easier to set up norms of reciprocity and create social bonds in locations where individuals exhibit local pride. However, our measure of civic capital, the completion of the Census form, requires a comparatively more sophisticated understanding of translating a positive emotion

[10]Using the 2020 Census gives very similar, albeit somewhat stronger, results.

[11]Barrios, Benmelech, Hochberg, Sapienza, and Zingales (2020) use another metric, voter turnout, targeted to picking up civic capital. We use this measure for robustness. The construction of each of our measures is discussed in the data section below.

[12]This "economy of agglomeration" has been studied in the literature, for example, by Arzaghi and Henderson (2008), Glaeser and Gottlieb (2009), and Rosenthal and Strange (2020).

into a public good. Thus, we expect local pride, while positive emotion, to have a smaller direct effect on PPP uptake.

Second, we also consider a targeted measure of civic capital, the extent to which inhabitants in a location that trust banks. This is of direct relevance since the PPP program and most external financing to small businesses are delivered through banks. The higher the trust in banks, the more likely it is that local inhabitants apply for the PPP, resulting in a value-enhancing transaction. Of particular interest is the interaction of this variable with indicators of bank branch proximity. As the distance from a bank branch increases, transaction costs increase, and we would expect that individuals with low trust in banks would less likely to explore PPP access.

While we expect higher social capital to predict higher PPP uptake, we expect that each of the components will have a different effect in dissimilar locations and for different size of stores. We discuss these interactions below.

2.3 Literature Review

The spatial heterogeneity of entrepreneurial firm formation and small business outcomes across locations has received a great deal of attention (for example, Moretti (2012), Chatterji et al. (2014), Autor (2020), Lychagin et al. (2016) Fazio et al. (2021), Glaeser et al. (2010). Observers have noted an increase in the polarization of economic opportunities over time (Economic Innovation Economic Innovation Group (2017)). However, finding an explanation for the observed variation has been challenging.

Guiso, Sapienza, and Zingales (2004), Glaeser, Kerr, and Kerr (2015) and Barrios, Hochberg, and Macciocchi (2021), among others, have connected entrepreneurial outcomes with local culture and social capital in specific contexts of creative instruments. This type of analysis is challenging in that, as Chatterji et al. (2014) note, "clustering due to natural advantages being empirically difficult to distinguish from clustering due to economic interactions among firms." In particular, it is difficult to separate the effect of location from the value of an investment opportunity at that location. By offering all small businesses across the U.S. the same forgivable PPP loan and using very localized fixed effects, we can substantially control for this heterogeneity using large samples of very granular contemporary data.

Multiple aspects of the PPP program have been examined by Faulkender et al. (2021), Granja et al. (2021), Chetty et al. (2020), Bartik et al. (2020a), Bartik et al. (2020b), and Maksimovic and Yang (2021) among others. Our paper differs from this work in that it takes PPP loans as an exogenous positive-NPV loan opportunity available to small enterprises across all locations in the

U.S. and studies how social capital, in conjunction with local market characteristics and nearby bank presence, affects the uptake of these projects. Howell et al. (2021a) and Chernenko and Scharfstein (2021) examine discrimination in access to PPP for minority-owned businesses.

Our work also builds on the extensive literature on the effects of local banks on businesses. Among papers that have addressed explored this issue are Black and Strahan (2002), Cetorelli and Strahan (2006), Gilje (2019), Guiso et al. (2004), and Kerr and Nanda (2009). Agarwal and Hauswald (2010), Nguyen (2019), Laderman (2008), and Amel and Brevoort (2005), among others, find that most small businesses borrow from nearby banks. This pattern suggests that being distant from retail banking locations can be costly. In measuring uptake across locations, we control for the proximity of bank branches. Our granular data enables us to control bank branch location very precisely (e.g., below, we use gradations such as "within 200 yards"), to classify banks across different categories, and to observe lending prior relationships using SBA-guaranteed loans.

The provision of banking services, particularly the proximity of bank branches and its effect on economic outcomes in underserved and minority communities, has received a great deal of attention (Friedline, Despard, and Birkenmaier, 2018). Celerier and Matray (2019) and Brown, Cookson and Heimer (2019) point to the benefits realized by policy initiatives that promote bank services in underserved communities. By contrast, Begley and Purnandam (2021) and Agarwal, Benmelech, Bergman, and Seru (2012) identify possible negative unintended consequences, such as misselling, of mandated increases in the provision of financial services to such localities. Since the location of bank branches was given before PPP, our study of the effect of the proximity of bank branches on the uptake of a particular product is not associated with the bank's decision to enter a market or potential gains from misselling.

In contrast to most existing studies on bank lending to small businesses, banks that process PPP loans do not assume credit risk. Thus, critical issues such as using hard and soft information in underwriting and information asymmetry are not directly relevant, and our analysis can abstract from customer and client financial liquidity and creditworthiness. As agents, banks play an informational role in this market. We can thus contrast the role of social capital in localities with the role of profit-motivated financial intermediaries in predicting the take up of PPP loans. We can also compare local financial intermediaries with FinTech loan providers.

Our paper focuses on investment by small retail businesses. There is a large literature that shows how the constraints facing small businesses firms differ from those facing larger firms (Beck, Demirgüç-Kunt, and Maksimovic (2005), Schoar (2009), Haltiwanger, Jarmin, and Miranda (2013), Alesina and Giuliano (2015)). More broadly, Decker, Haltiwanger, Jarmin, and Miranda (2016), Ayyagari and Maksimovic (2017) and Astebro, Braguinsky, and Ding (2020) discuss declines in business dynamism in the U.S.

3 Data

3.1 Foot Traffic from SafeGraph

We construct our sample of small retail businesses using data from SafeGraph. SafeGraph collects GPS location information from 45 million mobile devices, about 10% of total devices in the United States, whose users have opted into an app and given permission for their location to be tracked. All physical locations people can visit, except private residences, are recorded and defined as "points of interest" (POIs) by Safegraph. SafeGraph provides baseline information for 6 million commercial POIs within the U.S., including location name, street address, geographic coordinates, industry classification (6-digit NAICS code), and categorical coding, open hours, brand, and other business attributes. SafeGraph also updates granular information on raw counts of visits to POIs from the mobile location data panel weekly, answering how often people visit, how long they stay, where they live, and where else they go, among other things. Thus, we can observe the nearly real-time establishment-level foot traffic of businesses and the neighborhood in which they are located.

SafeGraph data covers a variety of sectors, such as retail trade, accommodation, food services, educational services, health care, manufacturing, and more. In this paper, our primary interest is in consumer-facing sectors, namely, retail (NAICS code 44-45), arts, entertainment, and recreation (NAICS code 71), accommodation and food services (NAICS code 72), and other services (NAICS code 82). For the primary analysis in the paper, we focus on establishments in 20 industries (4-digit NAICS) that usually operate as brick-and-mortar stores and rely on foot traffic. A list of industries and the sample distribution can be found in Panel A of Table 1.

To reduce measurement error, we drop stores that recorded no more than 10 total visits in January 2020. We exclude brand stores, given our focus on independent retail stores and drop stores whose last nonzero visit week is earlier than the PPP launch date for potential closures before the pandemic. Our final sample includes more than 1.2 million stores in over 14,000 zip codes (over 2,800 counties) across all 50 states, and Washington D.C. Table 1 Panel B presents the distribution of stores in our final sample by state. Figure 3 Panel A presents a heat map of our sample coverage at the county level.

Figure 3: [INSERT FIGURE HERE]

We use store-level weekly foot traffic data from 2018 to 2020 to capture key store and neighborhood characteristics, including size, growth trend, and the magnitude of shock experienced during the COVID pandemic. For our analysis, we use relative foot traffic, which is measured as the log difference of the same-store visits relative to the same week a year ago, to avoid any potential seasonal bias.

Table 1: [INSERT TABLE HERE]

3.2 Matching PPP Loans at the Store Level

We obtain loan-level PPP data from the Small Business Administration (SBA). The data provide borrower information, including business name, street address, and NAICS categorical coding; loan information, including approval date and loan amount; and lender information, including the names of the financial institutions that facilitated the loan application and distribution.

We then match the borrowers of PPP loans with stores in SafeGraph using an algorithm optimizing a similarity metric that compares business names, street addresses, geographic coordinates, and NAICS codes. We first clean the data by removing all punctuation and common suffixes in the business names, expanding all commonly used street suffixes or abbreviations in both data sets, and geocoding the street addresses of PPP borrowers to find the latitude and longitude. We join data sets to see all possible matches based on industry and a broad geographic category. This step is meant to generate a relatively large but noisy set of candidates, proving the next step with as much scope as possible to find the match. To disambiguate the noisy matches, we conduct the TF-IDF fuzzy string matching to calculate the similarity score for each pair of business names and street names. To find the best match, we combine the string similarity of names and addresses with other information, including NAICS code, street number, zip code, and geographic distance. Since the name of a business used to apply for PPP loans is not necessarily the same as the store name, we assign higher weights to the location information. We conduct multiple rounds of matching to find the best match and manually check the matching quality with a randomly-selected subsample. We provide more details on the match in the Appendix. About 20% of stores (non-brand) in our sample received PPP loans. The average percentage of PPP uptake at the zip-code level is 18.7%, with a standard deviation of 12.7%.

Figure 3 Panel B presents a heat map of the PPP uptake ratio at the county level. To quantify the matching rate, we compare the number of SafeGraph stores matched to the PPP data with the total number of PPP loans reported by the SBA at the zip code level. We take the ratio of their difference to the total number of stores from the SafeGraph as the non-match rate. In our final sample, the deviation (non-matched rate) is about 16%. Considering PPP loans reported by the SBA include the loans given to businesses without foot traffic, such as sole proprietors, independent contractors, and self-employed, making them unlikely to be tracked by SafeGraph, the non-match rate is reasonable. As a robustness check, we re-run our main regressions in a subsample of zip codes, in which the average non-matched rate is 8% (i.e., best-matched sample) and find very similar results. The results are reported in Appendix Table A6.

A concern using PPP data is the reports of fraud in applications involving non-existent or newly created businesses reported in Griffin, Kruger, and Mahajan (2022). However, by matching to Safegraph, we avoid this issue by requiring the firm to exist in 2019 and imposing minimum foot traffic criteria for inclusion in the sample.

3.3 Social Capital Measures

We measure the civic capital by the completion rate of Census forms by individuals following Knack (2002). Completing a Census form is an act of cooperation that is costly to an individual but is beneficial to the locality. As a result, an individual has a private incentive to free-ride by not completing a form. We collect the tract-level census response rate directly from the Census Bureau's website.[13]. To measure the response rate at the zip code level, we use the tract-to-zip mapping by residential ratio to allocate the census-responding population in each tract to corresponding zips. Then we aggregate the census-responding population at the zip level and divide the number by the total population in the zip code.

An alternative measure for civic capital is the voter turnover rate. Voter turnout at the zip code level is not directly available. Therefore, we construct the zip-level measure using presidential precinct data for the 2020 general election from Upshot.[14] Specifically, we obtain the coordinates describing the precinct boundaries using the nationwide precinct map and the coordinates describing the zip boundaries using the nationwide zip code map. We then aggregate the number of election returns from the precinct level to the zip level and estimate the zip-level voter turnout rate by taking the ratio of total votes to the voting-age population (VAP) reported by the US Census.[15]

[13] `https://www.census.gov/data/datasets/2010/dec/2010-participation-rates.html`, `https://www.census.gov/data/developers/data-sets/decennial-response-rates/2020.html`

[14] `http://www.nytimes.com/upshot`

[15] The precinct boundaries are in general very accurate but can be rough in no- or very-low-population places like business parks or uninhabited rural land, and therefore we also winsorize the zip-level total votes to reduce the influence of outliers.

We measure social connections among individuals within the community using (1) the percentage of residents that participate in local civic, business, or sports associations, (2) the percentage of residents with any religious affiliation, and (3) the percentage of residents that participate in Parent-Teacher Associations (PTA). Putnam (1995) and Chetty et al. (2014) use the fraction of religious individuals as a proxy for social capital, and the PTA participation rate is used as a proxy for social capital in Putnam (2001). We collect these measures from SimmonsLOCAL Consumer Survey in 2018 at the zip code level using samples of about 30,000 participants.[16] We expect to see a higher PPP rate in areas with greater social connections.

In addition, we consider two other variables related to the social capital mentioned above. First, we assess the extent to which local residents express pride in their community (City_Pride) using responses from the Gallup Daily Tracking Survey. Chuluun and Graham (2016) find that the average local happiness is positively related to R&D intensity and firm investment and attribute their finding to a higher level of satisfaction and happiness. Second, we consider a targeted measure of civic capital, the extent to which residents in a location trust banks (Trust_of_banks) using survey responses from Simmons LOCAL Consumer Insights. Since banks are the primary facilitator of PPP loans, we expect areas with stronger trust towards banks to experience higher PPP uptake.

Figure 4 presents the geographic distribution of our social capital measures, including the census response rate (Census Response Rate) and the percentage of residents who participate in local associations (Pct. of Membership). There is a significant amount of heterogeneity across counties. The pairwise correlation among these measures is 38 percent.

Figure 4: [INSERT FIGURE HERE]

Virtual connections extend social interactions from in-person to online and are likely to transmit information. We obtain Facebook Social Connectedness Index from the Humanitarian Data Exchange. [17] With 1.96 million daily active users in North America, Facebook is the biggest social networking platform.The index is constructed using a snapshot of Facebook users and their friendship networks to measure the intensity of connectedness between locations. Locations are assigned to users based on their information and activity on Facebook, including the stated city on their Facebook profile and device and connection information. We focus on Social Connectedness Index

[16] We calculate the percentage of association participation using the response to three questions: "Do you belong to any civic clubs?", "Do you belong to any business clubs?" and "Do you belong to any sports associations?" For religious affiliation, we use the response to the survey question, "Do you belong to any church, temple, synagogue, or mosque?" For the PTA membership, we use the response to the survey question, "Do you belong to the PTA?"

