Did FinTech Lenders Facilitate PPP Fraud?*

John M. Griffin† Samuel Kruger‡ Prateek Mahajan§

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Abstract

In the distribution of the Paycheck Protection Program's (PPP) $780 billion in funds, FinTech lenders began minimally but ramped up their market share to over 70% of originated loans by April 2021. We examine metrics related to potential misreporting including non-registered businesses, multiple businesses at residential addresses, abnormally high implied compensation per employee, and large inconsistencies in jobs reported with another government program. We assess these four metrics with five additional measures and extensive supporting analysis. FinTech loans exhibit sharp and discontinuous increases in misreporting at maximum loan thresholds and at round loan amounts. FinTech loans are more than 3.5 times as likely to be initiated by someone with a criminal background, strongly cluster in industries-county pairs to a degree that is infeasible based on U.S. Census data on establishment counts, and frequently exhibit suspiciously similar loan features within lender-county pairs. Certain FinTech lenders seem to specialize in dubious loans with more than 45% of their loans experiencing at least one misreporting indicator. Few of these loans seem to have been detected by authorities or repaid. FinTech lenders with the highest misreporting in the first two rounds of the program in 2020 increase both their market share and their misreporting substantially in the third round in 2021. While FinTech lenders likely expand PPP access, this may come at the cost of facilitating fraudulent credit.

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†McCombs School of Business, University of Texas at Austin. Email: John.Griffin@utexas.edu.

‡McCombs School of Business, University of Texas at Austin. Email: Sam.Kruger@mccombs.utexas.edu.

§McCombs School of Business, University of Texas at Austin. Email: Prateek.Mahajan@mccombs.utexas.edu.

The melding of financial technology and banking, also known as FinTech lending, has emerged at a rapid pace in the aftermath of the financial crisis. Buchak et al. (2018) find that increased regulatory burdens on traditional banks is the predominate driver in the rise of FinTech lending. A large aspect of the scrutiny and regulation of traditional banking was their role in the financial crisis, including facilitating wide-scale mortgage fraud as partially evidenced by over $137 billion in government fines and settlements (Griffin et al. 2019a). FinTech lenders offer a new banking model that replaces traditional lending relationships with online advertisements, app interfaces, and loan screening algorithms. Are FinTech lenders able to harness the power of technology to reduce loan maleficence?

The Paycheck Protection Program (PPP), a historic COVID-19 relief program for businesses, rapidly distributed over $780 billion in funds through 10.7 million loans in three short rounds spread between April 2020 and May 2021. Although FinTech lenders began with a slow start with less than 10% of loans in round 1, they ramped up their market share to over 70% of loans by April 2021, highlighting their growing importance. FinTech lending was hailed for broadening access to PPP loans and for facilitating quick and efficient lending at a time when many small businesses were in dire need due to the COVID pandemic. However, the rapid expansion of FinTech lending may have come at the expense of underwriting standards. Whereas traditional banks have established borrower relationships and extensive Bank Secrecy Act (BSA) and Know-Your-Customer (KYC) compliance programs, many FinTech lenders had few established relationships and may have been light on formal procedures with little reputation to protect.

Alternatively, FinTech lenders have been shown to use financial data with increased speed and accuracy. Fuster et al. (2019) find that FinTech mortgage lenders not only process government agency loans faster than traditional banks but have fewer defaults, indicating potentially superior loan screening. Peer-to-peer FinTech platforms utilize a rich set of alternative data and machine learning to optimize credit decisions (Jagtiani and Lemieux 2019). If used effectively, this enhanced technology and increased data access may be able to detect and prevent PPP applications from fictitious businesses and individuals. Do traditional or FinTech loans exhibit more features consistent with potential PPP misreporting? And how does this potential misreporting vary across individual traditional and FinTech lenders?

To investigate these questions, we perform a big data analysis of loan features on over ten million PPP loans with six disparate databases. We introduce four primary and five secondary indicators of whether a loan is potentially misstated. Each indicator creates an inference that a loan is suspicious but is not proof of misreporting on its own. The four primary measures are non-registered businesses, multiple loans at a residential address, abnormally high implied compensation relative to industry and CBSA norms, and large inconsistencies between the jobs reported by a borrower on its PPP application and another contemporaneous government program application. The five secondary measures are discontinuities around the maximum PPP compensation level of $100,000, rounded loan amounts, overrepresentation of PPP loans relative to U.S. Census data on the number of business entities in a particular industry and county, clustering of loans with similar features within county-lender pairs, and criminal records for PPP borrowers.

We assess each of the four primary indicators with multiple discontinuity and comparative analyses. First, we find discontinuously elevated levels of potential misreporting, based on each of the primary indicators, at the $100,000 compensation threshold. These discontinuities are much stronger for FinTech lenders. Second, loans often cluster at rounded monthly compensation values, and these spikes coincide with higher levels of each of the four potential misreporting indicators. FinTech lenders have both a higher percentage of loans at rounded values and larger spikes in misreporting at these values. Third, PPP lending at the industry-county level frequently exceeds the number of businesses listed for that industry and county in U.S. Census data. Overall, these excess loans represent 19.2% of first draw business loans. For FinTech lenders, 35.6% of loans exceed industry-county establishment counts, and 28.6% of loans exceed industry-county establishment counts by a factor of more than two.[1] Measures of misreporting monotonically increase as the ratio of PPP loans-to-businesses documented by the U.S. Census increases, particularly for FinTech lenders. Fourth, based on the idea that networks in a region may use recurring loan features, we construct a concentration ratio to measure clustering in loan amounts, number of jobs (excluding one job), and industries within each lender-county pair. Like the other secondary measures, FinTech lenders have higher levels of clustering along loan features and clustering is monotonically associated with higher levels of potential misreporting. Finally, we collect criminal background data for a sample of 150,000 individuals. FinTech borrowers are more than 3.5 times as likely to have a felony record, and borrowers flagged for potential misreporting based on the primary and other secondary measures are also more likely to have felony records.

Overall, we find more than 1.8 million questionable loans representing $76 billion in capital. FinTech loans are more than 2.7 times as likely to have at least one primary indicator of misreporting and 4.7 times as likely to have a primary indicator that is confirmed

[1] The corresponding figures for traditional lenders are 13.1% and 7.4%, respectively. Excess loan percentages are calculated by assigning a weight to each loan based on the inverse of its industry-county's loan-to-establishment ratio. Specifically, let r be the loan-to-establishment ratio in the loan's industry-county pair, the weight is 0 if $r \leq 1$ and $1 - 1/r$ if $r > 1$. For the 28.6% and 7.4% figures, the interval limits are changed to 2 instead of 1.

by an additional primary or secondary indicator. Some regions and lenders stand out with particularly high rates of suspicious PPP lending, with potential misreporting rates in excess of 45% for two large FinTech lenders. Moreover, potential misreporting increases over time with particularly high rates in round 3 even after the Office of the Inspector General for the Small Business Administration (SBA) flagged PPP fraud as a concern. Network graphs of the lending space indicate that many FinTech portals switch lenders and utilize multiple lenders even for the same individual. Several of the FinTech lenders with the highest suspicious loan rates are new lenders that did not start making PPP loans until round 3, and there is no evidence that lenders attempted to decrease misreporting over time. Instead, second-draw loans to borrowers with suspicious first-draw loans by the same lender are common, and lenders with high rates of misreporting in rounds 1 and 2 increased both their misreporting rates and their loan volume in round 3. For example, the largest three FinTechs, Cross River, Capital Plus, and Harvest, exhibited high and increasing rates of both misreporting and lending volume while receiving over $900 million in processing fees each. Finally, FinTech lenders often doubled, tripled, or even quadrupled their lending in zip codes with high levels potential misreporting in rounds 1 and 2 while also increasing their misreporting rates.

Our work is related to four literatures. First, there is a rapidly emerging literature on FinTech lending that highlights its growing importance and positive economic effects through filling gaps left by traditional banks in both residential (Buchak et al. 2018) and business lending (Gopal and Schnabl 2020). Fuster et al. (2019) find that FinTech mortgage lenders process loans faster and increase the odds of borrowers refinancing their loans at lower rates, all with fewer defaults, indicating that FinTechs are not simply engaged in lax screening as was the case for securitized lending in the run-up to the financial crisis (Keys et al. 2010; Purnanandam 2011). Erel and Liebersohn (2021) examine FinTech lending in the PPP and finds that FinTech lenders increased access to the PPP by lending more in zip codes with fewer traditional banks, lower incomes, and higher minority percentages.[2] With respect to FinTech lending before the PPP, Gopal and Schnabl (2020) find that FinTech lenders have positive economic effects by filling in gaps in lending to small businesses left by traditional banks following the financial crisis. While most of the FinTech literature finds benefits to FinTech lending such as increased competition, broader financial access, faster lending speed, and lower defaults, our paper analyzes a potential cost of FinTech expansion, leaving overall welfare analysis to future research.

Second, regarding the efficacy of the PPP, Chetty et al. (2020) find that the PPP increased

[2]Relatedly, Howell et al. (2020) find that FinTechs were more likely to provide PPP loans to black-owned businesses. In contrast, Bartlett et al. (2021) find that FinTech algorithms charge higher interest rates to minorities in residential mortgage lending.

employment at participating firms by only 2% at a cost of $377,000 per job saved, and Autor et al. (2020) find only slightly higher employment benefits of 2 to 4.5%. Granja et al. (2020) find small employment effects due to the PPP and a low correlation between regional COVID variation and PPP funding allocation. Additionally, there is evidence of differential access to the PPP based on knowledge of the program, distance to the closest bank branch, banking relationships, and personal banking connections (Amiram and Rabetti 2020; Bartik et al. 2020; Neilson et al. 2020; Duchin et al. 2021; Glancy 2021; Li and Strahan 2021). Our evidence adds an additional concern regarding the program's efficacy and fairness.

Third, although we are the first academic paper to examine wide-scale potential PPP loan misreporting, there have been a number of interesting press and investigative reports regarding suspicious PPP loans (Miami Herald 2020; The Wall Street Journal 2020; Bloomberg Businessweek 2020; Project on Government Oversight 2020; ProPublica 2021), some of which feature FinTech lenders. Law enforcement is pursuing investigations into some of these loans as indicated by U.S. Department of Justice (DOJ) press releases containing information on 162 criminal complaints regarding 355 loans. Concerns about PPP fraud have been flagged by the Office of the Inspector General for the SBA, and a congressional subcommittee recently launched an investigation into the role of FinTech lenders in PPP fraud.[3] Beggs and Harvison (2021) find that among the 1,090 registered investment advisors who took PPP loans, those with a history of financial misconduct received unusually large PPP loan allocations.

Finally, our work relates to a more general literature on loan misreporting and fraud. Widescale mortgage fraud and misreporting in securitized mortgages prior to the financial crisis included second-lien and owner-occupancy status misreporting (Piskorski et al. 2015; Griffin and Maturana 2016), misreported income (Jiang et al. 2014; Mian and Sufi 2017), misreported assets (Garmaise 2015), and inflated appraisals (Ben-David 2011; Kruger and Maturana 2020). This fraud involved both smaller, less-known mortgage originators and large bank underwriters who knowingly passed along these misrepresentations in mortgage-backed securities. FinTech lending emerged and grew against this backdrop and related regulation increases for traditional banks FinTech (Buchak et al. 2018). Our findings indicate that replacing traditional lending with FinTech lending may actually amplify misreporting problems, at least with respect to the PPP.

Our findings also have important practical implications regarding extent and nature of PPP misreporting, the expanding role of FinTech lending, waste in the PPP, the proliferation

[3]The SBA OIG report can be found at https://www.sba.gov/sites/default/files/2021-01/SBA%20OIG%20Report-21-07.pdf and a press release regarding the investigation by a congressional subcommittee is available at https://coronavirus.house.gov/news/press-releases/select-subcommittee-launches-investigation-role-fintech-industry-ppp-fraud.

of fictitious lending, and the insufficient deterrence of current policies and enforcement. The potential policy and practical implications of these finding and the role of forensic finance in examining related issues are discussed further in the conclusion.

1 Data and Summary Statistics

1.1 Data Sources

The basis for our sample is loan-level PPP data released on May 3, 2021 by the Small Business Administration (SBA). This dataset covers all PPP loans issued from the start of the program on April 3, 2020 through April 30, 2021 (which is all of rounds 1 and 2 and the majority of round 3) that had not been repaid as of May 3, 2021. At the loan-level, the data includes business name, address, business type (e.g., corporation, LLC, self-employed, etc.), NAICS code (industry), loan amount, number of employees, date approved, loan draw (i.e., initial, first-draw loan or repeat, second draw loan), and lender for 10,697,219 loans originated by 4,902 different lenders and with a total value of $782 billion. We follow Erel and Liebersohn (2021) and classify lenders as either traditional or FinTech based on automated name matching with bank identifiers from the Federal Financial Institutions Examination Council (FFIEC) with hand matching for remaining lenders.[4] We also use Erel and Liebersohn's (2021) methodology to classify FinTech lenders as online banks or non-bank lenders.

Concurrently with the PPP, the SBA provided businesses and individuals with the ability to receive an Economic Injury Disaster Loan (EIDL), with forgivable advances of up to $10k. EIDL Advance loan-level data was released on December 1, 2020 and covers all EIDL Advance issued in 2020.[5] To check for inconsistencies between the information borrowers provided on their PPP and the EIDL applications, we match businesses in the PPP and EIDL loan-level datasets based on zip code and business name.

We also match PPP borrowers with business registry data from OpenCorporates, a non-profit that maintains a database of companies around the world. OpenCorporates collects its data directly from state governments and covers 76 million businesses across all US states except Illinois. The data includes incorporation dates, dissolution dates (if applicable), and, implicitly, whether the business has ever registered. We match OpenCorporates data to the PPP loan-level data based on business name and address.

[4]We use Erel and Liebersohn's (2021) classifications for lenders that were active in rounds 1 and 2 (the sample period for Erel and Liebersohn (2021)) and use the same methodology for classifying round-3 lenders that were not active enough to be classified in the earlier rounds.

[5]The SBA has not released updated EIDL Advance data for 2021.

To examine previous criminal and financial activity, we collect criminal background data from LexisNexis based on the borrower's name and address for a random sample of 150,000 round 1 and 2 loans made to individuals (12.9% of rounds 1 and 2 PPP loans made to individuals).[6]

Finally, we use several U.S. governmental data sources for address and demographic information. We standardize addresses and distinguish residential and commercial addresses from one another based on the Address Validation Application Programming Interface from the United States Postal Service. For data on number of establishments and average compensation, we use the 2019 County Business Patterns (CBP) data from the US Census Bureau, aggregated by region (either core-based statistical area (CBSA) or county) and North American Industry Classification (NAICS) code. The CBP data includes the number of establishments, number of employees, and total wages for a given industry in a county or CBSA. Matching between the loan-level data and the CBP data is based the business's zip code and the first four digits of its NAICS code.

1.2 Summary Statistics

Panel A of Figure 1 shows the number of loans originated on the left axis and the total amount lent on the right axis by each of the top 75 PPP lenders. FinTech lenders are highlighted in red (non-bank FinTech lenders) and cream color (online banks). Six of the ten top lenders by number of loans are FinTech, with Cross River, Capital Plus, and Harvest in the top five alongside Bank of America and JP Morgan Chase.[7] Due to their larger average loan size (Erel and Liebersohn 2021), dollar lending volume tends to be higher for traditional banks.

Panel B of Figure 1 shows the total FinTech market share during each week throughout the three rounds of PPP lending. Total FinTech market share grew from only 1.4% of loans in the first week of round 1 to 7.6% in the last week of round 1. Round 2 continued the PPP after a short break of ten days in May 2020 with new funding for borrowers who did not receive a loan in round 1. By the end of round 2 in August 2020, FinTech market share grew to 49.1% of loans, over the last two weeks, for an overall market share of 5% in round 1 and 20% in round 2. Round 3 of the PPP, which includes both first-draw loans for new borrowers and second-draw loans for borrowers that already obtained loans in round 1 or 2,

[6] Because the LexisNexis searches require an individual's name, only loans with an individual name listed as the borrower (rather than a business name) and where the business type is a self-employed individual, an independent contractor, or a sole proprietor are included in this criminal search. The criminal records data is collected only from rounds 1 and 2 loans because round 3 data was released after the criminal records data was collected.

[7] Comparing this figure to Panel A of Figure IA.1 shows how the top lenders differ between the entire sample and solely rounds 1 and 2. In particular, the growth of Capital Plus and Harvest in round 3 is apparent.

started in January 2021 with a low FinTech market share of less than 20% for the first three weeks as traditional lenders were once again the fastest to originate PPP loans. However, FinTech share grew rapidly during round 3, reaching over 70% of loans by the end of April 2021 for an overall round 3 market share of 41%.[8]

Table I reports summary statistics on the 3.1 million FinTech and 7.6 million traditional bank loans in our sample. FinTech loans have an average loan amount of $27 thousand compared to $91 thousand for traditional banks loans. Despite these large differences in means, the median loan sizes of $18.7 and $20.8 thousand are similar. The average FinTech loan reports supporting 2.8 jobs compared to 10.5 for traditional banks. After normalizing loan size relative to reported jobs, FinTech loans have higher average ($61 thousand) and median implied compensation ($62.8 thousand) than traditional bank loans ($47 thousand average and $38.7k median). The business type distribution for FinTech loans is 22.8% businesses organized as corporations, S-corporations, or limited liability companies (LLC) compared to 65.8% for traditional banks lenders. FinTech loans were also less likely to be repeat loans, with 25.9% of round 3 FinTech loans going to borrowers with previous PPP loans, compared to 60.1% for round 3 traditional bank loans.

2 Suspicious Loan Measures

We introduce four primary indicators that a loan is potentially misstated. In this section, we define and introduce the indicators. Each indicator creates an inference that a loan is suspicious but is not definitive proof of misreporting on its own. In subsequent sections we validate the measures and explore how they relate to one another and other misreporting indicators.

2.1 Business Registry Flag

Businesses organized as corporations, S-corporations, and LLCs are required to file an article of incorporation or LLC filing with a state, either as a domestic company in their home state or as a foreign company in another state. Further, the SBA required businesses to be "in operation on February 15, 2020... [and] not permanently closed."[9] Based on these requirements, we check the following conditions for all corporation, S-corporation, and LLC borrowers:

1. Is the business found in the business registry for its home state or in another state

[8] Panel B of Figure IA.1 shows the number of loans originated each week of the PPP by type of lender.

[9] See loan application at https://www.sba.gov/sites/default/files/2021-03/BorrowerApplication2483ARPrevisions%20%28final%203-18-21%29-508.pdf.

while listing an address in its home state? ("Missing Business")

2. Was the business dissolved and inactive before being approved for a PPP loan? ("Dissolved Business")[10]

3. Is the earliest incorporation or initial filling date for the business after February 15, 2020? ("Late Incorporation/Filing")

These three subflags are combined to form an overall business registry flag. Panel A of Figure 2 plots the proportion of corporate and LLC borrowers with missing, dissolved, or late business registrations. The flag is plotted as a percent of corporation, S-corporation, and LLC loans because other PPP business entities, such as sole proprietorships, partnerships, and independent contractors, do not require business registrations. We also exclude businesses in Illinois because Illinois is missing from the business registry data.[11] Missing registrations are the most common type of business registry flag, representing 3.85% of corporate and LLC loans. Another 0.72% of corporate and LLC loans are to dissolved entities, and 0.20% have late registrations for a total business registry flag percentage of 4.77%. Nine of the ten lenders with the highest rates of business registry flags are FinTech lenders. These lenders have 8 to 25% of their corporate and LLC loans flagged for one of the three business registry issues, with the vast majority of the flagged loans simply not appearing in the business registry data. While it is possible that there could be errors in the data, and some businesses may have names that are difficult to match, detailed manual searches indicate no public records information for most missing business registrations even after searching for alternative name variations. Matching issues could explain why all of the lenders have at least some missing registrations with business registry flag rates of one to five percent common across many lenders. However, there is not an obvious explanation for why certain lenders (which also have elevated levels on other indicators) should have disproportionately high matching issues, particularly since most of the FinTech lenders have broad geographic dispersion in their PPP lending.

2.2 Multiple Loan Flag

While it is possible that a business owner may have multiple businesses registered to the same address, the presence of multiple loans at a residential address during the same draw is also a potential sign of fictitious operations. Using the business address disclosed in the

[10] To be flagged, the dissolution date of the business must be before the PPP loan approval date and, to screen out businesses that may be administratively dissolved (e.g., for not filling some paperwork), the business status must be listed as inactive.

[11] Illinois has very restrictive terms and conditions regarding the use of their business registry data and even has legislation in place to make it a criminal offense to collect or republish the data (see https://www.ilga.gov/legislation/ilcs/ilcs4.asp?ActID=1876&ChapterID=53&SeqStart=58900000&SeqEnd=59600000).

PPP loan-level data, we identify individual residential addresses associated with multiple loans during the same draw. To do so, we first standardize addresses and identify addresses that are known business or central addresses (e.g., office and apartment buildings) using the Address Validation Application Programming Interface from the United States Postal Service. Then, we find residential (i.e., non-business, non-central) standardized addresses with multiple loans within the same draw.

As an example, Panel A of Exhibit 1 shows 14 loans given to a single address, all with colorful business names, almost all in the same industry, most with the same loan amount, and all backing ten jobs. The address associated with all 14 loans is a modest single-family home in suburban Chicago (estimated to have a value of $170k per Zillow). The borrower associated with the first loan is an LLC that was registered in 2018, but the 13 subsequent loans during July and August of 2020 are to LLCs that were registered only shortly before the loans were approved, well after the February 15 eligibility cutoff. Detailed internet searches did not produce information for any of the other 13 business names and no indication of employees other than the owner. Panel B of Exhibit 1 shows another multiple-loan example, this one involving loans to four people in the same household, again in a modest suburban Chicago home, all of whom received loans for the same amount, $20,833, which corresponds to the PPP's maximum annual compensation of $100,000.[12] This income is at the top of the spectrum for the indicated industries, which have average compensation $25-46k in the Chicago CBSA according to the US Census CBP. The industries themselves are also somewhat suspicious in that two are equipment manufacturing and one is auto repair despite no evidence of these businesses in photos of the property.[13] Further, the borrower in the nail salon industry does not appear to have an Illinois nail technician license. One of the equipment manufacturing borrowers also switched to the nail salon industry in a second draw loan during round 3 of the PPP despite also not having a nail technician license. Loan level inspections of the data reveal numerous other suspicious loans flowing to addresses that do not seem to be the locations of identifiable businesses despite applications claiming to employ multiple workers. The multiple loan flag functions as a way to systematically analyze these loans.

Panel B of Figure 2 shows the percentage of PPP loans that involve multiple loans to the same residential address by lender. Nine of the ten top lenders with the highest multiple loan flag rates are FinTech lenders. For these lenders, 12.5 to 17.5% of their loans involve multiple loans to the same residential address, and most of their flagged loans are to

[12] All four of these individuals also received second draw loans for the same amount.

[13] SBA guidance asks the borrower for their business address.

individual borrowers identified as independent contractors, self-employed, or sole proprietors. This contrasts with traditional banks, which have fewer flagged loans (5.1% on average). Further, flagged loans for traditional banks are mainly to formally registered corporations, S-corporations, and LLCs, consistent with the incentives for owners of multiple legitimate businesses to formally register their businesses for tax and limited liability purposes. For example, the largest PPP lender, Bank of America, has 3.46% of its loans flagged for receiving multiple PPP loans at the same residential address, and most of these loans are to registered business entities. Some of these differences could be due to differences in loan composition across lenders composition which we examine in subsequent regression analysis. Interestingly, three FinTech lenders, Capital One, Square, and Intuit have lower than median levels of multiple loans at the same address.

2.3 High Implied Compensation Flag

PPP loan size is limited to 2.5 times a business's average monthly payroll expenses, including up to $100,000 in annual compensation per employee.[14] PPP loan applications report how many employees the business has, again based on 2019 averages or the same period over which average monthly payroll costs were determined in most cases. Using loan size and number of reported employees, we are able to impute implied average annual compensation. We first focus on the overall level of compensation, and in subsequent sections, we return to more granular patterns associated with compensation discontinuities and rounding.

