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Bank Types, Inclusivity, and Payroll Protection Program Lending During COVID-19

Mark K. Cassell[1], Michael Schwan[2] and Marc Schneiberg[3]

Abstract
How do differences in bank or lending institution type shape access to credit for small businesses in poor and/or minority communities in the United States? Banking systems are populated by lenders that differ qualitatively in their organizational forms, business models and missions, and that connect—or fail to connect—to small business borrowers and local communities in divergent ways. The authors analyze data on the Paycheck Protection Program and its over 11 million loans made to businesses across the United States to trace how these differences shaped the flow of credit to poor and minority communities. The authors find substantial differences across seven lender types, both in their propensities to avoid or lend to firms in traditionally marginalized communities, and in how much they lend to poor and majority–minority communities relative to their nonpoor and majority White counterparts. From this variety within American banking, the authors identify two potential pathways for more inclusive lending.

Keywords
paycheck protection program, COVID-19, bank lending, inclusivity

How do differences in bank or lending institution type shape access to credit for small businesses in poor and/or minority communities in the United States? The centerpiece of the American response to the employment collapse during the COVID-19 pandemic, the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) and its Paycheck Protection Program (PPP), represent the largest federal industrial policy intervention into the economy since the New Deal. Between April 2020 and May 2021, the PPP made over 11 million federally guaranteed, forgivable loans to small businesses primarily to keep employees on payroll. Critically, it did so through the American banking system. Overseen by the Small Business Administration (SBA), the PPP channeled nearly $1 trillion through the nation's preexisting privately owned and largely for-profit collection of banks and lending institutions. By working through that system, the PPP relied on institutions that had a long record of systematically denying poor and non-White communities access to credit and capital on comparable terms with White communities, through redlining, subprime lending in mortgage markets, and discrimination in loans to small businesses, with devastating effects on businesses and communities (Massey & Denton, 1993; Oliver & Shapiro, 2006; Rugh & Massey, 2010; Squires, 2003). Predictably, observers quickly questioned how PPP funds were allocated across communities, producing accumulating evidence that firms in disadvantaged, traditionally marginalized poorer and non-White communities received disproportionately fewer loans than firms elsewhere (Center for Responsible Lending, 2020; Fairlie, 2020; Grotto et al., 2020; Howell et al., 2021; Sanchez-Moyano, 2021; Schweitzer & Borawski, 2021).

American banking comprises lending institutions that differ qualitatively in their structure, business models, and missions, and by ecologies or mixes of institutions that vary markedly across regional banking markets. Prepandemic scholarship showed that such organizational differences matter for how banks and banking markets operate, how capital and credit are allocated, and the capacities of firms, states, regional economies, and industries to foster growth and adapt to economic shocks and change (Beck et al., 2018; Berger & Udell, 2002;

[1]Department of Political Science, Kent State University, Kent, OH, USA
[2]Cologne Center for Comparative Politics (CCCP), University of Cologne, Cologne, Germany
[3]Department of Sociology, Reed College, Portland, OR, USA

Corresponding author:
Mark K. Cassell, Professor of Political Science, Kent State University, 302 Bowman Hall, Kent, OH 44242, USA.
Email: mcassell@kent.edu

Cassell, 2021; Mettenheim, 2014; Schneiberg, 2011; Schneiberg & Parmentier, 2021; Schwan, 2021). Scholarship on the PPP confirmed their continued relevance. Community banks provided loans to small business more quickly and extensively than other institutions in the first round of lending (Allen & Whitledge, 2022; Balyuk et al., 2022; James et al., 2021; Li & Strahan, 2021) while financial technology firms (also known as fintechs) filled in for areas and industries underserved by banks in later rounds (Battisto et al., 2021; Berg et al., 2021; Erel & Liebersohn, 2022; Fei & Yang, 2022; Howell et al., 2021). The growing body of work on the PPP's impact on economic outcomes like unemployment or business closures has produced sustained analyses of lending differences across bank types as a strategy to isolate causal effects (Bartik et al., 2021; Faulkender et al., 2020; Granja et al., 2021; James et al., 2021; Li & Strahan, 2021). Nevertheless, until quite recently, studies of ethno-racial and class impacts or divides in American banking have commonly treated lenders as a uniform collection of institutions or have focused on a single type of (typically large) organization. And while studies in progress on the PPP break new ground by combining research on lender types and discrimination, they limit their focus mainly to pairwise contrasts between fintech and conventional banks. They take technology or automation as the central dimension and/or adopt a microlevel approach that analyzes PPP outcomes, lender type, and ethno-racial characteristics at the individual rather than community level.

Chernenko and Scharfstein (2022), Fei and Yang (2022), and Howell et al. (2021), for example, focused on how borrowers taking PPP loans from fintechs (or non-banks) and banks depend on borrowers' individual ethno-racial status, documenting divergent associations across the two. A minority status, especially Black, decreased the probability that an applicant got a PPP loan from a bank but increased the probability of getting one from a fintech or non-bank, suggesting substitution among minority businesses. Howell et al. (2021) extended the lender typology by differentiating among banks. They show first, that the negative impacts of minority status hold for small rather than medium-sized banks or the largest four lenders, and second, that small and medium-sized banks' outsourcing loan operations to a fintech increased the probability of their lending to Black-owned businesses. Notably however, this study added bank types to the analysis solely to array them by their technology, and to advance arguments that automation reduced racial disparities, reducing the typology to that single dimension. Howell et al. (2021) and Chernenko and Scharfstein (2022) also sought to isolate mechanisms of discrimination by incorporating contextual measures of racial animus, going beyond treating community characteristics as noise to be factored out of microlevel analyses (Fei & Yang, 2022). Both studies found greater impacts of ethno-racial identity on receiving PPP loans from fintechs or banks in places with the most racial animus. Yet, the interest in both studies is not in the direct impact of racial animus or other community characteristic on loan flows, but only in how animus moderates the microimpacts of individual ethno-racial characteristics. Only Erel and Liebersohn (2022) examined first-order community effects in analyzing inclusivity and types, using data on ZIP codes to show that communities relied more heavily on fintechs when they had large minority populations, low incomes, and sparse branch networks. But they, too, focused only on fintechs versus banks.

In this article, we (1) consider a full range of lending institutional types and (2) analyze the problem of access and inclusivity at the community rather than the microor individual level. We shift the focus from individual businesses to whether and how extensively communities receive loans from different lender types and how that varies by their class and ethno-racial compositions. To our knowledge, this is the first study to examine and compare how loan flows to communities vary across types of banks and non-bank lender organizations. Using SBA data on the entire corpus of almost 12 million loans, we analyze PPP lending for each of seven lender classes in more than 32,000 communities across all three rounds of the program (SBA, 2021). We ask: How might differences in institutional type or organizational form shape lender sensitivities to community characteristics and access to credit for small businesses in poor and/or minority communities? How might such differences shape government capacities to direct credit to firms in those communities through programs like the PPP that operate through the existing banking system? We consider the poverty and the minority status of communities. We analyze whether each type of institution did any PPP lending in (or avoided) communities and how extensively each type lent to places in which they made any loans. We compare and test for differences across lender types in the sensitivities of outcomes to communities' poverty and minority status. And we draw on economic sociology, organizational analyses of finance, and comparative political economy to understand how and why inclusivity varies by lender type. We go beyond technology and individual or firm-level dynamics to consider organizational and ownership form, core business models, missions, and how the systems or ecologies of lender institutions create social and organizational infrastructure for action and access in their communities.

The PPP is ideally suited for addressing these questions. Public officials introduced reforms into the program as it was underway to promote inclusivity and access at scale for borrowers. They worked to make it easier for a wider range of lending institutions to participate and realize those ends. Facing complaints early on that businesses in minority and traditionally underserved areas were not getting loans, and pressures by financial technology firms, Congress and the SBA enacted measures to empower more lender types, including non-banks and institutions with an explicit mission to support historically disadvantaged communities (Government Accountability Office [GAO], 2022). Key reforms included making nondepository and community financial institutions PPP and SBA eligible, setting aside a $10 billion fund for Community Development Financial Institutions (CDFIs), providing CDFIs and other small lenders balance sheet support through the Federal Reserve's PPP Liquidity Facility, and giving community financial institutions a few days head start in processing loans when the program re-opened in 2021 (Eggleston, 2021; GAO, 2022). Some changes were implemented shortly after the start of the program in April and May 2020, but other key changes occurred in 2021. These reforms increased participation by both financial technology and community-based institutions with histories of lending to poor and historically marginalized communities, particularly later in the program. They fostered institutional variety within the PPP, and explicitly built connections between lender types and inclusivity into the program's implementation and design.

Theory and Hypotheses

Institutions that make up American banking vary considerably in their ownership and internal structure, business models, charter or mission, and historical roots, underwriting important differences in how they operate, relate to, and shape local communities. This heterogeneity supports two classifications and sets of hypotheses about differences in institutions' PPP lending to firms in poor and minority communities.

Giant, market-based bank holding companies like JP Morgan Chase and Wells Fargo anchor the first classification. These are publicly traded, investor-owned, for-profit corporations that collect deposits, make loans, and operate on national or global scales in multiple financial markets. They face pressures to raise share prices and maximize shareholder value and rely heavily on transactional banking practices based in arm's length relationships with clients, abstract credit scoring, and standardized loan products (Davis, 2009; Johnson & Kwak, 2011; Tett, 2009). Critically, these institutions also stand out for how they embrace—and harness lending and deposit-taking—to market-based banking business models grounded in securitization, propriety trading in derivatives, fee generation, and the high-volume production, purchase, and sale of loans, and new financial instruments, funded partly by short-term borrowing in interbank and other money markets (Goldstein & Fligstein, 2017; Hardie et al., 2013).

In contrast to market-based bank giants stand large and-medium-sized commercial banks (LMCBs) that do a traditional banking business—and, more importantly, thousands of smaller-scale, locally operating "alternative banks" such as community banks, credit unions,[1] credit associations of the farm credit system[2] (FCS), and CDFIs[3] (Mettenheim, 2014; Pinsky, 2001). Alternative banks are typically locally owned as closely held (often family based) firms, cooperatives, or nonprofits that specialize in the "boring banking" strategies of making and holding loans (Federal Deposit Insurance Corporation [FDIC], 2012; GAO, 2012, p. 4), or that operate as nonprofit and for-profit loan funds with economic or community development missions. They provide credit to groups often underserved by large commercial banks, including working class families (credit unions), small businesses (community banks), and minority or low-income communities (CDFIs). They also commonly rely on relational banking practices that cultivate long-term personal ties and local networks with borrowers and communities to gather information, assess and screen clients, work out loan packages, and manage lending relations (Appleyard, 2011; Beck et al., 2018; Benjamin et al., 2004; Berger & Udell, 2002). They help connect business clients, participate in local development coalitions, and promote financial skills or awareness within communities as a part of their service-oriented missions.

Recently, fintechs have emerged as an important class of lenders. Fintechs rely heavily on data mining, automation, and online banking to provide credit to traditionally underserved customer groups who often lack relationships with traditional lenders (Berg et al., 2021; Gorman, 2020; Howell et al., 2021). They fit less neatly into the category of alternative banks, eschewing key features of those institutions—localism, relational banking, service-based missions—and embracing for-profit missions, volume strategies, abstract scoring, and completely impersonal data-based transactions with borrowers. Yet they stand as distinct alternatives to large, market-based bank corporations (and banks more generally) and, as we address below, relate to disadvantaged communities in distinctive ways.