[17] `https://data.humdata.org/dataset/social-connectedness-index`

at the zip-pair level.

3.4 Bank Access

We match the PPP lenders to bank identifiers in the Call Reports from the FDIC website by name and address. We classify large banks as those with total assets of more than $1 billion by the end of 2019 and use the community bank identifier from the Call reports. Following Erel and Liebersohn (2020), we define FinTech lenders as non-depository financial institutions and depository financial institutions with only one branch.

To identify nearby banks, we use the Summary of Deposits (SOD) from the FDIC, which lists branch office locations, their reported deposits as of June 30 each year, holding company or institution, and geographic location. We use the geo-coded address provided in the SOD to calculate the distance between bank branches and stores in our sample and locate bank branches within a radius of 200, 500, or 1000 yards from the focal store (D_Bank200, D_Bank500, D_Bank1000.) Faulkender et al. (2021) show that community banks played an important role in PPP lending. So, we also identify local community bank branches within a radius of 200, 500, or 1000 yards from the focal store (D_CBank200, D_CBank500, D_CBank1000). In our sample, about 66% of stores have access to bank branches within 1000 yards, and 23% of stores have at least one bank branch within 200 yards. Not surprisingly, the percentage is the highest in urban areas and the lowest in rural and small towns. We also aggregate the banking measures at the Census Block Group, Census tract zip code, and county levels.

To capture the local lending environment for small businesses, we obtain data on small business lending from the 7(a) Loan Program, SBA's most common loan program, in the past three years (from 2017 to 2019). Using the geocoded address of loan recipients, we calculate the percentage of local businesses (within 200 or 500 yards of our focal store) that received SBA loans (Pct of SBA Loans (200 yards) and Pct of SBA(500 yards))[18]. On average, about 6.4 percent of 200-yd peers have received at least one SBA loan in the last three years.

3.5 Other Data Sources

Our primary specification includes county-industry fixed effects, so we obtain local characteristics at the zip code level from the Census Bureau. We use Zip Business Patterns (ZBP) to measure annual statistics for businesses, including the number of establishments, total employment, and total

[18]To calculate the percentage, we first match local recipient reported by SBA with stores in our sample using similar algorithms as that used to match PPP loan borrowers. The percentage is calculated as the ratio between the number of stores that received SBA loans and the total number of stores in the SafeGraph)

annual payroll, and use the American Community Survey (ACS) for information on population, median household income, the number of households, age composition, education levels, minority rate, and unemployment rate. We also use the Business Dynamics Statistics (BDS) to get annual measures of business dynamism, including job creation and destruction, establishment births and deaths, and firm startups and shutdowns. We define business turnover as the sum of the percentage of entries and the percentage of exits. The BDS data is only available at the county level. For some of the analysis, we control for more granular demographic information at the census-tract level using data from the American Community Survey (ACS). We standardize all variables to have the mean as zero and the standard deviation as one.

Table 2 presents the summary statistics of variables used in the paper.

Table 2: [INSERT TABLE HERE]

4 Main Results

4.1 County-Level Results

First, we present some initial evidence at the county level. Figure 5 shows the scatter plot between the rate of PPP uptake and county characteristics. Counties with higher education, lower poverty rate, low employment rate, higher income, more banks, and higher business entry and exit rates take more PPP loans. The general pattern is consistent with the hypothesis that businesses in localities with better access to information and more business turnover also participate more in the positive-NPV PPP project offered during the pandemic.

Figure 5: [INSERT FIGURE HERE]

Figure 1 shows that country x industry fixed effects explain about 4.5% of the variations in store-level PPP uptake. For the rest of the paper, we will include county x industry fixed effects unless otherwise specified. Thus, we control for variations at the county level and focus on the effect of demographics, access to financial intermediaries, and social capital at a more granular level.

4.2 Neighborhood Effects

We define a neighborhood as a micro business environment (within a radius between 200 and 1000 yards) that surrounds the focal store. For each neighborhood, we measure the size - number of stores (Ln(# of Stores)), the density - the average number of visitors in 2019 (Ln(Avg Visits)), and the composition - the percentage of brand stores (Pct of Brand Stores). We also calculate changes in foot traffic for neighboring stores at the beginning of the pandemic (Chg_Visits_Peers) to control for the impact of Covid on the immediate surroundings.[19]

We include several variables to control for characteristics at the zip-code level, including population density (Pop Density), the number of households (Ln(# of Households)), the number of business establishments (Ln (# of Estabs)), the median income (Ln(Median Income)), the percentage of minorities (Pct of Minorities), and the percentage of residents with at least a college degree (Pct of Edu_BA). We also use four indicator variables to represent the market segment of the zip code (D_Urban, D_Sub, D_2ndCity, and D_Rural).

We also control for store characteristics. Large stores may have better access to information and resources and thus are more likely to receive PPP. We measure store size using its average foot traffic in 2019. Stores that were hit harder at the onset of the pandemic and stores on a positive growth trajectory before the pandemic may be in greater need of capital. So we include year-to-year changes in foot traffic at the beginning of the pandemic (in March) (Chg_Visits_Self) and changes in foot traffic last year from 2018 to 2019 (Chg_Visits_LastYr). Table 3 presents our findings.

Table 3, column 2 shows that stores located in less-densely populated zip codes with fewer minorities receive more PPP loans. Stores in higher-income and higher-education zip codes received more PPP loans. Stores in residential zip codes are more likely, while stores in business zip codes are less likely to receive PPP loans. Towns and rural areas have more PPP uptake than urban or suburban zip codes. Turning to characteristics of the immediate neighborhood, we find that stores located in busier neighborhoods with more stores and higher per-store foot traffic receive more PPP loans. The finding here on high PPP likelihood in high-traffic areas is consistent with the information channel whereby storekeepers learn from their neighbors.[20] PPP uptake is also higher if the immediate neighborhood has more brand stores. One possibility is that managers of nearby brand stores may receive information about financing opportunities from their headquarters and that filters through to nearby non-brand stores. In addition, Maksimovic and Yang (2021) show that neighborhoods with more brand stores are premium locations with different stores and consumers.

Store characteristics also matter for PPP uptake. As expected, large stores and stores on growing trajectories before Covid are more likely to get PPP. Not surprisingly, there is a significant correlation between Covid impact and PPP loans. Stores that were harder hit at the beginning of

[19]We measure changes in total foot traffic in March from 2019 to 2020.

[20]Maksimovic and Yang (2021) show that there is a strong peer effect in PPP uptake through the information channel.

the pandemic are more likely to receive PPP loans. Interestingly, we do not find the initial Covid impact of peer stores having a significant effect on the PPP uptake of the focal store.

Table 3: [INSERT TABLE HERE]

4.3 The Role of Banking

Unlike standard small-business loans, banks that process PPP loans do not assume credit risk. Therefore, in our context, local bank branches serve as the medium of information about PPP loans without the need to evaluate the creditworthiness of the borrower. There is considerable evidence that most small businesses borrow locally. Agarwal and Hauswald (2010) estimate that the firm's median distance to the lending branch is under three miles. Laderman (2008) finds that approximately 90 percent of small business lending is from banks with branches in the local market using filings from the Community Reinvestment Act. We expect that access to local banks is associated with higher PPP uptake. Table 4 provides our findings.

Table 4: [INSERT TABLE HERE]

We find a strong bank effect in PPP uptake. Having access to a local bank branch significantly increases the likelihood that a store will receive PPP loans, and the effect is stronger the closer the branch is to the store. For example, stores with at least one bank branch within 200 yards experience a 9.3 percent higher probability of receiving PPP loans relative to the sample mean, controlling for local and store characteristics. In comparison, the effect is about half (5.2 percent) if the bank branch is between 200 and 500 yards and one-third (2.7 percent) if the branch is between 500 and 1000 yards.

Community bank branches provide an additional boost in PPP uptake. The marginal effect of having a community bank branch in the nearby micro-environment is more than half of the general bank branch effect.

We also find that exposure to prior small business lending increases the likelihood of PPP uptake. A store is more likely to receive PPP when neighboring stores have borrowed more SBA loans in the past. One standard deviation increase in the previous SBA loan exposure increases the PPP likelihood by 4.5 percent relative to the sample mean, controlling for bank locations. Interestingly, exposure to finance professionals, even in a non-business setting, is positively related to PPP uptake. A store is more likely to receive PPP if it is in a census tract with a higher percentage of finance professionals. Thus, our findings suggest that physical access to local bank branches and previous experiences in getting business loans both help stores receive PPP loans during the pandemic. Our estimates are robust when we include zip code x industry instead of county x industry fixed effects.

How does the bank effect vary by store or local characteristics? In Table 5, we interact bank indicators (D_Bank_1000 and D_CBank1000) with store, neighborhood, zip, and county characteristics.[21] We find that small stores that grew fast before Covid benefit more from nearby bank branches. The evidence is consistent with the idea that small, high-growth firms are more likely to be financially constrained due to limited access to financing and high demand for capital. Recall that large stores are more likely to receive PPP loans on average. Thus, our finding here suggests that access to local bank branches helps mitigate the gap of receiving PPP loans between small and large stores. We also find that local bank branches are more important for stores in high-traffic neighborhoods.

Faulkender et al. (2021) show that community banks play a pivotal role in facilitating PPP loans, especially early in the program. We also find that community banks are more beneficial in low-traffic areas and areas with low education levels. This finding is consistent with the consensus that community banks help serve remote areas. On the other hand, at first glance, our estimation appears that community banks benefit large stores more, although banks, in general, are more beneficial to small stores. However, further exploration shows that the effect is only present in cases where the community bank is the only bank in the zip code. For community banks that co-exist with other banks, consistent with the general bank indicator, the interaction of store size and the community bank indicator is marginally negative.

In Panel B, we show that zip codes with lower education levels and more minorities, both of which are shown to have less exposure to PPP loans, benefit more from local bank branches. In addition, bank access is more beneficial to stores in zip codes with higher business turnover. Finally, conditional on bank access with any bank, access to community banks provides additional benefits to low-education zip codes. Taken together, our findings suggest that local bank branches help promote PPP loans for stores and communities with higher demand or less access to financing.

Table 5: [INSERT TABLE HERE]

[21] Results are qualitatively similar when we further separate banks by 200, 500, or 1000 yards.

4.4 The Effects of Social Capital

4.4.1 Main Effects

As discussed in Section 2, we focus on two channels through which social capital could affect small business dynamism, such as the uptake of PPP - the generalized reciprocity or civic capital as defined by Guiso et al. (2011), and the information facilitation through connections and social network as defined by Putnam (2001). Civic capital facilitates the directed flow of advice and information to benefit individual shopkeepers and, ultimately, benefit the community through spillovers, while social connections facilitate business information flow through information association and connections. In addition, residents who are more satisfied with their localities may provide business opportunities, and those who have more trust in banks may be more likely to apply for PPP loans. We use measures from all four social capital components - the census response rate for civic capital, the percentage of membership for social connections, the percentage of residents with city pride for local satisfaction, and the percentage of residents who trust banks for trust.

In Table 6, we estimate the effect of social capital on PPP uptake in a regression setting, controlling for store and neighborhood characteristics, bank access, and county x industry fixed effects. We standardize all measures to have a mean of zero and a standard deviation of one, so the coefficient can be interpreted as the economic effect given one standard deviation increase of the corresponding social capital measure.

We find that both civic capital and social connections are positively correlated with the PPP, individually or collectively. The census response rate, a measure of civic capital, has the biggest economic magnitude. One standard deviation increase in the census response rate increases the PPP uptake by 5 percent of the sample mean. The effect is bigger than the effect of having a bank branch within 1000 yards of the store. On the other hand, one standard deviation increase in social connections increases the PPP uptake by 1.3 percent. Both variables remain significant at a one percent level when they are included in Column 3. Collectively, one standard deviation in the social capital increases the PPP uptake by 1.2 percentage points (6.4 percent of the sample mean and 20% of the standard deviation of PPP percentage across zip codes), controlling for county x industry fixed effects.

Table 6: [INSERT TABLE HERE]

In Appendix Table 1, we re-estimate our specification using social capital variables used in

Rupasingha et al. (2006)[22] and other studies, including voter turnover rate, the percentage of religious affiliation, and the log of donation per capital for civic capital, and the percentage of PTA membership for social connection measures, and find qualitatively similar results. Both civic capital and social connections are positively related to the PPP uptake. In addition, we find that zip codes with more city pride and greater trust in banks also take more PPP.

4.4.2 Social Capital and Bank Access

So far, we have shown that bank access and social capital help promote PPP uptake, a positive NPV project. But do these two factors interact with each other? Are they complements or substitutes? In this section, we examine the potential interplay between social capital and bank access. Specifically, we are interested in investigating whether local access to banks has heterogeneous effects in areas endowed with different levels of social capital.

We use the indicator of bank branch within 1000 yards (D_Bank_1000) to measure local bank access and sort zip codes into three equal-sized groups - low, medium, and high using the social capital measure. We then construct dummy variables for each group and include their interaction terms with the local bank indicator. The low social capital group is treated as the benchmark in regressions. We use all four social capital measures individually for this test. Table 7 presents our results.

Table 7: [INSERT TABLE HERE]

Column 1 examines the effect of the civic capital, proxied by the census response rate. Both bank access and high social capital remain to be positively associated with the PPP rate. We find a positive interaction between the census response rate and the local bank access indicator, suggesting that civic capital and formal financial institutions are complements. Interestingly, the interaction is only significant at the 1 percent level for zip codes with medium social capital but is not statistically different from zero for the high civic capital group. One possibility is that since the PPP uptake is significantly higher in high civic capital areas, proximity to banks makes little difference at the margin. On the other hand, the benefit of locating near a bank branch is significantly higher for medium- than low-civic capital areas. The non-monotonicity of the interaction term suggests that formal financial intermediaries likely perform better in the context of PPP when civic capital is in a certain band.