Implied compensation at the borrower level is strongly related to average compensation in the borrower's industry (NAICS 4-digit) and CBSA (e.g., see Panel B of Figure IA.2). However, some borrowers have abnormally high implied compensation relative to their industry and geographic area. Panel A of Figure 3 plots the kernel density of implied average compensation for the borrower normalized by mean compensation across all firms in the borrower's industry-CBSA pair based on US Census Bureau CBP data separately for FinTech and traditional loans. The top plot, which is restricted to corporate and LLC borrowers, shows similar distributions for FinTech and traditional borrowers. The bottom plot, which includes all loans, reveals larger differences between FinTech and traditional borrowers. For traditional borrowers, normalized compensation is 1.14 on average, with a median of 0.92 and a standard deviation of 1.97. FinTech borrowers have a higher average and median normalized compensation of 1.83 and 1.39, respectively, with a standard deviation of 1.59. This difference is largely due to the right tail of the distribution being much larger for FinTech borrowers. Specifically, 21.5% of FinTech borrowers have normalized compensation above 3,

[14] See the Internet Appendix for details on how the loan size was to be calculated and exclusions.

compared to 4.1% of traditional borrowers.[15]

It is instructive to examine how normalized compensation relates to our first two suspicious loan flags. On the right axis of Panel A of Figure 3, we plot the percentage of loans with the business registry and multiple loan flags across the distribution of normalized compensation separately for FinTech and traditional lenders.[16] Both flags increase significantly as normalized compensation increases for loans made by FinTech lenders. Whereas 6.8% of corporate and LLC FinTech loans with normalized compensation below one have the business registry flag, 22.8% of loans with normalized compensation above three have the flag. Similarly, the multiple loan flag increases from 9.2% for FinTech loans with normalized compensation below one to 16.4% when normalized compensation is above three. Importantly, while FinTech loans exhibit a stronger relation between normalized compensation and the other loan flags, this pattern is not limited to FinTechs. Traditional bank loans also have more business registry and multiple loan flags when normalized compensation is higher suggesting that they also have loan misreporting issues, though at a much lower scale. Overall, the results show that while some variation in normalized compensation across firms is to be expected, high implied compensation is strongly related to other suspicious loan characteristics, particularly for FinTech loans.

For our main measure of high implied compensation, we conservatively only flag loans where the implied compensation per job reported is more than three times the industry-CBSA average compensation ("high implied compensation"). Because compensation is censored at $100,000 for most borrowers, this flag is only possible industry-CBSA pairs with average annual compensation below $33,333.33.[17] Within this set of industry-CBSA pairs, 47.8% of FinTech and 10.2% of traditional lenders have normalized compensation above three. Panel B of Figure 3 plots how the percentage of loans with the high compensation flag varies across lenders. Similar to the previous flags, nine of the ten lenders with the highest abnormal compensation percentages are FinTech. For all of these lenders, more than 40% loans have the high implied compensation flag. By contrast, the 43 of the 68 largest lenders have less than 10% of their loans flagged, and 41 of these lenders are traditional banks. Although most of the FinTechs cluster with high rates of abnormally high compensation,

[15]Most of this is due to round 3 FinTech loans, which had mean normalized compensation of 2.04 compared to mean normalized compensation of 1.18 for FinTech loans in rounds 1 and 2. This elevated compensation for FinTech in round 3 is evident in Panel A of Figure IA.2. Whereas implied compensation is similar for FinTech and traditional borrowers in rounds 1 and 2, FinTech implied compensation is much higher round 3 and appears to be almost completely disconnected from average industry-CBSA compensation.

[16]The business registry flag is calculated as a percentage of corporation, S-corporation, and LLC loans because the business registry flag can only be determined for these business types whereas the multiple loan flag can apply to any loan.

[17]Some loans are also outside of a CBSA or in an industry-CBSA pair that is too small to be included in the US Census CBP data. In total, 3,297,068 loans are in industry-CBSA pairs with average annual compensation below $33,333.33. The rates plotted in Panel B of Figure 3 represent percentages of loans within this subsample.

Capital One and Square again have low levels of flagged loans.

2.4 EIDL Advance Jobs > PPP Jobs Flag

Concurrently with the PPP, the SBA provided businesses and individuals with the ability to receive a forgivable Economic Injury Disaster Loan (EIDL) Advance of up to $10,000.[18] For all EIDL Advances issued in 2020, the advance amount was calculated as $1,000 per employee (up to the $10,000 maximum).[19] Thus, there was an incentive for borrowers to inflate the number of jobs reported on their EIDL application. We check for inconsistencies between implied jobs based on EIDL Advance amounts and reported jobs from PPP loan applications. For borrowers who take out the maximum EIDL Advance of $10,000, we can infer that the borrower claimed at least 10 employees of their EIDL Advance application. We focus on cases where EIDL jobs exceed PPP jobs because the job inflation incentive is provided by the EIDL Advance program (PPP loans are based on total payroll as opposed to number of jobs). While the EIDL > PPP jobs flag is primarily an indicator of misreporting on the EIDL application, applicants who misreport in one area are likely willing to misreport in other areas too.

Panel A of Figure 4 plots the distribution of differences between EIDL and PPP jobs. Three patterns stand out. First, consistent with the incentive to inflate EIDL jobs as opposed to PPP jobs, EIDL exceeds PPP by three or more jobs 8.2% of the time, whereas PPP exceeds EIDL by three or more jobs only 3.6% of the time. Second, the most common discrepancy between the programs is a difference of nine jobs, which implies that the borrower claimed 10 jobs and took out the maximum EIDL Advance of $10,000 despite only reporting one PPP job. Third, EIDL job inflation is much more pronounced in FinTech loans than in traditional loans. In particular, EIDL exceeds PPP by nine jobs 12.6% of the time for FinTech loans compared to 0.5% for traditional loans.

Panel B of Figure 4 shows the prevalence of this EIDL job inflation by lender. To be conservative, we only include cases where the EIDL implied number of jobs is at least three more than the PPP reported number of jobs. Nine of the ten lenders with most frequent discrepancies between EIDL and PPP jobs are FinTech. In particular, Capital Plus, Prestamos CDFI, Harvest, Benworth, Itria, Fountainhead, MBE, Cross River, and Kabbage (all FinTechs) have job reporting inconsistencies ranging from 10% to 64%. For all of these lenders except Kabbage and MBE, most of the inconsistencies are a full nine

[18] While the EIDL Advance program was billed as a forgivable advance with the potential for a larger non-forgivable loan, over 65.8% of EIDL Advances involved no additional EIDL loan. EIDL advances were immediately forgiven by the SBA.

[19] The EIDL Advance rules changed for 2021 to: A) provide the entire $10,000 regardless of employee count, and B) to target the advances to low-income communities and those with a demonstrated decrease in revenue. The SBA has not yet reported data on 2021 EIDL Advances.

jobs. Five FinTech lenders (Intuit, WebBank, Square, Capital One, and Live Oak) have levels of inconsistencies that are similar to traditional banks, which are typically less than five percent of their loans and a nine-job difference only in rare cases.

2.5 Are the Suspicious Loan Flags Related to One Another?

If the above indicators of potential misreporting are due to random data errors or honest mistakes, one might expect different types of indicators to occur randomly across loans and lenders. Therefore, multiple flags for the same loans create a heighted misreporting inference, and high lender flag rates across multiple indicators may be due to policies and practices that facilitate more misreporting.

In Table II, we examine how the four flags relate to one another by reporting odds ratios between each pair of flags. The odds ratios are calculated based on loans for which data to calculate both flags are available (e.g., corporate and LLC loans for the business registry flag and loans with matched EIDL Advances for the EIDL > PPP Jobs flag), with z-statistics calculated based on standard errors double-clustered by zip code and lender in parentheses. Panel A reports odds ratios for the full sample, all of which are above 1.4 and highly significant. In particular, the odds ratio between the high implied compensation and EIDL > PPP jobs flags is 14.270 and has a z-statistic of 15.20. Panel B reports odds ratios separately for FinTech and traditional loans with FinTech loans in the lower triangle and traditional loans in the upper triangle. The odds ratios are all positive and highly significant with consistently higher ratios for FinTech loans. To check that these relations are independent of one another and not explained by loan characteristics, Table IA.I regresses each of the flags jointly on the other flags, controlling for loan size and number of jobs with zip code, business type, and industry $\times$ CBSA fixed effects. Panel A estimates regressions without lender fixed effects, and Panel B adds lender fixed effects. With only one exception (the effect of EIDL > PPP Jobs on the business registry flag and vice versa), the coefficients between the flags are all positive, economically large relative to the mean flag rates, and highly statistically significant.

We also find that flag rates are significantly correlated with one another, and the same lenders frequently have high flag rates across all four flags (as shown in Figure IA.3). In particular, FinTech lenders Capital Plus, Prestamos CDFI, MBE, and Harvest have flagged rates in the top 10 for all four flags and Itria, Fountainhead, and Benworth for three of the flags. In contrast, no traditional lender is consistently in the top 10 for more than two flags. This pattern is exactly what we would expect if some lenders have looser underwriting standards and is difficult to explain with random mistakes or errors in the data.

2.6 FinTech Differences?

Table III summarizes the percentage of each of the four flags by FinTech and traditional lenders. The table also summarizes the percent of all loans with at least one flag and with two or more flags. For each individual measure, the denominator is the loans that could have such flag (i.e., only corporate and LLC loans for the business registry flag, only loans in industry-CBSA pairs with average compensation below $33,333.33 for high implied compensation, and only loans with a matched EIDL Advance loan for the comparison to EIDL). For the overall flag measures, the denominator is all loans in the sample, which understates the incidence of suspicious loans since most of the flags are only applicable to a minority of the loans. Differences between FinTech and traditional flag percentages are reported in column (3). For all four individual measures, FinTech lenders have flag rates that are two to four times as high as traditional lenders, with particularly large differences for the high implied compensation and EIDL > PPP jobs flags. Overall, 31.4% of FinTech loans have at least one of the flags, compared to 11.6% for traditional loans. Additionally, 5.03% of FinTech loans have at least two flags, compared to only 0.61% for traditional loans. These differences are all highly significant with standard errors double-clustered by zip code and lender to conservatively allow for potential geographic and within-lender correlations.

To account for potential compositional differences between FinTech and traditional loans, column (4) reports adjusted differences that control for geography, business type, and industry based on regressions controlling for loan size and number of jobs with zip code, business type and industry $\times$ CBSA fixed effects.[20] After accounting for these effects, the adjusted difference between FinTech and traditional flag rates is 2.8 ppt for the business registry flag (which is 65% of the mean rate for traditional loans), 2.9 ppt (57%) for the multiple loan flag, 9.4 ppt (92%) for the high implied compensation flag, and 5.9 ppt (123%) for the EIDL > PPP jobs flag. These results indicate that even though loan composition explains part of the difference between FinTech and traditional loans, flag rates remain much higher for FinTech loans even after controlling for all observable characteristics. It is possible that there are non-linear characteristics between FinTechs and traditional banks that might explain these differences. To further control for potentially non-linear loan characteristic effects, we match FinTech loans with traditional loans based on loan size, industry, county, and business type in column (5) FinTech with similar results.[21] It remains possible that other omitted variables or unobserved loan characteristics could explain more of the difference between FinTech and traditional loans, but these effects would have to be large to explain the results. Tests in the

[20]Corresponding regressions results with and without the control variables and fixed effects are reported in Table IA.II.

[21]Details on the matching process are provided in the Internet Appendix.

next section, including grouping around discontinuities and clustering, help to address this concern.

3 Suspicious Loans or Mistakes?

All of the misreporting indicators in the previous section have potentially innocent explanations. In this section, we develop and analyze five additional measures as external verification to assess the plausibility of alternative explanations. The additional measures involve discontinuities, rounded compensation levels, abnormal numbers of loans in a particular industries and geographic areas, clustering of loan features, and criminal records. We also explore relations between the indicators and differences between FinTech and traditional lenders that are difficult to rationalize with alternative explanations.

3.1 Discontinuities at $100,000 Compensation

PPP loan size is calculated as 2.5 times a borrower's average monthly payroll, including up to $100,000 in wages per employee.[22] This $100,000 cutoff is a hard maximum for self-employment compensation. For other employees, payroll expenses also include employer insurance and retirement contributions and unemployment taxes, which can push included payroll expenses above $100,000 per employee. Someone filling out a fraudulent PPP application might want to maximize their loan amount by submitting payroll expenses at or close to the $100,000 per employee limit without the additional expenses that are eligible with proper payroll details.

Figure 5 plots the distribution of implied compensation per employee and shows how it relates to the misreporting indicators from the previous section. The implied compensation distributions (up to $130,000) for FinTech and traditional loans are plotted as orange and gray bars, respectively. Panel A shows that FinTech loans stand out as having more clustering in business (corporation, S-corporation, and LLC) loans with high implied compensation right at and slightly under $100,000, and traditional banks have more loans with implied compensation in the range of $30,000 to 75,000. Business registry flag rates for FinTech and traditional loans are plotted as orange and gray dots along with third-degree polynomials and their associated 95% confidence intervals estimated separately above and below the $100,000 compensation bin. As compensation increase from $30 to $100k, the prevalence of business registry violations for FinTech loans increases from 1.5% to 7%. For traditional lenders the increase is much smaller and is concentrated in compensation levels that are at or just below $100,000. There is also a jump in FinTech business registry violations for loans

[22]See the Internet Appendix for details on the SBA guidance on how to calculate loan size.

with implied compensation per employee of \$96,000 to \$100,000 and a similar but smaller jump for traditional loans with implied compensation of \$98,000 to \$100,000. For loans with implied compensation above \$100,000, there is a sharp drop-off in the business registry flag, which indicates that businesses that followed the detailed SBA guidelines for including non-wage payroll expenses for employees with wages above \$100,000 are much less likely to have registry violations. Finally, FinTech and traditional loans both have more business registry violations as implied compensation decreases below \$20,000, which suggests that misreporting is also elevated for borrowers with abnormally low reported salaries.

Panels B, C, and D repeat the same analysis for the multiple loan, high implied compensation, and EIDL > PPP Jobs flags. The multiple loans plot includes all loans, the high implied compensation plot includes all loans for which we can determine the industry-CBSA average compensation, and the EIDL > PPP Jobs plot includes all loans with matched EIDL Advances. Panel B shows that FinTech loans have a much higher incidence of the multiple loans flag at higher implied compensation levels. The high implied compensation flag in Panel C naturally increases with implied compensation, but there is a much steeper slope for FinTech loans than for traditional loans, and FinTech loans have a sharp discontinuity above \$100,000. This pattern for FinTech loans suggests that high compensation levels for FinTech loans are often disconnected from industry-CBSA averages whereas high compensation traditional loans tend to be in industry-CBSA pairs where one would expect compensation to be high. The drop in the high implied compensation flag above \$100,000 indicates that borrowers with detailed insurance and tax expenses in excess of \$100,000 are also much more likely to be in industry-CBSA pairs with high compensations more generally. For loans with EIDL > PPP Jobs in Panel D, there is a sharp increase in job reporting inconsistencies for FinTech loans with implied compensation from \$60,000 to \$100,000, with a sharp decrease above \$100,000. In Table IA.III, we formally test for discontinuities at \$100,000 of compensation after controlling for loan characteristics including number of employees, loan size, business type, zip code, and industry × CBSA and find large and highly economically significant discontinuities for FinTech loans, and to a much lesser extent for traditional loans, for all four measures. Overall, the increasing patterns of flags with compensation and the discontinuities around \$100,000 are consistent with suspicious loans maximizing loan amounts. Innocuous explanations for why there should be more loans with business registry issues, multiple loans at the same address, abnormally high compensation, and discrepancies in number of jobs between government programs right before and at, but not above, \$100,000 are not readily apparent.

3.2 Rounded Loan Amounts

The PPP loan application instructs borrowers to enter their average monthly compensation and to calculate their loan amount as

$$\text{Loan Amount} = \text{Average Monthly Payroll} \times 2.5 + \text{EIDL Refinance Amount}.$$

Applicants are instructed to calculate average monthly payroll based on historical compensation (in 2019 in most cases) with detailed supporting documentation.[23] It is unlikely that actual monthly payroll would be a round number, especially after including unemployment insurance and employer insurance and retirement contributions. Rounded loan amounts suggest that the numbers are potentially fictitious as opposed to being based on actual documented data. In particular, PPP loan amounts in increments of $1,250, $2,500 or $5,000 imply that average monthly compensation is at a rounded $500, $1,000 or $2,000 increment, a potential red flag for fictitious data. If the flags we have previously identified reflect misreporting issues, then one might expect both a clustering of loans at round numbers and elevated flags at round numbers. However, if round numbers are simply a result of a borrower with valid documentation rounding numbers slightly downward to simplify calculations, then one would expect no elevated reporting issues at round numbers.

In Figure 6, we first examine the distribution of the last four digits of loan amounts, excluding EIDL Refinancing, for FinTech and traditional loans. Loan amounts within 50 cents of a $1,250 increment (which corresponds to $500 of implied monthly compensation) are plotted as thicker and slightly darker bars with all other loans binned into $1 wide bins plotted as the thinner, lighter bars. Loans with an implied compensation within ± $1,000 of $100,000 are excluded to make sure these results are distinct from the maximum compensation result shown in Figure 5. Panel A plots corporate and LLC loans (which are the relevant sample for the business registry flag). Both FinTech and traditional loans exhibit rounding at $1,250 increments, particularly at increments of $2,500 ($0, $2,500, $5,000, and $7,500 in the figure, corresponding to $1,000 increments of implied monthly compensation). FinTech lenders have moderately more rounding with 10.49% of loans rounded to $1,250 increments compared to 7.59% for traditional lenders.

The right axis of Panel A examines the business registry flag. Business registry flag prevalence at the $1,250 loan increments is plotted as solid dots and at other loan amounts (shown in $250 wide bins) is plotted as hollow dots. If rounded loans are more likely to be misreported, one would expect an elevated level of loans with improper or missing business

[23] See the Internet Appendix for details on how the loan size was to be calculated and exclusions.

registries at round number thresholds. For FinTech loans, this is exactly what we find. The business registry flag is 1.23 ppt consistently higher at the rounded increments and the difference is highly significant, which is easy to see by comparison to the dotted lines plotting a 95% confidence interval estimated with a third-degree polynomial estimated based on the non-rounded loans. For traditional lenders, there is only small and weak evidence of elevated business registry flags in some of the rounded bins. Thus, rounding appears to capture suspicious loans for FinTech lenders but less so for traditional lenders, which is also consistent with our findings in Figures 2, 3, and 4.

In Panels B, C, and D we consider the other three primary misreporting indicators. Panels B plots all loans, Panel C plots loans with an industry-CBSA pairs with average compensation of less than \$33,333.33, and Panel D plots loans with matched EIDL Advances. Panels B, C, and D show that rounded loans by FinTech lenders also have elevated levels of the multiple loan, high implied compensation, and EIDL > PPP Jobs flags. For traditional lenders, the multiple loan flag is slightly elevated levels at every other \$1,250 increments (but not \$2,500 increments), and there is no evidence of any relation between rounding and the other flags. Overall, the fact that all of the loan flags are elevated at round loan amounts for FinTech loans provides additional validation for the suspicious behavior underlying these loans.

3.3 Loan Overrepresentation

If there is an organized effort to obtain funds for non-existent businesses, networks of illegitimate borrowers may fill out multiple applications in a similar manner and could cluster on characteristics such as industry and geography. Exhibit 2 shows examples of 4,304 \$20,000 first draw loans made by Cross River to businesses in the "Insurance Agencies and Brokerage Industry" in Illinois, mainly in the Chicago area, almost all of which have one employee. These are followed by examples from 938 \$20,000 first draw loans by Cross River to business engaged in "All Other Miscellaneous Crop Farming," most of which have exactly one or eight employees.[24] Most of these loans are in urban areas of Chicago, frequently in apartment dwellings, where it is difficult to see how crop farming is performed. There are also another 3,056 \$20,000 first draw loans by Cross River in Illinois to borrowers in other industries (including 700 to business in "All Other Personal Services," 347 to "General Freight Trucking, Local," 337 to "Other Performing Arts Companies", and 229 to "New Single-Family Housing Construction (except For-Sale Builders)"), also primarily in the Chicago area. In addition to having the same loan amount and similar industries, these \$20,000 loans were almost

[24] There are an additional 1,574 loans for amounts besides \$20,000 by Cross River in Illinois to business in "Insurance Agencies and Brokerage Industry" and 643 to the "All Other Miscellaneous Crop Farming" industry.

non-existent until the very end of round 2. Specifically, 40% were originated in late July and early August of 2020 during the final two weeks of round 2, and the other 60% were originated in round 3. Overall, 48.9% of Cross River's Illinois loans between July 21, 2020 and August 8, 2020 and 19.8% of Cross River's Illinois round 3 loans are for $20,000, compared to 1.14% of Cross River's Illinois loans before July 21, 2020 and 2.14% of Cross River's loans in other states. This pattern is particularly suspicious given that the US Census CBP reports 2,207 "Insurance Agencies and Brokerage Industry" establishments in Cook County, Illinois, which is about half the number of first draw loans made in this industries by Cross River alone (4,388 loans, of which 3,328 are for exactly $20,000).[25] Further, excluding Cross River's loans, there are 1,657 first draw loans to Cook County businesses in this industry, which is already 75% of the establishment count provided by the CBP. To systematically look for similar patterns throughout the PPP data, we compare PPP numbers to overall establishment counts in the 2019 US Census CBP database. Because the CBP data does not include self-employed and independent contractors as establishments, we exclude these loans to these business types from our analysis.

Panel A of Figure 7 plots histograms of FinTech (red bars) and traditional (gray bars) lender loans by ratio of first-draw PPP loans to census establishments in the loan's county and industry. For traditional lenders, 72.1% of loans cluster below one, which means they tend to be in industry-county pairs where the total number of PPP loans is less than the number of establishments recorded in that industry-county by the CBP. For FinTech lenders the distribution is shifted to the right, and 58.9% of their loans are in industry-county pairs where there are more businesses receiving PPP loans than there are establishments reported by the CBP. The difference between FinTech and traditional lenders is even more striking for extreme disconnects between loan and establishment counts. For example, 6.20% of FinTech loans are in industry-county pairs with ratios of PPP first draw loans to CBP establishments higher than 10 compared to 0.72% of traditional loans. It is possible that some excess PPP loans may be due to the missing establishments in the CBP data, industry misclassifications, or other errors in the data. Nonetheless, the large excess loan rate for FinTech lenders is difficult to explain, particularly since it is so much higher than traditional lenders.

Panel A of Figure 7 also plots, for fintech and traditional lenders separately, the percentage of loans flagged by one of the four primary suspicious loan flags by the ratio between PPP first-draw loans and CBP establishments. The flag rate increases dramatically as the loan-to-establishment ratio increases, particularly for FinTech lenders. Whereas 21.46% of

[25] These loan counts are specific to Cook County and exclude self-employed and independent contractors because they are not included in the Census CBP data. Loan counts for "All Other Miscellaneous Crop Farming" also appear to be high, but the CBP data does not have a comparable establishment count for this industry because it does not include agricultural establishments.

FinTech and 9.46% of traditional loans with a loan-to-establishment ratio at or below one are flagged, the flag rate is 52.63% for FinTech and 17.90% for traditional loans with loan-to-establishment ratios above two.

Panel B of Figure 7 plots separate rates for each of the four suspicious loan flags, with consistent results for all measures. As one moves to ratios above one, indicating more PPP loans in an industry-county than listed in the CBP, the number of suspicious loans flagged increases dramatically for all of the suspicious loan measures. This is true for both FinTech and traditional lenders, but the increase is generally steeper for FinTech lenders, consistent with FinTech loans in industry-county pairs with high loan-to-establishment ratio being particularly suspicious.

3.4 Loan Clustering

In addition to exhibiting geographic and industry clustering, many of the Cross River examples discussed above also feature identical loan amounts and job numbers. If networks submitting fictitious loan applications repeat the same application information across multiple loans, lenders may have many loans in a geographic region with similar industries, loan amounts, or jobs reported. There will clearly be some loan similarities due to lender specialization and by chance, but it is instructive to quantify how many loans cluster. For each lender-county pair with at least 25 loans, we calculate concentration ratios for the industry, loan amount (rounded to \$100), and reported jobs (excluding one because it is common across all lenders and counties).[26] Then, we rescale each of the concentration ratios to have a median of 1,000 and an interquartile range (IQR) of 300.[27] The rescaling is done to ensure that the three concentration ratios have similar impacts on our overall concentration measure. Finally, we average the three concentration ratios for each lender-county pair.

The bars in Panel A of Figure 8 plots the distribution of scaled concentration ratios separately for FinTech and traditional loans. High concentration ratios are much more common for FinTech loans, which have an average scaled concentration ratio of 1,367 with 85.15% of loans in lender-counties with a scaled concentration ratio above 1,000, compared to an average of 966 for traditional loans with 21.35% of loans in lender-counties with a scaled concentration ratio above 1,000. The dots in Panel A of Figure 8 plot how the incidence of the four primary suspicious loan flags changes with concentration ratio. When the scaled

[26] For example, let $i = 1, 2, ..., n$ represent the n industries in a given lender-county pair, then $Concentration_{\text{industry}} = \sum_{i=1}^{n} s_i^2$ where s_i is the percentage of loans in the lender-county that are in industry i times 100 (e.g., 6.2 for 6.2%). Note that this concentration ratio is the same as a Herfindahl-Hirschman Index (HHI), which is commonly used to measure market concentration.