From an organizational, economic sociology, or comparative political economy perspective, these differences in core characteristics could support greater inclusivity in PPP lending by alternative banks than by giant market-based corporations. Pressure for short-term profits coupled with few charter commitments to serving disadvantaged groups and their ability to exit communities to seek profits elsewhere as opportunities arise, give market-based banks few incentives to use the PPP to help small business borrowers weather the pandemic in minority or low-income areas. Transactional banking practices also disadvantage market-based banks in connecting with qualified borrowers (especially in minority or low-income areas), whose small businesses are complex, idiosyncratic, and difficult to assess using standard credit screens, thus fostering forms of statistical discrimination. These practices did not affect the creditworthiness assessments of potential borrowers for PPP loans since government guarantees relieved the lenders of credit risk (Balyuk et al., 2022). Yet they could bias PPP lending through their effects on pre-COVID-19 business lending and prior relationships that left bank giants with especially weak or few ties to small businesses in poor or minority communities. During the hectic and oversubscribed first rounds of the PPP, market-based and other banks prioritized existing clients, both to help those clients with outstanding loans stay afloat or to secure their repeat business, and because existing clients had already cleared the SBA's and Bank Secrecy Act's time-consuming registration and verification hurdles (Balyuk et al., 2022; Granja et al., 2021; Li & Strahan, 2021). And even as these constraints eased, market-based banks still did not possess many connections in marginalized communities. If anything, their weak ties coupled with volume and fee-based emphasis would yield incentives for "cream skimming" larger business borrowers in large numbers from more concentrated, higher-income, and White urban communities (Baradaran, 2018).

In contrast, localism and cooperative, nonprofit, or closely held ownership coupled with service-oriented missions, relational banking practices, and community ties, leave alternatives like community banks or CDFIs less exposed to shareholder pressures for short-term profit and less prone to abandon communities to invest elsewhere. Having their fates tied to the economic wellbeing of the local communities they serve, lenders and loan officers at alternative banks are invested in promoting the PPP, encouraging their clients to apply, and helping them negotiate paperwork (Allen & Whitledge, 2022; James et al., 2021). Charter provisions require credit unions, FCS associations, and CDFIs to serve working-class, rural, low-income, and minority communities, respectively, and often engage lenders in community development, financial education, and the like. Personal ties and repeated interactions foster exchanges of idiosyncratic "soft" information between lenders and borrowers, creating in-depth knowledge of clients and local conditions and a willingness to customize loan terms (Beck et al., 2018; Bresler et al., 2006; Flögel, 2018; Hoffmann & Cassell, 2010), which enables community banks and other alternative lenders to serve borrowers that standard credit scoring practices would exclude. They also promote trust, patience, and a history that encourages communication and joint problemsolving rather than quick denials when unusual contingencies or difficulties emerge (Berger & Udell, 2002; Uzzi & Lancaster, 2003). Trust and communication channels can help lenders promote awareness of the PPP and overcome skepticism and confusion about it among business owners in poor or minority communities. They can also foster broader networks, information flows, and expectations that enable business owners there to advocate on their own behalf for PPP loans.

Like alternative banks, fintechs can support inclusive lending, albeit through very different mechanisms. They eschew the relational banking and localism that could tie lenders to minority or poor communities. Yet their reliance on completely impersonal data-based transactions, automation, and online operations simultaneously reduces the scope for personal and racial bias in lending and tempers minority borrowers' expectations of such treatment. Fintech systems allow them to make small loans in volume without branch networks, making them key conduits for PPP loans to minority-owned businesses that were quite often too small to be profitable for banks (Chernenko & Scharfstein, 2022; Erel & Liebersohn, 2022; Howell et al., 2021). LMCBs, in contrast, stand as intermediate cases. Their size and geographic scope anchor them less strongly in local communities and might support transactional banking, but they have not abandoned conventional banking for derivatives trading and the industrial production of loans or new instruments and may resemble community banks in cultivating relationships with businesses in their home regions.

We thus expect divergent profiles of PPP lending to poor or minority versus wealthier and White communities by lender types, rather than a simple replication of the overall pattern of poor and minority communities receiving relatively fewer loans or no loans at all.

> *H1a: Poor and minority communities will be less well served in the PPP by giant bank corporations than comparable non-poor or majority-White communities (receive fewer PPP loans or no loans at all).*
>
> *H1b: Poor and minority communities will be as well, if not better, served by alternative banks and fintechs in PPP lending than non-poor or White communities (receive as many, if not more, loans, and be as, if not more, likely to be served.*
>
> *H1c. LMCBs will occupy an intermediate position between the two poles in their PPP lending to communities.*

Research on American banking, race, and public policy supports a different set of expectations. Features of alternative banks can combine with segregation to foster exclusivity rather than inclusivity among some subtypes (Baradaran, 2018; Massey & Denton, 1993; Oliver & Shapiro, 2006; Rugh & Massey, 2010). In places characterized by high residential segregation, community banks' localism, small size, and reliance on personal ties can amplify tendencies toward homophily, promoting exclusive networks between bankers and business owners in White communities, but not in minority or poor communities. Credit unions' common bond requirements to serve members of employee groups, existing associations, or communities, could tie their lending profiles, outreach efforts, and boards to largely White working-class and middle-class communities. Such dynamics might particularly impact FCS associations if their charter commitments to serve agricultural businesses in rural regions combine with occupational and residential segregation to disconnect them from minority (if not poor) communities.

While also small scale, local lenders, and often community banks or credit unions, CDFIs are mission-driven organizations, subject to regulatory and certification requirements to serve disadvantaged communities. Historically, they have aggressively pursued ties with business owners, advocates, and nonprofits in low-income and minority communities, and have organized to promote these agendas (Pinsky, 2001). We expect CDFIs will therefore lend more heavily in poor or minority communities than in other places, mainly acting on their own initiative, but also by fostering networks, informational campaigns, and flows within segregated places that could prompt otherwise discouraged applicants to seek out PPP loans and support. Fintechs also stand out for inclusivity in segregated contexts but through different means. Relying on automation and online lending, fintechs mitigate fears among minority business owners of discriminatory treatment. They eliminate the need for branches entirely, thereby surmounting and even capitalizing on one of the most serious structural obstacles to credit access in segregated society: the absence of banks and bank branches in poor, and especially minority, communities (Erel & Liebersohn, 2022; Howell et al., 2021). In effect, fintechs combine technology, automated online operations, and a rejection of relational, mission-based banking, and traditional community engagement to carve out a new pathway to inclusivity.

Giant bank corporations, in contrast, remain relatively conventional lending institutions that may exhibit some degree of network neutrality and suffer less from the specific combinations of business relations, local ties, and segregation that afflict community banks and others in the first group. However, their size and ambitions leave them vulnerable to demands for more inclusive lending, including the Community Reinvestment Act and regulatory oversight in merger approval proceedings, generating policy, and political pressures, at a minimum, to avoid any appearance of racial discrimination (Friedman & Squires, 2005; Krippner, 2017). LMCBs might also attract such pressures since they span and serve larger and more heterogenous markets than community banks but remain rooted in conventional business lending strategies. We thus expect very different profiles and market level impacts by lender type than above:

H2a: Poor and minority communities will be less well served in PPP lending by community banks (and credit unions or FCS associations) than comparable non-poor or majority-White communities.

H2b: Poor and minority communities will be markedly better served in the PPP by CDFIs and fintech lenders, and as well if not better served by giant market-based bank corporations and perhaps LMCBs than non-poor or White communities.

Data and Methodology

Data

We create a unique data set from several sources. First, we obtained the full loan-level data provided by the SBA covering all PPP loans made throughout the duration of the program from March 27, 2020 through May 31, 2021. Second, we code each type of lender following Schneiberg and Parmentier (2021), federal financial regulators (Farm Credit Administration (FCA), Federal Deposit Insurance Corporation (FDIC), and National Credit Union Administration (NCUA)), the U.S. Treasury CDFI Fund, and scholarly work on fintechs (Erel & Liebersohn, 2022; Rooney, 2019; Stulz, 2019). We categorize each lender and PPP loan as one of the following types: top 50 derivative bank holding corporations ($N = 50$), LMCB ($N = 214$), community banks ($N = 3{,}890$), credit unions ($N = 887$), institutions of the FCS System ($N = 53$), CDFIs ($N = 416$), and fintechs ($N = 40$).[4]

Following, but slightly modifying, Erel and Liebersohn (2022) and Granja et al. (2021), we use ZIP Code Tabulation Areas (ZCTAs) as our unit of analysis and proxy for communityareas that in some cases adjust and combine ZIP codes to better represent contiguous and sensible residential or business district areas (U.S. Census Bureau, 2022). We use the ZIP Code to ZCTA Crosswalk file published by the Uniform Data System (UDS) to link PPP loan and lender to communities and their socioeconomic status, and to create our two key dependent variables for all loans and each lender type: a dummy variable indexing whether any PPP loans were made in the ZCTA, and a count variable of how many loans were made. Our analysis includes all the nation's 32,931 ZCTAs, including those where banks made no PPP loans, which lets us determine where different lenders did and did not lend, and how widely they lent across communities.

We use the 5-year estimates of the 2015 to 2019 American Community Surveys (ACS) to measure socioeconomic and community characteristics for each ZCTA. We identify economically disadvantaged communities with a dummy variable (POV20) for high poverty using a 20% cutoff within each ZCTA, a common threshold in social science research (Iceland & Hernandez, 2017) and the U.S. Census Bureau. To tap the racial characteristics of communities, we follow the Federal Reserve Bank of New York (Mills & Battisto, 2020) and create a dummy variable for minority communities (MajMin) where more than half the population in the ZCTA is not White. Finally, to control for conditions in banking markets that served communities, we follow Schneiberg and Parmentier (2021), Petach et al. (2021), and Li and Strahan (2021) and use county-level measures for banking markets but replicate our approach using commuter zones. We calculate branch-establishment ratios (number of bank and credit union branches per county over the number of establishments) to control for the overall coverage or lending capacity of local banking markets and counts of each lender type to control for the prevalence and availability of institutions of any given type in local markets. We calculate averages for returns on assets, capital ratios, core deposit ratios, and exposures to privately issued mortgage-backed securities for all banks doing business in a county, weighted by their branches' share of county deposits to control for the performance and stability of local markets. We use averages of the proportions of each bank's total branches that were located in the county for all banks operating in that county, weighted by their deposit shares there, to control for the overall localism in banking markets. We use the U.S. Census Bureau's 2010 relationship files to link our county and commuter zone-level market data to ZCTAs. Most ZCTAs (72%–77%) fall entirely within a single county or zone, so linking markets to local communities was a matter of simply assigning to each ZCTA the bank market data for the appropriate county or zone. For ZCTAs that span multiple counties, we create a composite market using the averages of the data for the ZCTA's counties or zones, weighted by the proportions of the ZCTA's population that fell in each place.

Methodology

We are interested in the sensitivities of lender types and their PPP loan flows to poor and minority communities and focus on PPP loans to ZCTA overall and for each institution type. We first present descriptive findings on the weight of each of our seven lender types in the PPP (How much did they lend?), on their spatial coverage (In what percentage of communities did they lend?), and on the differences in the lending across communities with different socioeconomic community (How much of their lending went to minority–majority and high-poverty ZCTAs?)

We then conduct a multilevel statistical analysis of whether associations between PPP lending outcomes and the socioeconomic status of communities vary by lender type. Our questions here are: Do loan flows of different lenders respond differently to whether a community is poor versus not poor or minority versus majority White? Are some lenders more or less deterred than others from issuing PPP loans? Are some lenders more or less attracted to poor or minority than to nonpoor and majority-White communities?