[22] https://aese.psu.edu/nercrd/community/social-capital-resources

In contrast, we find a substitution effect between social connections and bank access. Column 2 shows that the benefit of having a local bank branch decreases with social connections (proxied by the percentage of residents that belong to any associations). The marginal effect of a local bank branch is about four times higher in zip codes with low social connections than in zip codes with high social connections. Our finding suggests that a stronger social network can help mitigate the information disadvantage in neighborhoods without formal financial intermediaries.

4.4.3 The Effects across Neighborhoods

Next, we examine the differential effect of civic capital across the store, neighborhood, and zip characteristics in Table 8. We use measures from all four civic capital components - the census response rate for civic capital, the percentage of membership for social connections, the percentage of residents with city pride for local satisfaction, and the percentage of residents who trust banks for trust. Similar to the previous section, we use dummy variables to indicate the level of social capital, Low, Medium, and High. The Low level of social capital is treated as the benchmark in regressions. Table 8 presents our results.

Table 8: [INSERT TABLE HERE]

Social capital, collectively, benefits large, low-growth stores in areas with lower business turnover. This is in clear contrast with bank access, which was shown to be more beneficial to small, high-growth stores in more dynamic business areas. On the other hand, similar to bank access, social capital is more beneficial to stores located in low-education and more ethnically-diverse neighborhoods.

We find that it is medium civic capital that has the greatest interplay with demographic characteristics. Increasing the store density in the neighborhood, increasing the education level, and increasing the ethnicity diversity, are associated with greater increases of PPP in medium civic capital zips than in low or high civic capital zips. On the other hand, the social connectedness through local associations benefits stores in communities with fewer neighbors, fewer minorities (thus more homophily), and less business turnover. We find that stores in high-traffic areas benefit more from civic capital, while strong social connections have a greater effect on neighborhoods with fewer stores. The latter suggests that strong social connections compensate for having fewer peers in the neighborhood by promoting information flow within the community through informal association and connections.

Appendix Table 2 presents the results when we perform analyses on civic capital at the census tract level. Census tracts are small statistical subdivisions that have a population size between 1,200 and 8,000 people, with a targeted size of 4,000 people[23]. The more granular level allows us to focus on localities that are homogeneous in culture and business environment. However, of the four social capital measures, only the civic capital measure, census response rate, is available at the tract level. We obtain demographic information at the census tract level from the ACS.

It confirms our previous finding that social capital is positively related to the rate of PPP. The estimated coefficients are similar in magnitude between zip-level and tract-level analysis. We find qualitatively similar results as that presented in Table 8, using tract- or zip-code level variables on civic capital.

4.5 Virtual Connections

In the section 4.4, our results indicate a positive association between PPP uptake and social connections. The social environment in which a person lives expands far beyond local neighborhoods. Thus, social capital expressing the existence of social relations and values emerges in virtual connections. In this section, we turn to study the role of virtual social ties in explaining PPP uptake, and explore the interaction of virtual connections with attributes of the local community where a store is located. We also investigate to what extent the explanatory power of social capital shown in Section 4.4 might change when we explicitly control for the channel of virtual social connections.

The measures of virtual connections we use are based on the Facebook friendship network. Facebook has become an online social platform for more than a billion users, which makes it a good proxy for people's virtual networks. Prior research by Bailey, Cao, Kuchler, Stroebel, and Wong (2018) introduced a Facebook-based measure of social connectedness, the Social Connectedness Index (SCI), and made the data publicly available. We utilize the version of SCI representing the relative frequency of Facebook friendship links between every zip-pair in the United States. We calculate the social connection measure for each zip code using SCI standardized by population. Specifically,

$$Connections_i = \frac{\sum_j (Facebook\ Connections_{i,j})}{Population_i} \tag{4.1}$$

We also measure the virtual links with zip codes within the same county (inside-county connections) and the link with zip codes in other counties (outside-county connections), adjusting for population. We further divide the inside-county connections into inside-zip connections and

[23] https://www.census.gov/programs-surveys/geography/about/glossary.html

connections with other zips in the same county.

$$Inside\ Connections_i = \frac{Facebook\ Connections_{i,i}}{Population_i} \tag{4.2}$$

$$Outside\ Connections_i = \frac{\sum_{j \neq i}(Facebook\ Connections_{i,j})}{Population_i} \tag{4.3}$$

We first study whether virtual connections bring in additional advantage in terms of taking PPP loans on top of the impact of neighborhood, zip code characteristics, and access to local bank branches. We regress the indicator of PPP uptake on the log of connection measures. To make a point that virtual connections can capture an extra component of social capital besides what is represented by the "traditional" proxies discussed in the previous section, we include both virtual connections and four social capital measures described above, the Census response rate, the percentage of membership, the percentage of residents that feel proud of their city, and the percentage of residents who trust banks for their financial decisions. Table 9 presents our findings.

Table 9: [INSERT TABLE HERE]

The findings in Table 9 in general show an insignificant effect of virtual connections on the likelihood to get PPP. However, when decomposing virtual connections into inside and outside links, we find that inside connection are positively related to PPP uptake, while outside connections have no effect. Decomposing the inside connections into two parts, we find that both inside-zip connections and connections with other zips in the same county have a positive association. In particular, inside-zip connections have a larger impact, with a magnitude close to the effect of the census response rate. One standard deviation increase in the inside-zip connections increases the PPP uptake by 4.9 percent of the sample mean. One standard deviation increase in the connections with other zips in the same county increases the PPP uptake by 2.7 percent of the sample mean. The effects of other social capital components are consistent across specifications, suggesting that virtual connections do not impact the effect of local social capital on PPP uptake. Instead, virtual ties can be viewed as an expansion of in-person connections.

Next, we go back to the granular community where stores are located. Specifically, we test whether the effect of virtual connections varies by store, neighborhood, and zip code characteristics. Similar to our analysis of in-person social capital, we sort zip codes into three equal-sized groups - low, medium, and high using the inside and outside connection measures. We then construct dummy variables for each group and include their interaction terms with store size, growth rate, number of stores in the neighborhood, median household income, education level, and percentage of minorities in the zip code area. The low social capital group is treated as the benchmark in regressions. We include county x industry fixed effect and the full set of variables that have been discussed in the previous sections. Columns 1 to 7 in Table 10 present our results.

Table 10: [INSERT TABLE HERE]

We find that inside virtual connections are associated with higher uptake of PPP in already relatively advantaged areas. Specifically, inside connections provide more benefits to larger stores in the zip codes with higher education and greater prior growth. To examine the potential interplay between virtual connections and local access to a bank, we interact dummy variables for each virtual connection group with the local bank indicator (D_Bank_1000), the results of which are reported in Column 8. Unlike social connections, we do not find a substitution effect between virtual connections and bank access.

5 Discussion

5.1 PPP by Lender Type - Banks vs. FinTech

In section 4, we show that access to financial institutions, social capital, and virtual connections all have a positive effect on firms' uptake of a positive NPV project, in our context, the PPP loans. The PPP loans are administered through the banking system as well as non-bank lenders such as FinTech firms. Erel and Liebersohn (2020) show that FinTech lenders are disproportionately used in the zip codes with low income, high minority share and fewer bank branches. A natural question that arises is whether the effect of social capital or virtual connections varies by lender type. Are areas with higher social capital or more virtual connections associated with more PPP uptake issued by FinTech lenders? In this section, we explore whether very granular locality affects stores' uptake of PPP from certain types of lenders. Specifically, we focus on access to the local bank branches in the immediate neighborhoods. Then we examine whether various forms of social capital and virtual connections further make a difference in explaining the remaining heterogeneity in PPP uptake by lender type.

Following Erel and Liebersohn (2020), we define FinTech lenders as non-depository financial institutions and depository financial institutions with only one branch. In our sample, among the firms that received PPP loans, 10.5 percent received their PPP loans from non-bank lenders. First, we estimate two linear probability models separately to predict the PPP uptake separately by lender type. For each model, we define a dependent variable that equals one if the store has received a PPP loan from a bank or FinTech lender, respectively, and zero if no PPP loan is received. Table 11 columns 1 and 2 present our findings. Civic capital, social connections, and inside virtual connections are all positively related to PPP loans issued by banks, while only civic capital is associated with PPP loans from FinTech lenders. Interestingly, local bank access, experience with SBA loans, and exposure to financial professionals are all associated with higher PPP uptake, suggesting the effect of financial access/exposure goes beyond the physical access to banks.

Conditional on receiving a PPP loan, how do social capital and bank access influence the choice of lender type? In Column 3, we only include stores that received PPP loans to examine the lender type - the dependent variable equals one if the loan is from a FinTech lender and zero if it is from a bank. We find that zip codes with more outside-county virtual connections have a higher rate of using FinTech lenders, while zip codes with more inside virtual connections and more community banks are more likely to use bank lenders. Our finding on the community banks and FinTech lenders is consistent with Erel and Liebersohn (2020), which shows that FinTech is disproportionately used in zip codes with fewer bank branches. In addition, we find that zip codes with lower income and a higher percentage of minorities also rely more on FinTech lenders, consistent with findings in Howell et al. (2021b).

Table 11: [INSERT TABLE HERE]

5.2 Instrumenting the Civic Capital Measure

In our main specifications, we use the completion of 2010 Census forms to measure of civic capital. The 2010 Census occurred ten years before the PPP program; it is unlikely to be subject to the simultaneity problem such that omitted variables drive both the census response rate and the PPP uptake. However, social capital may have evolved over time. In this section, we examine the relation between PPP uptake and an alternative measure of civic capital, the latest census response rate in 2020, using an instrumented variable approach.

The PPP program was implemented concurrently with the 2020 Census. Thus, the response rate from the 2020 Census might be better for capturing the up-to-date status of the community. However, there might exist omitted variables that affect both behaviors, completing the Census form and taking the PPP, at the same time. To overcome the challenge, we instrument the 2020 Census response rate by the 2010 Census rate to isolate plausibly exogenous variation in local social capital. Appendix Table 3 reports the IV estimates. The first stage regressions (Columns 1), demonstrate a large and statistically significant effect of the 2010 Census rate on 2020 Census rate, with first-stage F statistics equal to 1163, which is far above relevant thresholds. The relevance of the instrument indicates the long-term nature of social capital embedded in the local community. The instrumented 2020 Census response rate (Column 2) shows a positive and larger effect on PPP uptake than in the OLS estimates.

Taken together, these estimates validate the positive effect on PPP uptake of local civic capital and suggest the baseline results we have shown for the 2010 Census response rate are not overstated.

5.3 Using Historical Bank Access

In section 4.3, we showed that bank access and social capital help promote the PPP uptake, controlling for store, neighborhood, and zip characteristics. However, the location of bank branches is not randomly assigned. Banks may locate their branches in areas with more business dynamism, for example, a neighborhood where stores respond more to investment opportunities and thus tend to have higher PPP uptake. To address this potential source of bias caused by the concurrent activities of banks and stores, we switch to using historical bank access.

We measure the store-level access to local bank branches using historical bank status five and ten years ago, following the same method of calculating bank indicators (D_Bank1000 and D_CBank1000) used in the section 4.3. Specifically, for each store in our SafeGraph sample, we evaluate whether there were any bank and community bank branches within a radius of 1000 yards in 2009 and 2014, and calculate the total number of bank branches at the zip code using historical bank data.

Appendix Table 4 presents our results. It reports regression results on predicting the PPP uptake at the store level based on local bank access using historical bank status (D_Bank, D_CBank, and Ln(# of banks in the zip)) in 2009 (columns 1), and 2014 (columns 2), controlling for store, neighborhood, and zip characteristics and county by industry fixed effects. We find historical bank access strongly predicts the PPP uptake. The magnitudes of the coefficient on the historical bank variables (D_Bank1000) are comparable with the results in section 4.3. For example, the magnitude of bank effects using current bank access is 4.4% and it is 3.4% using the 2014 bank and 3.5% using the 2009 bank. Although the effect of community bank access drops from 3.1% to 2.1% and 1.4% using bank access in 2014 and 2009 respectively, the estimated coefficient remains positive and significant at 1% level, confirming the additional boosting effects of community banks on PPP uptake. Given the result, it is unlikely that the bank effect we document is entirely driven by the unobservable simultaneity bias.

6 Robustness Checks

6.1 Unemployment Insurance and PPP Loans

A primary goal of PPP was to relieve the burden on outdated state UI systems and utilize the banking system to keep paychecks flowing. Faulkender et al. (2021) show that PPP loans help slow down the increase in unemployment insurance (UI) claims during the early days of the pandemic. One potential concern with our tests is that some results might be driven by the omitted variable, UI claims. It may be optimal for some businesses to both take out PPP loans and partially lay off part of the workforce. The laid-off workers would receive unemployment insurance (UI). Thus, the two programs may interact. To explore this interaction and to see whether it affects our estimates, we repeat our main analysis, explicitly controlling for the UI claims. Specifically, we focus on the initial UI claims, that is claims filed by newly-unemployed individuals after a separation from an employer from the week right after the first state issued a stay-at-home order to the end of May when most PPP loans have been approved.[24]

We repeat the regression of PPP uptake on a full set of variables and county X industry fixed effects for stores in California, including UI claims as the additional control variable. Appendix Table 5 reports our findings. We find consistent results on civic capital, social connections, virtual connections, and bank access as those reported in our full-sample tests. On the other hand, we do not see a significant association between UI claims and PPP uptake, with or without social capital variables.