[27] $Rescaled\ Concentration_{\text{industry}} = \frac{Concentration_{\text{industry}} - \text{Median}[Concentration_{\text{industry}}]}{75^{th}\text{Percentile}[Concentration_{\text{industry}}] - 25^{th}\text{Percentile}[Concentration_{\text{industry}}]} * 300 + 1000.$

concentration ratio is below 1,000, approximately 16% and 10% of FinTech and traditional loans, respectively, have at least one flag. However, when scaled concentration ratio is above 1,300, this grows to 48% for FinTech loans and 20% for traditional loans. Panel B of Figure 8 shows that similar patterns hold for each of the four suspicious loan flags individually. The overall pattern is similar to the previous measures: FinTech lenders have much higher loan concentration ratios, and high concentration ratios are highly predictive of the suspicious loan flags, particularly for FinTech loans. This pattern is exactly what one would expect if the indicators are picking up misreported FinTech loans and is difficult to explain with innocent mistakes or errors in the data.

3.5 Criminal Records

Recidivism statistics show that individuals with past criminal histories are much more likely to commit crimes in the future (Alper et al. 2018). The PPP originally prohibited loans to businesses more than 20% owned by individuals currently subject to criminal charges, incarceration, probation, or parole or who had been convicted of a felony within the past five year. These restrictions were relaxed somewhat in June 2020 to permit loans to businesses owned by individuals facing misdemeanor charges and those with convictions, probation, or parole for most felonies more than a year. The five-year criminal record prohibition was only retained for financial crimes such as fraud and embezzlement. As a result, many individuals with criminal records were legally eligible for PPP loans. Nonetheless, a criminal record is still a fraud risk factor, especially when combined with other risk flags. To assess the prevalence of criminal records among PPP borrowers, we collect the criminal histories for a random sample of 150,000 round 1 and 2 loans to individual names in the PPP data that can be matched to LexisNexis public records data.

Panel A of Figure 9 plots the percentage of borrowers with felony criminal records in 2000–2020 within the sample of 150,000 individual borrowers for whom we collected background information.[28] Ninety-five percent confidence intervals based on standard errors clustered by zip code and lender are plotted on top of the bars. The first takeaway from the figure is that criminal records are much more common among FinTech borrowers than traditional borrowers. Whereas 4.92% of non-bank FinTech borrowers and 4.55% of online bank FinTech borrowers have criminal records, only 1.36% of traditional borrowers have criminal records. There is also a strong relation between criminal records and the other suspicious loan flags for FinTech lenders, but not for traditional lenders. For example, FinTech borrowers with one of the primary suspicious loan flags have an elevated criminal record rate of 7.44%, whereas

[28] Panel A of Figure IA.4 replicates this figure using felonies from 2015-2020. While the percentage of borrowers with felonies is lower across the board, the relative results remain.

traditional borrowers with one of the primary flags have a criminal record rate of 1.79% which is similar to the overall average for traditional borrowers.[29] In the Internet Appendix, we confirm that these relations are robust and statistically significant by regressing an indicator for having a criminal record on the other primary and secondary risk flags for loans originated by FinTech lenders.[30]

Panel B of Figure 9 examines how criminal records vary across lenders with a clear positive relation between the percentage of a lender's sampled borrowers with criminal records and the percentage of its overall loans with one of the primary suspicious loan flags. In particular, the four lenders with the highest criminal record percentages (MBE, Cross River, Fundbox, and Kabbage, all of which are FinTech) also have the highest primary flag rates.[31]

3.6 Relation Between Primary and Secondary Flags

We have already seen that the primary flags are strongly predictive of one another, and the evidence in Figures 5–9 show strong relations between the primary and secondary flags. In Table IV, we more formally assess these relations with regression analysis controlling for loan size and number of jobs with zip code, business type, industry × CBSA, and lender fixed effects. The dependent variable in the regressions is an indicator variable for the loan having at least one of the primary flags. Standard errors are double clustered by zip code and lender. The secondary flags are a) whether the implied compensation of the loan is within $1,000 of the maximum allowed amount of $100,000, b) whether the loan amount is rounded to an interval of $1,250 (which represents $500 in monthly compensation) but does not have implied compensation within $1,000 of $100,000, c) whether the loan is in a industry-county pair where there are more first draw loans than establishments per the US Census CBP, d) whether the loan is in a lender-county pair where the concentration ratio of industry, loan amount, and jobs reported is above the 75th percentile, and e) whether the borrower has a felony charge on their criminal record from 2000-2020. The secondary flags are all interacted with an indicator variable for FinTech loans, so the direct coefficients represent effects for traditional loans. Four of these five effects are positive and significant

[29] The primary loan flags for this analysis are multiple loans, high implied compensation, and EIDL > PPP Jobs because the business registry flag is only relevant to corporate and LLC loans. Because the criminal background analysis is for loans made to individuals, loans in this sample cannot have the business registry flag.

[30] Results are reported in Table IA.IV. The regressions control for loan size and number of jobs with business type, industry × CBSA, and lender fixed effects. Standard errors are double-clustered by zip code and lender. In all cases except monthly rounding, the coefficients are positive, statistically significant, and economically large for FinTech loans (Panel A) with almost no relation between the misreporting indicators and criminal records for traditional loans (Panel B).

[31] Panel B of Figure IA.4 replicates this figure using felonies post-2005, post-2010, and post-2015. While the percentage of borrowers with felonies decreases as the time period is decreased, the relative results remain. Additionally, Panel C of Figure IA.4 replicates this figure using bankruptcy fillings post-2015 and finds similar results. Lastly, Panel D of Figure IA.4 shows that there is an uptick in the percentage of borrowers with felonies as the implied compensation of the loan approaches $100k.

with magnitudes ranging from 4.6% to 20.0% of mean misreporting rate.

Even more importantly, all of the interactions between the secondary flags and the indicator for FinTech loans are large, positive, and significant.[32] As a result, all of the secondary flags strongly predict the primary flags for FinTech loans, with relations that are much stronger than for traditional loans. For rounded compensation and compensation near $100,000, the effect for FinTech is over five times the effect for traditional loans. Further, for high loan concentration and felony, the effects for FinTech are over 1.75 times as large as the non-FinTech effects. Lastly, for industry overrepresentation, there are strong FinTech effects despite essentially zero relations for traditional loans. In Figure IA.5 we examine relations between the primary and secondary flags at the lender level with similar results. Apart from monthly rounding, lenders with high levels of each secondary flags tend to be the same lenders that have high levels of the primary flags. Overall, the strong relations between the primary and secondary flags, particularly for FinTech lenders make it highly unlikely that the differences in flag rates across lenders are driven by honest mistakes or errors in the data.

3.7 How Many PPP Loans Are Suspicious?

In this section, we quantify ranges of suspicious loans based on the primary and secondary flags developed in the previous two sections. Panel A of Figure 10 plots flag rates for each of the four primary flags along with overall suspicious lending rates. Our primary measure consists of loans that have at least one primary flag, plotted as the total height of the bars. By this measure, 1,848,329 loans representing 17.3% of the PPP and totaling $76.3B are suspicious.[33]

FinTech lenders are responsible for a disproportionate share of suspicious loans. Combined, non-bank FinTech and online bank FinTech originated 963,868 suspicious FinTech loans totaling $21.3B. This means FinTech lenders originated 52.1% of flagged loans despite, substantially outpacing their overall FinTech 28.7% market share of loans.[34] As a share of loans originated by each lender type, 11.6% of traditional loans have at least one of the primary suspicious loan flags compared to 32.0% for non-bank FinTech and 30.6% for online bank FinTech.

While some of the loans flagged as suspicious by the primary measure may be honest

[32]The prevalence of the secondary flags is also higher for FinTech loans (see Table IA.V).

[33]In addition, the EIDL > PPP flag also provides an indication of misreporting in the EIDL and EIDL Advance program; in particular, 186,149 EIDL Advances (9.6% of those matched to a PPP loan), totaling $1.6B, have potential misreporting.

[34]FinTech represents a larger share of suspicious loans than suspicious loan dollar volume because FinTech loans tend to be smaller. The same pattern is reflected in FinTech overall market share, which is 28.7% of PPP loans and 10.9% of PPP dollar lending volume.

mistakes or errors in the data, these four measures also surely miss many fraudulent loans. This is particularly true for the business registry and EIDL > PPP Jobs flags, which only apply to subsets of loans (corporate/LLC loans and loans with matched EIDL Advances, respectively). Despite having much higher rates for these flags within the relevant subsets of loans, overall, these flags are relatively uncommon for FinTech lenders because most of their loans are to individuals and sole proprietorships without EIDL Advances. As a more lenient measure of suspicious lending that is less sensitive to these restrictions, Panel A of Figure IA.6 plots suspicious loan rates including all loans with any primary or secondary flag. By this measure, 5,223,126 loans totaling $283B are suspicious. FinTech is again overrepresented with 2,089,656 suspicious FinTech loans (40% of flagged loans) totaling $50.3B.

As a more conservative estimate, we consider loans that have at least one primary flag plus an additional primary or secondary flag. While this measure almost certainly misses a lot of misreporting, it has the benefit of dropping any honest mistakes or errors in the data that are isolated to a single measure. Under this conservative measure, 1,200,580 loans totaling $37.9B are suspicious. Of these loans, 786,859 ($17.0B) are FinTech. This is an even larger FinTech share than for the primary measure because 81.6% of FinTech loans flagged by at least one primary flag are further confirmed by an additional flag while the corresponding figure is only 46.8% for traditional loans. The higher confirmation rate for FinTech loans is consistent with FinTech loans being far more likely to be fraudulent as opposed to simply reflecting honest explanations or errors in the data.

The last three bars of Panel A plot suspicious lending rates by round with the clear pattern that suspicious lending increased over time. In round 1, 8.7% are suspicious, compared to 12.0% in round 2 and 23.2% in round 3. The conservative measure with an additional confirmatory flag follows the same pattern.

In Panel B of Figure 10, we plot suspicious loan rates by lender. The total height of the bars plot the percent of loans with at least one primary flag, and the solid part of the bars plot the percent of loans with a primary flag that is confirmed with an additional primary or secondary flag. Average rates for the two measures are plotted as solid and dashed horizontal lines, respectively. Disparities across lenders are striking. Using the at least one primary flag measure, 13 out of 20 FinTech lenders have above average suspicious loan rates, and the 10 lenders with the most suspicious loans (nine of which are FinTech) all have at least 28.7% of their loans implicated compared to the overall average of 17.3%. In the extreme, Capital Plus and Prestamos CDFI have primary flag rates of 51.7% and 46.5%, respectively. Even with the more conservative measure, requiring an additional primary or secondary flag, these two lenders have flag rates of 50.9% and 45.0%. Capital Plus is particularly striking because it is the second largest FinTech lender and fourth largest lender overall with 380,377 loans. Cross River (largest FinTech lender and second largest overall lender with 471,609 loans) and Harvest (third largest FinTech lender and fifth largest overall lender with 377,620 loans) are also well above the average flag rate with primary flag rates of 28.7% and 38.2%, respectively. While most of the FinTech lenders cluster among the lenders with the most suspicious loans, there are a few exceptions. In particular, Square, Intuit, and Capital One have misreporting rates that are well under the average misreporting rates across all lenders.

3.8 Geography of Suspicious Lending

In addition to varying across lenders, suspicious lending also varies across geographies. Panel A of Figure 11 plots the percent of loans with at least one primary flag in each county across the U.S with considerable variation.[35] Areas with a particularly high percentage of flagged loans cluster near New Orleans, Atlanta, and surrounding areas in Mississippi, Georgia. Chicago and parts of South Carolina also exhibit elevated levels. Many counties in these areas have suspicious lending rates in excess of 35% whereas large parts of the country have suspicious loan rates under 15%. The geographic pattern is somewhat regional with elevated fraud rates in the Southeast, but there are elevated counties scattered across the country. There are also big differences across large cities. For example, Cook County, IL has a suspicious loan rate of 35.5% compared to suspicious loan rates of 8.9% in New York County and 9.4% on Los Angeles County.

In Panel B of Figure 11, we examine the relation between FinTech market share and suspicious loan rates across counties and zip codes. Each dot represents a zip code. The x-axis plots the percent of loans flagged in at the county level, and the y-axis plots the percent of loans flagged at the zip code level. There is significant variation across zip codes within counties with flagged loan rates varying from 20% to 50% in many counties. Additionally, FinTech market share (represented by the color of the dots) is strongly related to the percent of flagged loans not only across counties, but also across zip codes within counties—zip codes with the highest flagged loan rates consistently have the highest FinTech market share.[36]

Is geographic variation in suspicious lending related to poverty, crime, or culture? Or does suspicious lending cluster in ways beyond that exceed what can be explained by cultural and criminal factors? Table V further analyzes the geography of suspicious PPP lending by considering relations with demographic and cultural measures that are associated with other forms of financial misconduct (Grullon et al. 2010; Parsons et al. 2018; Griffin et al. 2019b).

[35] Panel A Figure IA.7 shows geographic variation in FinTech market share.

[36] Within a county, a 10 ppt rise in FinTech market share in a zip code is associated a 4.27 ppt rise in suspicious lending (see Table IA.VI).

The dependent variable is an indicator for whether a loan is flagged by at least one primary flag and the explanatory variables are county-level cultural and demographic measures.[37] In column (1), public corruption convictions and religious affiliation, have a positive relation with the probability of a loan being flagged as suspicious and usage of a marital infidelity website (Ashley Madison) has a negative relation. The strongest relation is for the public corruption measure. A one standard deviation increase in per capita public corruption convictions is associated with a 1.0 ppt increase in the suspicious loan rate, which is 5.9% of the mean. The other two cultural variables are statistically significant but economically much less important. In column (2), we add county-level demographic control variables for population density, median income, percentage of non-white population, percentage of adults who are college educated, and pre-pandemic unemployment. In general, suspicious lending rates decrease with population density, median income and increase with percentage of non-white population and pre-pandemic unemployment. Coefficients on all but percentage of non-white population are economically small.

In column (3), we add county-level FinTech market share. A one standard deviation increase (13.6 ppt) in FinTech market share in the county is associated with a 2.4 ppt increase in the suspicious loan rate, which is 12.6% of the mean misreporting rate.[38] This is a much stronger relation than any of the other county variables, and coefficients for the cultural and demographic variables generally decrease or become statistically insignificant once FinTech market share is added to the regression. It is important to note that this regression specification is not conducive to a causal interpretation but indicates a strong association.

Why does suspicious lending vary so much across geographies? Strong clustering in certain counties and zip codes suggests that suspicious borrowing is driven by more than just the idiosyncratic decisions of individual borrowers. One possibility is that referral fee programs, agent fees, kickback schemes, or local networks may arise in certain areas to systematically attract and facilitate suspicious lending.[39] Because we do not observe the

[37]The regressions are at the loan level to control for jobs reported, loan size, business type and industry code $\times$ state fixed effects. Standard errors are double clustered by zip code and lender. The independent variables are standardized to have mean of 0 and standard deviation of 1 at the county-level. Thus, the coefficients can be interpreted as the change in the probability of a loan being flagged for a one standard deviation change in the variable. Table IA.VII shows equivalent regressions at the county-level.

[38]An equivalent regression at the county-level shows that a one standard deviation increase in FinTech market share is associated with a 0.586 standard deviation increase (3.9 ppt) in suspicious loan rate (see Table IA.VII).

[39]For example, Amur Equipment offered a referral fee program and explicitly stated that the referral program required "zero-touch and follow up on your end." (https://twitter.com/Amur_EF/status/1361801770452672515). The PPP allowed lenders to pay agents 1% on loans up to $350k, 0.5% on loans between $350k and $2M, and 0.25% on loans above $2M (https://home.treasury.gov/system/files/136/PPP%20Lender%20Information%20Fact%20Sheet.pdf). Further, some people filed PPP loans in return for upfront and backend fees or kickbacks, which was against SBA rules (e.g., see https://www.justice.gov/usao-ndil/pr/suburban-chicago-tax-preparer-charged-covid-relief-fraud, https://www.justice.gov/criminal-fraud/file/1380216/download, and https://www.justice.gov/usao-sdfl/pr/

identity of agents directing or assisting the PPP borrowers, this possibility is difficult to directly test. That said, the geographic clustering of suspicious loans shown in Figure 11 is what we would expect if agents in certain areas are encouraging suspicious borrowing and steering suspicious borrowers to FinTech lenders. If agents are utilizing more than one FinTech lender to clear fraudulent loans, one might expect counties with many potentially misreported loans by one lender to have elevated levels of suspicious loans and FinTech more generally. Consistent with this hypothesis, the lower triangle of Figure IA.8 indicates that that when one FinTech lender has a high flagged loan rate in a county, other FinTech lenders also tend to have elevated flagged loan rates. The upper triangular shows that FinTech lenders with the highest overall flagged loan rates have a high correlation in their market shares at the county-level, whereas market-share correlations between most other lenders are slightly negative.

4 Why Does Suspicious Lending Concentrate in FinTech?

FinTech lenders on average have much higher suspicious lending rates than traditional lenders, and Tables III, IA.II, and IA.V show that their elevated suspicious lending is not explained by observable facets of loan composition. What could be driving the elevated flag rates for FinTech lenders?

4.1 FinTech Lender Background and Incentives

4.1.1 FinTech Lender Background

Differences across FinTech lenders give a first clue to this puzzle. While most FinTech lenders have high suspicious loan rates, Square and Intuit have among the lowest suspicious loan rates of all lenders. Online lending does not appear to be the problem in and of itself. One thing that sets Square and Intuit apart is that they have established relationships with customers based on a broad suite of payment, accounting, payroll, and other financial support services.

By contrast, the largest FinTech PPP lender, Cross River, is a small community bank in New Jersey that acts as conduit for partner FinTechs. Similarly, Capital Plus Financial, the second largest FinTech PPP lender, is a small mortgage lender in Texas that traditionally focused on supporting Hispanic home ownership but now appears to be almost entirely focused on PPP lending. The number three FinTech lender, Harvest Small Business Finance, is also

southern-district-florida-takes-sweeping-action-against-cares-act-fraud).

a small lender with limited history. Now that the PPP has ended, Harvest's only current product appears to be SBA 7(a) commercial real estate loans. Benworth, Fountainhead, and Itria, the other FinTech lenders in the top 10 by number of PPP loans originated, follow a similar pattern with high suspicious flag rates and limited business outside of PPP lending. Table IA.VIII systematically examines the relation between suspicious loan flag rates and past SBA lending with a similar finding. Lenders who have fewer SBA loans pre-pandemic, have lent in SBA programs for fewer years, and for whom the PPP was their first experience with SBA lending (in particular new FinTechs) all have higher rates of flagged loans.

The six largest FinTech lenders all primarily originated loans that were sourced from other FinTech platforms. Cross River adopted this business model early in round 1 by partnering with other FinTechs such as Intuit and Kabbage to originate PPP loans (New York Times 2020). The other large FinTech lenders almost exclusively originated loans sourced by two marketing FinTechs that did not do any PPP lending until round 3, Womply and BlueAcorn (New York Times 2021). Womply is a marketing technology firm with no lending history before participating in the PPP. It launched a platform called Fast Lane to facilitate PPP applications that were then originated by partner lenders including Harvest, Capital Plus, Benworth, and Fountainhead. BlueAcorn was founded in April 2020 exclusively to source PPP loans in partnership with Capital Plus and Prestamos CDFI. Both firms relied heavily on online advertising promoting easy access to PPP money, and anecdotal discussions on forums such as Reddit suggest that both employed identity verification that was not rigorous.

4.1.2 FinTech Fluidity

To examine relationships between these lenders, Panel A, Figure 12 plots the network of relationships between lenders based on originating loans in the same draw to the same non-commercial address as identified by the multiple loan flag. The edges between lenders represent the number of addresses to which both lenders originated a loan within the same draw. Node size is based on the number of loans at addresses flagged for having multiple loans. The thicker edges between FinTech lenders shows that FinTech borrowers receiving multiple loans often received funds from more than one FinTech lender even within the same draw. Specifically, 66.0% of FinTech borrowers with multiple loans to the same address split their loans across multiple lenders. Shared FinTech lending to the same address is largely explained by FinTech portals sourcing loans for multiple lenders. For example, the plot shows a strong relationship between Prestamos CDFI and Capital Plus, the two lenders that partnered with BlueAcorn. This is likely from borrowers applying for multiple loans through BlueAcorn, some of which were originated by Prestamos CDFI while others were directed to Capital Plus. Similarly, there are strong relationships between Harvest, Benworth, Capital

Plus, and Fountainhead, all of which are Womply partners. By contrast, there are fewer relationships between traditional lenders, and 70% percent of traditional borrowers who took out multiple loans received all their loans from the same lender. Some exceptions include Customers Bank, Amur Equipment, and Bank of America. The first two at least have known FinTech affiliations even though they do not meet the formal FinTech criteria.[40] Overall, 205 thousand FinTech loans are at the same address as a loan originated by a different FinTech lender with the same draw and 45 thousand by a traditional lender. For traditional banks, there were only 81 thousand loans at addresses where the borrower received another loan from a different traditional bank within the same draw and 42 thousand loans from a FinTech lender.

As another way to examine relationships between lenders, we track borrowers switching lenders between their first and second PPP loan draws. If a borrower already submitted information in the first draw through a particular lender, obtaining the second draw only required refreshing the application with some additional information.[41] This provided a strong incentive for borrowers to use the same lender. For borrowers with first draw loans flagged for potential misreporting that subsequently took out second draw loans, Panel B of Figure 12 shows the movement of these loans across rounds to different lenders.[42] The thickness of the edges between lenders is proportional to the number of flagged loans that changed lenders between the first and second draws. The switches between the first and second draw are clockwise. Node size is based on the number of first draw loans (with a matching second draw) and second draw loans by each lender. The large movements and connections between FinTech lenders may reflect online lending portals switching lenders. For example, many FinTech originators, such as Intria and Intuit, cleared loans though Cross River in the first two rounds but became SBA authorized lenders by round 3, and Kabbage originated many loans for Customers Bank in the first two rounds. Overall, the graphs highlight the fluid nature of the FinTech space where online portals originating loans can easily originate their loans through different lenders, and suspicious borrowers can utilize several platforms or switch platforms. The lack of relationship banking within the FinTech space may be advantageous to expand access to capital (Erel and Liebersohn 2021), but it also appears to be expedient for dubious lending.

[40] Customers Bank directly worked with multiple FinTech lenders, in particular Kabbage and Cross River (https://newsroom.kabbage.com/wp-content/uploads/2020/07/Kabbage-Paycheck-Protection-Program-PPP-Report.pdf).

[41] For example, question 55 of the January 29, 2021 PPP FAQ (https://www.sba.gov/sites/default/files/2021-01/Paycheck-Protection-Program-Frequently-Asked-Questions.pdf) says "information a lender obtained from a borrower in connection with a First Draw PPP Loan can be relied upon by that lender for a Second Draw PPP Loan application."

[42] Figure IA.9 replicates this figure using all second draw loans.

4.1.3 FinTech Revenue

PPP lending had the potential to be a profitable business for lenders. Lenders were initially compensated with processing fees of 5% for loans up to $350,000, 3% for loans between $350,000 and $2,000,000, and 1% for loans of $2,000,000 or more. For loans made in 2021, fees for small loans were increased to the lesser of 50% or $2,500 for loans below $50,000.[43] Based on this fee schedule, we estimated that PPP lending generated $36.2B of lender processing fees, $7.2B of which went to FinTech lenders (see Table IA.IX). The top 3 FinTech lenders alone likely generated $2.9B in processing fees, including $1.0B to Cross River, $926M to Capital Plus, and $925M to Harvest, all of which appear to have little business other than PPP lending. On a percentage basis, these figures imply that the average processing fee for FinTech PPP loans was 12.8% of the loan balance, largely driven by the high processing fees for small loans in round 3.[44] We lack data on cost structure associated with PPP lending and do not observe how lender fees are shared with partner organizations that FinTech lenders used to source the loans such as Womply and BlueAcorn. Nonetheless, costs were presumably lower for FinTech lenders than for traditional lenders given their limited interactions with borrowers, and their number of employees, where observable, are small.[45] The large scale of PPP lending from small and relatively unknown PPP lenders also suggests that costs were probably limited.[46]

PPP lenders were required to follow SBA lending guidelines but did not bear any credit risk themselves. While the lenders were required to collect documentation from loan applicants and to follow Bank Secrecy Act requirements, they were explicitly allowed to rely on borrower certifications and representations and do not face liability for borrower misstatements.[47] Up-front processing fees on a per-loan basis combined with no credit risk potentially created an incentive for lax underwriting standards, particularly for specialized PPP lenders

[43] See https://home.treasury.gov/system/files/136/Updated-Guidance-PPP-Lender-Processing-Fee-Payment-1502-Reporting-Process.pdf.

[44] The average processing fee for round 1 and 2 was 4.9%. This dramatically increased to 20.2% in round 3.

[45] For example, Capital Plus (the second largest FinTech lender and fourth largest lender overall) received a PPP loan of $376,800, reportedly to cover payroll for its 28 employees. The loan was approved in April 2020, potentially before their business opportunities as a PPP lender, most of which occurred in round 3, were apparent. Similarly, Benworth Capital Partners (fourth largest FinTech and eighth largest lender overall) received a PPP loan of $100,600 for its 13 employees on April 5, 2020, DreamSpring received a PPP loan of $757,753 for its 54 employees on April 27, 2020, and Amur Equipment was approved for a PPP loan of $2,817,846 on May 2, 2020 but then repaid/canceled its loan 12 days later.