We analyze separately two lending outcomes for empirical and theoretical reasons: (1) whether firms in a community received any PPP loan from a particular lender and (2) the number of PPP loans that firms in a community received (if they received any) loans from that lender type. One feature of the data is a very large number of zeros, reflecting significant variation in how different lender types operate and make loans across communities. Coverage rates vary from 94% (community banks) to 28% (FCSs). Moreover, the factors that determine whether a lender makes any loans in a ZCTA might differ in kind or impact magnitude from what determines the number of loans eventually made in the ZCTA. As discussed above, historical legacies, SBA and Bank Secrecy Act filing, registration, and verification requirements create hurdles for potential customers and conduits for the influence of existing business relationships and prepandemic conditions. These conditions could directly affect whether lender types make PPP loans, especially during the first PPP rounds, in ways that matter less as to the number of loans lenders make once they lend, which might be more sensitive to current conditions and more or less influence communities' poverty or minority status.

We use Hurdle-Negative Binomial models to address these data and analytical challenges (Greene, 2008, p. 922; Terza & Wilson, 1990). These combine a dichotomous model for the first stage with a truncated count model for the second stage. In our application, they let us estimate two separate equations. First, a logistic regression for whether banks or a bank type do not issue any loans in a ZCTA (inflate) and second, a truncated negative binomial regression for the number of PPP loans if they do issue some in a ZCTA (count). This technique is suitable for count data with excess zeros, which is the case in our study since bank types do not lend in all ZCTAs and some specialist bank types lend in relatively few. This technique can handle overdispersion, which is also a feature of our data. It also allows for simultaneously estimating models of whether lenders lend in a ZCTA, as well as the count of loans made conditional on their lending, and it lets the effects of covariates differ for the two outcomes.[5]

We fit hurdle models for each lender type to generate type-specific estimates of the sensitivities of PPP loan flows to communities' poverty and minority status. To isolate those associations, we include variables for population and the number of businesses within ZCTAs as controls for community size and potential demand for PPP loans.[6] We include county-zone and commuter-zone level variables for the size, localism, composition, and performance of banks in the local lending market, and model-specific counts for each lender type to control for the size and other characteristics of banking markets that serve their communities.[7] Whether or how much lender types lend in ZCTAs could depend heavily on the presence or prevalence of that type in the local banking market, especially for small, local, and relationally oriented alternative banks. We also extend our multilevel strategy to incorporate random effects for states to account for unmeasured effects of state-level factors.

Finally, to assess whether poverty and minority community effects on PPP provision significantly differ across lender types, we use Generalized Structural Equation Models (GSEM) to jointly estimate type-specific logistic regressions for whether ZCTAs received loans, and then negative binomial count regressions by type, which allows for Wald tests for the equality of coefficients across models.

Descriptive Findings

PPP outputs varied markedly across lender institution types. Figure 1 shows the coverage rates, or the percentage of ZCTAs in which each type of lender made any PPP loans. Coverage reflects the size and scope of each subsystem and where lender types choose to make loans. Roughly 98% of all ZCTAs received at least one PPP loan, but coverage across types is uneven, with some institutions playing a targeted role. While community banks made loans in 94% of all ZCTAs, fintechs, Top 50 banks, CDFIs, and LMCBs all made loans in 72% to 75% of ZCTAs. The performance of CDFIs and fintechs is particularly surprising given their small numbers compared with the large banks and community banks. Credit unions and the even more specialized FCS institutions lent in 53% and 19% of ZCTAs, respectively.

Figure 2 charts the share of each lender type in terms of the total number and dollar amount of PPP loans. The figure points to differences in bank types' role in the program and the types of loans made by each bank. Together, community banks, Top 50 banks, and LMCBs account for two-thirds of all loans in the program but 85% of the total value of loans, suggesting that some in this group made much larger loans than others. CDFIs and fintechs accounted for 14% and 22%, respectively, but for only 5% and 8% of the value of all loans, suggesting smaller and more targeted lending. This may reflect policy changes that admitted alternative lenders later in the program.

While Top 50 and community banks stand out as the most active PPP lenders, fintechs made as many loans as the Top 50 banks. In addition, despite the concentration of assets in Top 50 banks and claims about the virtue or necessity of giant, diversified banking behemoths, the smaller decentralized community banking system was more effective in delivering PPP loans to small businesses in terms of loan numbers, value, and geographic conference. Alternatives figured prominently in the PPP.

Figure 3 depicts the average and median size of loans by bank types. These data confirm concerns that large bank holding companies make much larger loans than other banks given their focus on lending to large corporations, supporting worries at the start of the PPP that large banks' lending to large corporations left out SMEs. The average size loan by a Top 50 and LMCB was $102,234 and $127,429, respectively. In contrast, median loan amounts are much smaller and more similar across bank types, reflecting the small proportions of very large loans, especially among the Top 50 and large-sized and medium-sized banks. However, the rank ordering generally holds here. Firms serviced by CDFIs, credit unions, FCS's, and fintechs received smaller loans and were likely smaller (averaging less than $25,000) than loans to firms serviced by community banks.

Bank Types, Poverty, and Race

Figures 4 and 5 break down the coverage ratios across poor and minority ZCTAs by each bank type. Overall, all bank types lent in a higher percentage of low-poverty than high-poverty ZCTAs, but the drop off in coverage rates of high-poverty areas varies by bank type. Credit unions and FCS institutions marked particularly pronounced drops in coverage rates in moving from low to high poverty communities. CDFIs show the least difference in coverage ratios between low-poverty and high-poverty ZCTAS.

Findings for race are different. Two institutions—community banks and FCS lenders—made loans in a larger share of White than non-White ZCTAs. The five other lender types show the opposite trend: CDFIs, credit unions, fintechs, Top 50 banks, and LMCBs lent in a higher percentage of minority than majority White ZCTAs. CDFIs display the greatest proclivity to lend more widely in minority than majority White places.

Figure 6 illustrates the priorities of each lender type by describing the percentage of loans made to poor and minority ZCTAs. Overall, high-poverty ZCTAs (i.e. those with poverty rates 20% or more) make up 18.6% of all ZCTAs in the United States, yet they received 16.1% of all PPP loans. These amounts vary dramatically by bank type. Community banks, Top 50 banks, credit unions, FCS institutions, and LMCBs each channeled approximately 10% of their PPP loans to poor ZCTAs. Fintechs and CDFIs, on the other hand, concentrated their lending far more heavily in these places. More than 25% of CDFI loans and 20% of fintech loans went to high-poverty ZCTAs.

The pattern is even more extreme in minority ZCTAs. These make up 8.5% of all ZCTAs, and nearly 20% of all PPP loans went to businesses there. At one extreme stand FCS, which made <2% of their PPP loans to minority places, followed by credit unions and community banks, who channeled <10% of their loans there. Top 50 s and LMCBs directed approximately 15% and 10% of their lending toward those communities, respectively. CDFIs and fintechs channeled nearly 40% and 33% of their PPP loans to minority ZCTAs, respectively.

Our descriptive analysis indicates stark differences in PPP loan flows across lender types. CDFIs and fintechs prioritize majority non-White and poor communities whereas Top 50 banks and especially community banks, credit unions, and FCS lenders appear to avoid or lend less to poor and especially minority communities. We investigate these trends further through our statistical models below.

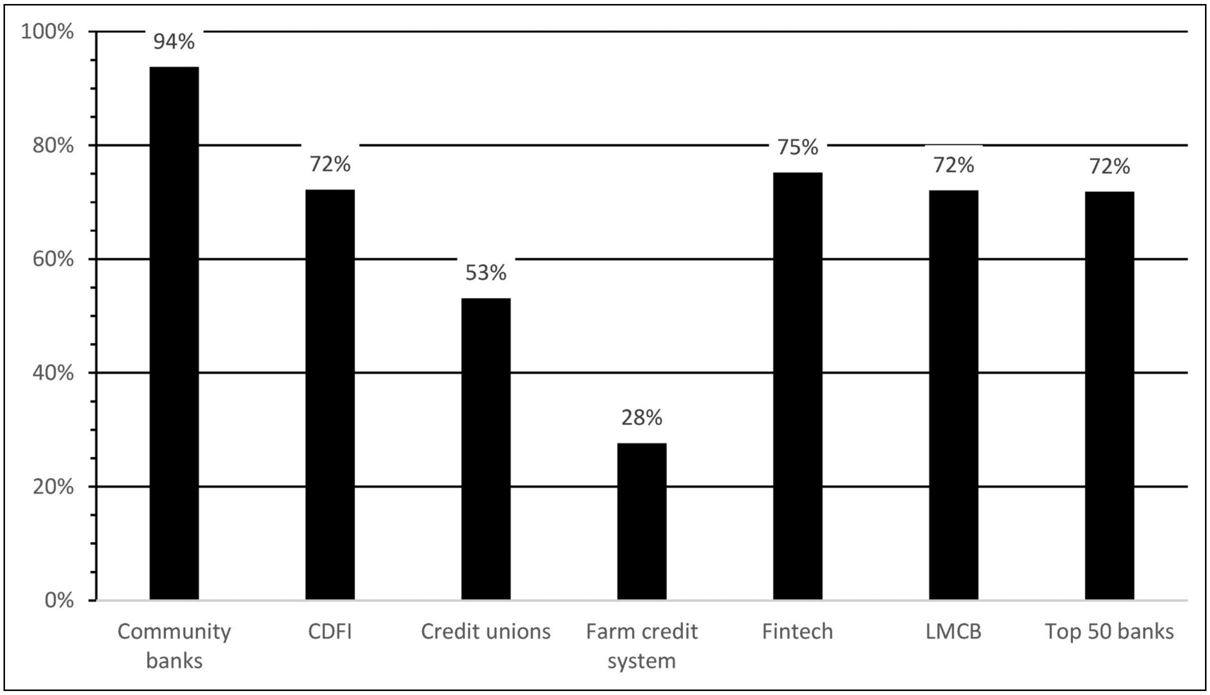

Figure 1. *ZCTA coverage rate by bank type.* Note: The overall coverage rate is 97.6% (i.e., 32,148 of 32,931 ZCTAs have received at least one PPP loan, while 783 ZCTAs have not). PPP= Paycheck Protection Program; ZCTA= ZIP Code Tabulation Areas.