6.2 Subsamples: Best-Matched Samples and Vacant Homes

We identify a store's PPP status by matching the borrowers of PPP loans with stores in SafeGraph using an algorithm optimizing a similarity metric that compares business names, street addresses, geographic coordinates, and NAICS codes. In our main sample, the deviation between the number

[24]On March 19, California issued Statewide Stay-at-Home Order as pandemic control measure. California was the first state to issue a stay-at-home order, mandating all residents to stay at home except to go to an essential job or shop for essential needs. The majority of PPP loans (97.19%) were approved by the end of May 2020. We collect data on Unemployment Insurance claims in each locality from the state government website: https://www.labormarketinfo.edd.ca.gov/LMID/UI_Claims.html

of PPP loans issued in the SBA data and the number of PPP-receiving stores identified in Safegraph at the zip code level is about 16%. Some possibilities of unmatched PPP loans include businesses without foot traffic, such as sole proprietors, independent contractors, and self-employed. As a robustness check, we re-run our main regressions in a subsample of zip codes, in which the non-matched rate is within 10% (i.e., best-matched sample) and find qualitatively similar results. The results are reported in the Appendix Table 6 Column 1.

Moreover, zip codes with a high percentage of vacant homes - for seasonal, recreational, or occasional use - are associated with very low Census response rates. Thus, the census response rate may not be a good measure of civic capital for the locality. The local businesses in these areas populated with second homes which residents only visit a few times a year may be different from normal businesses. They might stay closed with or without the pandemic, and thus, the PPP loans don't apply to them. To exclude the effect of the seasonal-home zips, we construct a subsample of stores in the zip codes with no more than 0.5% percentage homes vacant and rerun our main. Appendix Table A6 Column 2 presents our results. We find the effects of neighborhood characteristics, access to banks and social capital on PPP uptake are consistent with the results reported in earlier tables.

7 Conclusion

Small business dynamism varies greatly across locations in the U.S. It is unclear how much these differences arise because of different investment opportunities, skill levels, social capital, as well as differential access to finance and underwriting criteria in different locations. We take advantage of a natural experiment to analyze the uptake of risk-free, positive net-present-value financing opportunities by retail stores across different geographies. The setting enables us to be abstract from addressing endogenous business projects and loan underwriting. The industry, retail, is widely distributed across the country and does not require rare skills.

We use granular data to measure how local agglomeration, demographics, nearby banks, local social capital, and localities' virtual connections on Facebook are related to the uptake of positive NPV projects. For social capital, we separate metrics measuring civic capital, the "set of values and beliefs that help a group overcome the free-rider problem in the pursuit of socially valuable activities," from metrics measuring social connections, which may merely transmit information.

We find very wide variation in uptake, much of which is at the census tract and block group level. Store agglomeration and proximity to local banks matter for project uptake. Controlling for these, we find a large and economically significant relation between social capital and loan uptake. Disaggregating social capital measures, we find civic capital, the ability to overcome the free-rider problem in pursuit of socially valuable activities, has a large positive effect. Increasing the civic capital metric by one standard deviation increases the PPP loan uptake by 5 percent of the sample mean, and this magnitude is greater than the effect of having a bank branch within 1000 yards. The social connections metric also has a positive effect on the loan, although with a smaller magnitude. Collectively, civic capital and social connections explain about 20 percent of the variation of PPP uptake at the zip code level.

Civic capital and social connections also interact differently with local banks. The association between increasing bank branch proximity and loan take-up is highest in areas of moderate civic capital. By contrast, in the context of PPP, nearby banks and social connectedness appear to be substitutes for predicting PPP uptake. These results suggest that profit-motivated financial intermediaries have a comparative advantage in accessing a particular profile of entrepreneurs and that they are complements of certain components of social capital (civic capital) and substitutes with other components (social connectedness).

Different components of social capital interact differently with geographic and population characteristics in predicting the uptake of PPP. Civic capital has a greater association with PPP uptake in high-traffic neighborhoods with many stores, while the prevalence of local associations has a greater association with PPP in less store-dense neighborhoods. Both civic capital and social connections benefit more for larger stores in areas with low business turnover. Our results also indicate that social capital - civic, local connections, and virtual connections, are all positively associated with PPP uptakes from banks - local or out of state. On the other hand, we do not find a significant relation between social capital measures and PPP from FinTech lenders. The presence of nearby banks is particularly beneficial for businesses in high business density and high growth locations with high business turnover. Trust in banks, local connections, and local pride are also positively associated with project uptake.

We also find limited evidence that higher bank density in high minority areas is associated with economically significant gains in loan uptake. Our estimates suggest that the economic effect of bank proximity is positive in locations with a higher percentage of minorities. The absolute effect is quite small. By contrast, the differences in our metric of civic capital in high-minority locations have a larger association with PPP uptake. In contrast, social connections and virtual connections benefit predict uptake more strongly in locations with low minority populations.

Overall, locations in the U.S. differ significantly and predictably in their uptake of financing opportunities beyond the well-studied differences in the availability of investment opportunities and differences in underwriting in banks across locations. These differences are policy-relevant and may grow if the polarization of economic opportunities in the U.S. continues. Some trade-offs, such as changing access to bank branches to compensate for low social connections in a neighborhood, are now clear. However, further research is required on how to compensate for low civic capital.

Appendix: Matching PPP Data with Safegraph POI

This section explains the steps we take to link businesses from PPP loan borrowers with SafeGraph POI. We exploit the information of business names and street addresses in the PPP data and SafeGraph to match the loan borrowers with stores. Specifically, the algorithm optimizes a similarity metric that compares business names, street addresses, geographic coordinates, and NAICS codes.

We obtain loan-level PPP data from the Small Business Administration (SBA). The data provide borrower information, including business name, street address, and NAICS categorical coding; loan information, including approval date and loan amount; and lender information, including the names of the financial institutions that facilitated the loan application and distribution.

The first step is to find the geographic coordinates of business locations using the street address and zip code in PPP data through address geocoding. We successfully obtain the latitudes and longitudes of 91.4% businesses through a valid street address, and for the remaining businesses, we obtain the coordinates of their zip codes. Since SafeGraph already provides geographic coordinates of all POIs, we can calculate the geographic distance between any potential match.

The second step is to preprocess and standardize the business name and address in two datasets. We clean the data by removing all punctuation and common suffixes in the business name. Then we correct the spelling errors in city and state and convert all commonly used street suffixes or abbreviations in the address to the full expansion according to the list by USPS. [25]

The third step is to form a sample of potential matches. We join two data sets to see all possible matches based on the NAICS code and a broad geographic category. State is used in this step to ensure a full scan of all possible matches since the city and postal code can be inconsistent across different data sets for the same business. For example, a store located in the area on the periphery of a large town might be linked with the name of a suburb in one data set while with the name of the downtown in another. This step is meant to generate a relatively large but noisy set of candidates, proving the next step with as much scope as possible to find the match.

The fourth step is to measure the string similarity between business names and addresses for all pairs of matching candidates. We conduct the TF-IDF fuzzy string matching to calculate the similarity score for each pair of business names and street names. TF-IDF analyzes the corpus of words as a whole and weights each token as more important to the string if it is less common in the corpus. This means that if two strings have a relatively rare term (such as proper nouns "Red Roof" and "Starbucks") in common, this outweighs the importance of two more common terms (such as "north" and "street" in the street address and "Inn" and "Cafe" in the business name).

The final step is to use all the information we just obtained to disambiguate the noisy matches and find the best match. We combine the string similarity of names and addresses with other information, including street numbers, zip codes, and geographic distance. Since the name of a business used to apply for PPP loans is not necessarily the same as the store name, we assign higher weights to the location information. We conduct multiple rounds of sensitive matching.

[25] https://pe.usps.com/text/pub28/28apc_002.htm

Specifically, in the first round, we pick the store-borrower pairs as the best match when both the street addresses and names are almost perfectly matched. For the remaining stores without a first-best match, we moderately relax the restriction on name similarity and require a perfect matching of street address and geographic distance. In the third-round matching, we moderately relax the restriction on street address similarity and require a good matching of business name and geographic distance. In the fourth-round matching, for the remaining stores without any previous match, we focus on the candidate borrower with the highest street address similarity, same first digit of street number, and very short distance. To weed out false positives, we only view them as a match if the store is the only business in its NAICS category located at the address and the PPP borrower also is the only business in the same NAICS category located at the address.

To check the matching quality, we also manually check a randomly-selected subsample of stores in Maryland. For stores with PPP loans, we compare the information from SafeGraph and PPP data to make sure they are not false positives. For stores without PPP loans, we search the PPP database for any business in MD with the same NAICS code that has at least one word in common in terms of their business name. And then we search these PPP borrowers online for their detailed business information including the stores they own and their locations and compare them with the SafeGraph store. It is rare to find them matched.

[Appendix Table 1: Social Capital and PPP Uptake (Alternative Measures)]

[Appendix Table 2: Civic Capital - Cross-Sectional Effects - Census Tract Level]

[Appendix Table 3: Census Response Rate - IV Approach]

[Appendix Table 4: Historical Local Bank Access]

[Appendix Table 5: Robustness Check - Controlling for UI Claims]

[Appendix Table 6: Robustness Checks: Best-Matched Sample and Excluding Vacant Homes]

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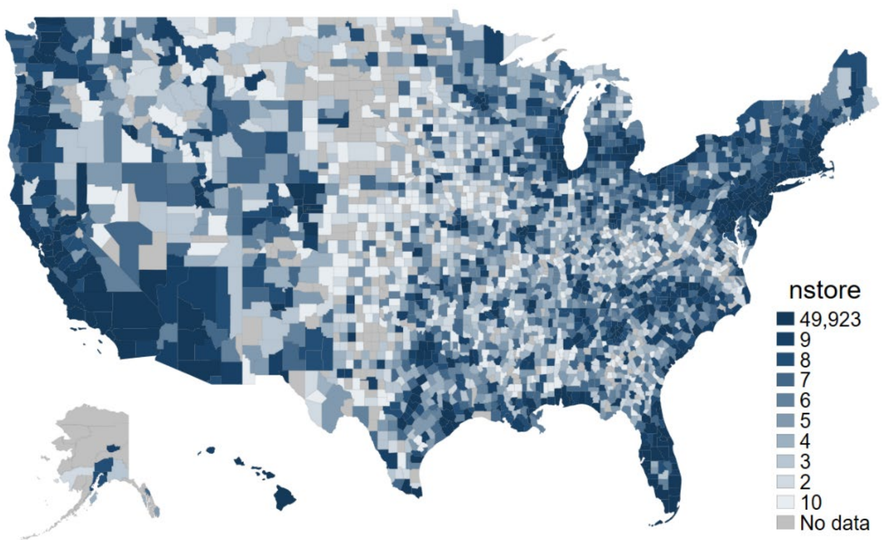
Appendix: Variable Definitions	
Variable	**Definition**
Census Response Rate	Zip-level 2020 Census self-response rates
Census Response Rate 2010	Zip-level 2010 Census self-response rates
Census Response Rate 2010 (tract)	Tract-level 2010 Census self-response rates
Chg_Visits_LastYr	Growth rate of foot traffic in 2019 for a store itself
Chg_Visits_Peers	Average hange of monthly foot traffic in March from the same month last year for nearby stores within 200 yards
Chg_Visits_Self	Change of monthly foot traffic in March from the same month last year for a store itself
City Perfect	Zip-level average agreement to the statement "The city or area where I live is a perfect place for me" from Gallup survey
City Proud	Zip-level average agreement to the statement "I am proud of my community or the area where I live" from Gallup survey
City Safe	Zip-level average agreement to the statement "I always feel safe and Secure" from Gallup survey
Crime Rate Of The County	Crime rate in the county
D_2nd City	Indicator variable that equal one if the percentage of second city households is greater than 50% in the zip code
D_AMZ	Indicator for whether people in the zip code use Amazon frequently
D_Bank (1000 Yds)	Indicator for local presence of any bank within 1000 yards
D_Bank (200 - 500 Yds)	Indicator for local presence of any bank within 200 to 500 yards
D_Bank (200 Yds)	Indicator for local presence of any bank within 200 yards
D_Bank (500 - 1000 Yds)	Indicator for local presence of any bank within 500 to 1000 yards
D_Community_Bank (1000 Yds)	Indicator for local presence of community banks within 1000 yards
D_Community_Bank (200 - 500 Yds)	Indicator for local presence of community banks within 200 to 500
D_Community_Bank (200 Yds)	Indicator for local presence of community banks within 200 yards
D_Community_Bank (500 -1000 Yds)	Indicator for local presence of community banks within 500 to 1000
D_PPP	Indicator for whether the store received a PPP loan
D_Rural	Indicator variable that equals one if the percentage of town and rural households is greater than 50% in the zip code
D_Suburb	Indicator variable that equals one if the percentage of suburban households is greater than 50% in the zip code
D_Urban	Indicator variable that equals one if the percentage of urban households is greater than 50% in the zip code
Donation	Log number of household average cash donation to charities in the zip
Ln (# of Banks in the County)	Log number of banks in the county
Ln (# of Banks in the Zip)	Log number of banks outside of the 1000-yards neighborhood in the zip code
Ln (# of Estabs)	Log number of establishments in the zip code
Ln (# of Households)	Log number of households in the zip code
Ln (# of Nearby Stores)	Log number of nearby stores within 200 yards
Ln (Avg. # of Visits in Nearby Store)	Log number of average visits for nearby stores within 200 yards
Ln (Median Income)	Log median household income in the zip code
Ln (Median Income) (county)	Log median household income in the county
Ln (Median Income) (tract)	Log median household income in the tract
Ln (Pop Density)	Log population density in the zip code
Ln (Pop Density) (county)	Log population density in the county
Ln(Conn_CTY)	Log number of Facebook connections per capita within the county

Ln(Conn_CTY_excl_ZIP)	Log number of Facebook connections per capita within the county excluding own zip code
Ln(Conn_outside_CTY)	Log number of Facebook connections per capita out of the county
Ln(Conn_outside_STATE)	Log number of Facebook connections per capita out of the state
Ln(Conn_State_excl_CTY)	Log number of Facebook connections per capita within the state excluding own county
Ln(Conn_ZIP)	Log number of Facebook connections per capita within the zip code
Log(Total Jobs in census tract)	Log number of total jobs in all industries in the census tract
Pct (Jobs in Finance in census tract)	Percentage of jobs in the finance industry in the census tract
Pct of Any Membership	Percentage of residents that belong to a local club (civic, business, or sports) in the zip code
Pct of Brand Stores	Percentage brand store within 200 yards
Pct of Community Banks (county)	Percentage of community banks in the county
Pct of Edu (At Least BA) (county)	Percentage of population with at least a bachelor's degree in the county
Pct of Edu (At Least BA) (tract)	Percentage of population with at least a bachelor's degree in the tract
Pct of Edu_BA	Percentage of population with at least a bachelor's degree in the zip
Pct of Minorities	Percentage of minority in the zip code
Pct of Minorities (tract)	Percentage of minority in the tract
Pct of Population Age 17 To 34 (county	Percentage of population aged from 17 to 34 in the county
Pct of Population Age 35 To 49 (county	Percentage of population aged from 35 to 49 in the county
Pct of PTA Membership	Percentage of population with PTA membership in the zip code
Pct of Religious Affiliation	Percentage of population with religious affiliation in the zip code
Pct of SBA Loans (200 Yds)	Number of SBA loans approved within 200 yards, divided by the number of nearby stores
Pct of SBA Loans (500 Yds)	Number of SBA loans approved within 500 yards, divided by the number of nearby stores
Pop Change (county)	Population growth rate in the county
Rural-Urban Code (county)	Code indicating rural-urban degree of the county
Size	Log average weekly visits in 2019 plus 1
Trust Bank	Percentage of population trusting money to a bank in the zip code
Unemployment Rate (county)	Unemployment rate in the county
Voter Turnout Rate	Zip-level 2020 presidential election voter turnout rate

Figure 3: Sample Distribution

Panel A presents the distribution of stores at the county level in our sample and Panel B presents the percentage of stores that received PPP loans by county.