[46] Accounting guidance from the FDIC (https://www.fdic.gov/coronavirus/smallbusiness/faq-sb.pdf) indicates that PPP loan processing fees should be recognized over the life of the loan or upon its sale. As a result, it is likely too early to see most of the impact of PPP processing fees on bank Call Reports. Nonetheless, Cross River's net profits have already more than quadrupled to $156M for March 31, 2020 to 2021 compared to $34M for March 31, 2019 to 2020 per their Call Reports filled with the FFIEC. Similarly, a financial disclosure by Capital Plus's parent company shows that it received $464.1M in PPP fees during the second quarter of 2021 (http://crossroads.mediaroom.com/2021-06-14-Crossroads-Systems-Reports-Fiscal-Second-Quarter-2021-Financial-Results?pagetemplate=widgetpopup).

[47] See and https://home.treasury.gov/system/files/136/PPP--IFRN%20FINAL.pdf and https://home.treasury.gov/system/files/136/Paycheck-Protection-Program-Frequently-Asked-Questions.pdf.

with little reputation risk to other business interests.

4.2 Did FinTech Lenders Improve Standards Over Time?

While a full exploration of the incentives and culpability of PPP lenders is beyond the scope of this paper, we can gain insight into the economic structure of PPP lending by studying patterns of suspicious lending over time. We consider two potential scenarios under which suspicious lending could arise:

- Scenario A: The lender does not want to facilitate fictitious loans but is not performing great due diligence. As it learns over time, the lender cracks down on the fraud.
- Scenario B: The lender is aware of the existence of or potential for fraud within its PPP loans but ignores this risk because they are earning fees from the loans and there is little if any downside to fraud for the lender. This may be particularly true for lenders with little reputation or other business to protect.

Under scenario A, we would expect that when lenders are new to PPP lending, they may facilitate questionable loans, but over time as they experience more loans with improbable features, they should originate fewer of these loans. In this case, borrowers who wish to commit loan fraud would need to rotate among lenders. In scenario B, in which the lender is willing to turn a blind eye or encourage fictitious loans, the amount of suspicious lending could grow through time as lenders develop a reputation for attracting more suspicious borrowers.

Scenario A predicts:

1. Loan misreporting will decrease over time as lenders become more aware and develop systems to screen out suspicious loans.
2. Suspicious borrowers will be less likely to receive a repeat loan from the same lender compared to other borrowers.
3. Regions with high misreporting in rounds 1 and 2 will face extra scrutiny from lenders, which will decrease round-3 misreporting.

Scenario B predicts:

1. Loan misreporting will grow over time as borrowers learn about the potential for fraud and lenders do little to stop it.
2. Borrowers with suspicious first draw loans in rounds 1 and 2 will be able to obtain second draw loans in round 3 from the same lenders.

3. Regions with high misreporting in rounds 1 and 2 will have the same or more misreporting in round 3 because lenders are maximizing loan volume with little regard to potential fraud.

Did lenders improve their loan screening over time? We have already seen that the overall rate of suspicious lending grew over time from round 1 to round 3. Panel A of Figure 13 plots more granular suspicious loan rates on a weekly basis separately for non-bank FinTech, online bank FinTech, and traditional lenders. For the FinTech lenders, loans became more suspicious over time throughout rounds 1 and 2. The rate of suspicious lending dropped at the beginning of round 3, likely due to pent up demand for second draw loans from legitimate borrowers. Most round 3 FinTech lending occurred later in round 3 (see Figure 1), and as round 3 progressed, the suspicious loan rate rose dramatically, with around 40% of loans flagged as suspicious in the closing weeks of round 3. Suspicious lending by traditional lenders also grew over time, but at a much lower rate. FinTech and traditional lenders both started the PPP with suspicious loan rates of around 10%, but by the end of the program the FinTech suspicious loan rate was close to 40%, more consistent with scenario B.[48]

We also examine lending growth and suspicious loan rates in the different rounds by lender. Panel A of Figure IA.11 shows that almost all lenders had higher suspicious lending rates in round 3 than in rounds 1 and 2.[49] Additionally, many of the FinTech lenders with the highest suspicious loan rates in round 3 also had the most growth. In particular, Fountainhead, Harvest, and Itria originated almost all their loans in round 3, and more than 30% of their loans are flagged. Overall, other than Kabbage which was acquired by American Express before round 3,[50] In Table VI, we regress indicators for the four primary flags in round 3, individually and combined, on lenders' rounds 1 and 2 misreporting rates for the same flags. As in previous regressions, we control for loan size and jobs with zip code, business type, industry × CBSA fixed effects. For FinTech lenders, we find highly economically and statistically significant relations across the board with weaker relations for traditional lenders. In other words, the suspicious lending behavior of FinTech lenders is highly persistent over time. Overall, there is little evidence that suggest most FinTech lenders are taking steps to screen out dubious loans.

Regarding prediction 2, if lenders are taking steps to screen out questionable loans, then

[48] Panel B of Figure IA.6 shows similar trends for each primary flag individually.

[49] Panel B of Figure IA.11 shows that that the growth of misreported loans is also present, and even stronger for some lenders, when considering only first draw loans.

[50] Kabbage had a high suspicious loan rate for rounds 1 and 2 but a lower suspicious loan rate in round 3 that is also accompanied by lower lending volume. Two other large round 3 FinTech lenders, Capital Plus and Benworth, also have round 3 suspicious lending rates in excess of 35% but are not included in the plot because they did not have enough earlier lending to calculate a suspicious loan rate for rounds 1 and 2.

their borrowers with questionable first draw loans in rounds 1 and 2 may get rejected when they apply for a second draw loan in round 3. To examine this, we estimate regressions to determine whether a first draw borrower is more or less likely to receive a second draw loan from the same lender if its first draw loan is flagged by one of the primary misreporting indicators. Table VII shows that traditional loans which are flagged in the first two rounds have a statistically significant decrease in the probability of receiving a second draw loan from the same lender of 1.83 ppt (with t-stat of -9.64) and FinTechs have a statistically insignificant increase of 0.77 (-1.83 + 2.61) ppt (with t-stat of 0.81). [51] This provides some indication that traditional banks were less likely to continue lending to borrowers with previous suspicious borrowing, but FinTechs do not seem to be screening or implementing procedures which make it less likely for questionable borrowers to continue receiving funds in the form of a second draw. Columns (3) and (4) of Table VII condition on the borrower receiving a second draw (either from the same or different lender) with similar results.[52]

To assess prediction 3, we examine whether areas with high misreporting in rounds 1 and 2 had higher or lower misreporting in round 3. Panel B Figure 13 plots the percentage of loans flagged in rounds 1 and 2 in each zip code on the x-axis, and the percentage of flagged loans in round 3 in the same zip code on the y-axis. The left subpanel uses all loans, middle uses FinTech loans, and right uses traditional loans. Each dot represents a zip code, and the size of the dots corresponds to the number of loans in the zip code. Purple to blue colors indicate that a zip code had fewer loans in round 3 than in rounds 1 and 2, light blue to light yellow colors indicate that a zip code had about the same number of loans in round 3 compared to rounds 1 and 2, and orange to red colors correspond to an increase in the number of loans in the zip code. Darker colors correspond to higher degrees of decline or growth.

The figure displays three interesting findings. First, most zip codes (90.9%) are above the 45-degree line in the left subpanel, indicating that misreporting rates increased in round 3 almost everywhere. In many zip codes (34.3%), the percentage of loans that are flagged as suspicious in round 3 is more than twice as high as in rounds 1 and 2. Second, the zip codes with the highest suspicious loan rates experienced the most growth in lending. Many zip codes with the highest level of flagged loans in round 3 have more than three times the number of loans in round 3 compared to rounds 1 and 2, suggesting that significant

[51] These results are based on $Same\ Lender_i$ being set to 0 if the borrower did not get a second draw at all. Columns (3) and (4) of Table VII condition on the borrower receiving a second draw loan and show similar results.

[52] In Figure IA.10, we show results separately for individual lenders with lender fixed effects and lender interactions. The inclusion of the lender fixed effects ensures that the reported coefficient is due solely to differences in the lender's behavior towards flagged and nonflagged loans rather than systematic changes in the lender's behavior. For most traditional lenders, borrowers with a flagged first-draw loan are less likely to receive a second draw loan from the same lender, but for several FinTech lenders, suspicious first-draw borrowers are slightly more likely to receive a second draw.

portions of zip code level loan growth in round 3 may be due to suspicious lending practices. Third, the middle and right subpanels differentiate between FinTech and traditional lenders and show that lending growth and increased misreporting rates are almost entirely from FinTech lenders. Traditional lenders had only small increases in suspicious loan indicators, and their lending generally a decreased. In contrast, FinTech lenders increased the number of loans they originated and increased their suspicious lending rates in almost all zip codes. Additionally, FinTech growth was highest in zip codes with the highest misreporting rates.[53] We also test these results at the zip code-lender level in Table IA.X with zip code and lender fixed effects and find that a 10 ppt increase in flagged loans in a zip code-lender pair in rounds 1 and 2 is associated with an 18.9 ppt increase in lending for a FinTech lender and an insignificant increase of 1.5 ppt for a traditional lender. There is also strong persistence of suspicious lending across rounds within zip code-lender pairs.

4.3 Repayments and Enforcement Actions

The economics of crime depend crucially on a crime's expected penalty and probability of detection (Becker 1968). The US Department of Justice is pursuing criminal complaints alleging PPP fraud, and some borrowers have voluntarily repaid their loans without applying for loan forgiveness. However, the magnitude of these enforcement actions is tiny. Compared to the 1.8 million loans we identify as suspicious, the DOJ has publicized 162 criminal complaints regarding only 355 loans, and SBA data indicates that only 16,930 round 1 and 2 loans were repaid between December 1, 2020 and June 30, 2021.[54] In Figure IA.12, we descriptively summarize enforcement actions and repayments that we are able to match to the PPP loan data with the result that both are elevated for FinTech lenders and for loans flagged as suspicious by our measures.[55] While it is possible that more enforcement actions will be forthcoming, there appears to be no penalty for most suspicious lending thus far.

5 Conclusion

We examine four primary and five secondary metrics related to potentially misreported loans. FinTech loans are highly suspicious at a rate of almost five times that for traditional lenders. Nine of the ten lenders with the highest rates of suspicious loans are FinTech lenders and the remaining traditional bank (Amur Equipment) is in many ways similar to a FinTech lender. We estimate the total amount of potential misreporting at 1.8 million

[53] Results are similar at the county and state level. See Panels C and D of Figure IA.11. Panel B of Figure IA.7 also plots lending growth by county.

[54] Of the DOJ enforcement action loans with enough data to be matched to the PPP loan level data, 153 loans were originated by FinTech lenders and 126 were originated by traditional banks. There are likely other cases that are still sealed, are in early stages of investigation, or are not included on the DOJ website for other reasons.

[55] Regressions in Table IA.XI also show evidence of elevated repayment and enforcement action rates for flagged loans.

loans with a balance of $76.3 billion based on the four primary metrics, and $37.9 billion (1.2 million loans) under a more conservative estimate requiring an additional indicator. The total amount of misreporting is likely larger than either estimate because many of our indicators are only available for a subset of loans, and 5.2 million loans with a balance of $283 billion are flagged at least one of our nine indicators. In the early stages of the PPP, about 10% of FinTech loans were potentially misreported, but the percentage of suspicious FinTech loans increased to more than 40% by the end of round 3. These findings highlight the large costs of low oversight and lack of sufficient negative ramifications to borrowers and lenders for poor lending practices in the PPP.

Our findings have important practical policy implications. First, with the focus on rapid distribution of funds, the PPP did not include robust verification requirements. Traditional banks may have been more apt to follow standard practices anyway. The lack of rigorous verification seems to have led to substantial costs to taxpayers. Second, FinTech lending, though quite successful at adapting to new environments and quickly disbursing funds, needs to improve due diligence practices. Two established FinTech lenders persistently have low rates of misreporting, indicating that FinTech lending need not be substandard. Third, our evidence, along with convincing evidence that the PPP saved relatively few jobs at an extremely high cost (Autor et al. 2020; Chetty et al. 2020; Granja et al. 2020), provides growing evidence that the PPP seems to have been a poor allocation of capital. Fourth, incentives in the PPP appear misaligned in that FinTech lenders made billions of dollars dispersing loans with widespread indicators of misreporting. While there are limitations to what our data and analysis can discern, the sheer scope of the tens and hundreds of thousands of suspicious loans originated by many FinTech lenders suggests that many lenders either encouraged such loans, turned a blind eye to them, or had extremely lax oversight procedures.

Finally, the increasing scope of the misreporting through time indicates that current penalty and enforcement systems are not effective. If the system is not changed, the most likely outcome is more of the same. This paper is also an example of how forensic finance research can more fully investigate the rent-seeking dimension of finance (Zingales 2015). Government agencies can assist this transparency goal by making detailed data available to the public. We hope to see future research with additional forensic investigation of the PPP as well as other recent government and private lending programs.

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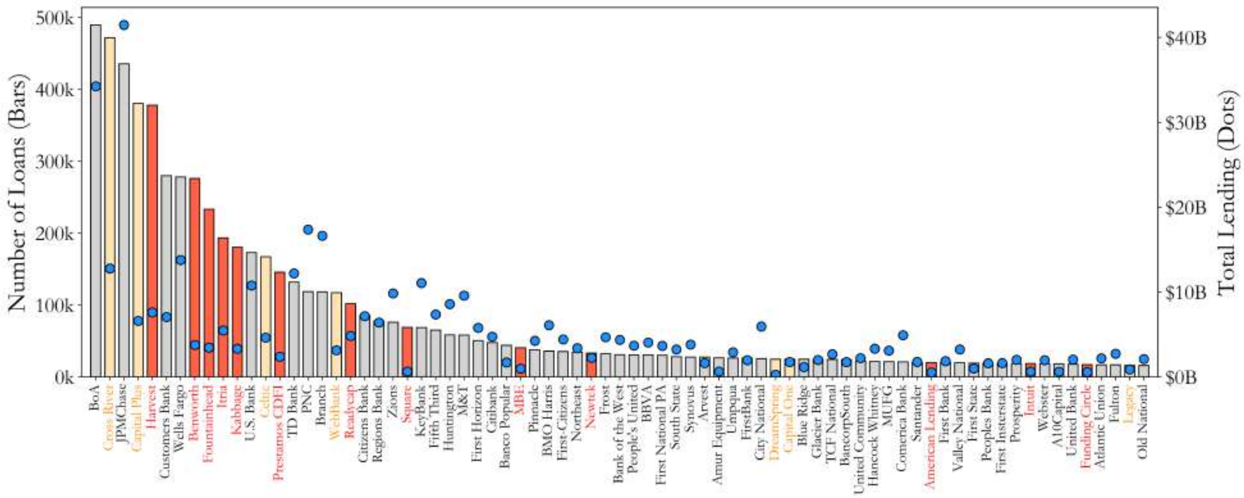
Figure 1. Fintech Market Share

This figure shows the role that fintech lenders played in the PPP. Panel A shows the number of loans (bars) and dollar value of loans (dots) originated by the top 75 lenders (by number of loans). Panel B shows the percentage of loans originated by fintech lenders during each week of Round 1, 2, and 3 of the PPP on the left axis and the total number of loans originated each week on the the right axis. In both panels, red represents non-bank fintech lenders, cream represents online bank fintech lenders, and grey represents traditional lenders. Note that mid-August through December 2020 is not shown in Panel B since no PPP loans were originated during this period.

Panel A. Number of Loans and Dollar Value of Loans, by Lender (Top 75)



Panel B. Fintech Market Share, by Week

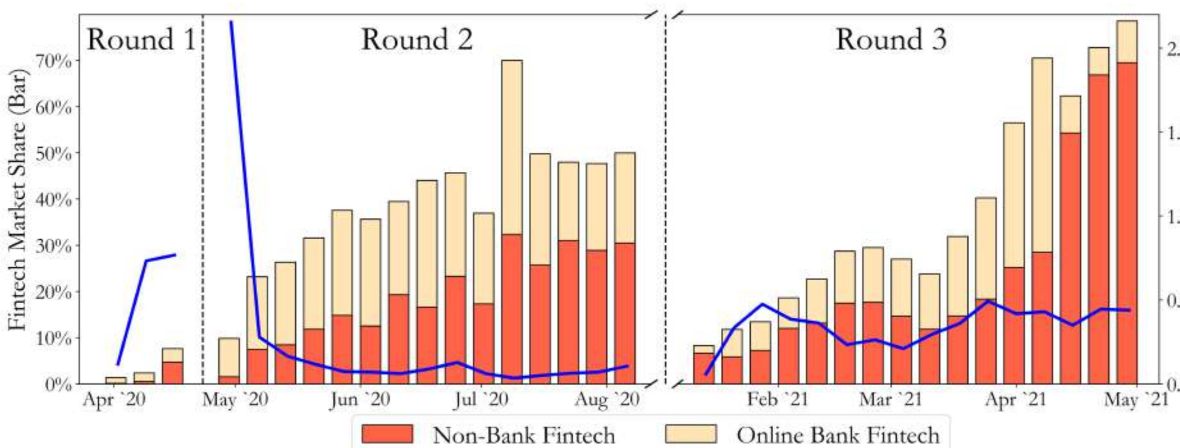
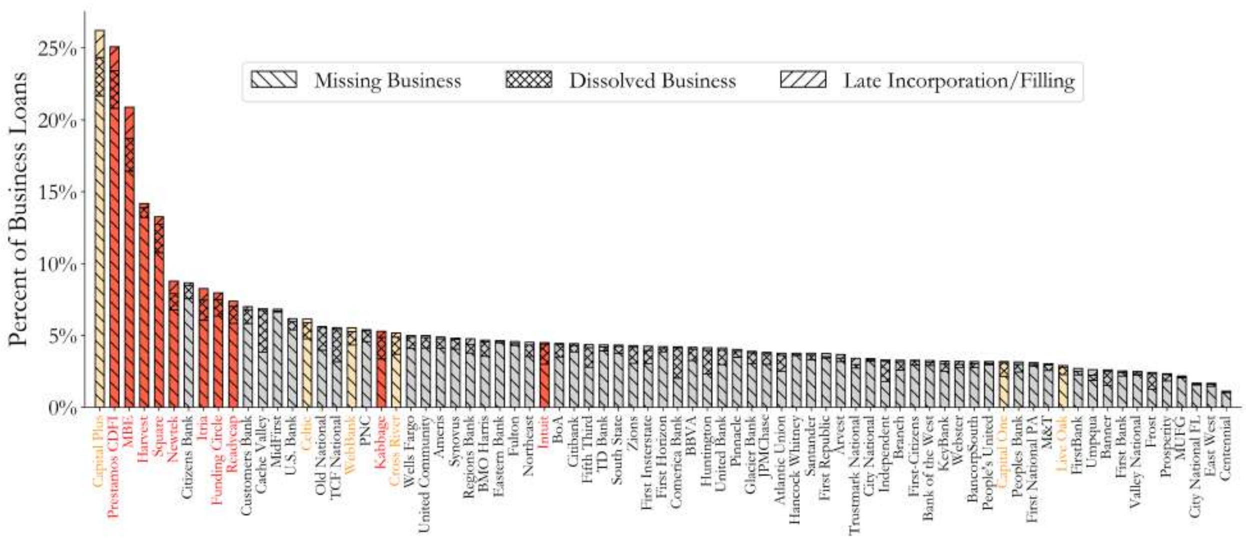


Figure 2. Business Registry and Multiple Loans Flags

This figure shows the prevalence of the business registry and multiple loans flagged loans by lender. Panel A shows the percentage of loans flagged for being incorporated after February 15, 2020 ("Late Incorporation/Filling"), being dissolved and inactive before approved for a PPP loan ("Dissolved Business"), or not being found in the business registry for its home state or in any other state while listing an address in its home state ("Missing Business"). Panel B shows the percentage of loans flagged as being located at a non-business, non-central (e.g., not an apartment or office building) address that received more than one loan within the given loan's draw (i.e., the first or second draw). For Panel A, only loans to businesses organized as a corporation, subchapter S corporation, or LLC and not based in Illinois or a territory are considered; lenders originating at least 10,000 loans fitting these criteria are shown. For Panel B, all loans are considered and lenders originating at least 15,000 loans are shown. In both panels, red represents non-bank fintech lenders, cream represents online bank fintech lenders, and grey represents traditional lenders.

Panel A. Business Registry Flagged Loans, by Lender



Panel B. Multiple Loans Flagged Loans, by Lender

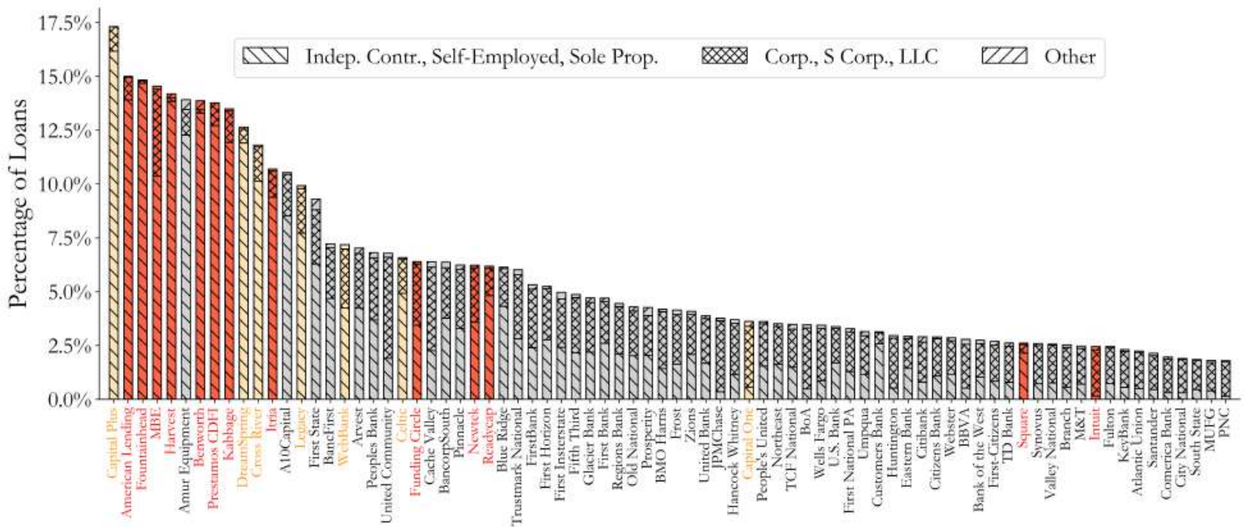
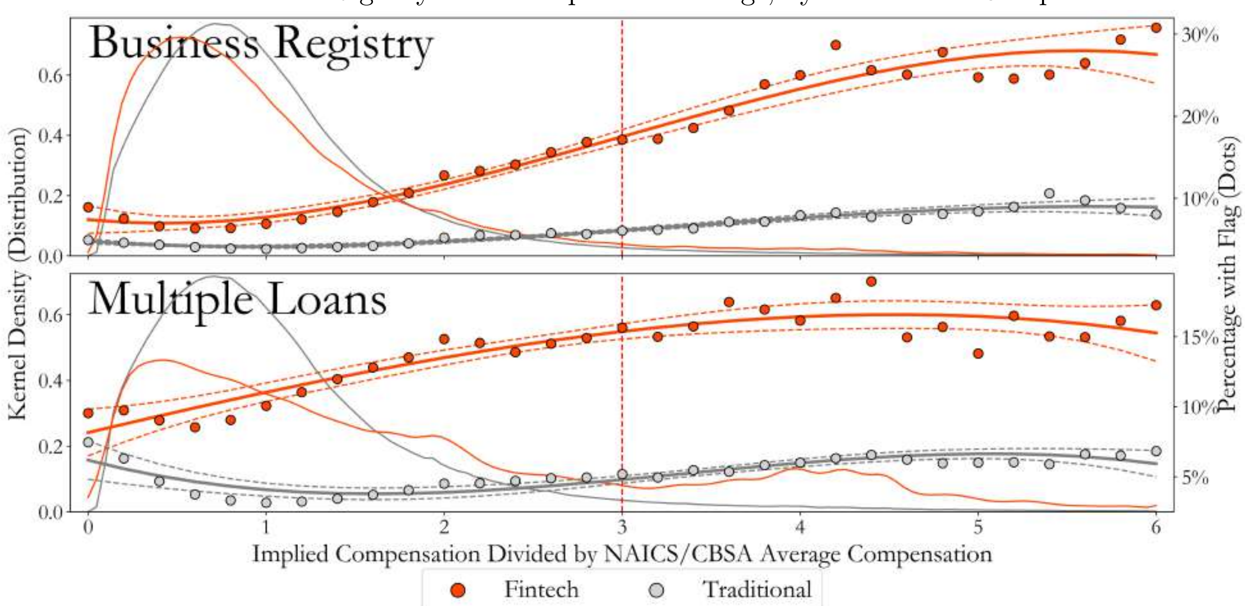


Figure 3. High Implied Compensation Flag

This figure shows the relation between a loan's implied compensation per employee and the average compensation in the loan's industry (represented by NAICS [North American Industry Classification System] code) and region (represented by CBSA [core-based statistical area]). We define normalized compensation by dividing the implied compensation of the loan by the average compensation in the loan's industry-CBSA. Panel A shows the relation between normalized compensation and the business registry (top subpanel) and multiple loans flags (bottom subpanel). Panel B shows the percentage of loans with normalized compensation above 3 (i.e., implied compensation is more than three times the NAICS/CBSA average). For Panel A, the left axis (distribution) shows the kernel density of loans and the right axis (dots) shows the percentage of flagged loans in each bin, where each bin is 0.2 units wide. The solid lines are third-degree polynomial fits for the percentage flagged and the dashed lines are the 95% confidence intervals. For the business registry subpanel, only loans to businesses organized as a corporation, subchapter S corporation, or LLC and not based in Illinois are considered. For Panel B, only loans where the average compensation in the loan's industry-CBSA is less than $33,333.33 are considered; lenders with at least 5,000 loans fitting this criterion are shown.