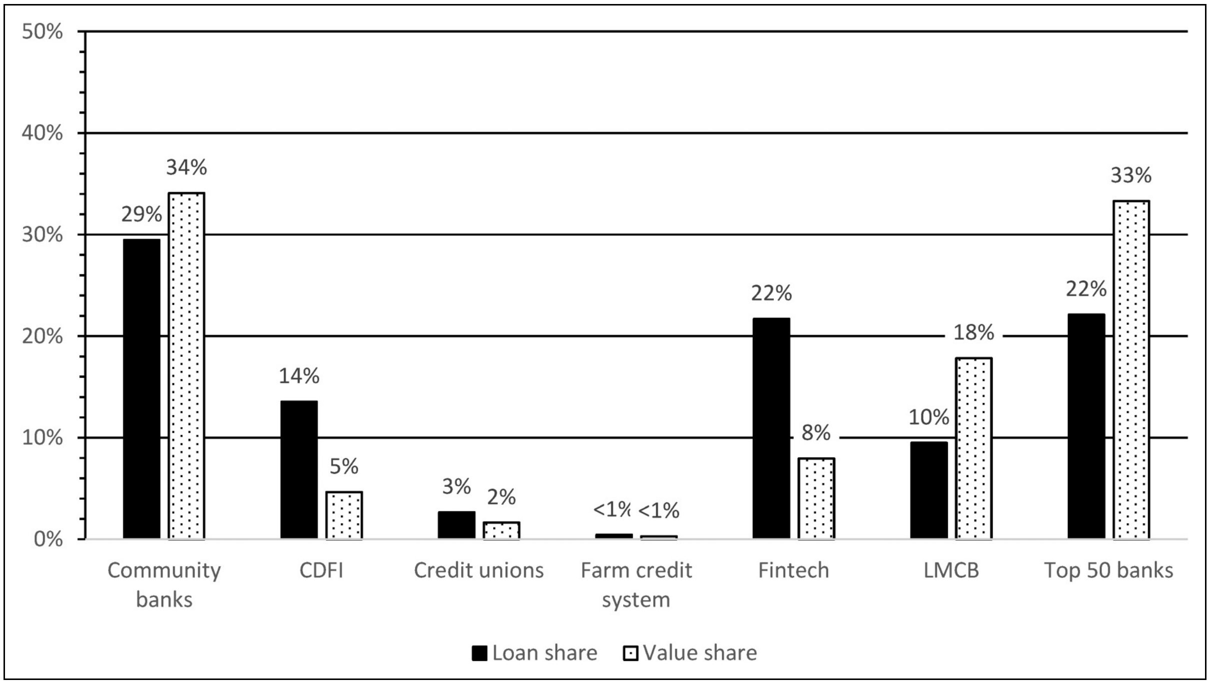

Figure 2. *Number and value of loans, share by bank type.* Note: The total number of PPP loans in our dataset is 11,656,667, with a total value of $791,688,326,866 (SBA, 2021). PPP= Paycheck Protection Program

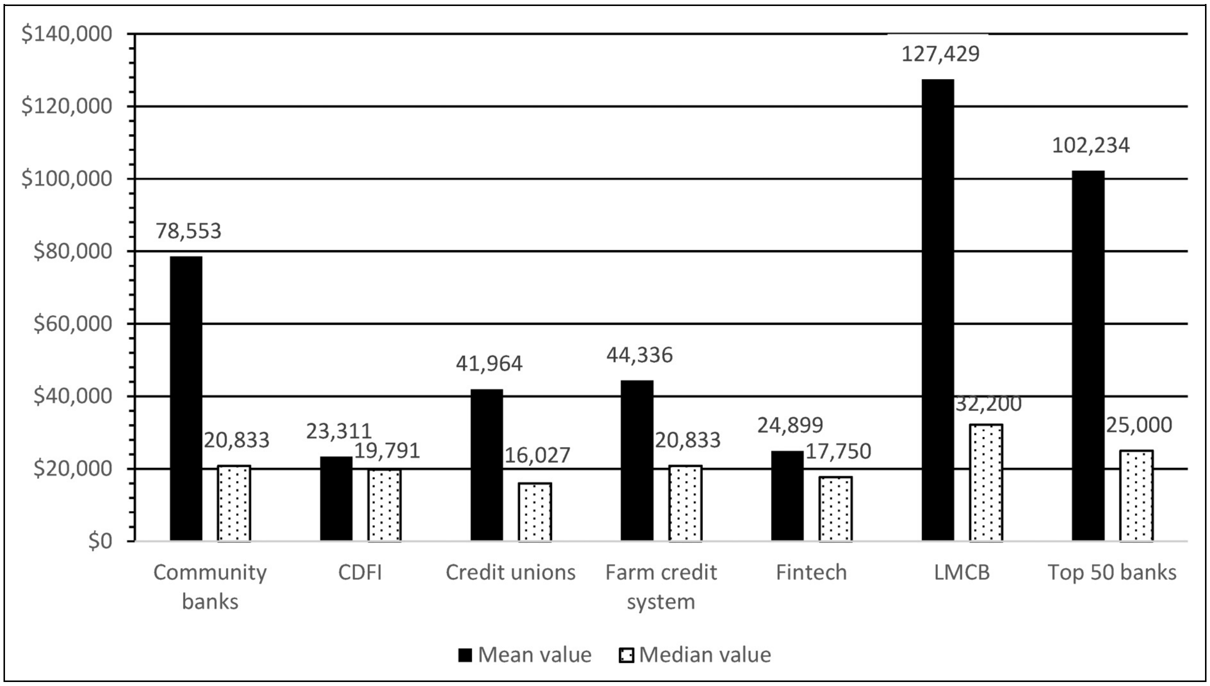

Figure 3. *Average and median loan values by bank type.* Note: The average PPP loan in our sample has a value of $67,917. PPP= Paycheck Protection Program

Statistical Models

Table 1 presents results from our hurdle-count models of PPP loan flows to communities for all lenders and each of the seven lender types. These have two components, a logistic regression or hurdle model for what affects the probability of zero (i.e. a lender type not making any loans in a ZCTA), and a count model for the number of loans a type made in a ZCTA. The rationale is that there are two distinct lending outcomes of interest, and that the processes shaping whether a lender type is active in (or avoids) a ZCTA may differ from those shaping a type's lending levels once it is active there. The parameter estimates for the hurdle and count models resemble two regressions and are stacked on top of each other in Table 1, with results for the hurdle (zero loans) model in the lower panel and those for the conditional count model in the top one.[8] Figure 7 presents coefficient plots based on the results from Table 1 for the hurdle and count model estimates of the effects of high poverty and minority status on loans flows to communities for the seven lender types. Finally, Table 2 presents results from four separate Wald tests for the equality of coefficients across the logistic and count models for the high poverty and minority community status variables.[9]

The Wald tests results in Table 2 confirm that we can reject the null hypotheses of equal coefficients across models in all four cases, indicating that the differences in lender-type sensitivities to community poverty and minority status observed in Table 1 and Figure 7 are statistically significant.

Results from the "zero loans" hurdle models depicted in the bottom panels of the table and figure confirm patterns depicted in our descriptive findings. Results for community banks and FCS institutions are consistent and qualify them as standouts. For both types, the likelihood of not making loans is significantly higher both in high-poverty than in low-poverty ZCTAs and in minority than in majority White ZCTAs. These effects are substantial. Controlling for minority status, number of businesses, banking market characteristics, and the presence of each lender type in the regional market, moving from a low-poverty to a high-poverty status increases the odds of a community not receiving any PPP loans from community banks by 58% and from FCS lenders by 144%. Controlling for poverty, number of businesses, and the like, moving from a White-majority to minority–majority status increases the odds of a community not getting any PPP loans from community banks by 62% and FCS lenders by 169%.

A second group of credit unions, LMCBs, and Top 50 banks displays a more mixed to neutral profile. Credit unions and the Top 50 banks were more prone to not make loans to high-poverty than to low-poverty communities. Credit unions stood out here, with effects akin to community banks; the effects for the Top 50 were roughly a third of that. Poverty effects for LMCBs were not significant. All three showed indifferent behavior vis-à-vis minority ZCTAs and

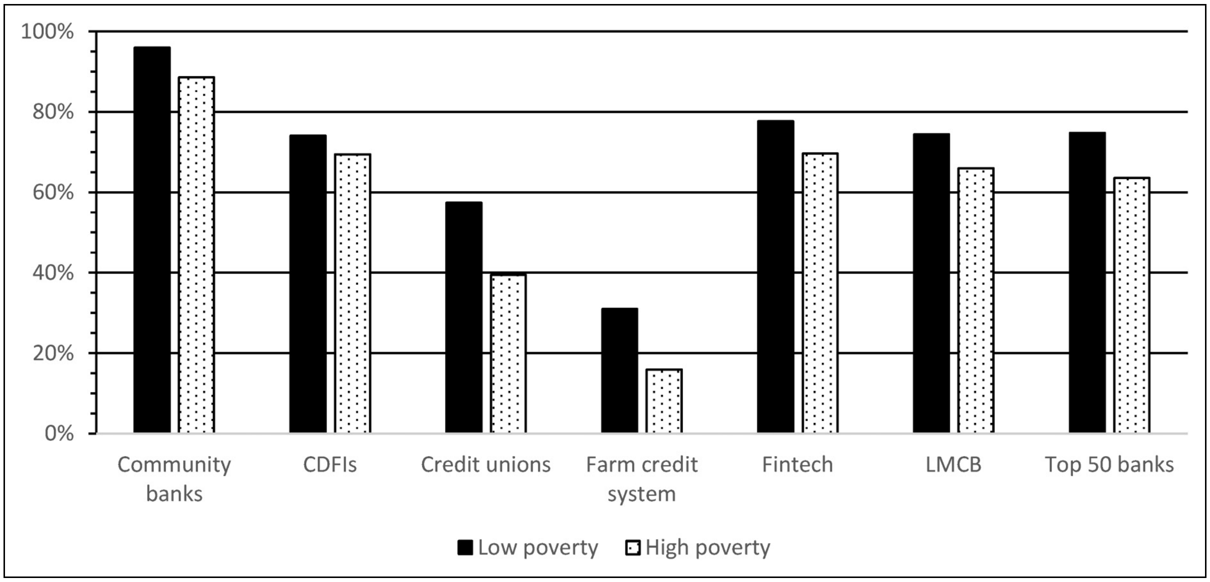

Figure 4. *Coverage rate of ZCTAs by bank type and poverty rate.* Note: 98.7% of all low poverty and 95.6% of all high poverty ZCTAs have received at least one PPP loan. PPP= Paycheck Protection Program; ZCTA= ZIP Code Tabulation Areas.

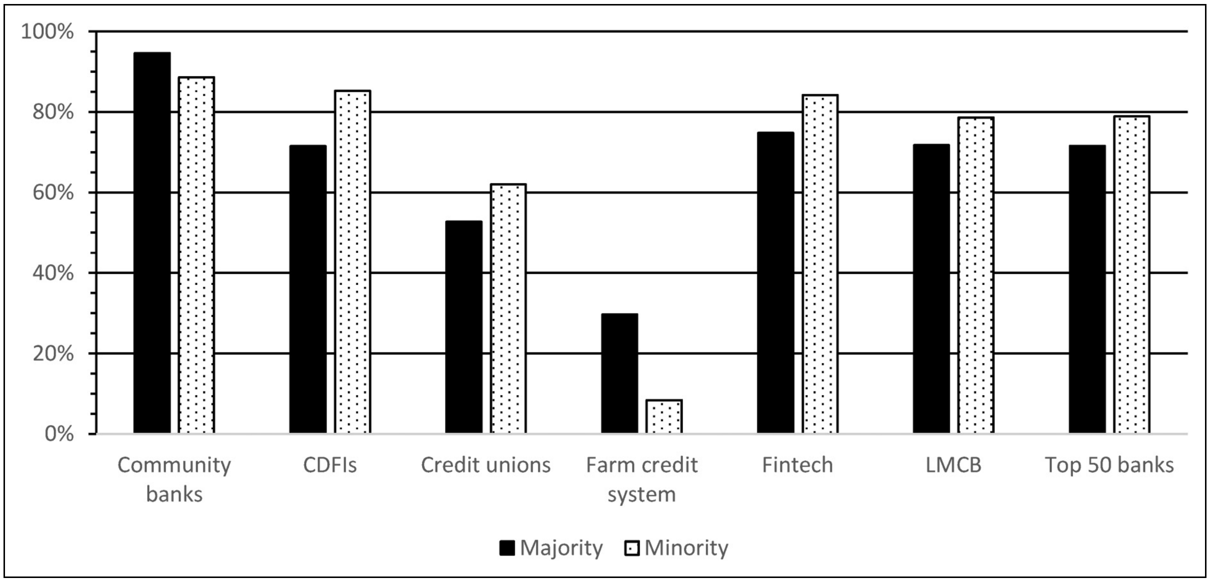

Figure 5. *Coverage rate of ZCTAs by bank type and minority population.* Note: 98.1% of all majority and 95.4% of all minority ZCTAs have received at least one PPP loan. PPP= Paycheck Protection Program; ZCTA= ZIP Code Tabulation Areas.

insignificant coefficients for that variable, indicating that they were just as likely to make loans to minority as to White communities.