Panel A: Stores by County



Panel B: The Percentage of PPP by County

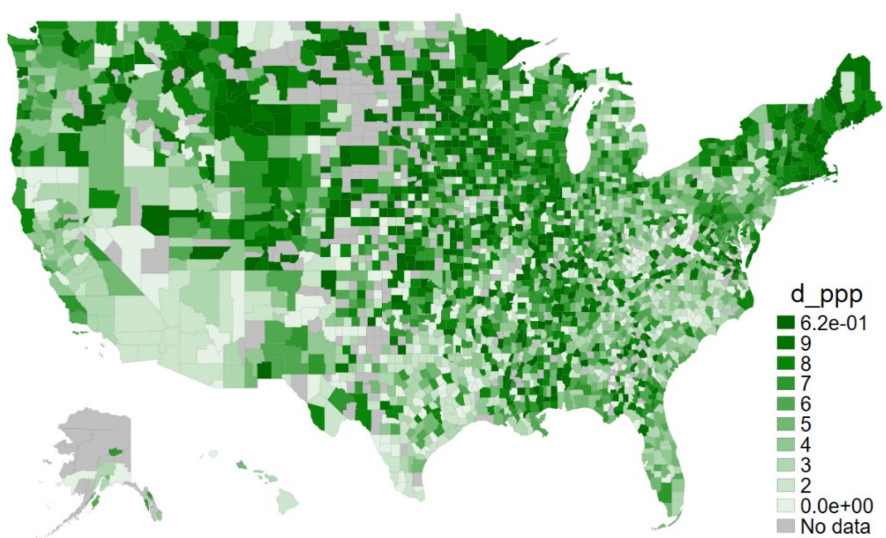
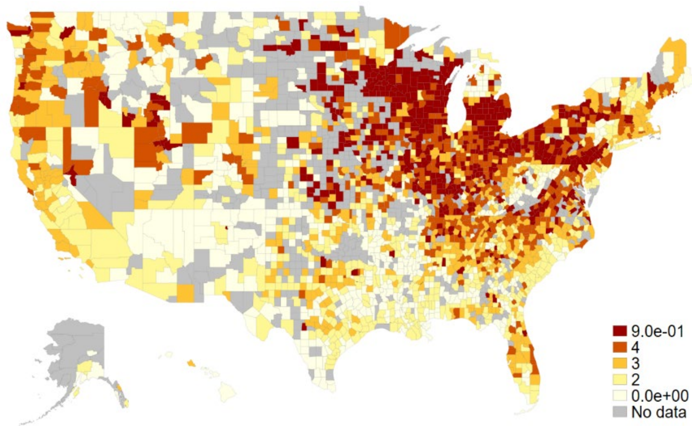


Figure 4: Social Capital Measures

The figure below presents the distribution of four social capital measures, including the Census response rate (top) and the percentage of residents with membership in local civic, business, or sports association (bottom).

Panel A: Census Response Rate



Panel B: Pct of Membership

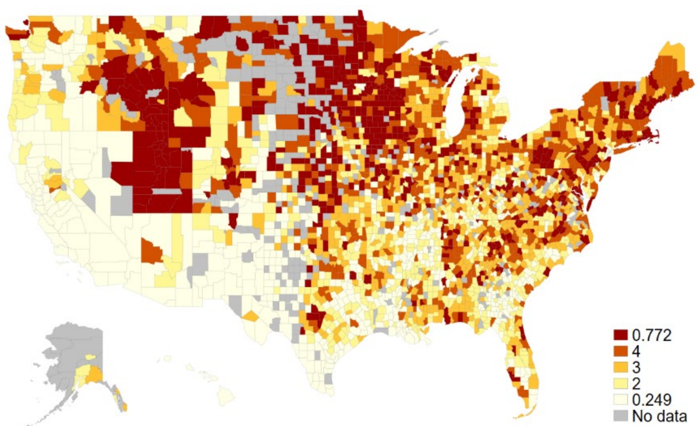


Figure 5: PPP Percentage and County Characteristics

The figures below present the binscatter plots between the percentage of stores that received PPP loans and county characteristics, including (1) the percentage of adults with less than high-school education (2) poverty rate, (3) percentage of adults not working, (4) the median income ratio (relative to the national average), (5) the logarithm of the number of banks, (6) the entry rate of establishments, (7) the exit rate of establishments, and (8) the turnover rate of establishments. In all regressions, we control for the logarithm of county population.

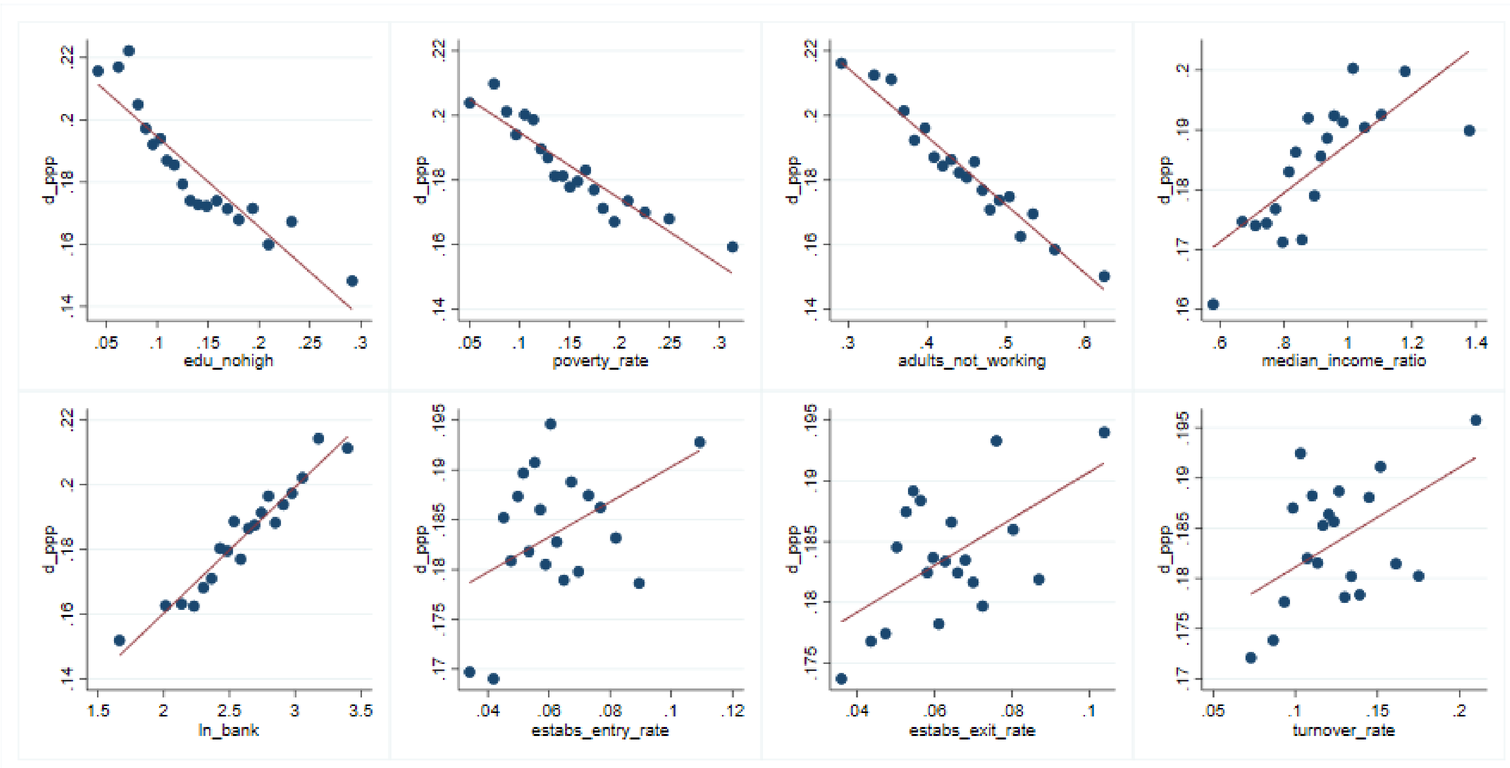


Table 1: Sample Distribution

This table presents the sample distribution over industry (panel A) and

Panel A: Distribution over Industries

NAICS	NAICS Description	N	Percent
4411	Auto Dealers	34,730	2.81
4412	Other V Dealer	17,183	1.39
4413	Auto Parts	35,479	2.87
4421	Furniture Stores	23,785	1.92
4441	Building Material	44,556	3.60
4451	Grocery Stores	54,762	4.43
4453	Liquor Store	26,478	2.14
4461	Personal Care Store	63,982	5.17
4471	Gas Station	43,449	3.51
4481	Clothes Store	35,093	2.84
4482	Shoe Store	5,111	0.41
4483	Jewelry Store	16,399	1.33
4511	Sporting Hobby	58,647	4.74
4512	Book Store	9,518	0.77
4531	Florists	22,777	1.84
7139	Amusement Recreatioı	103,522	8.37
7211	Hotels	26,036	2.11
7225	Restaurants	434,979	35.17
8111	Auto Repair	98,673	7.98
8121	Personal Care SVC	81,685	6.60
Total		1,236,844	100

Panel B: Distribution over States

State	N	Percent	State	N	Percent
AK	2,733	0.2	MS	10,516	0.9
AL	17,533	1.4	MT	4,764	0.4
AR	10,994	0.9	NC	36,273	2.9
AZ	23,903	1.9	ND	2,616	0.2
CA	171,496	13.9	NE	6,837	0.6
CO	23,396	1.9	NH	5,528	0.4
CT	15,128	1.2	NJ	39,813	3.2
DC	3,709	0.3	NM	7,091	0.6
DE	3,540	0.3	NV	10,807	0.9
FL	87,085	7	NY	84,376	6.8
GA	37,087	3	OH	36,981	3
HI	7,548	0.6	OK	13,836	1.1
IA	10,787	0.9	OR	18,828	1.5
ID	7,020	0.6	PA	48,587	3.9
IL	45,803	3.7	RI	5,393	0.4
IN	21,035	1.7	SC	19,514	1.6
KS	9,719	0.8	SD	3,109	0.3
KY	13,059	1.1	TN	23,992	1.9
LA	18,437	1.5	TX	103,829	8.4
MA	30,234	2.4	UT	10,326	0.8
MD	19,168	1.5	VA	26,208	2.1
ME	5,253	0.4	VT	2,766	0.2
MI	35,441	2.9	WA	28,323	2.3
MN	16,774	1.4	WI	21,534	1.7
MO	20,903	1.7	WV	4,615	0.4
			WY	2,597	0.2
Total				1,236,844	100

Table 2: Summary Statistics

Panel A provides the summary statistics for variables used in the paper. Panel B provides the correlation matrix between social capital measures used in the paper and other key variables at the zip-code level.