Panel A. Business Registry and Multiple Loans Flags, by Normalized Compensation



Panel B. High Implied Compensation, by Lender

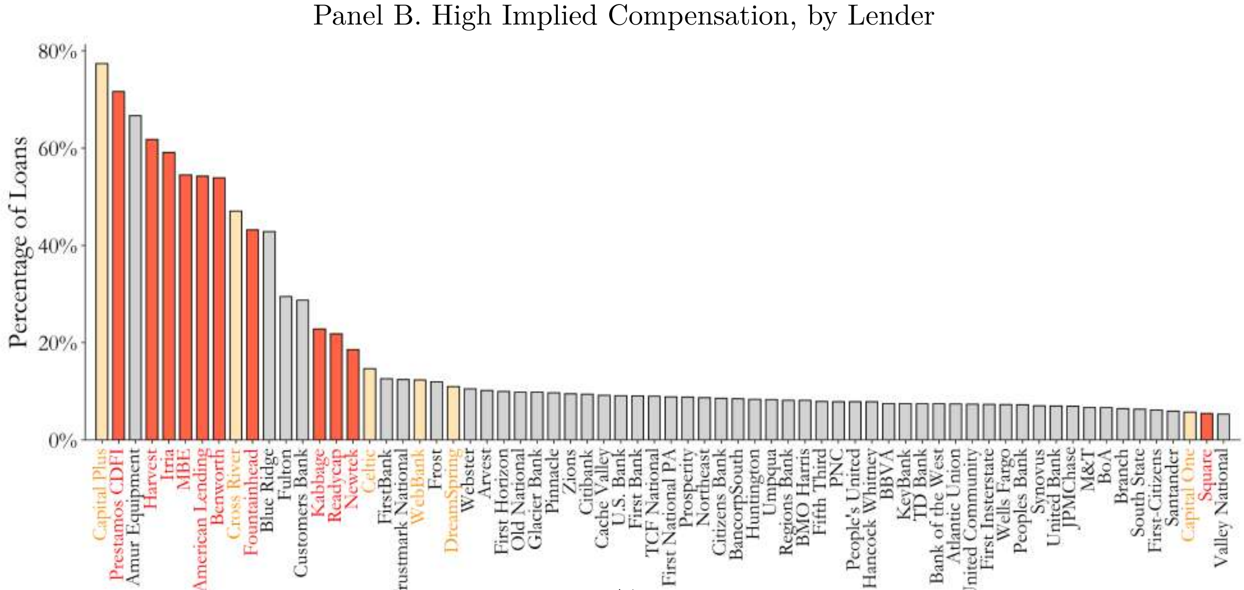
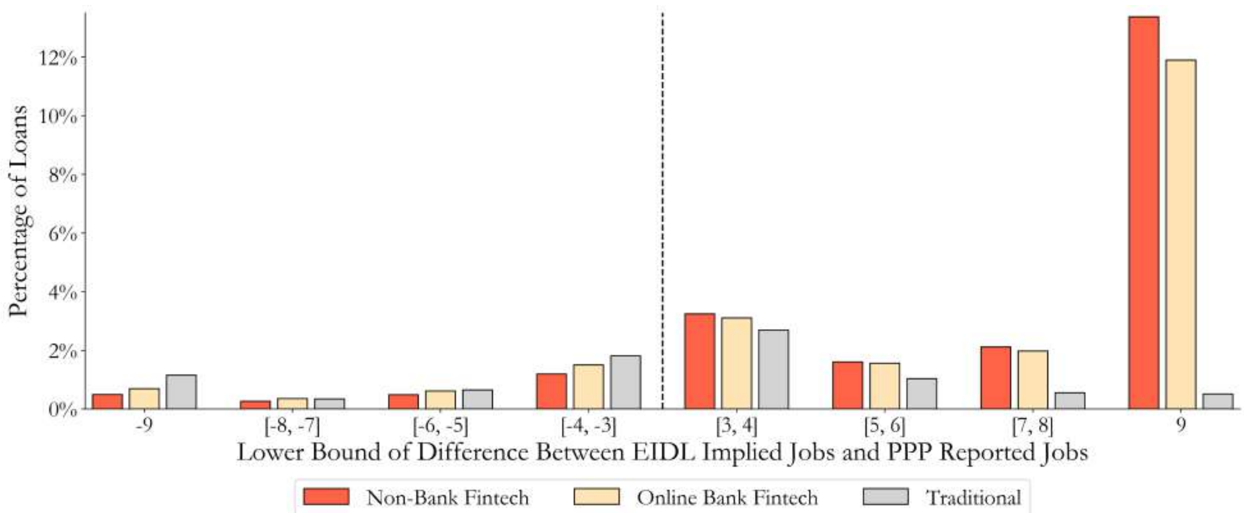


Figure 4. EIDL > PPP Jobs Flag

This figure shows the difference between the number of employees implied by a business's EIDL Advance amount ("EIDL Implied Jobs") and the number of jobs reported by the business on its PPP application ("PPP Reported Jobs"). Panel A shows the lower bound (in the absolute value sense) of the difference between the EIDL implied jobs and PPP reported jobs by lender type. Panel B shows the percentage of loans by each lender where the EIDL implied jobs is at least three more than the PPP reported jobs. In both panels, only loans with a matched EIDL Advance are consider; lenders with at least 5,000 loans fitting this criterion are shown in Panel B. In both panels, red represents non-bank fintech lenders, cream represents online bank fintech lenders, and grey represents traditional lenders.

Panel A. Difference Between EIDL Implied Jobs and PPP Reported Jobs



Panel B. EIDL > PPP Jobs, by Lender

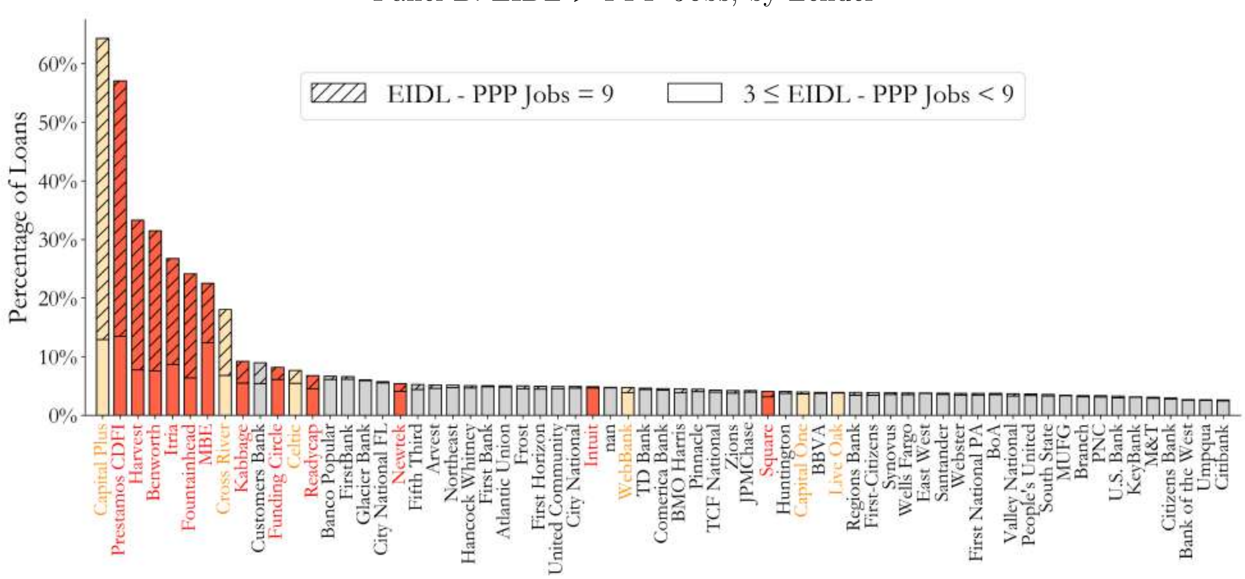
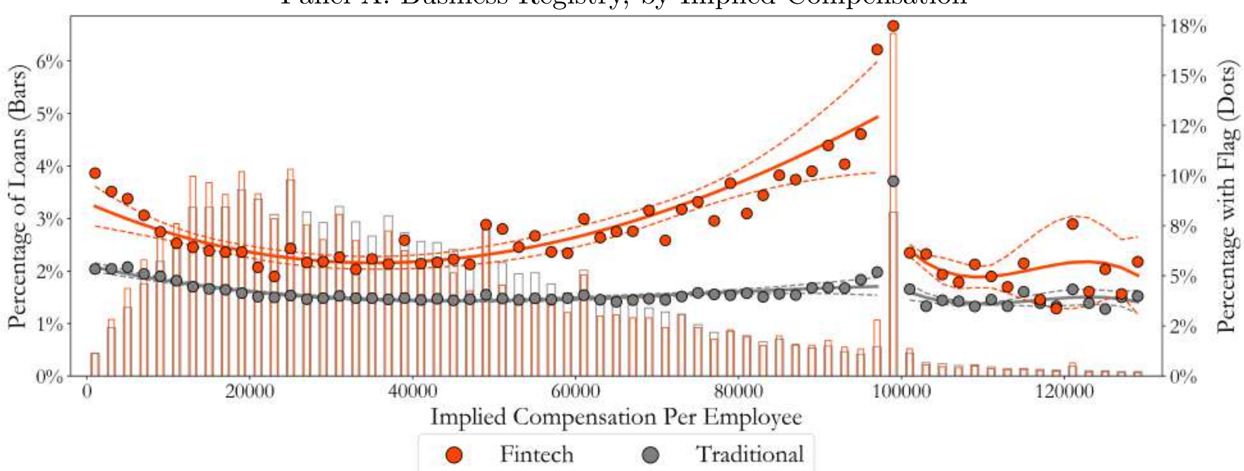


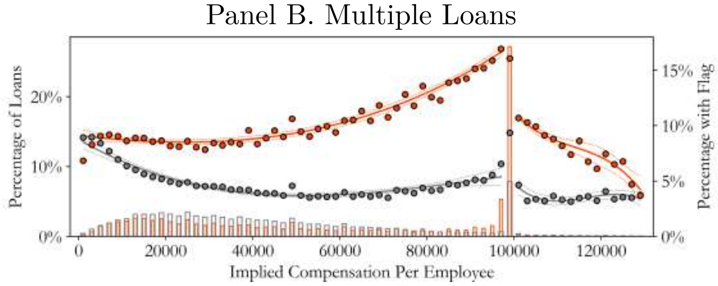
Figure 5. Discontinuities at $100,000

This figure shows the prevalence of various flags by the implied compensation per employee. Panel A shows the prevalence of the business registry flag, Panel B the multiple loans flag, Panel C the high implied compensation flag, and Panel D the EIDL > PPP jobs flag. For all panels, loans are binned into $2,000 wide bins (i.e., ($0k, $2k], ... , ($98k, $100k], ... ,($128, $130k]), the left axis shows the percentage of loans that in each bin (bars) and the right axis shows the percentage of the loans in the bin that have the given flag (dots). Loans are filtered to corporation, S-corporation, and LLC loans for Panel A, loans for which we can determine CBSA/NAICS average compensation for Panel C, and loans with a matched EIDL Advance for Panel D. The solid lines are third-degree polynomial fits (weighted based on number of loans in the each bin), which are separately fitted for loans below $98,000 and loans above $100,000, and the dashed lines are the 95% confidence intervals. Red represent fintech loans and grey represent traditional loans.

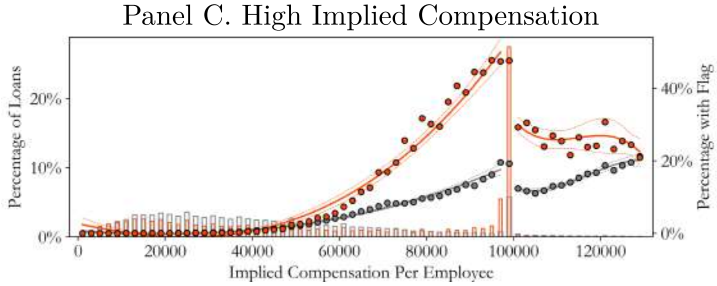
Panel A. Business Registry, by Implied Compensation



Panel B. Multiple Loans



Panel C. High Implied Compensation



Panel D. EIDL > PPP Jobs

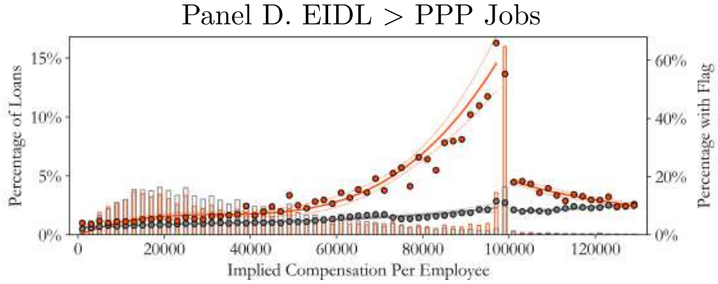
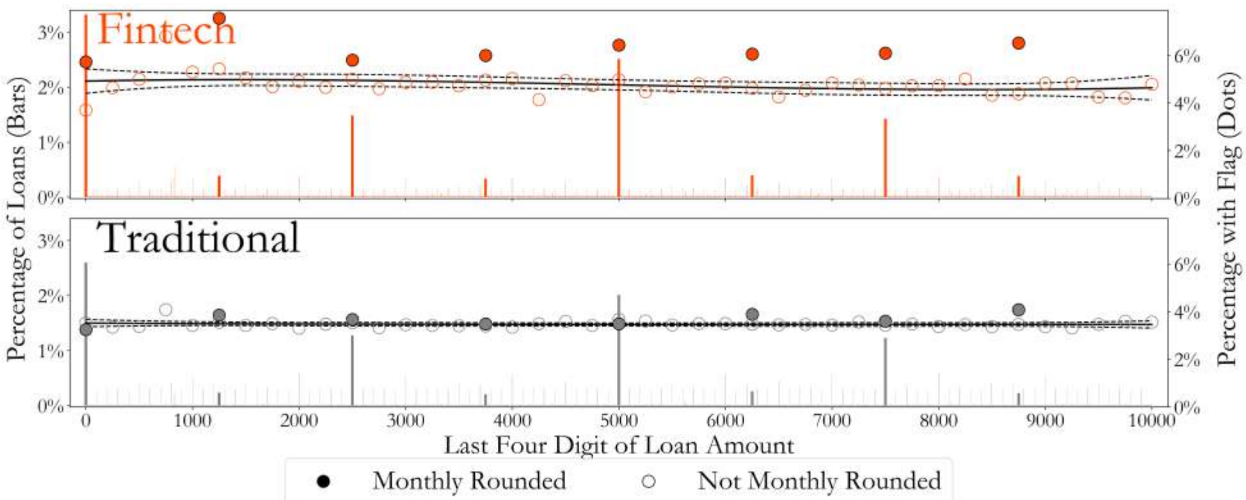


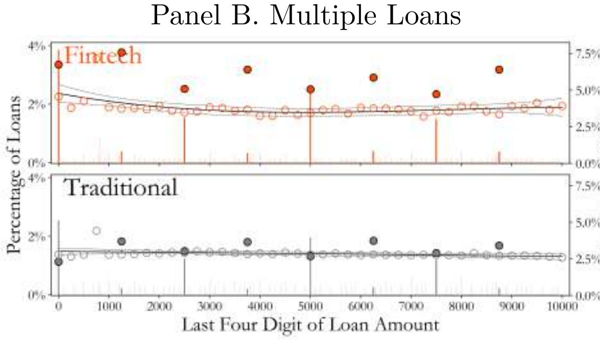
Figure 6. Rounded Compensation

This figure shows the prevalence of each flags by whether the total monthly implied compensation of a loan is rounded to an interval of \$500 (i.e., loan amount is within ± 50 cents of an interval of \$1,250). Panel A shows the business registry flag, Panel B the multiple loans flag, Panel C the high implied compensation flag, and Panel D the EIDL > PPP jobs flag. The top subpanel is for fintech loans and the bottom for traditional loans. For all panels, the last four digits of the loan amount is considered (i.e., \$123,456.78 → \$3,456.78). The left axis shows the percentage of loans in each \$1 wide bin (bars for rounded compensation are thickened) and the right axis shows the percentage of loans that are flagged within each \$1 bins for monthly rounded (solid dots) and \$250 wide bins for non-rounded (hollow dots). Loans are filtered to corporation, S-corporation, and LLC loans for Panel A, loans with CBSA/NAICS average compensation less than \$33,333.33 for Panel C, and loans with a matched EIDL Advance for Panel D. Additionally, loans with one job reported, loans with implied compensation within ± \$1,000 of \$100,000, and second draw loans to hospitality businesses are excluded from all Panels. The solid lines are third-degree polynomial fits for the percentage flagged in the non-rounded bins and the dashed lines are the 95% confidence intervals.

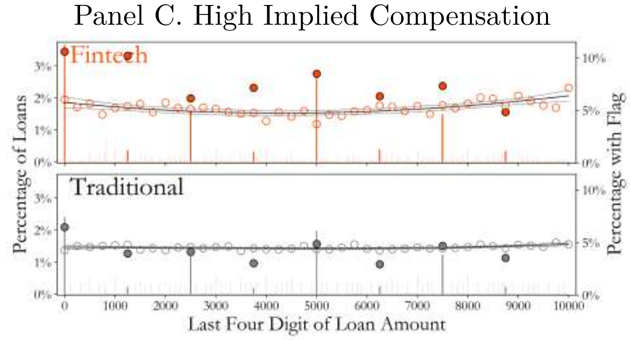
Panel A. Business Registry Flag, by Lender Type and Rounding



Panel B. Multiple Loans



Panel C. High Implied Compensation



Panel D. EIDL > PPP Jobs

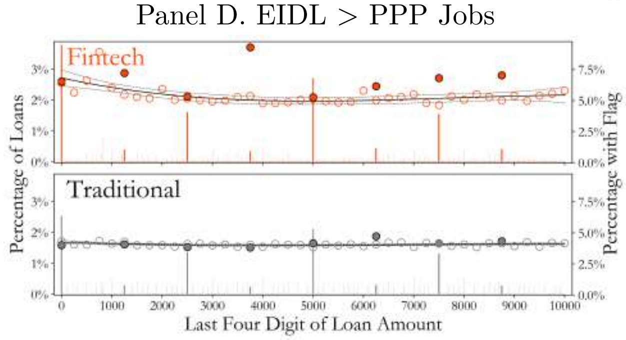
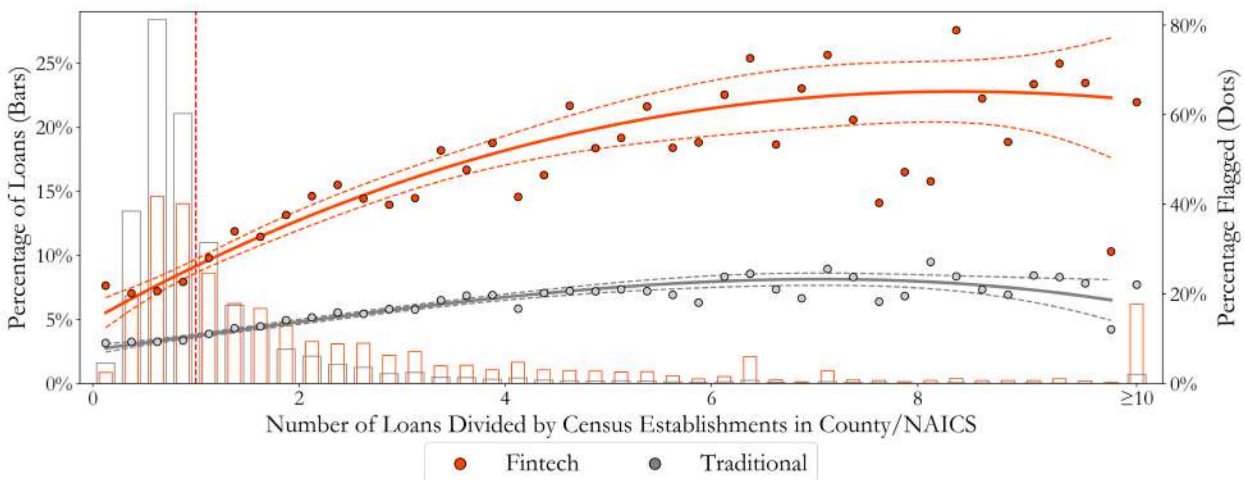


Figure 7. Overrepresentation of Industries in Counties

This figure shows overrepresenation of loans to industry-county pairs. We define normalized number of loans as the number of first draw loans divided by the number of establishments (per the 2019 US Census County Business Patterns dataset) in an industry (represented by NAICS [North American Industry Classification System] code) and county. Panel A shows the relationship between normalized number of loans and our four main flags combined together as at least one flag and Panel B shows the relationship for each flag separately. Since the CBP does not include self-employed and independent contractors as establishments, we exclude loans to these business types. Note that 6.20% of fintech and 0.72% of traditional loans are in industry-county pairs with ratios of at least 10; these loans are represented in Panel A by the bars and dots at the far right labeled "≥ 10". In both panels, loans are binned into 0.25 unit wide bins. The solid lines are third-degree polynomial fits for the percentage of flagged loans and the dashed lines are 95% confidence intervals.