At the other end of the spectrum, fintechs and CDFIs are the most inclusive PPP lenders. The poverty coefficient for fintechs was insignificant, indicating that high-poverty communities were neither more nor less likely than low poverty ones to receive PPP loans from fintechs. Yet the minority coefficient for fintechs and both the poverty and minority for CDFIs were negative and statistically significant, indicating fintech and CDFIs were more likely to make PPP loans to firms in minority than in White communities. Controlling for poverty, businesses, and the like, moving from White-majority to minority–majority status reduces the odds of a community receiving no PPP loans from CDFIs by 62% and fintechs by 58%. Moving from a low-poverty to high-poverty status reduces the odds of a community not receiving loans from CDFIs by 20%.

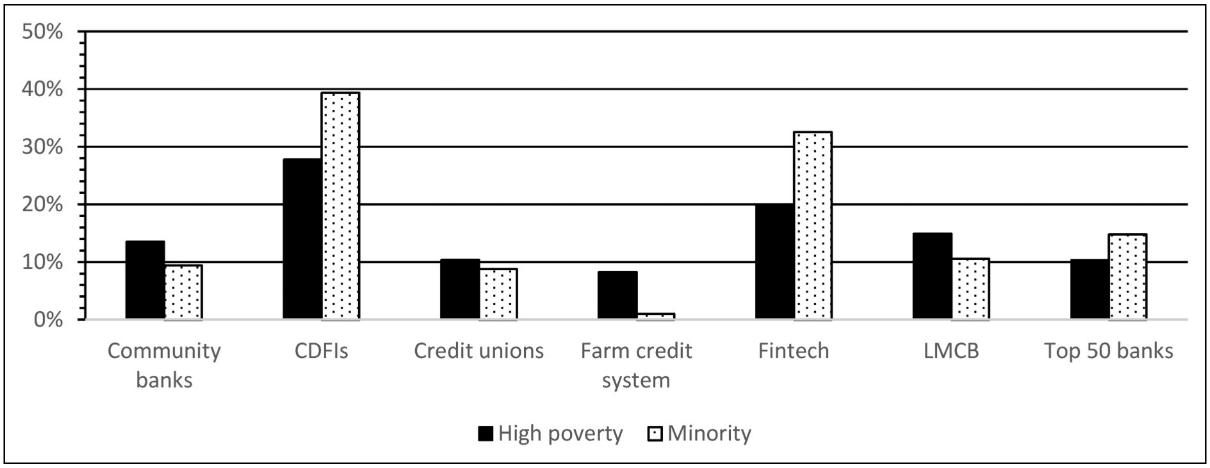

Figure 6. *Lending specificity by bank type, loan shares in high poverty and minority ZCTA.* Note: There are 6,115 (or 18.6%) high-poverty ZCTAs. They have received a total of 1,868,376 (or 16.1%) PPP loans. There are 2,812 (or 8.5%) minority ZCTAs. They have received a total of 2,287,874 (or 19.7%) PPP loans. PPP= Paycheck Protection Program; ZCTA= ZIP Code Tabulation Areas.

The count model results in the upper half of Table 1 and the top two plots in Figure 7 shed more light on variability in inclusivity, generally confirming our grouping. Five lender types returned significant negative coefficients in Table 1 for high poverty and minority status, and exponentiated coefficients of <1 in Figure 7. Community banks and FCS institutions, which were both more likely to not make loans in high poverty and minority than other communities, also made fewer PPP loans on average to the high-poverty than to the low-poverty communities in which they did any lending, and fewer loans, on average, to minority than to White communities. Credit unions, Top 50 s, and LMCBs, which displayed a more neutral profile in terms of not making PPP loans, also made fewer loans, on average, to high-poverty than to low-poverty and minority communities than to White communities, though declines in expected loan counts for disadvantaged communities were relatively small, ranging from 13% to 15% for Top 50 banks and credit unions, respectively. In contrast, fintechs and CDFIs are the only two PPP lender types for which high-poverty ZCTAs and communities of color were associated with increasing average loan counts, a markedly inclusive profile that replicated their no-loan results. Net of their other status, number of businesses, bank market characteristics, and so on, high-poverty communities received, on average, 14% more PPP loans from fintechs and 39% more PPP loans from CDFIs than did low-poverty communities. Minority communities received on average 116% more PPP loans from fintechs and 153% more loans from CDFIs than did White communities.

Conclusion

COVID-19 exacerbated socioeconomic, racial, and gender inequalities, the rural–urban divide, and decimated small businesses across the country (Blundell et al., 2020; Van Dorn et al., 2020). Moreover, in implementing its recovery efforts through an established system of private lending institutions with a troubled history in marginalized poor and minority communities, the PPP disproportionately benefited businesses in low-poverty and White-majority communities, reproducing class and ethno-racial fractures in business and local economic and community development. To address this problem and promote inclusivity, the SBA admitted new lenders—including nondepository institutions–developed guidelines to help self-employed individuals participate in the program and did a better job of targeting funds to minority-owned businesses (GAO, 2021). Our study highlights the importance of devoting sustained attention to the heterogeneity of lenders as unique systems with different missions, business models, governing structures, and impacts on the social and institutional infrastructure in local economies. We also demonstrate each type's distinctive role in shaping the deployment of PPP funds, particularly in underserved poor and minority communities.

We find that by empowering private lenders as the gatekeepers of the PPP, poor and minority communities are disadvantaged. We also find that lender types significantly impact how the benefits of the PPP are distributed and how dramatically they differ in their sensitivities lending practices to communities with poverty and minority status. Prior work identified the size of banks (Li & Strahan, 2021) as important and produced studies that have begun to document differences by lender type, particularly between banks and fintechs, in racial disparities and access to credit (Chernenko & Scharfstein, 2022; Erel & Liebersohn, 2022; Fei & Yang, 2022; Howell et al., 2021). We contribute an analysis across a full range of lender types that shows how their lending practices vary by communities' class and ethno-

Table 1. Hurdle-Negative Binomial Regression Results.

	All banks	Community banks	CDFIs	Credit unions	Farm credit	Fintech	LMCB	Top 50 banks
Count model				*Dependent variable: number of loans*				
High poverty	−0.13*** (0.01)	−0.17*** (0.01)	0.33*** (0.02)	−0.17*** (0.03)	−0.16** (0.05)	0.13*** (0.01)	−0.12*** (0.02)	−0.14*** (0.01)
Majority minority	0.34*** (0.01)	−0.10*** (0.01)	0.93*** (0.02)	−0.15*** (0.03)	−0.45*** (0.10)	0.77*** (0.02)	−0.25*** (0.02)	−0.15*** (0.02)
Controls (ZCTA)								
Population (log)	0.19*** (0.01)	0.08*** (0.01)	0.67*** (0.01)	0.18*** (0.02)	0.16*** (0.04)	0.55*** (0.01)	−0.03* (0.01)	0.10*** (0.01)
# Businesses (log)	0.68*** (0.01)	0.73*** (0.01)	0.31*** (0.01)	0.64*** (0.02)	0.18*** (0.04)	0.44*** (0.01)	0.83*** (0.01)	0.72*** (0.01)
Controls (county)								
Branches	0.04*** (0.01)	0.04*** (0.01)	0.09*** (0.01)	0.29*** (0.02)	0.03 (0.02)	−0.14*** (0.01)	−0.09*** (0.01)	−0.39*** (0.01)
Return on assets	0.06*** (0.01)	0.05** (0.01)	0.13*** (0.03)	0.09* (0.05)	0.21*** (0.06)	−0.06** (0.02)	0.01 (0.02)	−0.01 (0.03)
Bank market localism	0.19*** (0.02)	0.72*** (0.02)	−0.39*** (0.04)	−0.20*** (0.06)	0.29*** (0.09)	−0.21*** (0.03)	−0.96*** (0.04)	−0.89*** (0.03)
# Lenders of same type	0.01*** (0.00)	0.02*** (0.00)	0.04*** (0.00)	−0.04*** (0.00)	−0.02*** (0.00)	0.04*** (0.00)	0.01*** (0.00)	0.10*** (0.00)
Population (log)	−0.00 (0.00)	−0.15*** (0.00)	0.17*** (0.01)	0.20*** (0.01)	−0.09** (0.03)	0.25*** (0.00)	−0.01 (0.01)	0.13*** (0.01)
Intercept	−0.29*** (0.07)	−1.15*** (0.09)	−7.33*** (0.15)	−5.87*** (0.21)	−1.14** (0.36)	−6.89*** (0.10)	−0.92*** (0.18)	−2.69*** (0.12)
Zero model				*Dependent variable: making no loans*				
High poverty	0.50*** (0.10)	0.46*** (0.07)	−0.22*** (0.04)	0.61*** (0.04)	0.89*** (0.04)	−0.02 (0.05)	0.08 (0.04)	0.17*** (0.05)
Majority minority	0.25 (0.15)	0.48*** (0.10)	−0.97*** (0.09)	−0.02 (0.06)	0.99*** (0.07)	−0.87*** (0.09)	−0.09 (0.07)	−0.15 (0.08)
Controls (ZCTA)								
Population (log)	−0.17*** (0.05)	−0.09* (0.04)	−0.81*** (0.03)	−0.27*** (0.03)	0.06* (0.03)	−0.84*** (0.03)	−0.34*** (0.03)	−0.73*** (0.03)
# Businesses (log)	−1.38*** (0.06)	−1.28*** (0.04)	−0.45*** (0.03)	−0.53*** (0.03)	−0.44*** (0.03)	−0.54*** (0.03)	−0.55*** (0.03)	−0.45*** (0.03)
Controls (county)								
Branches	0.10 (0.05)	0.08* (0.04)	0.12*** (0.02)	0.22*** (0.02)	−0.33*** (0.02)	0.13*** (0.02)	0.18*** (0.02)	0.42*** (0.03)
Return on assets	−0.29* (0.14)	−0.25* (0.10)	−0.12* (0.06)	−0.15* (0.06)	−0.19** (0.05)	0.02 (0.06)	−0.08 (0.05)	0.12* (0.06)
Bank market localism	−0.52* (0.24)	−1.58*** (0.18)	0.27** (0.09)	0.51*** (0.08)	−0.95*** (0.07)	0.46*** (0.09)	0.91*** (0.08)	1.17*** (0.10)
# Lenders of same type	−0.03*** (0.01)	−0.19*** (0.01)	−0.29*** (0.02)	−0.01*** (0.00)	0.01*** (0.00)	−0.03 (0.03)	−0.27*** (0.01)	−0.46*** (0.02)
Population (log)	0.41*** (0.07)	0.63*** (0.03)	0.04* (0.02)	−0.19*** (0.02)	0.27*** (0.02)	−0.26*** (0.01)	0.37*** (0.02)	0.17*** (0.03)
Intercept	−2.95*** (0.80)	−4.12*** (0.43)	6.34*** (0.26)	6.08*** (0.25)	0.17 (0.23)	9.12*** (0.27)	−0.02 (0.25)	3.77*** (0.29)
AIC	348873.0	299785.3	198775.2	141863.6	76000.5	209432.2	211563.5	214029.5
Log likelihood	−174414.5	−149870.7	−99365.6	−70909.8	−37978.2	−104694.1	−105759.8	−106992.8
Number of observations (ZCTA)	32,093	32,093	32,093	32,093	32,093	32,093	32,093	32,093
Number of groups: state	50	50	50	50	50	50	50	50
Var (count model): STATE (intercept)	0.11	0.20	0.61	0.70	1.29	0.21	0.92	0.21

***$p < .001$; **$p < .01$; *$p < .05$.

CDFI= Community Development Financial Institutions; LMCB=large-and-medium-sized commercial bank; ZCTA= ZIP Code Tabulation Areas.