Panel A: Summary Statistics

	Mean	Std. Dev.	Median	P25	P75
Store and Neighborhood Characteristics					
Size	3.314	1.063	3.327	2.541	4.043
Chg_Visits_Self	-0.214	0.541	-0.235	-0.54	0.086
Chg_Visits_Peers	-0.193	0.315	-0.172	-0.403	0
Chg_Visits_LastYr	0.184	0.306	0.179	0	0.353
Ln (# of Nearby Stores)	1.666	1.053	1.792	0.693	2.398
Ln (Avg. # of Visits in Nearby Store)	4.44	2.028	5.108	4.357	5.648
Pct of Brand Stores Nearby	0.217	0.275	0.1	0	0.364
Zip Code Characteristics					
Ln (# of Households)	9.169	0.787	9.341	8.814	9.697
Ln (# of Estabs)	6.506	0.831	6.625	6.023	7.088
Ln (Median Income)	11.153	0.378	11.138	10.905	11.412
Ln (Population Density)	7.166	1.842	7.502	5.892	8.454
Pct of Minority	0.306	0.217	0.252	0.134	0.436
Pct_Edu (≥BA)	0.198	0.092	0.184	0.124	0.262
D_Urban	0.246	0.431	0	0	0
D_Suburb	0.213	0.41	0	0	0
D_2ndCity	0.125	0.331	0	0	0
D_Rural	0.3	0.458	0	0	1
Bank Access					
D_Bank (200 yds)	0.214	0.410	0	0	0
D_Bank (200 - 500 yds)	0.222	0.416	0	0	0
D_Bank (500 - 1000 yds)	0.203	0.403	0	0	0
D_Bank (1000 yds)	0.203	0.403	0	0	0
D_CBank (200 yds)	0.087	0.281	0	0	0
D_CBank (200 - 500 yds)	0.129	0.335	0	0	0
D_CBank (500 -1000 yds)	0.153	0.36	0	0	0
D_CBank (1000 yds)	0.368	0.482	0	0	1
Ln (# of Banks in Zip)	2.008	0.743	2.079	1.609	2.565
Ln (# of Banks in Zip - excl. 1000 yds)	1.603	0.901	1.792	1.099	2.303
Pct of SBA Loans (200 yds)	0.064	0.193	0	0	0.043
Pct of SBA Loans (500 yds)	0.069	0.148	0.026	0	0.091
Social Capital Variables					
Census Response Rate 2010	0.739	0.078	0.749	0.700	0.791
Census Response Rate 2020	0.676	0.111	0.689	0.607	0.760
Tract-Level Census Response Rate 2010	0.732	0.091	0.743	0.68	0.792
Tract-Level Census Response Rate 2020	0.663	0.128	0.679	0.586	0.756
Pct of Any Membership	0.478	0.086	0.487	0.431	0.533
Pct of Being Proud of the City	0.804	0.147	0.828	0.714	0.913
Pct of Trusting Banks	0.255	0.055	0.255	0.221	0.287
Virtual Connections Variables					
Ln(Conn_CTY)	7.217	0.444	7.244	6.945	7.507
Ln(Conn_ZIP)	5.485	0.956	5.489	4.869	6.114
Ln(Conn_CTY_excl_ZIP)	6.756	1.078	6.955	6.504	7.303
Ln(Conn_outside_CTY)	8.095	0.313	8.106	7.923	8.291
Ln(Conn_State_excl_CTY)	7.136	0.695	7.228	6.88	7.523
Ln(Conn_outside_STATE)	7.507	0.412	7.519	7.248	7.789
PPP Uptake					
D_PPP (store level)	0.196				
Pct_PPP (zip-code level)	0.187	0.127	0.182	0.119	0.237
Observations	1,236,847				

Panel B: Correlation Matrix

	Census Response Rate	Pct. of Membership	Pct. of Being Proud of the City	Pct. that Trusting Banks	Ln (Population Density)	Ln (Median Income)	Pct. of Minority	Pct. of Education > BA	Ln (# of Banks)
Census Response Rate	1								
Pct. of Membership	0.378***	1							
Pct. of Being Proud of the City	0.290***	0.271***	1						
Pct. that Trusting Banks	0.327***	0.412***	0.304***	1					
Ln (Population Density)	-0.151***	-0.312***	-0.147***	-0.152***	1				
Ln (Median Income)	0.446***	0.328***	0.446***	0.353***	0.102***	1			
Pct. of Minority	-0.452***	-0.451***	-0.406***	-0.471***	0.437***	-0.310***	1		
Pct. of Education > BA	0.251***	0.247***	0.438***	0.362***	0.332***	0.712***	-0.194***	1	
Ln (# of Banks)	0.134***	0.0757***	0.118***	0.128***	0.240***	0.224***	-0.101***	0.372***	1

*** Significant at 1% level.

Table 3: Neighborhood Characteristics and PPP Uptake

This table reports regression results to predict the PPP uptake at the store level. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

DEP VAR = D_PPP	(1)	(2)	(3)
Size	0.0357***	0.0365***	0.0406***
	(0.0009)	(0.0008)	(0.0010)
Ln (# of Nearby Stores)	0.0283***	0.0270***	0.0271***
	(0.0008)	(0.0008)	(0.0009)
Ln (Avg. # of Visits in Nearby Store)	0.0004	0.0019***	0.0018***
	(0.0006)	(0.0006)	(0.0007)
Pct of Brand Stores Nearby	0.0039***	0.0022***	0.0023***
	(0.0006)	(0.0006)	(0.0007)
Chg_Visits_Self	-0.0016***	-0.0017***	-0.0020***
	(0.0004)	(0.0004)	(0.0005)
Chg_Visits_Peers	0.0006	0.0003	-0.0001
	(0.0005)	(0.0005)	(0.0005)
Chg_Visits_LastYr	0.0040***	0.0029***	0.0021***
	(0.0005)	(0.0004)	(0.0004)
Ln (# of Households)		0.0078***	
		(0.0011)	
Ln (# of Estabs)		-0.0026**	
		(0.0011)	
Ln (Median Income)		0.0050***	
		(0.0016)	
Ln (Pop Density)		-0.0036**	
		(0.0016)	
Pct of Minorities		-0.0106***	
		(0.0011)	
Pct_Edu (≥BA)		0.0062***	
		(0.0011)	
D_Urban		0.0005	
		(0.0029)	
D_Suburb		0.0007	
		(0.0019)	
D_2nd City		0.0061**	
		(0.0025)	
D_Rural		0.0036*	
		(0.0021)	
Constant	0.2068***	0.2053***	0.2088***
	(0.0002)	(0.0014)	(0.0003)
Observations	1,228,845	1,227,963	1,181,814
R-squared	0.0880	0.0893	0.1673
FE	County x Ind	County x Ind	Zip x Ind

Table 4: Local Bank Access and PPP Uptake

This table reports regression results to predict the PPP uptake at the store level based on local bank access. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. In addition to the variables shown, we control for all variables included in Table 3 (Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, and D_Rural). Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

DEP VAR = D_PPP	(1)	(2)	(3)	(4)
D_Bank (1000 Yds)	0.0083***		0.0068***	
	(0.0012)		(0.0013)	
D_Bank (200 Yds)		0.0177***		0.0161***
		(0.0018)		(0.0021)
D_Bank (200 - 500 Yds)		0.0097***		0.0086***
		(0.0016)		(0.0017)
D_Bank (500 - 1000 Yds)		0.0050***		0.0048***
		(0.0012)		(0.0015)
D_CBank (1000 Yds)	0.0058***		0.0039***	
	(0.0011)		(0.0014)	
D_CBank (200 Yds)		0.0081***		0.0072***
		(0.0021)		(0.0025)
D_CBank (200 - 500 Yds)		0.0043***		0.0036**
		(0.0016)		(0.0019)
D_CBank (500 -1000 Yds)		0.0032**		0.0019
		(0.0013)		(0.0016)
Ln (# of Banks in the Zip)	0.0068***	0.0072***	0.0039***	0.0061***
	(0.0009)	(0.0008)	(0.0013)	(0.0013)
Pct of SBA Loans (200 Yds)	0.0087***	0.0086***	0.0080***	0.0079***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Pct of SBA Loans (500 Yds)	0.0040***	0.0041***	0.0036***	0.0036***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Pct (Finance Jobs in Census Tract)	0.0029***	0.0030***	0.0016*	0.0016*
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
Observations	1,227,536	1,227,536	1,180,655	1,180,655
R-squared	0.0902	0.0904	0.1678	0.1678
FE	County x Ind	County x Ind	ZIP x Ind	ZIP x Ind

Table 5: Access to Local Banks - Cross-Sectional Effects

This table reports the estimated effects of bank access to PPP uptake by store or zip code characteristics. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. In addition to the variables shown, we control for all variables included in Table 4, including Size, Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, D_Rural, Pct of SBA Loans (200 Yds), Pct of SBA Loans (500 Yds), and Pct of Finance Jobs in Census Tract. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Panel A: Store Charateristics

DEP VAR = D_PPP	(1)	(2)	(3)	(4)	(5)	(6)
VAR =	Size		Prior Growth		# of Nearby Stores	
D_Bank_1000	0.0072***	0.0069***	0.0084***	0.0084***	0.0094***	0.0087***
	(0.0013)	(0.0014)	(0.0012)	(0.0012)	(0.0013)	(0.0012)
D_CB_1000	0.0058***	0.0063***	0.0057***	0.0058***	0.0058***	0.0069***
	(0.0011)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
VAR	0.0391***	0.0390***	0.0020***	0.0020***	0.0249***	0.0250***
	(0.0010)	(0.0010)	(0.0005)	(0.0005)	(0.0011)	(0.0011)
D_Bank_1000 x VAR	-0.0042***	-0.0061***	0.0016**	0.0014	0.0030***	0.0058***
	(0.0011)	(0.0013)	(0.0007)	(0.0009)	(0.0010)	(0.0011)
D_CB_1000 x VAR		0.0032**		0.0004		-0.0050***
		(0.0013)		(0.0010)		(0.0014)
Ln (# of Banks in the Zip)	0.0067***	0.0068***	0.0067***	0.0067***	0.0069***	0.0066***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Observations	1,227,536	1,227,536	1,227,536	1,227,536	1,227,536	1,227,536
R-squared	0.0903	0.0903	0.0903	0.0903	0.0903	0.0903
FE	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind

Panel B: Zip Characteristics

DEP VAR = D_PPP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VAR =	Median Income		Education		Pct of Minorities		Business Turnover	
D_Bank_1000	0.0082***	0.0082***	0.0080***	0.0076***	0.0079***	0.0081***	0.0026	0.0022
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0022)	(0.0026)
D_CB_1000	0.0058***	0.0059***	0.0059***	0.0065***	0.0063***	0.0062***	0.0062***	0.0067***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0022)
VAR	0.0056***	0.0056***	0.0066***	0.0064***	-0.0110***	-0.0109***		
	(0.0014)	(0.0015)	(0.0014)	(0.0014)	(0.0011)	(0.0011)		
D_Bank_1000 x VAR	-0.0004	0.0001	-0.0018*	0.0003	0.0029***	0.0022**	0.0074***	0.0078***
	(0.0009)	(0.0011)	(0.0010)	(0.0011)	(0.0009)	(0.0009)	(0.0024)	(0.0029)
D_CB_1000 x VAR		-0.0009		-0.0039***		0.0014		-0.0007
		(0.0013)		(0.0015)		(0.0012)		(0.0025)
Ln (# of Banks in the Zip)	0.0068***	0.0068***	0.0067***	0.0066***	0.0068***	0.0068***	0.0067***	0.0067***
	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)
Observations	1,227,536	1,227,536	1,227,536	1,227,536	1,227,536	1,227,536	1,227,536	1,227,536
R-squared	0.0903	0.0903	0.0903	0.0903	0.0903	0.0903	0.0903	0.0903
FE	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind

Table 6: Social Capital and PPP Uptake

This table reports regression results to predict the PPP uptake at the store level based on social capital measures. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. We use the Census response rate in 2010 to measure civic capital and the percentage of residents that belong to a local club (civic, business, or sports) to measure social connections. In addition to the variables shown, we control for all variables included in Table 4, including Size, Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, and D_Rural. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

DEP VAR = D_PPP	(1)	(2)	(3)
Civic Capital	0.0095***		0.0095***
	(0.0012)		(0.0012)
Social Connections		0.0032***	0.0025***
		(0.0009)	(0.0009)
D_Bank (1000 Yds)	0.0076***	0.0080***	0.0075***
	(0.0012)	(0.0012)	(0.0012)
D_CBank (1000 Yds)	0.0056***	0.0057***	0.0055***
	(0.0011)	(0.0011)	(0.0011)
Ln (# of Banks In The Zip)	0.0066***	0.0067***	0.0065***
	(0.0008)	(0.0008)	(0.0008)
Pct of SBA Loans (200 Yds)	-0.0011	-0.0005	-0.0013
	(0.0019)	(0.0019)	(0.0019)
Pct of SBA Loans (500 Yds)	0.0064**	0.0056**	0.0062**
	(0.0026)	(0.0025)	(0.0026)
Pct (Jobs in Finance in the Census Tract)	0.0032	0.0038*	0.0032
	(0.0021)	(0.0021)	(0.0021)
Constant	0.1988***	0.1983***	0.1990***
	(0.0015)	(0.0015)	(0.0016)
Observations	1,159,364	1,220,572	1,154,181
R-squared	0.0883	0.0903	0.0883
FE	County x Ind	County x Ind	County x Ind

Table 7: Social Capital and Bank Access

This table reports results to predict the interaction between the social capital and bank access on the PPP uptake. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. For each social capital variable, we categorize it into three levels - Low, Medium, and High, based on terciles at the zip-code level, with the Low group treated as the benchmark. In addition to the variables shown, we control for all variables included in Table 4, including Size, Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, D_Rural, Pct of SBA Loans (200 Yds), Pct of SBA Loans (500 Yds), and Pct of Finance Jobs in Census Tract. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

DEP_VAR = D_PPP	(1)	(2)	(3)	(4)
Civic Capital	0.0093***			
	(0.0012)			
Civic Capital (Med)		0.0071***		
		(0.0019)		
Civic Capital (High)		0.0157***		
		(0.0026)		
Social Connections			0.0050***	
			(0.0010)	
Social Connections (Med)				0.0034*
				(0.0018)
Social Connections (High)				0.0085***
				(0.0022)
D_Bank (1000 Yds)	0.0077***	0.0060***	0.0078***	0.0114***
	(0.0012)	(0.0017)	(0.0012)	(0.0016)
Civic Capital x D_Banks_1000	0.0003			
	(0.0009)			
Civic Capital (Med) x D_Banks_1000		0.0042**		
		(0.0020)		
Civic Capital (High) x D_Banks_1000		-0.0002		
		(0.0023)		
Social Connections x D_Banks_1000			-0.0027***	
			(0.0009)	
Social Connectsion (Med) x D_Banks_1000				-0.0038*
				(0.0019)
Social Connectsion (High) x D_Banks_1000				-0.0080***
				(0.0022)
	(0.0015)	(0.0019)	(0.0015)	(0.0018)
Observations	1,159,364	1,159,364	1,220,572	1,220,572
R-squared	0.0883	0.0882	0.0903	0.0903
FE	County x Ind	County x Ind	County x Ind	County x Ind