Panel A. Percentage Flagged, by Normalized Number of Loans in Industry-County Pair



Panel B. Individual Flags, by Normalized Number of Loans in Industry-County Pair

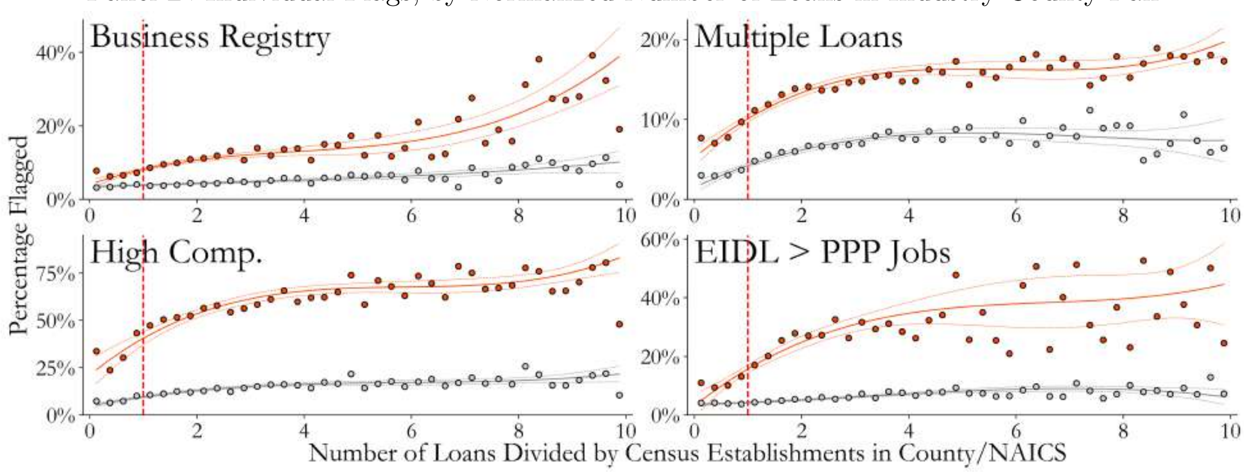
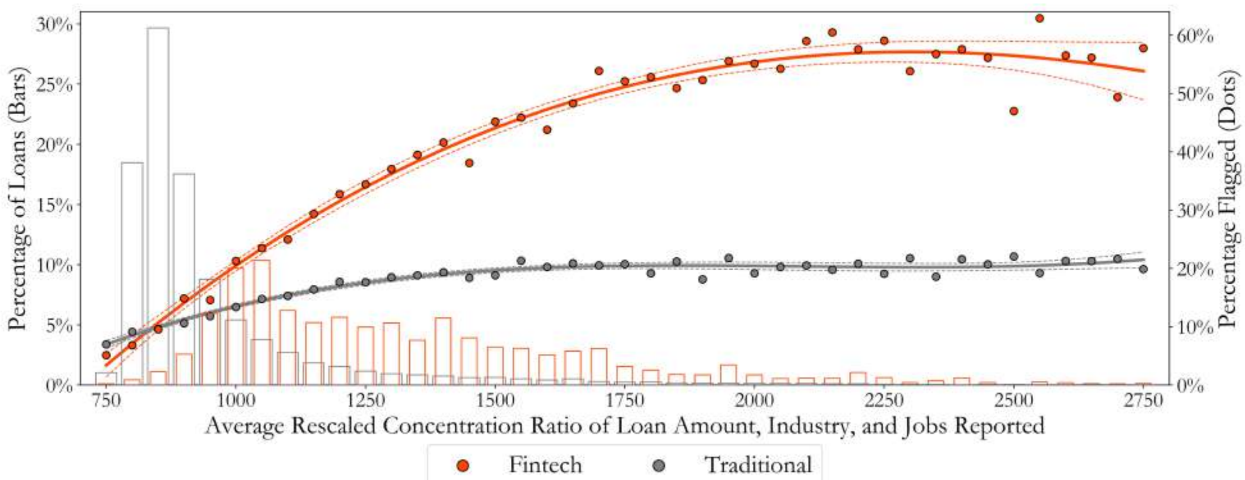


Figure 8. Clustering Within Lenders and Counties

This figure shows clustering of loans within lenders-county pairs. We calculate the concentration ratios of industries, loan amount (rounded to \$100), and jobs reported (excluding 1) for first draw loans in each lender-county pair, rescaled each concentration ratio to a median of 1,000 and IQR (interquartile range) of 300, and then take the average of the three rescaled concentration ratios. For example, let $i = 1, 2, ..., n$ represent the n industries in a given lender-county pair, then $Concentration_{\text{industry}} = \sum_{i=1}^{n} s_i^2$ where s_i is the percentage of loans in the lender-county pair that are in industry i times 100 (e.g., 6.2 for 6.2%). Then, $Rescaled\,Concentration_{\text{industry}} = \frac{Concentration_{\text{industry}} - \text{Median}[Concentration_{\text{industry}}]}{75^{th}\text{Percentile}[Concentration_{\text{industry}}] - 25^{th}\text{Percentile}[Concentration_{\text{industry}}]} * 300 + 1000$. Panel A shows the relationship between the average rescaled concentration ratio and our four main flags combined together as at least one flag and Panel B shows the relationship for each flag separately. In both panels, only lender-county pairs with at least 25 loans are considered. Note that 2.4% of fintech loans and 0.5% traditional loans are outside the average rescaled concentration ratio range shown in Panel A. In both panels, loans are binned into 50 unit wide bins; in Panel B, bins with fewer than 100 loans for each the given flag can be determined are excluded. The solid lines are third-degree polynomial fits for the percentage of flagged loans and the dashed lines are 95% confidence intervals.

Panel A. Percentage Flagged, by Average Rescaled Concentration Ratio in Lender-County Pair



Panel B. Individual Flags, by Average Rescaled Concentration Ratio in Lender-County Pair

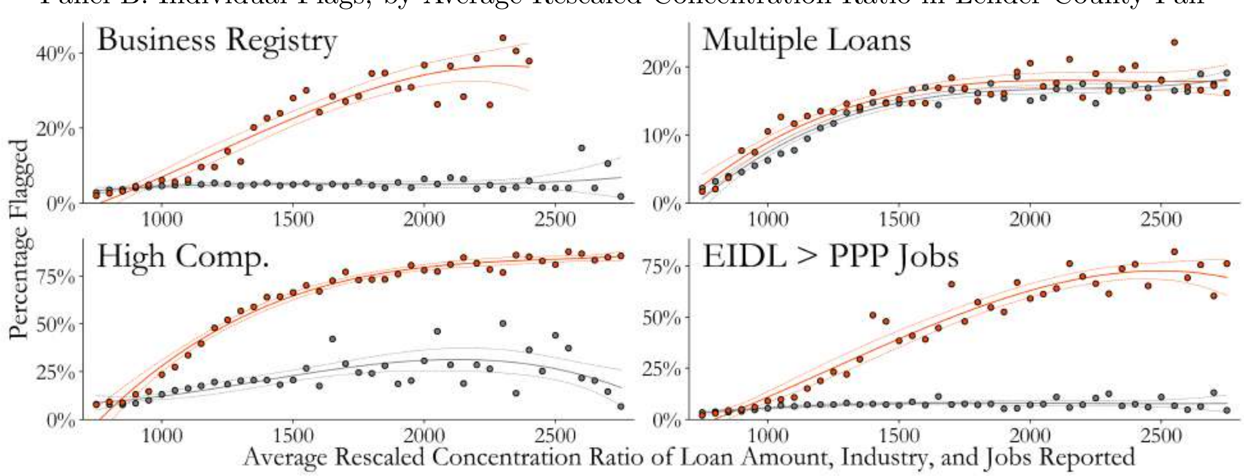
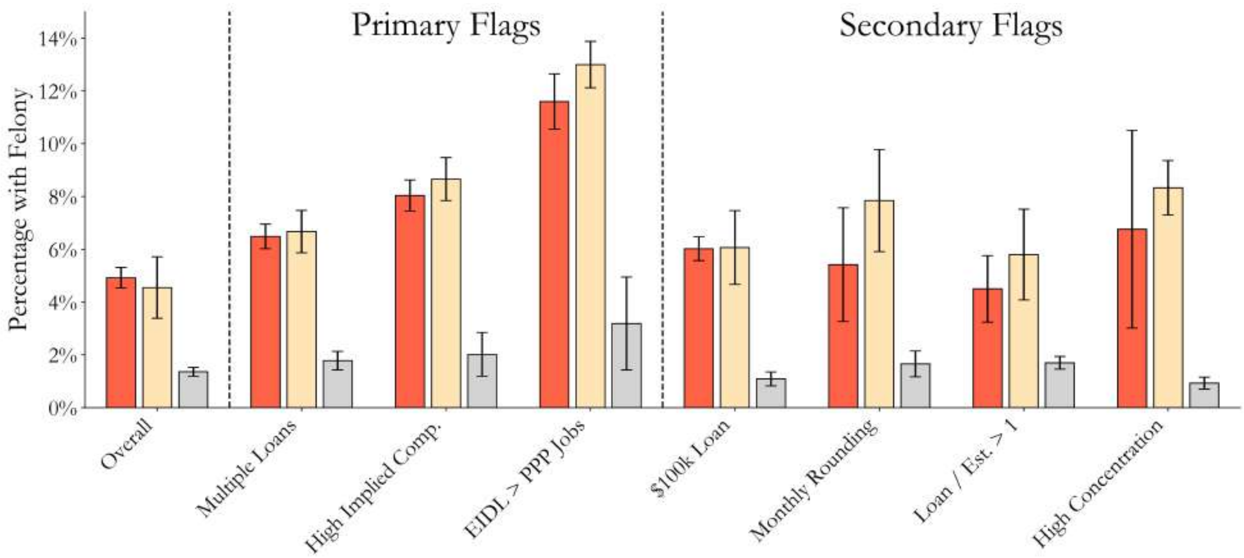


Figure 9. Criminal Records

This figure shows criminal records for a sample of 150,000 Round 1 and 2 loans to self-employed individuals, independent contractors, and sole-proprietorships. Panel A shows the percentage of loans where the borrower has a felony from 2000 or after on their record by lender type and whether the loan has various features. The error bars denote 95% confidence intervals (based on standard errors clustered by zip code and lender) for each percentage. Panel B shows the relationship between the percentage of loans in this sample that are flagged by at least one primary flags and the percentage of borrowers that have a felony from 2000 or after on their record by lender. Lenders with at least 0.2% of the sample (300 loans) are shown. The dashed line is a linear fit and correlation is shown in the bottom left corner. In both panels, red represents non-bank fintech lenders, cream represents online bank fintech lenders, and grey represents traditional lenders.

Panel A. Percentage Felony, by Lender Type and Presence of Misreporting Indicators



Panel B. Percentage Flagged vs. Felonies

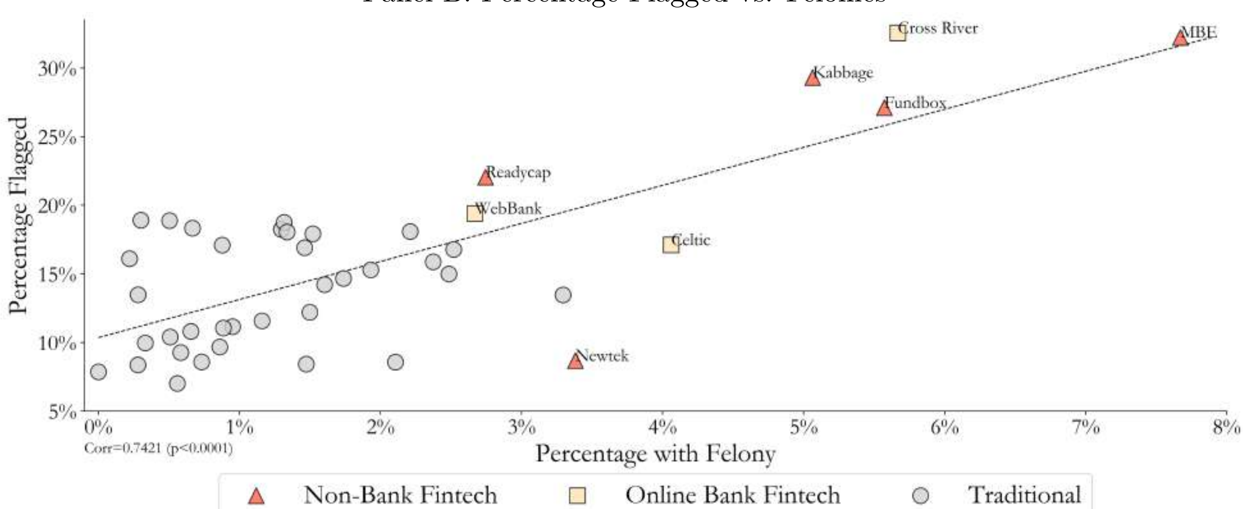
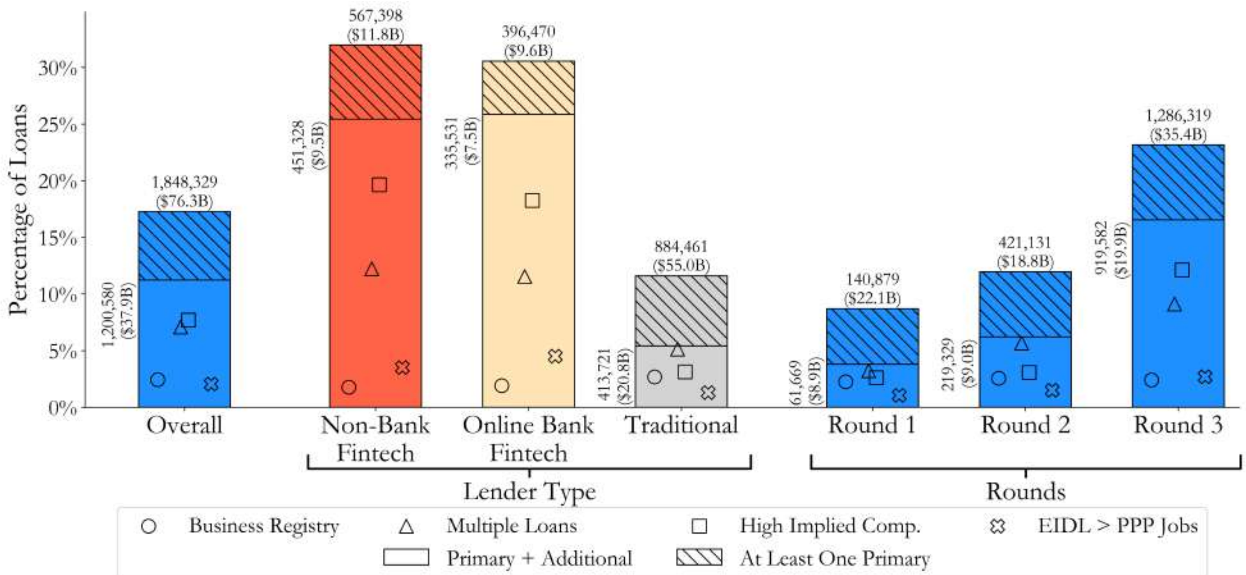


Figure 10. Lender Level

This figure shows the variation in percentage of loans flagged. Panel A shows the percentage and dollar amounts of flagged loans by lender type and round. Panel B shows the percentage of flagged loans by lender for the top 75 lenders (by number of loans). In both panels, the plain solid filled in section represents the percentage of loans flagged by one primary flag and an additional flag (either another primary or a secondary) and the entire bar (plain and stripped combined) represents loans flagged by at least one primary flag. In Panel A, the set of numbers to the left of each bar represent the number of loans and dollar value of loans flagged one primary flag and an additional flag and the set on top of each bar by at least one primary. The markers within each bar represent the percentage of loans flagged by each of the primary flags. In Panel B, the two horizontal lines represent the overall sample percentage of loans flagged by each measure (dashed for loans flagged by one primary flag and an additional flag and solid by at least one primary). In both panels, red represents non-bank fintech lenders, cream represents online bank fintech lenders, and grey represents traditional lenders.

Panel A. Percentage of Loans Flagged, by Lender Type and Rounds



Panel B. Percentage of Loans Flagged, by Lender

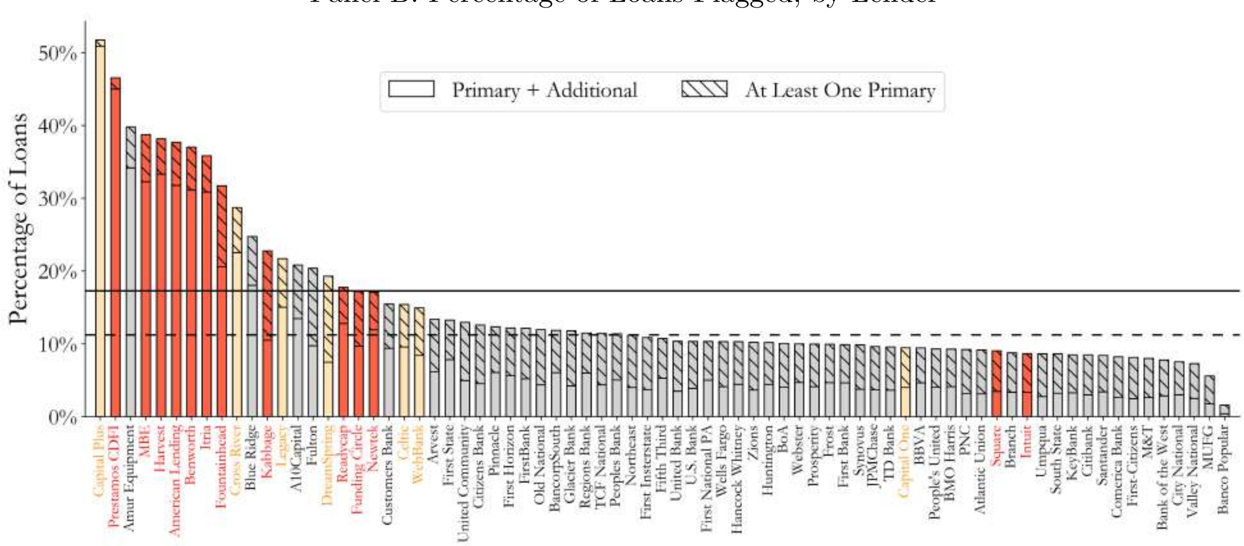
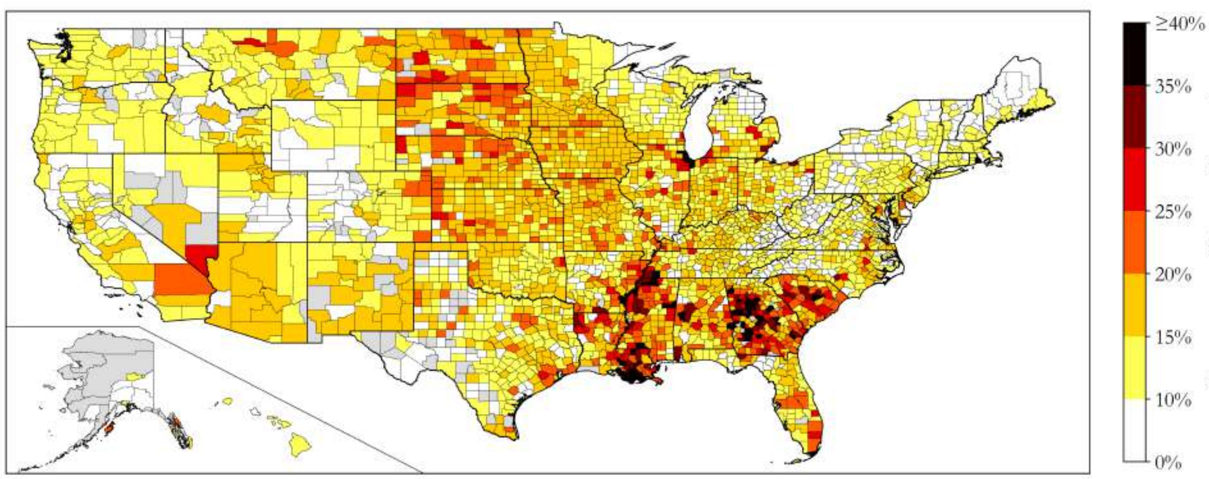


Figure 11. Geography of Flagged Loans

This figure shows the geographic variation in flagged loans. Panel A shows the percentage of flagged loans in each county and Panel B shows within county variation. In Panel A, counties are colored based on the color scheme shown in the bar to the right of the map and counties with fewer than 100 loans are colored grey. Panel B shows the percentage of flagged loans in each zip code on the vertical axis and the percentage of flagged loans in the corresponding county on the horizontal axis. Dots are colored by the percentage of fintech loans in each zip code and sized based on the number of loans in the zip code. Zip codes with at least 100 loans are shown. The dashed line is a linear fit and the correlation is shown in at the bottom left corner.

Panel A. Percentage of Flagged Loans, by County



Panel B. Within County Variation

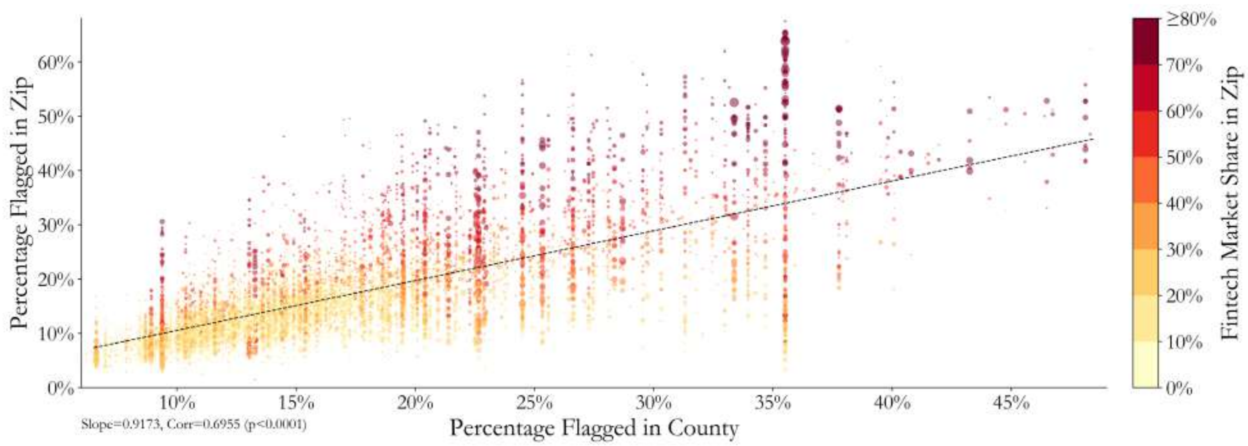
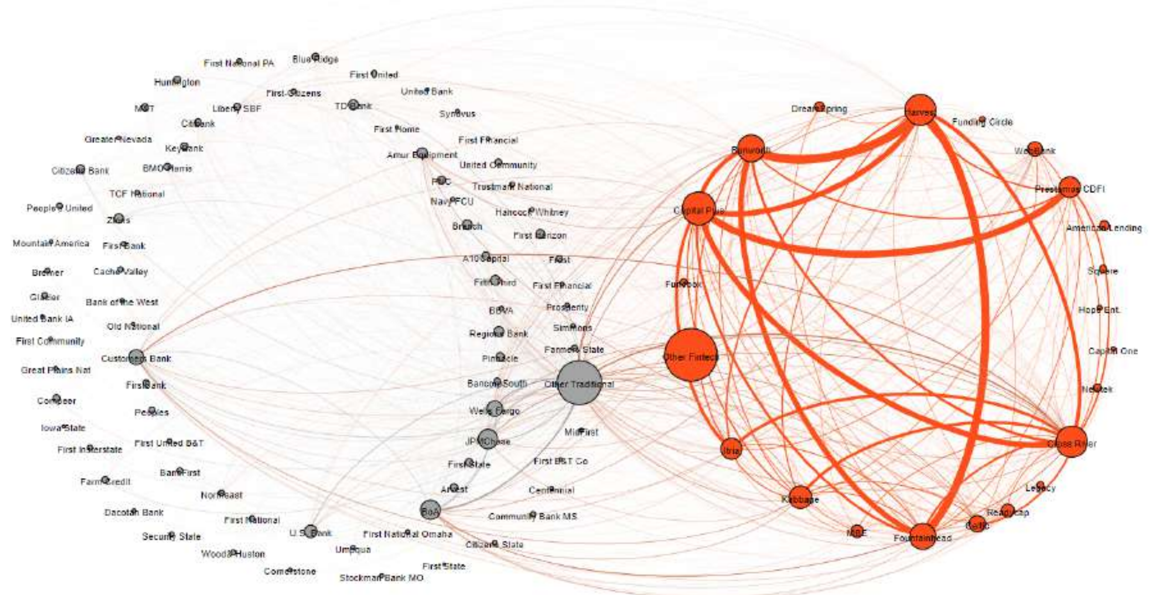


Figure 12. Lender Network

This figure shows connections between lenders. Panel A shows connections between lenders that were used by borrowers at the same address within the same draw. Panel B shows connections between lenders used by the flagged first draw borrowers across draws. In Panel A, node size is proportional to the number of loans with the multiple loans at the same address flag originated by each lender, edges are not directed, and edge width is proportional to the number of addresses that used both lenders. In Panel B, node size is proportional to the number of first draw loans (that also got a second draw loan from the same or different lender) and second draws originated by the lender, edges are directed, edge width is proportional to the number of flagged first draw borrowers moving clockwise from the first draw lender to the second draw lender. In both panels, red nodes are fintech lenders and grey nodes are traditional lenders. Further, pure red edges are between two fintech lenders, pure grey edges are between two traditional lenders, and darker red edges are between a fintech and traditional lender. Top 100 lenders (by the ssme measure that node size is based on) are shown and the remainder are combined into the “Other" nodes (one for other fintech lenders and one for other traditional lenders).