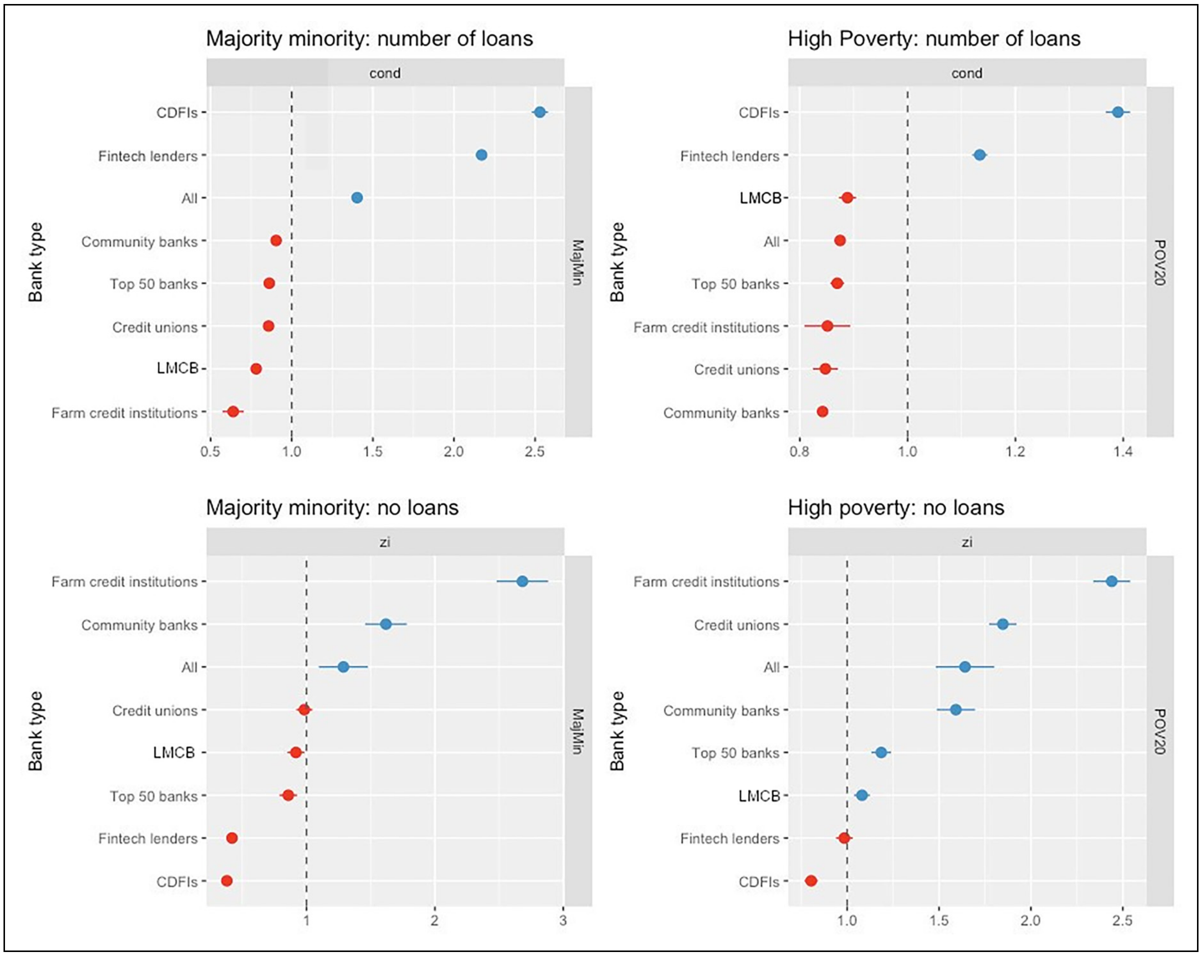

Figure 7. Exponentiated coefficient plots with 95% confidence intervals.

Table 2. Wald Test for Equality of Coefficients.

	H0: Equality of minority coefficients all groups	H0: Equality of poverty coefficients all groups
Count models (number loans)	$\chi^2 = 5644.02$ $p < .0001$	$\chi^2 = 2226.40$ $p < .0001$
Logit models (no loans)	$\chi^2 = 413.34$ $p < .0001$	$\chi^2 = 489.20$ $p < .0001$

racial compositions. We analyze both whether each class of institutions did any PPP lending in (or avoided) communities and how extensively each lender class lent to places in which they made any loans. We compare, test for, and find marked differences across lender types in their outcomes in poor and minority communities. And we look beyond technology and size to consider competing hypotheses about how these differences are rooted in institutions' organizational and ownership forms, core business models, and missions. We see how the ecologies of lender institutions shape social and organizational infrastructure in their communities.

Contrary to our first set of hypotheses, we find that the dichotomy of "alternative banks versus market-based bank corporations" is too broad a theoretical container to capture the subtle differences in inclusivity vis-à-vis business in poor and minority communities receiving credit and relief through the PPP. Instead, variations across lender types in how loans flowed to communities were consistent with our second set of hypotheses, which highlighted how size, relational banking, localism, and mission combined with segregation and the historical legacies of marginalization in different ways. Fintechs, and especially CDFIs, appear to proactively engage businesses in poor and minority communities. This significantly increases their lending activity when they move from low-poverty to high-poverty or from White-majority to minority communities. Community banks and FCS institutions, in contrast, stand out as the least inclusive lenders, being more likely to avoid any lending (or less lending) to poor or minority communities relative to better off and White communities. Moreover, to varying degrees, market-based derivative giants, LMCBs, and perhaps credit unions fall in the middle. All three issued relatively fewer PPP loans to high-poverty and minority communities, while market-based bank giants, and especially credit unions, were more likely to not make any loans to high-poverty communities. Yet all three seemed undeterred by a community's minority status. Market-based giants and credit unions made almost as many PPP loans in marginalized, low-poverty, or majority White communities. We started with two conflicting sets of hypotheses. We find more support for Hypotheses 2a and 2b than for Hypotheses 1a and 1b. Alternative banks displayed striking heterogeneity, marking the two poles and market-based bank giants and LMCBs displayed some marked neutrality toward doing at least some PPP lending in minority communities.

Offering a first look at a complex topic through a unique data set, our findings have several policy implications and suggest puzzles for future research. One implication of our research is that relying on private lenders as gatekeepers may have some advantages, but without proper oversight and regulation it will likely disadvantage poor and marginalized communities. A second policy implication is that CDFIs and possibly fintechs are bank types that governments should support and empower if their objective is to help businesses in poor and marginalized communities. CDFIs, in particular, whose mission is to support poor and marginalized communities, are the keys to financial inclusivity.

As is typical, our paper raises more questions than it answers. One question is about how the program evolved over time and goes to the heart of the oversight problem. In response to pressures for inclusivity, the SBA made significant changes in the PPP over its three phases. This article examines the program in its entirety, including the entire universe of loans, leaving unclear how changes in phases 2 and 3 shaped bank type lending across communities. Preliminary analyses suggest our rankings of inclusivity by race and poverty shift somewhat over time as lending institutions, their SME customers, and policy makers evolve in response to political pressure and experienced policy learning over the program's phases. This raises important questions about how oversight, policy changes, and variety in organization form can interact to foster credit inclusivity, which we examine in an upcoming paper.

Our results also highlight the need to compare fintechs in all their forms and CDFIs. The two bank types could not be more different in terms of their size, governance, relationships with and connections to their customers. Yet fintechs and CDFIs are the most inclusive bank types in terms of PPP lending to firms in poor and minority communities. Such a finding begs the causal question of why these two bank types are the most inclusive. Do fintechs and CDFIs lend to the same types of businesses and on the same terms? Are there multiple paths to inclusivity in credit markets?

Finally, our research highlights the potential importance of the organizational composition of banking markets. How do the ecologies of lenders that populate local markets vary, and how might that shape the behavior, inclusivity, or exclusivity of different lender type? Might the presence of more inclusive lenders like fintechs or CDFIs alter other institutions' lending behavior and sensitivities? We intend to address all these puzzles in future papers.

In the end, our analyses suggest two crucial insights about lending and inclusivity. The first pertains to some potentially powerful liabilities of relational banking as practiced by community banks and suggest that "fast ain't fair." With dedicated staff, proximity, and established relationships to business borrowers, community banks stood out as being able to get loans immediately into small firms' hands in the first weeks of the PPP, which was vital for keeping them afloat and their workers employed (Allen & Whitledge, 2022; Faulkender et al., 2020; Granja et al., 2021; Li & Strahan, 2021). Our findings indicate that speed comes at a price. Relational banking, in combination with homophily in network ties and residential segregation, can bias flows of loans away from poor and traditionally marginalized communities of color.

Second, there seem to be two roads to inclusivity, each associated with different trade-offs, strengths, and weaknesses. One is based on technology and digital interfaces, the other on mission, relationship building, trust, and dedicated ties to marginalized communities. CDFIs epitomize the latter while the former lies in new, or recently transformed, fintech lenders (some of which were set up for disbursing PPP loans). Traditionally, CDFIs' core strengths lay in how they combine an explicit mission to help the historically disadvantaged by using regulatory support and collaborations with community-based and other financial institutions with their in-depth knowledge of customers, as well as a relational approach to banking that nurtures businesses' long-term development. With a few notable exceptions, CDFIs pursue a high-touch, labor-intensive approach involving sustained one-on-one interactions with business borrowers. Yet this is a business model that does not scale up easily and was particularly an acute problem during the pandemic among CDFIs that stayed with their traditional course. Moreover, CDFIs' primary customer base may lack the resources and savings to generate sustainable interest or fees, making them dependent on public or nonprofit support. These trade-offs, in our view, raise key questions for future exploration of whether and how CDFIs might overcome these constraints at scale, and whether recent or proposed ways of combining CDFI models with elements of other lending forms are productive ways to proceed.

Fintechs, in contrast, have succeeded with quite a different business model, especially with the PPP, and have evoked justifiable excitement for their potential to reduce racial disparities in small business lending. They demonstrated abilities to scale up quickly, reach large numbers of often difficult-to-reach customers, and exploit economies of scale to profit on making very small loans, while avoiding the historical racial baggage of traditional banks, and engaging with customers through convenient online processes that rely on computer algorithms that are quick and perceived by customers as unbiased. Yet unlike the longer-range, community-oriented, mission-based lending path pursued by CDFIs, fintechs do little, if anything, to build infrastructures for economic or individual business development within marginalized communities or to create sustainable ties between businesses, households, creditors, and community organizations. Since they are not embedded in any community, fintechs lack both the local knowledge or the incentive to improve a community or region, and connections with local development officials and community-based organizations that have worked hard for decades to help businesses survive and thrive in marginalized communities. Furthermore, since they short-circuit traditional labor-intensive lending processes, online fintech lenders may not only be uniquely vulnerable to lax oversight and large-scale fraud (Griffin et al., 2023), but may, once appropriate oversight and checks are in place, prove most suitable for minority small businesses that are least in need of extensive technical support and a personal touch to navigate requirements. Indeed, important questions remain for future work about how extensively a fintech model can sustain the level of inclusivity it traced during the PPP in settings where lenders assume credit risk. How does a model based on a relentlessly impersonal approach help businesses who, in the past, have relied on extensive one-on-one relationships with the community-based organizations and lenders to thrive? How many and which businesses were served well by these lenders in poor or Black and Brown communities? And how can fintech lenders be thoughtfully integrated into the economic development efforts of communities who have been seriously harmed and are justifiably wary of flocks of new lenders and predatory practices?