Table 8: Social Capital - Cross-Sectional Effects

This table reports the estimated effects of social capital on PPP uptake by store or zip code characteristics. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. For each social capital variable, we categorize it into three levels - Low, Medium, and High, based on terciles at the zip-code level, with the Low group treated as the benchmark. In addition to the variables shown, we control for Size, Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, D_Rural, D_Banks_1000, D_CBanks_1000), Ln(# of banks in the zips), Pct of SBA Loans (200yds), Pct of SBA Loans (500yds), and Pct of Finance Jobs in Census Tract.. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Panel A

Social Capital = Civic Capital	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VAR =	Size	Prior Growth	# of Nearby Stores	Median Income	Pct_Edu (>BA)	Pct_Minorities	Business Turnover
Social Capital (Med)	0.0111***	0.0097***	0.0096***	0.0101***	0.0096***	0.0092***	0.0114***
	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0016)	(0.0016)	(0.0014)
Social Capital (High)	0.0180***	0.0155***	0.0152***	0.0133***	0.0149***	0.0139***	0.0172***
	(0.0026)	(0.0025)	(0.0025)	(0.0023)	(0.0022)	(0.0025)	(0.0021)
VAR	0.0312***	0.0030***	0.0262***	0.0019	0.0041***	-0.0084***	
	(0.0011)	(0.0007)	(0.0010)	(0.0020)	(0.0015)	(0.0012)	
Social Capital (Med) x VAR	0.0069***	-0.0004	0.0035***	0.0019	0.0037***	0.0026*	-0.0054**
	(0.0013)	(0.0009)	(0.0011)	(0.0013)	(0.0012)	(0.0014)	(0.0023)
Social Capital (High) x VAR	0.0110***	-0.0004	0.0011	0.0047**	0.0030	-0.0015	-0.0073*
	(0.0016)	(0.0010)	(0.0014)	(0.0020)	(0.0019)	(0.0027)	(0.0044)
Observations	1,159,364	1,159,364	1,159,364	1,159,364	1,159,364	1,159,364	1,159,364
R-squared	0.0883	0.0882	0.0882	0.0882	0.0882	0.0882	0.0882
FE	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind
Cluster	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind

Panel B

Social Capital = Social Connections	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VAR =	Size	Prior Growth	# of Nearby Stores	Median Income	Pct_Edu (>BA)	Pct_Minorities	Business Turnover
Social Capital (Med)	0.0025*	0.0011	0.0011	0.0012	0.0012	0.0015	0.0019
	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0013)
Social Capital (High)	0.0043**	0.0033*	0.0031	0.0025	0.0033*	0.0022	0.0043**
	(0.0020)	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0019)	(0.0017)
VAR	0.0326***	0.0026***	0.0284***	0.0053***	0.0059***	-0.0084***	
	(0.0013)	(0.0007)	(0.0010)	(0.0020)	(0.0017)	(0.0011)	
Social Capital (Med) x VAR	0.0071***	0.0010	-0.0015	-0.0020	-0.0020	-0.0002	-0.0027
	(0.0013)	(0.0009)	(0.0010)	(0.0015)	(0.0017)	(0.0014)	(0.0022)
Social Capital (High) x VAR	0.0053***	0.0001	-0.0029**	0.0014	-0.0006	-0.0044**	-0.0050*
	(0.0015)	(0.0010)	(0.0013)	(0.0018)	(0.0020)	(0.0018)	(0.0029)
Observations	1,220,572	1,220,572	1,220,572	1,220,572	1,220,572	1,220,572	1,220,572
R-squared	0.0903	0.0903	0.0903	0.0903	0.0903	0.0903	0.0903
FE	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind
Cluster	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind

Table 9: Virtual Connections and PPP Uptake

This table reports regression results to predict the PPP uptake at the store level based on virtual connections measures. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. In addition to the variables shown, we control for Size, Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, D_Rural, D_Banks_1000, D_CBanks_1000), Ln(# of banks in the zips), Pct of SBA Loans (200yds), Pct of SBA Loans (500yds), and Pct of Finance Jobs in Census Tract. We use county-industry fixed effects and include county characteristics. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

DEP VAR = D_PPP	(1)	(2)	(3)
Ln(Conn)	0.0010		
	(0.0012)		
Ln(Conn_inside_CTY)		0.0061***	
		(0.0012)	
Ln(Conn_ZIP)			0.0097***
			(0.0013)
Ln(Conn_CTY_excl_ZIP)			0.0049**
			(0.0021)
Ln(Conn_outside_CTY)		-0.0016	-0.0010
		(0.0012)	(0.0012)
Civic Capital	0.0096***	0.0090***	0.0091***
	(0.0011)	(0.0012)	(0.0012)
Social Connections	0.0024***	0.0022**	0.0019**
	(0.0009)	(0.0009)	(0.0009)
D_Banks_1000	0.0075***	0.0074***	0.0070***
	(0.0012)	(0.0012)	(0.0012)
D_Cbanks_1000	0.0056***	0.0055***	0.0053***
	(0.0011)	(0.0011)	(0.0011)
Observations	1,151,482	1,151,482	1,151,482
R-squared	0.0881	0.0881	0.0882
FE	County x Ind	County x Ind	County x Ind
Clust	County x Ind	County x Ind	County x Ind

Table 10: Virtual Connections - Cross-Sectional Effects

This table reports the estimated effects of virtual connection on PPP uptake by store or zip code characteristics. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. For each social capital variable, we categorize it into three levels - Low, Medium, and High, based on terciles at the zip-code level, with the Low group treated as the benchmark. In addition to the variables shown, we control for Size, Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, D_Rural, Pct of SBA Loans (200yds), Pct of SBA Loans (500yds), and Pct of Finance Jobs in Census Tract. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

DEP VAR = D_PPP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VAR =	Size	Prior Growth	# of Nearby Stores	Median Income	Education	Pct. of Minorities	Business Turover	D_Banks_1000
Ln(Conn_inside_CTY) (Med)	0.0053***	0.0046***	0.0043***	0.0036**	0.0036**	0.0043***	0.0047***	0.0058***
	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0021)
Ln(Conn_inside_CTY) (High)	0.0108***	0.0094***	0.0088***	0.0082***	0.0083***	0.0088***	0.0092***	0.0112***
	(0.0026)	(0.0025)	(0.0025)	(0.0023)	(0.0024)	(0.0025)	(0.0024)	(0.0027)
VAR	0.0317***	0.0004	0.0279***	-0.0007	0.0040**	-0.0062***		0.0095***
	(0.0012)	(0.0007)	(0.0011)	(0.0017)	(0.0016)	(0.0017)		(0.0019)
Ln(Conn_inside_CTY) (Med) x VAR	0.0053***	0.0023**	0.0003	0.0030	0.0039**	-0.0007	-0.0007	-0.0023
	(0.0015)	(0.0011)	(0.0012)	(0.0020)	(0.0020)	(0.0016)	(0.0019)	(0.0022)
Ln(Conn_inside_CTY) (High) x VAR	0.0098***	0.0043***	-0.0004	0.0028	0.0055**	-0.0006	-0.0038	-0.0037
	(0.0017)	(0.0010)	(0.0014)	(0.0020)	(0.0022)	(0.0019)	(0.0032)	(0.0023)
Ln(Conn_outside_CTY)	-0.0037	-0.0028	-0.0032	-0.0032	-0.0047	-0.0031	-0.0032	-0.0031
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0037)	(0.0041)	(0.0038)	(0.0039)
Civic Capital	0.0092***	0.0092***	0.0092***	0.0091***	0.0092***	0.0092***	0.0092***	0.0092***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Social Connections	0.0024***	0.0024***	0.0024***	0.0024***	0.0024***	0.0024***	0.0023***	0.0024***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
D_Bank (1000 Yds)	0.0073***	0.0074***	0.0074***	0.0074***	0.0073***	0.0074***	0.0074***	
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	
D_CBank (1000 Yds)	0.0055***	0.0055***	0.0055***	0.0056***	0.0056***	0.0056***	0.0056***	0.0055***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Ln (# of Banks In The Zip)	0.0065***	0.0065***	0.0064***	0.0064***	0.0064***	0.0065***	0.0065***	0.0065***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Pct of SBA Loans (200 Yds)	0.0086***	0.0086***	0.0086***	0.0086***	0.0086***	0.0086***	0.0086***	0.0086***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Pct of SBA Loans (500 Yds)	0.0039***	0.0039***	0.0039***	0.0039***	0.0039***	0.0039***	0.0039***	0.0039***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Pct (Finance Jobs in Census Tract)	0.0030***	0.0030***	0.0030***	0.0030***	0.0029***	0.0030***	0.0030***	0.0030***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Observations	1,151,482	1,151,482	1,151,482	1,151,482	1,151,482	1,151,482	1,151,482	1,151,482
R-squared	0.0882	0.0881	0.0881	0.0881	0.0881	0.0881	0.0881	0.0881
FE	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind
Clust	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind

Table 11: PPP Uptake - Banks vs Fintech

This table reports results to predict the PPP uptake by lender type at thes store level based on nearby banks, social capital, and virtual connections. The dependent variable is an indicator variable that equals 1 if a store received a PPP loan from a bank (FinTech lender) and 0 if the store does not receive a PPP loan for Column 1 (2). In Column 3, we only include stores that receive PPP loans and the dependent variable is an indicator variable if a store receives the PPP loan from a FinTech lender. Standard errors clustered by state x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Sample	All Stores	All Stores	Stores with PPP Loan
DEP VAR	D_PPP_Bank	D_PPP_FinTech	FinTech
Civic Capital	0.0085***	0.0015***	-0.0000
	(0.0011)	(0.0004)	(0.0015)
Social Connections	0.0020**	0.0003	-0.0003
	(0.0009)	(0.0004)	(0.0014)
Inside-County Connections	0.0062***	0.0001	-0.0028*
	(0.0012)	(0.0004)	(0.0017)
Outside-County Connections	-0.0024**	0.0009	0.0052**
	(0.0010)	(0.0006)	(0.0022)
D_Bank (1000 Yds)	0.0065***	0.0016***	0.0005
	(0.0011)	(0.0005)	(0.0021)
D_CBank (1000 Yds)	0.0062***	-0.0005	-0.0057***
	(0.0011)	(0.0005)	(0.0019)
Ln (# of Banks In The Zip)	0.0062***	0.0008**	-0.0016
	(0.0008)	(0.0003)	(0.0013)
Pct of SBA Loans (200 Yds)	0.0079***	0.0016***	0.0009
	(0.0004)	(0.0002)	(0.0006)
Pct of SBA Loans (500 Yds)	0.0039***	0.0002	-0.0020***
	(0.0004)	(0.0001)	(0.0006)
Pct (Finance Jobs in Census Tract)	0.0026***	0.0008***	0.0008
	(0.0007)	(0.0003)	(0.0012)
Size	0.0371***	0.0017***	-0.0182***
	(0.0009)	(0.0002)	(0.0010)
Ln (# of Nearby Stores)	0.0258***	0.0047***	-0.0018
	(0.0008)	(0.0003)	(0.0012)
Ln (Avg. # of Visits in Nearby Store)	-0.0004	-0.0005*	0.0004
	(0.0006)	(0.0002)	(0.0011)
Pct of Brand Stores Nearby	0.0021***	0.0010***	0.0023**
	(0.0006)	(0.0003)	(0.0010)
Chg_Visits_Self	-0.0018***	-0.0001	0.0021***
	(0.0004)	(0.0002)	(0.0008)
Chg_Visits_Peers	0.0003	0.0000	0.0010
	(0.0005)	(0.0002)	(0.0008)
Chg_Visits_LastYr	0.0023***	0.0007***	0.0000
	(0.0004)	(0.0002)	(0.0009)
Ln (# of Households)	0.0019*	0.0020***	0.0071***
	(0.0010)	(0.0004)	(0.0015)
Ln (# of Estabs)	-0.0052***	-0.0025***	-0.0057***
	(0.0011)	(0.0005)	(0.0019)
Ln (Median Income)	0.0018	-0.0007	-0.0045**
	(0.0015)	(0.0006)	(0.0020)
Ln (Pop Density)	-0.0026	0.0004	0.0057**
	(0.0016)	(0.0006)	(0.0024)
Pct of Minorities	-0.0079***	0.0003	0.0105***
	(0.0009)	(0.0004)	(0.0018)
Pct_Edu (≥BA)	0.0072***	0.0009*	-0.0030
	(0.0011)	(0.0005)	(0.0020)
D_Urban	0.0008	0.0003	-0.0028
	(0.0025)	(0.0010)	(0.0044)
D_Suburb	-0.0014	0.0003	-0.0007
	(0.0018)	(0.0008)	(0.0031)
D_2nd City	0.0048**	0.0016*	-0.0022
	(0.0024)	(0.0009)	(0.0035)
D_Rural	0.0032	0.0009	0.0061**
	(0.0021)	(0.0008)	(0.0031)
Constant	0.1822***	0.0253***	0.1113***
	(0.0015)	(0.0006)	(0.0026)
Observations	1,127,116	948,463	217,861
R-squared	0.0898	0.0340	0.1047
FE	County x Ind	County x Ind	County x Ind

Appendix Table 1: Social Capital and PPP Uptake (Alternative Measures)