Panel A. Multiple Lenders at Same Address



Panel B. Changes Between Draws

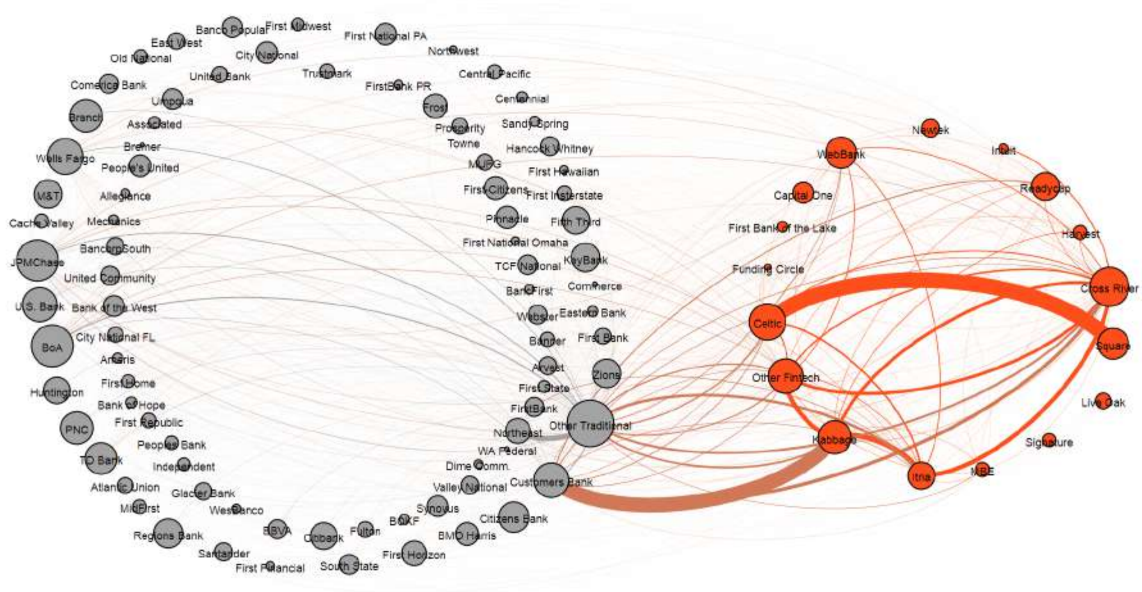
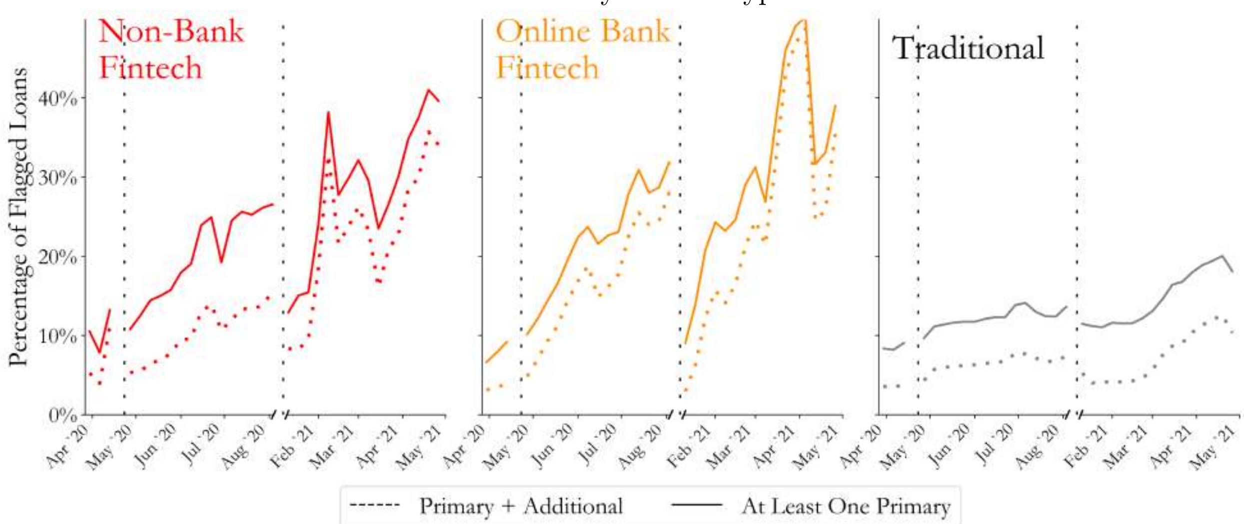


Figure 13. Persistence and Growth Across Rounds

This figure shows the persistence and growth of flagged loans across the PPP lending rounds. Panel A shows this by lender type and Panel B by zip code. In Panel A, each subpanel shows a lender type and each series is the percentage of loans flagged by the given measure across time. In Panels B, the percentage of loans flagged in rounds 1 and 2 are shown on the horizontal axis and round 3 on the vertical axis. For Panel A, the vertical dotted lines split each subpanel into the three PPP lending rounds. The solid lines are loans flagged by at least one primary flag and the dashed line is loans flagged by at least one primary flag and an additional flag (either another primary or a secondary). For Panel B, the left subpanel uses all loans, middle uses fintech loans, and right uses traditional loans. Zip codes with at least 100 loans and, for the fintech and traditional subpanels, 25 loans by the given lender type are shown. The black line is a 45-degree line and the correlation is presented in the bottom of each panel. The circle size corresponds to the number of loans in the zip code by the given lender type and color corresponds the growth/decline in lending in the zip code.

Panel A. By Lender Type



Panel B. By Zip Code

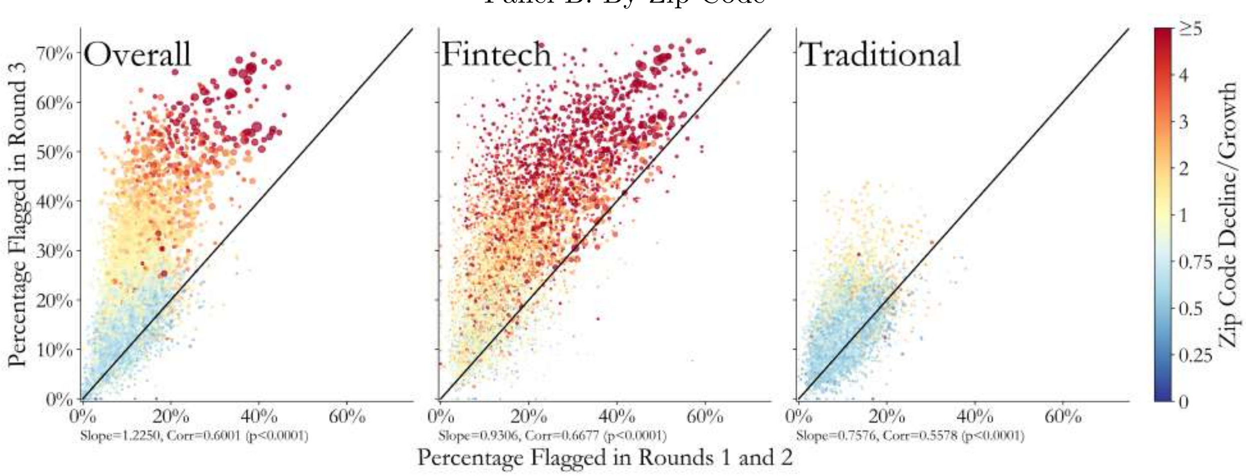


Exhibit 1. Examples of Suspicious Loans

This exhibit shows some examples of suspicious loans.

Panel A. 14 Loans to The Same Address, 13 Incorporated Late

Business Name (Redacted)	Date Incorporated	Date Approved	Lender	Industry	Loan Amount	Jobs Reported
FDML	4/2/2018	5/13/2020	Celtic	Indep. Artists, Writers, Performers	$62,083	10
JTBCL	8/5/2020	8/5/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
GGITL	7/30/2020	8/1/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
EIEL	7/22/2020	7/30/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
FML	7/27/2020	7/30/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
DYJNL	7/22/2020	7/26/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
CTWIL	7/23/2020	7/23/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
CAYL	7/21/2020	7/22/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
BLNL	7/19/2020	7/21/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
ATYL	7/19/2020	7/21/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
STWL	7/16/2020	7/17/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
KYHUL	7/15/2020	7/16/2020	Kabbage	Misc. Schools & Instruction	$91,770	10
LTTBTL	7/15/2020	7/15/2020	Kabbage	Misc. Schools & Instruction	$53,229	10
DREL	7/7/2020	7/8/2020	Kabbage	Musical Groups & Artists	$53,125	10

Panel B. Four Loans to Same Household

Individual Name (Redacted)	Age	Date Approved	Lender	Industry	Loan Amount	Jobs Reported
A. P.	20	7/15/2020	Kabbage	Nail Salons	$20,833	1
O. P.	21	7/10/2020	Kabbage	Lawn/Garden Equipment Manuf.	$20,833	1
G. P.	46	7/15/2020	Kabbage	Other Automotive Repair	$20,833	1
T. P.	49	7/10/2020	Kabbage	Lawn/Garden Equipment Manuf.	$20,833	1

Exhibit 2. Cross River Case Study

This exhibit shows examples of $20,000 first draw loans by Cross River Bank in Illinois.

Individual Name (Redacted)	Date Approved	Lender	Industry	Loan Amount	Jobs Reported
J. C.	7/29/2020	Cross River	Insurance Agencies and Brokerages	$20,000	1
R. J.	7/29/2020	Cross River	Insurance Agencies and Brokerages	$20,000	1

4,304 $20k Loans by Cross River in Illinois (Mostly in Chicago Area) to Individuals/Businesses (98% with 1 Employee) in "Insurance Agencies and Brokerages" Industry.

C.C.	7/29/2020	Cross River	All Other Miscellaneous Crop Farming	$20,000	8
M. A.	7/29/2020	Cross River	All Other Miscellaneous Crop Farming	$20,000	8

938 $20k Loans by Cross River in Illinois (Mostly in Chicago Area) to Individuals/Businesses (56% with 8 Employee and 22& with 1 Employee) in "All Other Miscellaneous Crop Farming" Industry.

C.M.	8/7/2020	Cross River	Other General Government Support	$20,000	50
K. K.	7/30/2020	Cross River	All Other Miscellaneous Manufacturing	$20,000	9

3,056 $20k Loans by Cross River in Illinois (Mostly in Chicago Area) to Individuals/Businesses in Various Industries (Including 700 to “All Other Personal Services,” 347 to “General Freight Trucking, Local,” 337 to “Other Performing Arts Companies”, and 229 to “New Single-Family Housing Construction.”)

Table I. Summary Statistics

This table presents summary statistics for our sample. The sample includes all PPP loans approved from the start of the program (March 2020) through most of Round 3 (April 2021) that have not been repaid as of May 3, 2021. Fintech lenders are determined following Erel and Liebersohn (2021). *Loan Amount* is the initial approved amount minus any portion used to refinance an EIDL loan. *Implied Comp.* is determined following the guidelines in place when the loan was approved and is based on loan amount and jobs reported. *CBSA/NAICS Avg. Comp.* is from the US Census CBP and *Normalized Comp.* is the ratio of *Implied Comp.* and *CBSA/NAICS Avg. Comp.*. *Loans (Within Draw) at Address* is the number of loans (within the loan's draw) at the same residential address. *Frac. Corp, S Corp, LLC* is the percentage of loans to these business types, *Frac. Second Draw* is the percentage of Round 3 loans that are the borrower's second draw from the PPP, *Frac. Matched EIDL Advance* is the percentage of loans with a matching EIDL Advance, and *Frac. $10k EIDL Adv. (Given Matched)* is the percentage of loans with a matching EIDL Advances that are for $10,000 (the maximum possible). *Frac. Fintech (Either Type)*, *Frac. Non-bank Fintech*, and *Frac. Online Bank Fintech* are the percentages of loans that are originated by the given type of lender.

	Fintech			Traditional		
	Mean	SD	Median	Mean	SD	Median
Num. Loans [Pct. Loans]	3,071,586 [28.7%]			7,625,633 [71.3%]		
Loan Amount	27,708	112,175	18,750	91,427	308,121	20,833
Jobs Reported	2.842	11.151	1.000	10.483	29.507	3.000
Implied Comp.	61,598	40,664	62,840	47,008	67,228	38,775
CBSA/NAICS Avg. Comp	47,288	38,702	37,453	49,727	37,343	42,800
Normalized Comp.	1.826	1.593	1.338	1.142	1.979	0.917
Num. Loans (Within Draw) at Address	1.314	0.816	1.000	1.192	0.789	1.000
Frac. Corp, S Corp, LLC	0.228			0.658		
Frac. Second Draw (Given Round 3)	0.259			0.601		
Frac. Matched EIDL Advance	0.202			0.270		
Frac. $10k EIDL Adv. (Given Matched)	0.228			0.257		

	Round 1	Round 2	Round 3
Num. Loans [Pct. Loans]	1,619,446 [15.1%]	3,523,411 [32.9%]	5,554,362 [51.9%]
Loan Amount	198,875	57,852	46,160
Jobs Reported	20.470	7.912	4.976
Implied Comp.	48,024	43,841	56,788
CBSA/NAICS Avg. Comp	49,342	51,829	47,012
Normalized Comp.	1.178	1.055	1.609
Num. Loans (Within Draw) at Address	1.275	1.208	1.247
Frac. Fintech (Either Type)	0.048	0.204	0.409
Frac. Non-bank Fintech	0.025	0.075	0.265
Frac. Online Bank Fintech	0.023	0.129	0.145
Frac. Corp, S Corp, LLC	0.829	0.656	0.372
Frac. Second Draw	-	-	0.461
Frac. Matched EIDL Advance	0.292	0.301	0.206
Frac. $10k EIDL Adv. (Given Matched)	0.385	0.178	0.262

Table II. Odds Ratios

In this table, we present the odds ratios between each of our four main indicators. Panel A shows the odds ratios for fintech and traditional loans combined. Panel B shows the odds ratios for fintech loans only in the lower triangular and traditional loans only in the upper triangular. Note that odds ratios are symmetric, which is why only values for the lower triangular are provided. Robust standard errors are double clustered by zip code and lender.

Panel A. Fintech and Traditional Loans Combined

	Business Registry	Multiple Loans	High Implied Comp.	EIDL > PPP Jobs
Business Registry	-			
Multiple Loans	1.607***	-		
	(6.52)			
High Implied Comp.	2.572***	2.830***	-	
	(8.75)	(14.47)		
EIDL > PPP Jobs	1.403***	3.027***	14.270***	-
	(6.07)	(10.80)	(15.20)	

Panel B. Fintech Loans (Lower Triangular) and Traditional Loans (Upper Triangular)

	Business Registry	Multiple Loans	High Implied Comp.	EIDL > PPP Jobs
Business Registry	-	1.262***	1.836***	1.177***
		(10.64)	(11.28)	(6.09)
Multiple Loans	2.349***	-	1.550***	1.405***
	(12.42)		(4.58)	(7.53)
High Implied Comp.	3.548***	1.886***	-	5.636***
	(11.48)	(4.81)		(20.11)
EIDL > PPP Jobs	1.964***	2.606***	17.240***	-
	(5.45)	(11.75)	(27.14)	

z-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table III. Prevalence of Flags by Lender Type

This table presents the percentage of loans flagged by the four main flags, at least one of four flags, and at least two of the four flags. In Panel A, column (1) shows the percentage of fintech loans with the given flag, column (2) shows the percentage of traditional loans with the given flag, and column (3) shows the difference between the fintech and traditional percentages, column (4) shows the adjusted differences with zip code, business type, and NAICS × CBSA fixed effects and jobs and loan size controls, and column (5) shows the differences between matched pairs of fintech and traditional loans. The N values show is the number of loans for which the flag can be determined and robust standard errors are double clustered by zip code and lender. For the matched differences, robust standard errors are four-way clustered by the zip code and lender of both matched loans. The full regression results for the unadjusted differences and adjusted differences are reported in Panel A and Panel B, respectively, of Table IA.II.

	(1) Fintech	(2) Traditional	(3) Unadjusted Difference	(4) Adjusted Difference	(5) Matched Difference
Business Registry	0.0837 N = 671,298	0.0427 N = 4,777,168	0.0409*** (3.12)	0.0276*** (3.47)	0.0204*** (3.20)
Multiple Loans	0.119 N = 3,071,586	0.0513 N = 7,625,633	0.0681*** (7.16)	0.0290*** (3.85)	0.0479*** (2.68)
High Implied Comp.	0.478 N = 1,215,857	0.102 N = 2,081,163	0.376*** (6.27)	0.0943*** (5.74)	0.0776*** (2.99)
EIDL > PPP Jobs	0.194 N = 621,785	0.0478 N = 2,057,611	0.146*** (3.80)	0.0590*** (3.76)	0.0686*** (3.98)
At Least One Flag	0.314 N = 3,071,586	0.116 N = 7,625,633	0.198*** (6.19)	0.0733*** (6.31)	0.0682*** (5.21)
At Least Two Flags	0.0503 N = 3,071,586	0.00605 N = 7,625,633	0.0442*** (5.42)	0.0164*** (5.90)	0.0259*** (3.89)

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IV. Secondary Flags

In this table, we examine the relationship between our four main flags, which we combine to form At Least One Flag, and the secondary flags. We estimate OLS regressions with *At Least One Flag* as the dependent variable and the five secondary flags as independent variables. Each specification also include an interaction between the secondary flag and an indicator for whether the loan was originated by a fintech lender. *$100k Implied Comp.* is a dummy variable equal 1 if the implied compensation per job is within ± $1,000 of $100,000. *Monthly Rounding* is a dummy variable equal 1 if the loan amount is within ± 50 cents of an interval of $1,250. *Overrep. in County/NAICS* is a dummy variable equal 1 if the number of first draw loans to businesses not listed as self-employed and independent contractors in a loan's county/NAICS pair exceeds the number of establishments in the county/NAICS according to the US Census CBP. *High Concentration* is a dummy variable equal 1 if the average rescaled concentration ratio in the loan's county/lender pair is above the 75th percentile. *Felony Post-2000* is a dummy variable equal 1 if the borrower has a felony on their criminal record from 2000 or after. *1(Fintech)* is a dummy variable equal 1 if the loan was originated by a fintech lender. For all specifications, loans are filtered to the sets for which we can determine the secondary flag. Further, for specification (2), one job loans and loans where 1(*$100k Implied Comp.*) = 1 are excluded. Fixed effects are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Dep. Variable: At Least One Flag

	(1)	(2)	(3)	(4)	(5)
$100k Implied Comp.	0.0258**				
	(2.29)				
Monthly Rounding		0.00467***			
		(5.60)			
Overrep. in County/NAICS			-0.00225		
			(-0.72)		
High Concentration				0.0207***	
				(5.96)	
Felony Post-2000					0.0387***
					(3.12)
× 1(Fintech)	0.118***	0.0187***	0.0509***	0.0166***	0.0292*
	(11.19)	(2.74)	(6.86)	(2.75)	(1.73)
ln(Jobs Reported)	Yes	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	No
Business Type FE	Yes	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes
Observations	10,043,853	5,077,092	5,788,553	6,938,580	123,745
Num. Lenders	4,860	4,775	4,808	4,213	2,582
R^2	0.274	0.102	0.314	0.300	0.281
Mean of Dep. Variable	0.176	0.080	0.180	0.192	0.194

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table V. County Cultural Features

In this table, we examine the relationship between our four main flags, which we combine to form *At Least One Flag*, and cultural/regional features. We estimate OLS regressions with *At Least One Flag* as the dependent variable and the cultural/regional features as independent variables. All independent variables are rescaled at the county level to have a mean of 0 and standard deviation of 1. *Political Corruption* is the number of public corruption convictions per million residents in 2004-13 (as reported by the DOJ). *Religious Adherence* is the percent of the county's population with a religious affiliation as of 2010 (as reported by the Association of Religious Data Archives). *Ashley Madison Usage* is the paid Ashley Madison usage rate in the county (as reported by Griffin et al. (2019b)). *Population Density* is the population per square mile as of 2019, *Median Income* is the median household income as of 2019, *Pct. Non-White* is the percentage of the population that is not white as of 2019, *College Educated* is the percentage adults with a bachelor's degree or higher as of 2015-19, and *2019 Unemployment* is the unemployment rate as of 2019 (all from the Economic Research Service of the U.S. Department of Agriculture). *Pct. Fintech* is the percentage of PPP loans in the county originated by a fintech lender. Fixed effects are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Dep. Variable: At Least One Flag

	(1)	(2)	(3)
Public Corruption	0.0103***	0.00760***	0.00328***
	(5.53)	(4.86)	(2.71)
Religious Affiliation	0.00180*	-0.000870	0.0000323
	(1.93)	(-0.82)	(0.03)
Ashley Madison Usage	-0.00505***	0.00393**	-0.00224
	(-7.36)	(2.30)	(-1.56)
Population Density		-0.00160***	-0.00143***
		(-6.26)	(-4.93)
Median Income		-0.00219**	0.000213
		(-2.03)	(0.22)
Pct. Non-White		0.0188***	-0.00162
		(8.20)	(-1.17)
College Educated		-0.00750***	-0.00325***
		(-4.97)	(-3.18)
2019 Unemployment		0.00203	0.00292**
		(1.40)	(2.10)
Pct. Fintech			0.0237***
			(7.31)
ln(Jobs Reported)	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes
NAICS × State FE	Yes	Yes	Yes
Observations	10,589,326	10,589,114	10,589,114
Num. Lenders	4,886	4,886	4,886
R^2	0.194	0.195	0.196
Mean of Dep. Variable	0.174	0.174	0.174

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table VI. Persistence of Lender Behavior Across Rounds

In this table, we examine the persistence of lender behavior across rounds. We estimate OLS regressions with dummies for whether each Round 3 loan is flagged by our four main flags individually (specifications (1) through (4)) and at least one of them (specification (5)) as the dependent variables and the percentage of the lender's loans were flagged by the same flag in rounds 1 and 2 as the independent variable. Interactions with whether the loam was originated by a fintech or traditional lender are include in all specification. Specifications (1) through (4), loans are filtered to the sets for which we can determine the flag (same as in Figures 2-4). Further, to ensure we have accurate measures of past behavior, we require that each lender have at least 100 loans in Round 1 and 2 (combined) for which we can determine the given flag. Fixed effects are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Dep. Variable:	(1) Business Registry	(2) Multiple Loans	(3) High Implied Comp.	(4) EIDL > PPP Jobs	(5) At Least One Flag
Past Pct. This Flag					
× 1(Fintech)	0.794***	0.776***	0.369***	0.750***	0.619***
	(3.59)	(5.95)	(3.23)	(3.08)	(5.69)
× 1(Traditional)	0.209	0.421***	-0.277*	-0.111	0.164*
	(1.07)	(3.30)	(-1.89)	(-0.93)	(1.52)
ln(Jobs Reported)	Yes	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes	Yes
Observations	1,753,188	4,562,655	1,512,743	938,143	4,562,655
Num. Lenders	2,481	3,142	1,580	1,440	3,142
R^2	0.124	0.097	0.642	0.317	0.307
Mean of Dep. Variable	0.065	0.082	0.326	0.119	0.219

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table VII. Second Draw

In this table, we examine whether lenders were more/less likely to provide a second draw loan to a borrower who's first draw loan is flagged by at least one of our primary flags. We estimate OLS regressions with a dummy for whether the same lender provided the first and second draw loans as the dependent variable and a dummy for whether the first draw loan was flagged by at least one of the primary flags as the independent variable. In specifications (1) and (2), if a borrower did not receive a second draw loan, the dependent variable is set to 0, and in specifications (3) and (4), only borrowers that received both a first and second draw loans are included in the sample. In the even specification, an interaction with whether the first draw loan was originated by a fintech lender is included. Fixed effects are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Dep. Variable: 1(First and Second Draw by Same Lender)

	(1)	(2)	(3)	(4)
	Unconditional of Receiving Second Draw		Conditional on Receiving Second Draw	
First Draw Flagged	-0.0123***	-0.0183***	-0.00715	-0.0144***
	(-3.68)	(-9.64)	(-1.40)	(-5.86)
× 1(Fintech)		0.0261**		0.0294
		(2.55)		(1.44)
ln(Jobs Reported)	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Observations	4,853,956	4,853,956	1,552,196	1,552,196
Num. Lenders	4,742	4,742	4,523	4,523
R^2	0.122	0.122	0.427	0.427
Mean of Dep. Var.	0.275	0.275	0.846	0.846

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Internet Appendix

Loan Size Calculation

Average monthly payroll expenses are to be based on the full 2019 calendar year for most loans. Exceptions include seasonal businesses which may use average monthly payroll for any twelve-week period between February 15, 2019 and February 14, 2020, and new businesses may use average monthly payroll over the period from January 1, 2020 to February 29, 2020. Additionally, second draw loans by businesses in the hospitality industry (NAICS starting with 72) were allowed to receive 3.5 times their average monthly payroll, which we account for while computing implied compensation. See SBA guidance entitled "How to Calculate First Draw PPP Loan Amounts," which was updated over time. A list of all versions can be found at https://www.sba.gov/document/support-how-calculate-first-draw-ppp-loan-amounts.

In determining the high implied compensation flag and for the $100k discontinuity and rounding analyses, we subtract any portion of the loan amount used to refinance an EIDL. Second draw loans to the hospitality industry represent about 2% of loans and we exclude these loans for the rounding analysis.

Matching Analysis

The matching analysis reported in Table III is based on a combination of propensity score matching and exact matching. First, we estimate a propensity score for whether a loan is originated by a FinTech lender using a logistic regression and the following variables: 4-digit NAICS code (industry), CBSA, business type, loan amount, jobs reported, lending draw, lending round, week of loan approval, and whether the borrower received an EIDL Advance. Second, for each loan originated by a FinTech lender, we identify loans made by traditional lenders such that the loans were made to borrowers in the same industry, CBSA, business type, and year (either 2020 or 2021) and either both received EIDL Advances or did not. Exactly matching on these characteristics ensures that we can determine each of our flags for both loans. Finally, among the loans that match exactly on these features, we match the loans that have smallest absolute difference in propensity scores. In total, 2,791,287 of 3,071,586 FinTech loans are matched. Note that a traditional loan may be matched to more than one FinTech loan.