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ORCID iDs

Mark K. Cassell https://orcid.org/0000-0002-3043-8834
Michael Schwan https://orcid.org/0000-0003-0089-2742
Marc Schneiberg https://orcid.org/0000-0002-3974-5670

Notes

1. Credit unions are cooperatives owned and operated by their depositor-members and organized democratically, at least in principle, according to a "one member, one vote" rule (e.g., Hoffmann, 2001; Walter, 2006).
2. The FCS is a nationwide network of cooperative lending institutions that provides credit to US agriculture (Dang et al., 2014). FCS banks make primarily long-term real-estate loans, although they also lend directly to cooperatives and other entities. The banks obtain funds by issuing system-wide debt securities, common and preferred equities, and subordinated debt (FCA, 2017).
3. CDFI is a federal certification administered by the US Department of Treasury and applied to various financial institutions, including community banks, credit unions, nonprofit and for-profit loan funds, venture funds, and community development corporations. To be eligible for certification, CDFIs must have an explicit mission to provide credit, technical assistance, financial education, and other financing services to low-income individuals and reinvest in low-income or economically distressed, often minority, communities.
4. We code for top derivative holdings rather than just size to capture specifically the embrace of a market-based banking business model among the largest bank corporations, which is itself a critical determinant of bank behavior (Davis, 2009; Hardie et al., 2013; Tett 2009), and to distinguish these lenders from other large national banks who remain committed to conventional banking. We code for community banks using FDIC (2012) protocols, which are based on asset thresholds for size, limit on geographical scope and numbers of branches to ensure localism, and high loan-to-asset ratios and other measures to ensure a conventional banking status. We exclude CDFIs from this group and from credit unions. Of our CDFIs, 167 are community banks, 164 are credit unions, and the remaining 85 are nondepository institutions, including development corporations, and loan and venture funds. To code for fintechs, we begin with Erel and Liebersohn (2022), but then researched and hand coded all the remaining nondepository institutions and banks in our PPP dataset not otherwise already coded using websites, the business press, and other sources to identify platform-based online

lenders, focused on large-scale origination of loans, and technological interfaces like AI-based software solutions to interact with consumers. This let us include a handful of select banks that recently transformed their business model to serve effectively as platforms for fintech lenders.

5. We opted for hurdle regressions over zero-inflated count models given the structural constraints on doing any PPP loans in a place, and our sense that virtually any lender that could issue a PPP loan in a place did so by the end of the program. Zeros in this case were likely structural, not statistical.
6. These data come from the U.S. Department of Housing and Urban Development's (HUD) aggregated USPS administrative data on address vacancies as made available by the Center for Investigative Reporting's Reveal network (Oh et al., 2021). The data includes addresses of nonvacant businesses on the census tract level and ACS counts of full-time, unincorporated self-employed. We use the population weights in the HUD "ZIP-TRACT" crosswalk file to calculate the number of businesses for each ZCTA.
7. The results for the two specifications are quite similar, so we report only county-level results.
8. We ran numerous robustness checks and different model specifications. We substituted commuter zones for county-level controls, ran linear models with state dummies, standard mixed-models, nonhierarchical negative binomial regressions, and zero-inflated estimations. We ran several logit models poking at the effects of poverty and diversity on making a loan. While ICC, AIC overdispersion, and zero-inflation tests indicate that the models we present in Table 1 best fit our data, the effects of both high poverty and minority majority have been consistent throughout all other specifications and estimation strategies. Diagnostics revealed no alarming multicollinearity. Further tests for overdispersion and zero inflation, as well as plotting residual versus predicted values, show a substantial improvement in model fit using hurdle-negative binomial estimations. We detected the presence of a few potentially disturbing outliers but opted to keep them in the model.
9. These are based first on a set of seven jointly estimated logistic models, one for each lender type, which used GSEM routines to return coefficients for the effects of community poverty and minority status on whether each type made any loans to a ZCTA, and second, on a separate jointly estimated set of negative binomial models providing coefficients for the effects of poverty and minority for each type on the number loans made to communities. Coefficients from the GSEMs for each outcome are tabled in online Appendix A6.

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Author Biographies

Mark K. Cassell is a political scientist whose research is at the intersection of public policy and administration courses, and comparative political economy and urban politics. His scholarship is mainly concerned with public sector transformations and the use of public/private hybrid organizations to solve public problems.

Michael Schwan is a political economist whose scholarship focuses on the rise of financial markets and their influence on politics, economics, and society. He has worked on changes in sovereign debt management, the transformation of banking, regional variation within political economies, and new institutional ownership in the nonfinancial sector.

Marc Schneiberg is an economic and organizational sociologist whose work focuses mainly on the rise, contemporary fates, and socioeconomic impacts of organizational diversity and alternatives to giant, shareholder corporations in American capitalism. He has also worked on regulation and self-regulation, and institutions and their relationships with social movements.

Table A1. Average and Median Loans by Bank Type and ZCTA.

	High poverty		Low poverty		Minority		Majority	
	Average	Median	Average	Median	Average	Median	Average	Median
Community banks	$78,590	$20,832	$78,453	$20,833	$90,527	$20,833	$77,240	$20,833
CDFI	$23,040	$20,207	$23,392	$19,133	$21,248	$24,626	$20,250	$18,750
Credit unions	$48,155	$16,200	$41,232	$16,373	$45,163	$15,200	$41,640	$16,105
Farm credit system	$49,583	$20,833	$43,855	$20,833	$86,979	$20,833	$43,677	$20,833
Fintech	$21,498	$19,845	$24,641	$16,417	$21,895	$19,960	$25,047	$15,777
LMCB	$132,363	$32,800	$126,434	$31,650	$162,034	$40,275	$123,228	$31,300
Top 50 banks	$123,097	$27,767	$99,707	$24,442	$110,669	$25,000	$100,672	$25,000

CDFI=Community Development Financial Institution; LMCB=large-and-medium-sized commercial bank.

Table A2. Summary Statistics.

	N	Mean	Standard deiation	Minimum	Maximum
Dependent var.: # Loans					
All banks and lenders	32,903	354.31	629.39	0	11,251
Community banks	32,903	104.47	155.76	0	2,566
CDFIs	32,903	47.99	145.52	0	4,412
Credit unions	32,903	9.41	25.84	0	600
Farm Credit System	32,903	1.56	5.03	0	214
Fintech	32,903	76.89	219.79	0	5,378
LMCB	32,903	33.67	74.45	0	1,331
Top 50 banks	32,903	78.37	186.08	0	4,934
Independent variables					
Poverty rate	32,260	13.41	11.61	0	100
High poverty	32,260	0.19	0.39	0	1
Population % White	32,589	83.37	20.84	0	100
Majority minority	32,589	0.09	0.28	0	1
Controls (ZCTA)					
# Businesses	32,903	404.31	659.30	0	8,012
Population	32,903	9,846	14,659	0	128,294
Controls (county)					
Branches	32,901	0.02	0.01	0	0.19
Return on assets	32,735	1.28	0.28	−6.02	3.70
Population	32,903	438,605	1,161,082	86	10,039,107
Bank market localism	32,735	0.24	0.19	0.00	1
# Financial institutions					
All financial institutions	32,903	25.95	34.95	0	234
Community banks	32,903	7.22	8.57	0	65
CDFI	32,903	0.35	1.26	0	10
Credit unions	32,903	8.91	16.44	0	118
Non-depository lenders	32,903	0.74	2.20	0	29
Other (residual)	32,903	5.49	8.32	0	58
Top 50 banks	32,903	3.98	4.19	0	21

CDFI=Community Development Financial Institution; LMCB=large-and-medium-sized commercial bank; ZCTA= ZIP Code Tabulation Areas.

Table A3. Correlation Matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(1) High poverty	1	0.24	−0.13	−0.16	−0.06	−0.09	−0.12	0.00	−0.13	−0.15	−0.11	−0.10	0.08	−0.09	0.02	−0.02	0.06	−0.16	−0.11	−0.13	−0.02	−0.11	−0.06
(2) Majority minority	0.24	1	0.13	0.02	0.21	0.09	0.12	0.25	−0.13	0.07	0.10	0.13	−0.15	0.13	0.04	−0.10	0.26	0.02	0.13	0.11	0.18	0.11	0.14
Loans																							
(3) All banks and lenders	−0.13	0.13	1	0.92	0.87	0.77	0.80	0.82	0.11	0.69	0.94	0.50	−0.38	0.90	0.10	−0.05	0.31	0.44	0.46	0.52	0.37	0.46	0.46
(4) Community banks	−0.16	0.02	0.92	1	0.68	0.61	0.62	0.63	0.24	0.57	0.84	0.30	−0.19	0.77	0.05	0.12	0.17	0.45	0.29	0.36	0.25	0.26	0.26
(5) Fintechs	−0.06	0.21	0.87	0.68	1	0.76	0.86	0.88	−0.11	0.67	0.88	0.65	−0.54	0.90	0.10	−0.20	0.36	0.37	0.57	0.60	0.42	0.61	0.60
(6) LMCBs	−0.09	0.09	0.77	0.61	0.76	1	0.71	0.72	−0.07	0.57	0.78	0.51	−0.44	0.77	0.12	−0.22	0.28	0.26	0.44	0.49	0.33	0.47	0.59
(7) Top 50 banks	−0.12	0.12	0.80	0.62	0.86	0.71	1	0.77	−0.11	0.70	0.84	0.72	−0.62	0.85	0.10	−0.28	0.29	0.38	0.65	0.67	0.46	0.74	0.65
(8) CDFIs	0.004	0.25	0.82	0.63	0.88	0.72	0.77	1	−0.11	0.61	0.83	0.56	−0.45	0.85	0.12	−0.17	0.42	0.31	0.49	0.52	0.37	0.52	0.55
(9) Farm Credit System	−0.13	−0.13	0.11	0.24	−0.11	−0.07	−0.11	−0.11	1	−0.01	0.05	−0.24	0.27	0.001	−0.01	0.17	−0.17	0.03	−0.20	−0.16	−0.18	−0.22	−0.25
(10) Credit unions	−0.15	0.07	0.69	0.57	0.67	0.57	0.70	0.61	−0.01	1	0.70	0.54	−0.46	0.70	0.12	−0.18	0.17	0.34	0.55	0.54	0.37	0.53	0.47
Controls																							
(11) # Businesses	−0.11	0.10	0.94	0.84	0.88	0.78	0.84	0.83	0.05	0.70	1	0.56	−0.44	0.96	0.09	−0.12	0.28	0.39	0.51	0.55	0.38	0.52	0.52
(12) Population (County)	−0.10	0.13	0.50	0.30	0.65	0.51	0.72	0.56	−0.24	0.54	0.56	1	−0.72	0.60	0.08	−0.22	0.33	0.61	0.90	0.95	0.61	0.90	0.87
(13) Branches	0.08	−0.15	−0.38	−0.19	−0.54	−0.44	−0.62	−0.45	0.27	−0.46	−0.44	−0.72	1	−0.47	−0.21	0.38	−0.24	−0.25	−0.57	−0.60	−0.47	−0.73	−0.64
(14) Population (ZCTA)	−0.09	0.13	0.90	0.77	0.90	0.77	0.85	0.85	0.001	0.70	0.96	0.60	−0.47	1	0.09	−0.17	0.28	0.37	0.54	0.57	0.38	0.56	0.55
(15) Return on assets	0.02	0.04	0.10	0.05	0.10	0.12	0.10	0.12	−0.01	0.12	0.09	0.08	−0.21	0.09	1	−0.23	0.03	−0.09	0.06	0.06	0.04	0.12	0.15
(16) Bank market localism	−0.02	−0.10	−0.05	0.12	−0.20	−0.22	−0.28	−0.17	0.17	−0.18	−0.12	−0.22	0.38	−0.17	−0.23	1	−0.03	0.23	−0.19	−0.14	−0.10	−0.34	−0.29
(17) # CDFIs	0.06	0.26	0.31	0.17	0.36	0.28	0.29	0.42	−0.17	0.17	0.28	0.33	−0.24	0.28	0.03	−0.03	1	0.22	0.31	0.33	0.33	0.29	0.37
(18) # Community banks	−0.16	0.02	0.44	0.45	0.37	0.26	0.38	0.31	0.03	0.34	0.39	0.61	−0.25	0.37	−0.09	0.23	0.22	1	0.60	0.75	0.45	0.48	0.48
(19) # Credit unions	−0.11	0.13	0.46	0.29	0.57	0.44	0.65	0.49	−0.20	0.55	0.51	0.90	−0.57	0.54	0.06	−0.19	0.31	0.60	1	0.93	0.60	0.81	0.78
(20) # All banks and lenders	−0.13	0.11	0.52	0.36	0.60	0.49	0.67	0.52	−0.16	0.54	0.55	0.95	−0.60	0.57	0.06	−0.14	0.33	0.75	0.93	1	0.61	0.86	0.86
(21) # Nondepository lenders	−0.02	0.18	0.37	0.25	0.42	0.33	0.46	0.37	−0.18	0.37	0.38	0.61	−0.47	0.38	0.04	−0.10	0.33	0.45	0.60	0.61	1	0.54	0.61
(22) # Top 50 banks	−0.11	0.11	0.46	0.26	0.61	0.47	0.74	0.52	−0.22	0.53	0.52	0.90	−0.73	0.56	0.12	−0.34	0.29	0.48	0.81	0.86	0.54	1	0.78
(23) # Other (residual)	−0.06	0.14	0.46	0.26	0.60	0.59	0.65	0.55	−0.25	0.47	0.52	0.87	−0.64	0.55	0.15	−0.29	0.37	0.48	0.78	0.86	0.61	0.78	1