This table reports regression results to predict the PPP uptake at the store level based on alternative social capital measures. In addition to the variables shown, we control for all variables included in Table 4, including Size, Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, and D_Rural. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Civic Capital		Social Connections	Other Var.	
Social Capital Measures =	Voter Turnout	Donation	Pct of Religious	Pct of PTA Membership	City Pride	Trust of Banks
Social Capital	0.0024***	0.0022***	0.0028***	0.0011*	0.0026***	0.0014***
	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0006)	(0.0005)
D_Bank (1000 Yds)	0.0082***	0.0082***	0.0080***	0.0077***	0.0081***	0.0081***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
D_CBank (1000 Yds)	0.0059***	0.0058***	0.0057***	0.0059***	0.0059***	0.0058***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Ln (# of Banks In The Zip)	0.0067***	0.0069***	0.0067***	0.0061***	0.0068***	0.0068***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
Pct of SBA Loans (200 Yds)	0.0087***	0.0087***	0.0087***	0.0087***	0.0087***	0.0087***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Pct of SBA Loans (500 Yds)	0.0040***	0.0040***	0.0040***	0.0040***	0.0040***	0.0040***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Pct (Jobs in Finance in census tract)	0.0031***	0.0028***	0.0028***	0.0028***	0.0029***	0.0029***
	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0007)
Observations	1,225,629	1,227,007	1,219,061	1,158,305	1,224,278	1,218,469
R-squared	0.0903	0.0903	0.0903	0.0917	0.0904	0.0903
FE	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind

Appendix Table 2: Civic Capital - Cross-Sectional Effects (Census Tract Level)

This table reports the estimated effects of social capital on PPP uptake at the Census tract level. We follow the same specification as that in Table 8 of the paper census response rate at the Census Tract level. We categorize social capital variables with three levels, Low, Medium, and High, based on terciles of the zip-co capital measure. The Low level of social capital is treated as a benchmark in regressions. In addition to the variables shown, we control for Size, Chg_Visits_Se Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), L of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, D_Rural, D_Banks_1000, D_CBanks_1000), Ln(# of banks in the zips), Pct of SBA Loans (200 Loans (500yds), and Pct of Finance Jobs in Census Tract. Fixed effects included in each regression are indicated in the column. Standard errors clustered by co reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VAR =	Size	Prior Growth	# of Nearby Stores	Median Income	Pct_Edu (>BA)	Pct_Minorities
Social Capital (Med)	0.0117***	0.0098***	0.0102***	0.0108***	0.0105***	0.0099***
	(0.0015)	(0.0014)	(0.0013)	(0.0015)	(0.0014)	(0.0014)
Social Capital (High)	0.0183***	0.0158***	0.0160***	0.0156***	0.0159***	0.0158***
	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0018)	(0.0019)
VAR	0.0306***	0.0048***	0.0261***	0.0020	0.0037**	-0.0087***
	(0.0011)	(0.0008)	(0.0010)	(0.0019)	(0.0015)	(0.0011)
Social Capital (Med) x VAR	0.0078***	-0.0028***	0.0037***	0.0022*	0.0038***	0.0017
	(0.0012)	(0.0010)	(0.0012)	(0.0012)	(0.0011)	(0.0013)
Social Capital (High) x VAR	0.0102***	-0.0037***	0.0023*	0.0038**	0.0036**	0.0008
	(0.0014)	(0.0010)	(0.0014)	(0.0016)	(0.0017)	(0.0018)
Observations	1,177,501	1,177,501	1,177,501	1,177,501	1,177,501	1,177,501
R-squared	0.0882	0.0882	0.0882	0.0882	0.0882	0.0881
FE	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind
Cluster	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind	County x Ind

Appendix Table 3: Census Response Rate - IV Approach

This table reports the estimated effects of civic capital on PPP uptake using an instrumented variable approach. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. In the first stage, we instrument 2020 census response rate with 2010 census response rate . We only include non-brand stores in the sample. In addition to the variables shown, we control for Size, Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, D_Rural, D_Bank (200 yds), D_Bank (200-500 yds), D_Bank (500-1000 yds), Ln(# of banks in the zip - beyond 1000 yds), D_Community_Bank (200 yds), D_Community_Bank (200-500 yds), D_Community_Bank (500-1000 yds), Pct of SBA Loans (200yds), and Pct of SBA Loans (500yds) in both panels. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	(1) IV: 1st stage	(2) IV: 2nd stage
Census Response Rate 2010	0.4925***	
	(0.0144)	
Census Response Rate 2020		0.0203***
		(0.0024)
D_Bank (1000 Yds)	0.0231***	0.0051***
	(0.0037)	(0.0011)
D_CBank (1000 Yds)	-0.0132***	0.0038***
	(0.0040)	(0.0012)
Ln (# of Banks in the zip)	0.0206***	0.0040***
	(0.0067)	(0.0008)
Pct of SBA Loans (200 Yds)	0.0023***	0.0086***
	(0.0006)	(0.0004)
Pct of SBA Loans (500 Yds)	0.0032***	0.0037***
	(0.0007)	(0.0004)
Pct (Finance Jobs in Census Tract)	-0.0010	0.0030***
	(0.0037)	(0.0007)
Size	-0.0121***	0.0368***
	(0.0012)	(0.0009)
Chg_Visits_Self	0.0049***	-0.0019***
	(0.0007)	(0.0004)
Chg_Visits_Peers	0.0200***	-0.0000
	(0.0018)	(0.0005)
Chg_Visits_LastYr	0.0098***	0.0026***
	(0.0011)	(0.0004)
Ln(# of Stores)	-0.0243***	0.0273***
	(0.0025)	(0.0008)
Ln(Avg # of Visits)	0.0129***	0.0000
	(0.0020)	(0.0006)
Pct of Brand Stores	0.0128***	0.0022***
	(0.0012)	(0.0006)
Ln (# of Households)	0.1412***	0.0030***
	(0.0082)	(0.0010)
Ln (# of Estabs)	-0.0734***	-0.0057***
	(0.0095)	(0.0012)
Ln (Median Income)	0.4013***	-0.0066***
	(0.0194)	(0.0022)
Ln (Pop Density)	0.1369***	-0.0066***
	(0.0105)	(0.0019)
Pct of Minorities	-0.0115	-0.0066***
	(0.0131)	(0.0010)
Pct of Edu_BA	-0.0962***	0.0088***
	(0.0114)	(0.0013)
D_Urban	-0.0468**	0.0019
	(0.0187)	(0.0026)
D_Suburb	0.0686***	-0.0018
	(0.0120)	(0.0019)
D_2nd City	-0.0888***	0.0086***
	(0.0147)	(0.0026)
D_Rural	-0.0612***	0.0042**
	(0.0124)	(0.0021)
Observations	1,148,254	1,148,254
R-squared		0.0132
Fixed Effects	CTY x Ind	CTY x Ind
First-stage F-statistic		1163

Appendix Table 4: Historical Local Bank Access

This table reports regression results to predict the PPP uptake at the store level based on local bank access using historical bank status (D_Bank, D_CBank, and Ln(# of banks in the zip) in 2009 (columns 1 and 2), and 2014 (columns 3 and 4). In addition to the variables shown, we control for all variables included in Table 3 (Chg_Visits_Self, Chg_Visits_Peers, Chg_Visits_LastYr, Ln(# of Stores), Ln(Avg # of visits), Pct of Brand Stores, Ln(# of Households), Ln(# of Estabs), Ln(Median Income), Ln(Pop Density), Pct of Minorities, Pct of Edu_BA, D_Urban, D_Sub, D_2nd City, and D_Rural). Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	(1)	(2)
DEP VAR = D_PPP	Bank: 2009	Bank: 2014
D_Bank (1000 Yds)	0.0066***	0.0064***
	(0.0011)	(0.0011)
D_CBank (1000 Yds)	0.0026**	0.0039***
	(0.0011)	(0.0011)
Ln (# of Banks in the zip)	0.0026***	0.0035***
	(0.0008)	(0.0008)
Pct of SBA Loans (200 Yds)	0.0087***	0.0087***
	(0.0004)	(0.0004)
Pct of SBA Loans (500 Yds)	0.0041***	0.0041***
	(0.0004)	(0.0004)
Pct (Finance Jobs in Census Tract)	0.0029***	0.0030***
	(0.0007)	(0.0007)
Observation	1,227,536	1,227,536
R-Square	0.0901	0.0902
FE	County x Ind	County x Ind

Appendix Table 5: Robustness Check - Controlling for UI Claims

This table reports regression results to predict the PPP uptake at the store level based on store, zip, local bank access, controlling for UI claims. This table uses the subsample of non-brand firms in California. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

DEP VAR = D_PPP	(1)	(2)
UI Claims (Zip*Industry)	0.0007	0.0017
	(0.0040)	(0.0039)
Civic Capital		0.0078**
		(0.0034)
Social Connections		0.0019
		(0.0016)
Inside-County Connections		0.0100**
		(0.0043)
Outside-County Connections		-0.0027
		(0.0027)
D_Bank (1000 Yds)	0.0084***	0.0075***
	(0.0022)	(0.0022)
D_CBank (1000 Yds)	0.0001	0.0001
	(0.0030)	(0.0030)
Ln (# of Banks in the zip)	0.0092***	0.0085***
	(0.0019)	(0.0019)
Pct of SBA Loans (200 Yds)	0.0109***	0.0109***
	(0.0012)	(0.0012)
Pct of SBA Loans (500 Yds)	0.0043***	0.0043***
	(0.0011)	(0.0011)
Pct (Finance Jobs in Census Tract)	0.0002	0.0002
	(0.0023)	(0.0025)
Size	0.0303***	0.0305***
	(0.0038)	(0.0039)
Chg. in # of visits	-0.0030*	-0.0030*
	(0.0017)	(0.0017)
Chg. in # of visits (peers)	0.0016	0.0012
	(0.0017)	(0.0017)
Chg. in # of visits (from 19 to 20)	0.0014	0.0012
	(0.0014)	(0.0013)
Ln (# of Nearby Stores)	0.0341***	0.0340***
	(0.0022)	(0.0022)
Ln (Avg. # of Visits in Nearby Store)	-0.0004	-0.0004
	(0.0020)	(0.0020)
% of Brand Stores Nearby	0.0011	0.0011
	(0.0019)	(0.0019)
Ln (# of Households)	0.0039	0.0029
	(0.0030)	(0.0029)
Ln (# of estabs)	-0.0121***	-0.0116***
	(0.0029)	(0.0028)
Ln (Median Income)	0.0125***	0.0079**
	(0.0043)	(0.0034)
Ln (Population Density)	0.0009	0.0014
	(0.0036)	(0.0035)
Pct of Minorities	-0.0036*	-0.0019
	(0.0021)	(0.0029)
Pct_Edu (≥BA)	0.0077**	0.0097***
	(0.0034)	(0.0028)
D_Urban	0.0063	0.0055
	(0.0066)	(0.0065)
D_Suburb	-0.0006	0.0002
	(0.0053)	(0.0053)
D_2ndCity	0.0185**	0.0160**
	(0.0078)	(0.0077)
D_Rural	0.0037	0.0062
	(0.0076)	(0.0073)
Constant	0.1666***	0.1680***
	(0.0052)	(0.0060)
Observations	153,576	153,576
R-squared	0.0607	0.0609
FE	County x Ind	County x Ind

Appendix Table 6: Robustness Check: Best-Matched Sample and Excluding Vacant Homes

This table reports regression results to predict the PPP uptake at the store level in two subsamples for robustness checks. The dependent variable is an indicator variable that equals one if the store has received a PPP loan and zero otherwise. In Column (1), we only include matched zip codes in which the non-matched rate (between our sample and the PPP data from the SBA) is lower than 10%, and in Column (2), we exclude zip codes in which vacant homes is greater than 0.5%. Standard errors clustered by county x industry are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	(1)	(2)
VARIABLES	Best Matched Sample	Excl. Vacant Homes
Civic Capital	0.0101***	0.0103***
	(0.0015)	(0.0015)
Social Connections	0.0027**	0.0015
	(0.0012)	(0.0009)
Inside-County Connections	0.0068***	0.0054***
	(0.0014)	(0.0014)
Outside-County Connections	-0.0008	-0.0010
	(0.0018)	(0.0012)
D_Bank (1000 Yds)	0.0059***	0.0057***
	(0.0015)	(0.0012)
D_CBank (1000 Yds)	0.0060***	0.0053***
	(0.0016)	(0.0012)
Ln (# of Banks in the zip)	0.0054***	0.0055***
	(0.0012)	(0.0008)
Pct of SBA Loans (200 Yds)	0.0086***	0.0084***
	(0.0006)	(0.0005)
Pct of SBA Loans (500 Yds)	0.0035***	0.0037***
	(0.0006)	(0.0004)
Pct (Finance Jobs in Census Tract)	0.0008	0.0027***
	(0.0010)	(0.0008)
Size	0.0439***	0.0371***
	(0.0011)	(0.0009)
Chg. in # of visits	-0.0012**	-0.0017***
	(0.0006)	(0.0005)
Chg. in # of visits (peers)	0.0001	-0.0002
	(0.0006)	(0.0005)
Chg. in # of visits (from 19 to 20)	0.0029***	0.0032***
	(0.0005)	(0.0004)
Ln (# of Nearby Stores)	0.0280***	0.0283***
	(0.0011)	(0.0009)
Ln (Avg. # of Visits in Nearby Store)	-0.0015*	0.0006
	(0.0008)	(0.0007)
% of Brand Stores Nearby	0.0039***	0.0023***
	(0.0007)	(0.0006)
Ln (# of Households)	-0.0016	0.0018
	(0.0018)	(0.0012)
Ln (# of estabs)	-0.0026	-0.0047***
	(0.0017)	(0.0013)
Ln (Median Income)	0.0055**	0.0020
	(0.0021)	(0.0017)
Ln (Population Density)	-0.0008	-0.0022
	(0.0021)	(0.0019)
% of Minority	-0.0072***	-0.0072***
	(0.0014)	(0.0010)
% of BA (education)	0.0091***	0.0071***
	(0.0018)	(0.0012)
D_Urban	0.0019	0.0028
	(0.0035)	(0.0028)
D_Suburb	0.0002	-0.0017
	(0.0028)	(0.0019)
D_2ndCity	0.0082***	0.0051*
	(0.0031)	(0.0026)
D_Rural	0.0043	0.0030
	(0.0029)	(0.0023)
Constant	0.2079***	0.2001***
	(0.0020)	(0.0017)
Observations	577,894	1,002,367
R-squared	0.1067	0.0874
FE	County x Ind	County x Ind