CDFI=Community Development Financial Institution; LMCB=large-and-medium-sized commercial bank; ZCTA= ZIP Code Tabulation Areas.

Table A4. List of Fintechs.

Lender name	Originating lender state
Ally Bank	UT
American Express National Bank	UT
American Lending Center	CA
Axos Bank	CA
Benworth Capital	FL
Bluevine Capital Inc.	CA
Business Development Company	RI
Capital One, National Association	VA
Celtic Bank Corporation	UT
Centerstone SBA Lending, Inc.	CA
CRF Small Business Loan Company, LLC	MN
Cross River Bank	NJ
FC Marketplace, LLC (DBA Funding Circle)	CA
Finwise Bank	UT
First Internet Bank of Indiana	IN
Fountainhead SBF, LLC	CA
Fountainhead SBF, LLC	FL
Fundbox, Inc.	TX
Fundbox, Inc.	CA
Fund-Ex Solutions Group, LLC	NY
Green Dot Bank	UT
Hana Small Business Lending, Inc.	CA
Harvest Small Business Finance, LLC	CA
Intuit Financing Inc.	CA
Itria Ventures, LLC	DE
Itria Ventures, LLC	NY
Kabbage, Inc.	GA
Lendingclub Bank, National Association	CA
Lendingclub Bank, National Association	UT
MBE Capital Partners	NJ
Newtek Small Business Finance, Inc.	FL
Newtek Small Business Finance, Inc.	NY
Onewest Bank, A Division of	CA
Radius Bank	MA
Readycap Lending, LLC	NJ
Square Capital, LLC	CA
The Bancorp Bank	DE
Tiaa Bank, A Division Of	FL
Timepayment Corp.	MA
Webbank	UT

Table A5. High Poverty and Majority–Minority ZCTAs in Urban and Rural Areas by State.

	High poverty		Majority minority		High poverty and majority minority	
State	Rural	Urban	Rural	Urban	Rural	Urban
Alabama	173	41	99	43	61	30
Alaska	93	4	138	7	85	4
Arizona	112	33	53	2	50	0
Arkansas	195	15	54	7	37	6
California	242	106	47	285	21	36
Colorado	55	15	2	2	2	0
Connecticut	3	20	1	16	1	11
Delaware	4	4	0	3	0	2
Florida	98	66	18	54	12	25
Georgia	178	38	82	92	55	29
Hawaii	11	1	53	26	10	1
Idaho	46	3	3	0	2	0
Illinois	93	70	7	66	4	33
Indiana	30	63	2	26	0	19
Iowa	35	19	0	2	0	1
Kansas	71	14	0	4	0	2
Kentucky	315	26	1	7	1	6
Louisiana	151	34	77	43	47	22
Maine	65	5	0	1	0	0
Maryland	15	19	9	73	3	10
Massachusetts	11	35	0	21	0	9
Michigan	88	77	3	49	3	36
Minnesota	38	18	15	11	11	6
Mississippi	168	15	145	19	104	11
Missouri	194	45	2	35	1	22
Montana	85	4	21	1	18	1
Nebraska	34	7	4	2	3	2
Nevada	16	11	8	11	4	5
New Hampshire	7	3	0	0	0	0
New Jersey	9	28	4	66	0	20
New Mexico	134	7	69	1	48	0
New York	120	100	9	147	4	55
North Carolina	155	32	80	45	50	15
North Dakota	27	2	15	0	10	0
Ohio	78	130	0	66	0	52
Oklahoma	150	26	24	7	16	7
Oregon	80	11	1	0	1	0
Pennsylvania	85	112	3	44	2	28
Rhode Island	0	9	0	3	0	3
South Carolina	113	20	91	12	52	3
South Dakota	49	0	38	0	32	0
Tennessee	131	39	12	28	2	22
Texas	248	123	34	86	10	28
Utah	27	5	9	1	7	0
Vermont	11	3	0	1	0	1
Virginia	133	24	52	46	10	14
Washington	78	11	19	20	13	0
West Virginia	257	32	4	2	1	0
Wisconsin	30	20	6	13	5	9
Wyoming	29	0	2	0	2	0

Note: In total there are 6,115 high-poverty ZCTAs of which one-third (1,545) is rural. There are 2,812 majority–minority ZCTAs of which slightly more than a half (1,496) are urban.
ZCTA= ZIP Code Tabulation Areas.

Table A6. Generalized Structural Equation Model Results (N = 32,085).

	Community banks	CDFIs	Credit unions	Farm credit	Fintech	LMCB	Top 50 banks
Negative binomial				*Dependent variable: number of loans*			
High poverty	−0.31*** (0.01)	0.45*** (0.02)	−0.50*** (0.03)	−0.87*** (0.04)	0.20*** (0.01)	−0.05* (0.02)	−0.14*** (0.02)
Majority minority	−0.17*** (0.02)	1.21*** (0.02)	−0.26** (0.04)	−1.16*** (0.07)	1.07*** (0.02)	−0.22*** (0.03)	−0.20*** (0.02)
Controls (ZCTA)							
Population (log)	0.01 (0.01)	0.87*** (0.01)	0.15*** (0.02)	0.11** (0.03)	0.71*** (0.01)	0.10*** (0.01)	0.30*** (0.01)
# Businesses (log)	0.83*** (0.01)	0.23*** (0.01)	0.73*** (0.02)	0.38*** (0.03)	0.37*** (0.01)	0.79*** (0.01)	0.59*** (0.01)
Controls (county)							
Branches	0.07*** (0.01)	0.08*** (0.01)	−0.05** (0.02)	0.38*** (0.02)	−0.14*** (0.01)	−0.16*** (0.01)	−0.41*** (0.01)
Return on assets	0.13*** (0.01)	0.32*** (0.03)	0.53*** (0.04)	0.45*** (0.06)	0.02 (0.02)	0.06** (0.02)	−0.09*** (0.02)
Bank market localism	1.08*** (0.03)	−0.13*** (0.04)	−0.19*** (0.05)	1.19*** (0.09)	−0.27*** (0.03)	−0.93*** (0.04)	−1.29*** (0.03)
# Lenders of same type	0.04*** (0.00)	0.09*** (0.00)	−0.01*** (0.00)	−0.02*** (0.00)	0.03*** (0.00)	0.04*** (0.00)	0.14*** (0.00)
Population (log)	−0.31*** (0.00)	−0.06*** (0.01)	0.08*** (0.01)	−0.21*** (0.02)	0.21*** (0.00)	−0.18*** (0.01)	0.08*** (0.01)
Constant	2.66*** (0.06)	−6.15*** (0.11)	−4.78*** (0.15)	−1.08*** (0.27)	−7.44*** (0.08)	0.14 (0.11)	−3.10*** (0.09)
lnalpha	−0.66	0.16	0.75	1.69	−0.53	0.38	−0.33
Bernoulli/Logit				*Dependent variable: making zero loans*			
High poverty	0.46*** (0.07)	−0.22*** (0.05)	0.61*** (0.04)	0.89*** (0.04)	−0.02 (0.05)	0.08 (0.04)	0.17*** (0.05)
Majority minority	0.48*** (0.10)	−0.97*** (0.09)	−0.02 (0.06)	0.99*** (0.07)	−0.87*** (0.09)	−0.09 (0.07)	−0.15 (0.08)
Controls (ZCTA)							
Population (log)	−0.09* (0.04)	−0.81*** (0.03)	−0.27*** (0.03)	0.06* (0.03)	−0.84*** (0.03)	−0.34*** (0.03)	−0.72*** (0.03)
# Establishments (log)	−1.28*** (0.04)	−0.45*** (0.03)	−0.53*** (0.03)	−0.44*** (0.03)	−0.54*** (0.03)	−0.55*** (0.03)	−0.45*** (0.03)
Controls (county)							
Branches	0.08* (0.04)	0.12*** (0.02)	0.23*** (0.02)	−0.33*** (0.02)	0.13*** (0.02)	0.18*** (0.02)	0.42*** (0.03)
Return on assets	−0.25* (0.10)	−0.12* (0.06)	−0.15* (0.06)	−0.19** (0.05)	0.02 (0.06)	−0.08 (0.05)	0.12* (0.06)
Bank market localism	−1.58*** (0.18)	0.26** (0.09)	0.50*** (0.08)	−0.94*** (0.07)	0.47*** (0.09)	0.91*** (0.08)	1.16*** (0.10)
# Lenders of same type	−0.19*** (0.01)	−0.29*** (0.02)	−0.01*** (0.00)	0.01**** (0.00)	−0.03 (0.03)	−0.26*** (0.01)	−0.46*** (0.02)
Population (log)	0.63*** (0.03)	0.04* (0.02)	−0.19*** (0.02)	0.27*** (0.02)	−0.25*** (0.02)	0.37*** (0.02)	0.17*** (0.03)
Constant	−4.12 (0.43)	6.31*** (0.26)	6.06*** (0.25)	0.18 (0.23)	9.12*** (0.27)	−0.01 (0.25)	3.75*** (0.29)

***$p < .001$; **$p < .01$; *$p < .05$.

CDFI=Community Development Financial Institution; LMCB=large-and-medium-sized commercial bank; ZCTA= ZIP Code Tabulation Areas.