Repayment and Enforcement Action Data

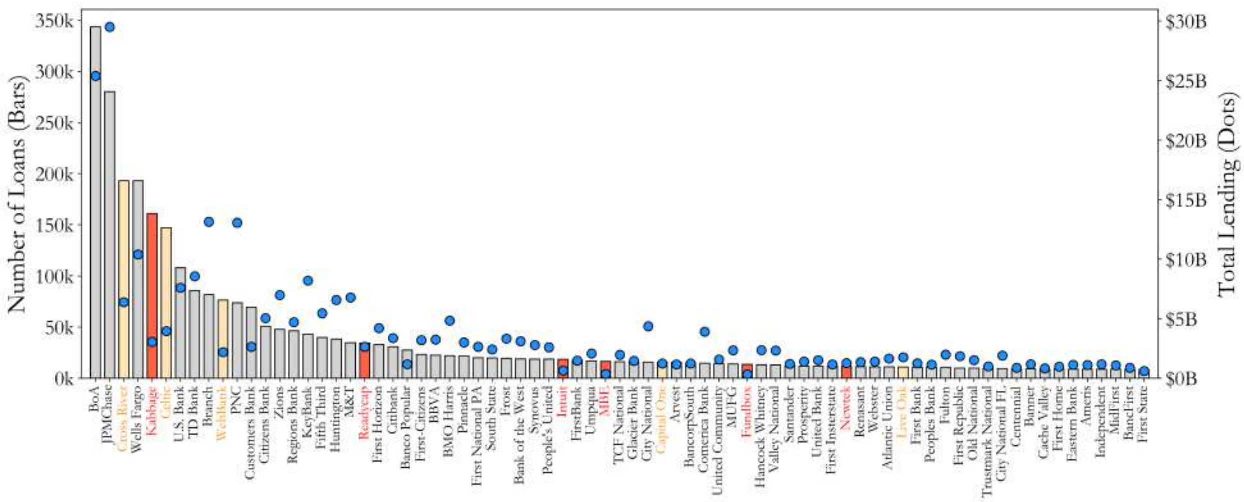
To examine round 1 and 2 loans that have been repaid, we use PPP loan level data released by the SBA on December 2, 2020 and data from USASpending.gov as of May 15, 2021. The USASpending data provides monthly updates on the PPP loans, which allows us to observe which loans have been repaid by the borrower, but does not have all the loan level details. The earlier version of the PPP loan level data provides the same details as the main PPP data and covers all loans that had not been repaid as of December 2020.

To examine enforcement actions by the government, we collect information from Department of Justice crime complaints against PPP borrowers that purportedly committed fraud based on https://www.justice.gov/criminal-fraud/cares-act-fraud and https://www.arnoldporter.com/en/general/cares-act-fraud-tracker. In total, we collect data on 162 complaints involving 355 loans. Of these 355 loans, 279 include enough information to be matched to the December 2020 version of the PPP loan level data (most of the unmatched loans were repaid before December 2020 and thus are not in the loan level data).

Figure IA.1. Fintech Market Share

This figure shows the role of fintech lenders during the PPP (expanding on Figure 1). Panel A replicates Figure 1, Panel A based on loans from only rounds 1 and 2. Panel B shows the number of loans originated by lender type during each week of the PPP. In both panels, red represents non-bank fintech lenders, cream represents online bank fintech lenders, and grey represents traditional lenders. Note that mid-August through December 2020 is not shown in Panel B since no PPP loans were originated during this period.

Panel A. Rounds 1 and 2 Lenders (Top 75)



Panel B. Lender Composition, by Week

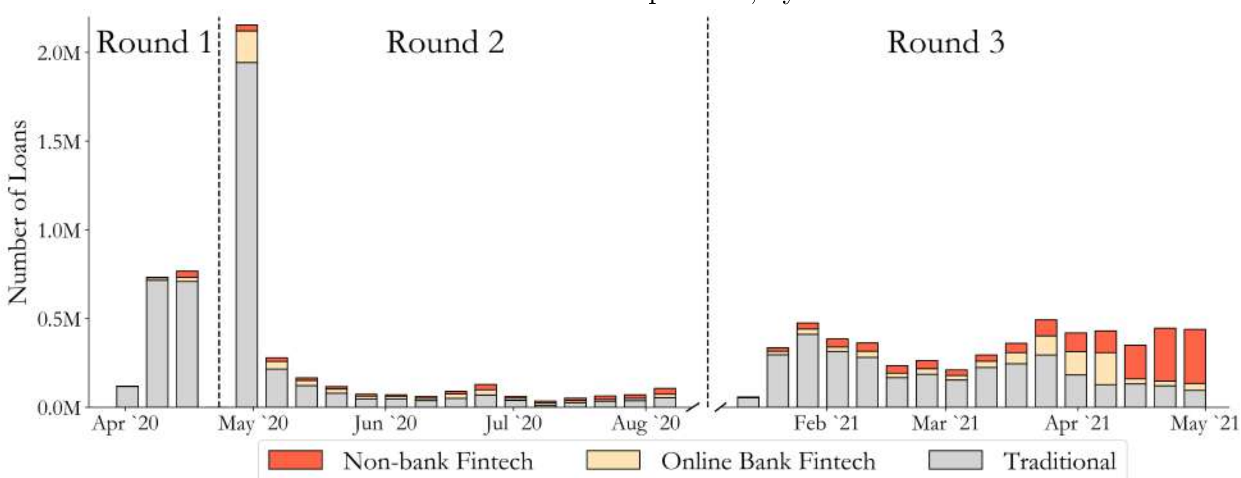


Figure IA.2. Implied Compensation

This figure shows the distribution of implied compensation. Panel A compares the implied compensation of loans to the average compensation in its industry (NAICS) and CBSA. Panel B shows the percentage of loans by annualized implied compensation and demonstrates the presence of rounding. In Panel A, loans are split by round (rounds 1 and 2 in left subpanel and round 3 in right subpanel) and lender type, sorted based on their CBSA/NAICS average compensation, and binned into bins of 50,000 (10,000 for fintech in rounds 1 and 2) loans. The median annualized compensation and CBSA/NAICS average compensation of each bin is shown. The solid line is a 45-degree line. In Panel B, annualized implied compensation is binned it into $1,000 wide bins (e.g., $36,500 to $37,500) and loans with annualized implied compensation within ± $1 of an interval of $1,000 (orange dots) are split from those that are not (blue dots). The dashed lines are every $12,000 ($1,000 in monthly compensation) and the dotted lines are every $6,000 ($500 in monthly compensation). Note that 1.6% to 11% on the vertical axis is excluded since there are no data points in this region.

Panel A. Implied Compensation vs. CBSA/NAICS Average Compensation

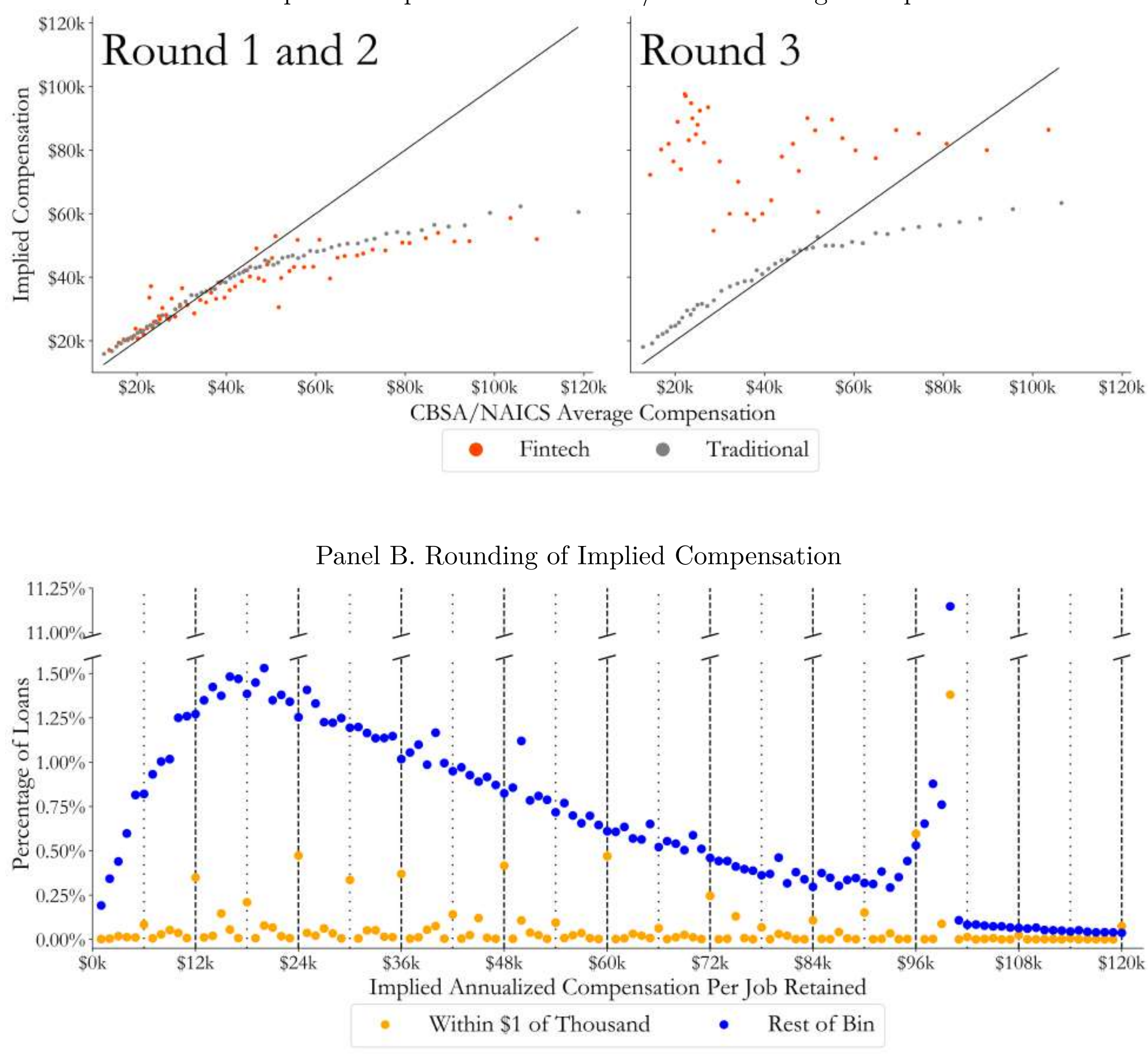


Figure IA.3. Relation Between Flags

This figure shows the relationship between the primary flags (business registry, multiple loans, high implied compensation, or EIDL > PPP jobs flags) at the lender level. Each subpanel is a scatterplot with the percentage of loans flag by one of the flags on each axis. Loans are filtered to the sets for which we can determine each flag (same as in Figures 2-4) for each axis separately (i.e., we do not require that both flags be able to be determined for a given loan). Lenders with at least 5,000 loans are shown; for the subpanels with the EIDL > PPP jobs flag, we additionally require that the lender have at least 1,000 loans with a matched EIDL Advance. The dashed line is a linear fit and the correlation is shown in the bottom left corner of each subpanel. Red triangles represent non-bank fintech lenders, cream squares represent online bank fintech lenders, and grey circles represent traditional lenders.

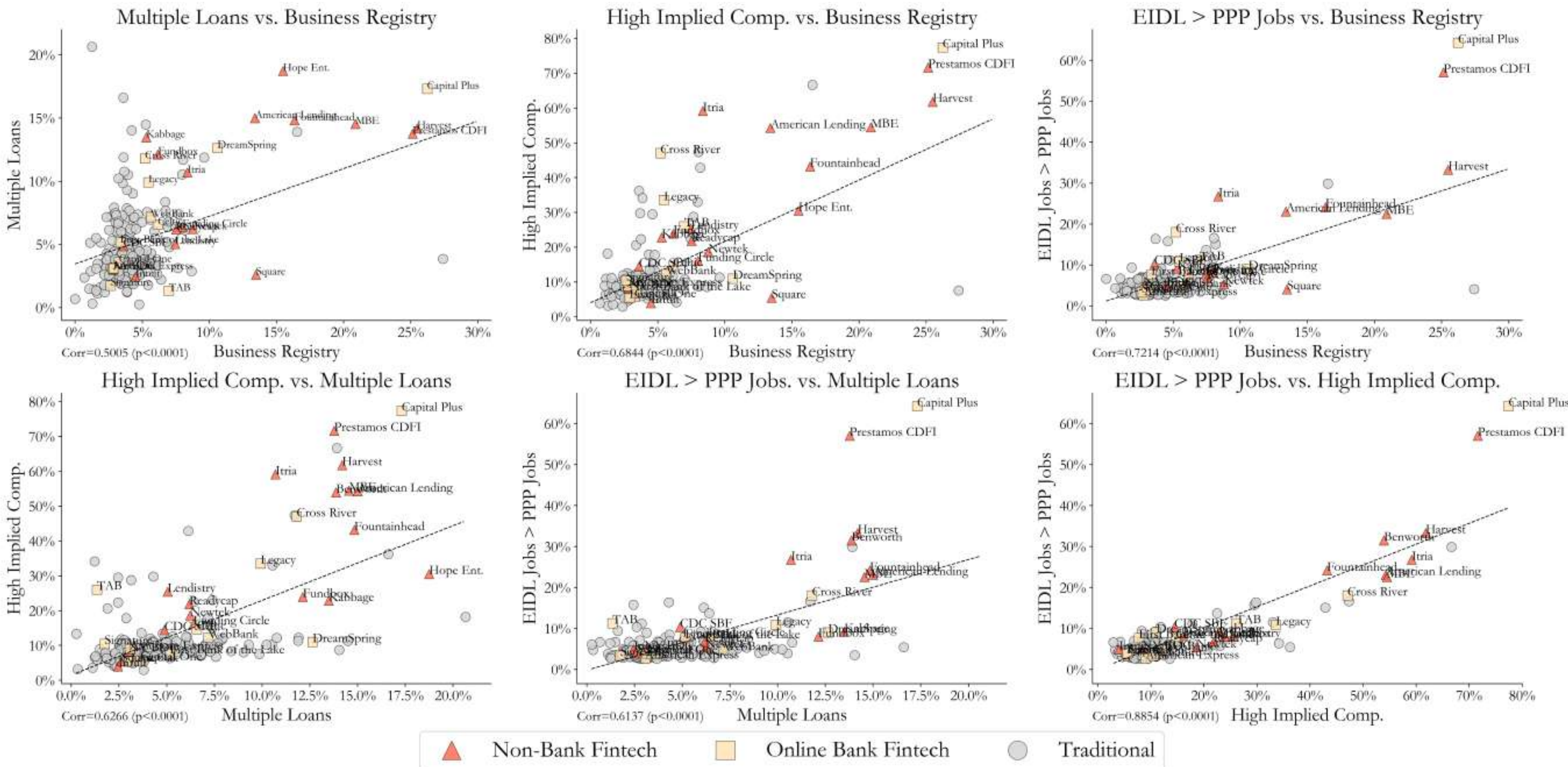
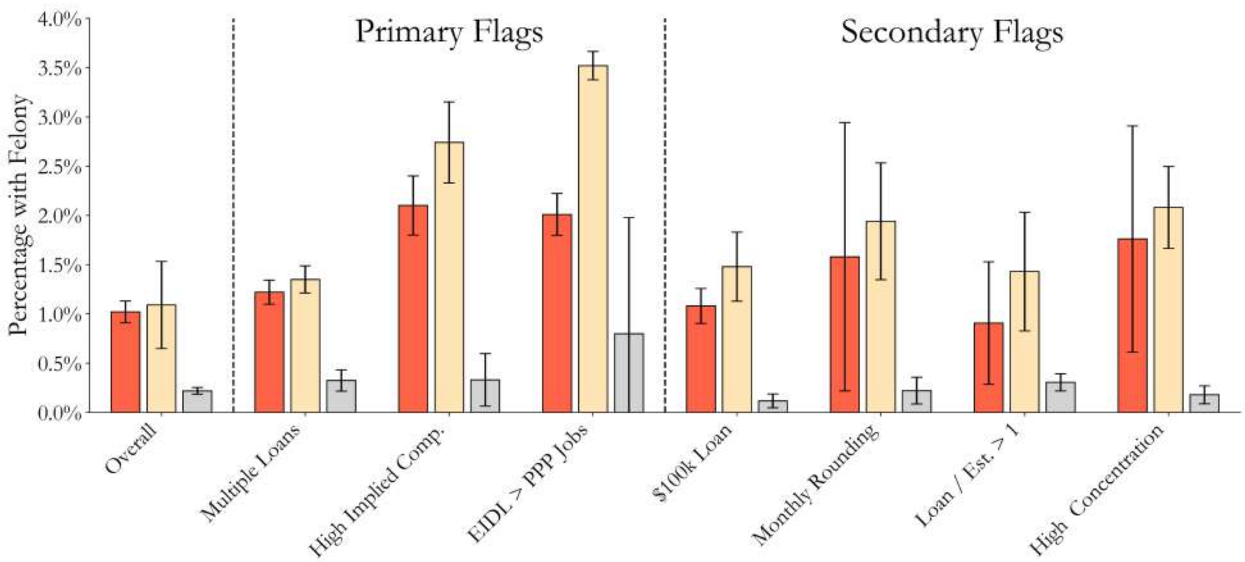


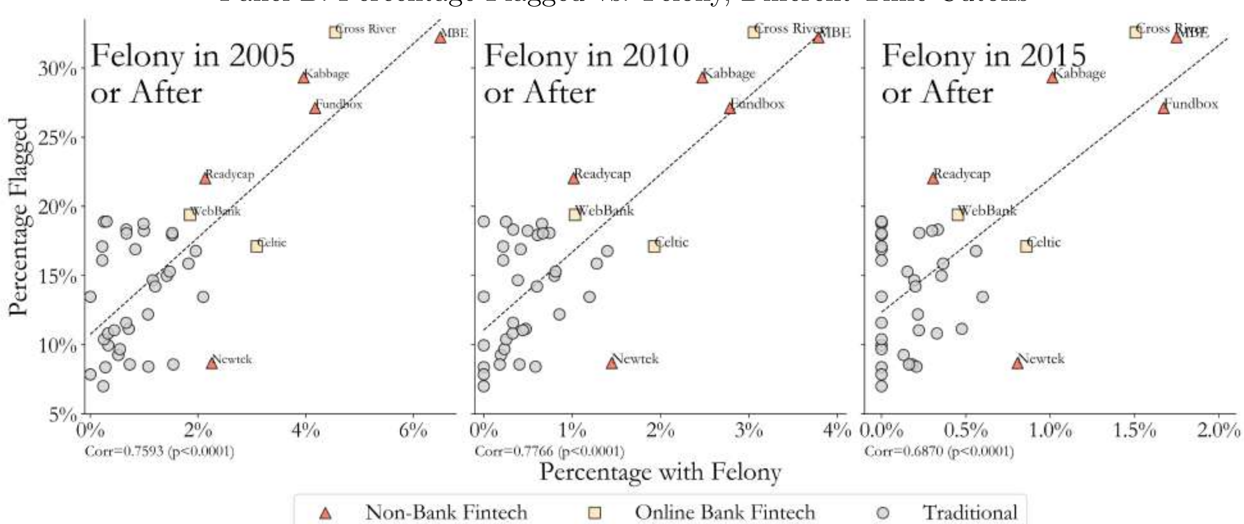
Figure IA.4. Criminal Records

This figure shows additional features (expanding on Figure 9) of the criminal records for a sample of Round 1 and 2 loans. Panel A replicates Figure 9, Panel A using felonies post-2015, Panel B replicates Figure 9, Panel B using various time cutoffs, Panel C replicates Figure 9, Panel B using bankruptcies (2015 or after), and Panel D shows the percentage of felonies (2000 or after) by lender type and across implied compensation. In Panels B and C, lenders with at least 0.2% of the loans in the sample (300 loans) are shown. The dashed lines are linear fits and correlations are in the bottom corner. In Panel D, loans are binned into $4,000 wide bins, solid lines are third-degree polynomial fits, and the dashed lines are 95% confidence intervals.

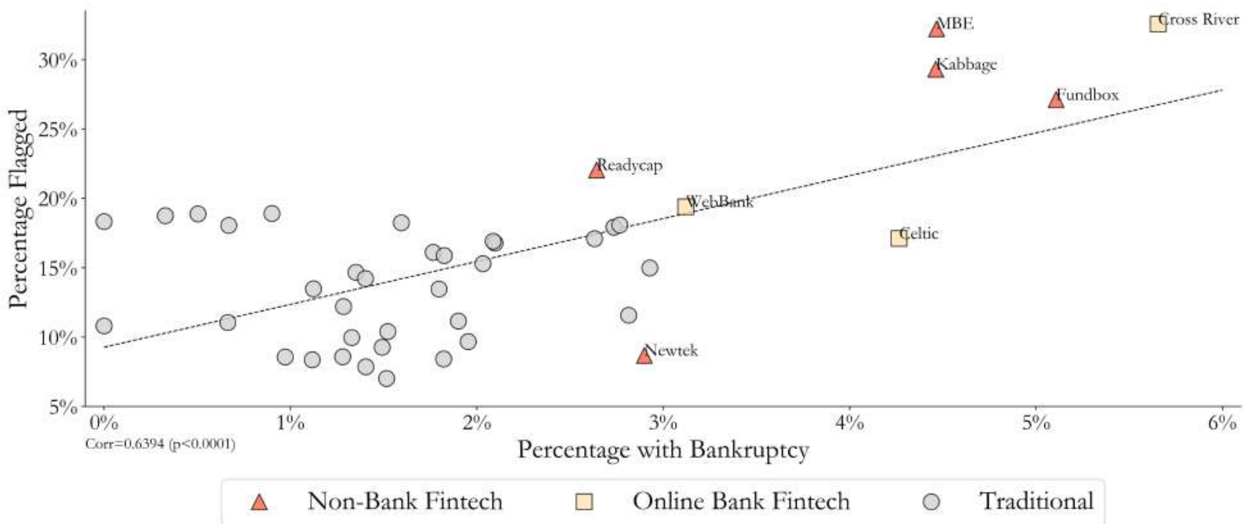
Panel A. Percentage Felony, by Lender Type and Various Features (2015 or After)



Panel B. Percentage Flagged vs. Felony, Different Time Cutoffs



Panel C. Percentage Flagged vs. Bankruptcies



Panel D. Percentage with Felony, by Implied Compensation

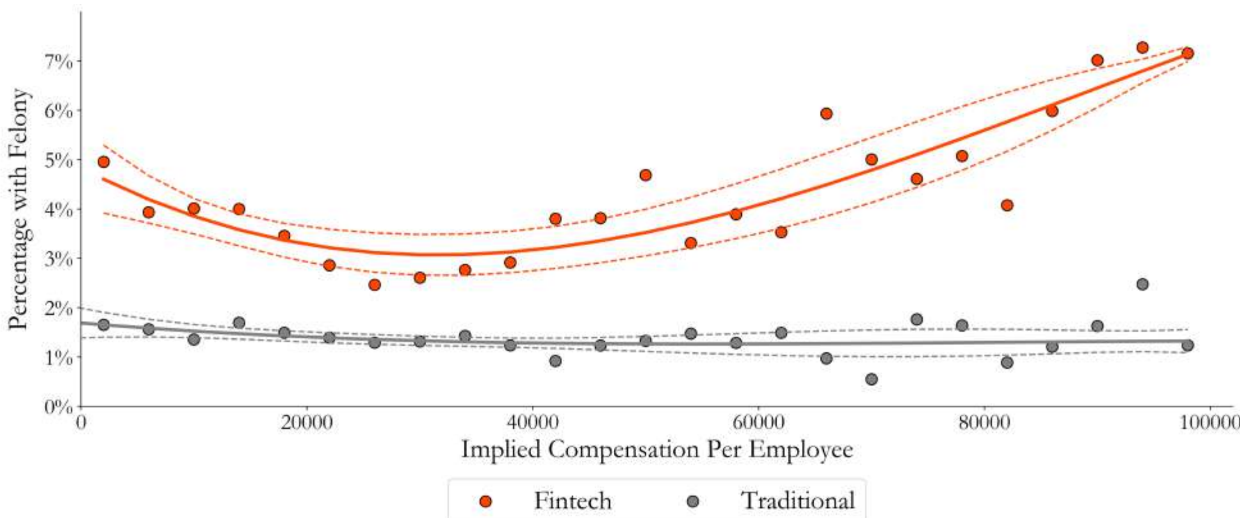


Figure IA.5. Secondary Flags

This figure shows the relationship between the secondary flags and the percentage flagged by lender. For maxed loans, loans with null/zero jobs reported are excluded; for monthly rounding, loans with null/zero or one job reported are exclude; for overrepresentation, loans to self-employed and independent contractors, second draw loans, and loans in a county/NAICS not in the CBP are excluded; for high HHI, second draw loans and loans in a county/lender with fewer than 25 first draw loans are excluded. No loans are excluded for percentage flagged. Lenders with at least 5,000 loans are shown. The dashed line is a linear fit and the correlation is in the bottom corner of each panel. Red triangles represent non-bank fintech lenders, cream squares represent online bank fintech lenders, and grey circles represent traditional lenders.

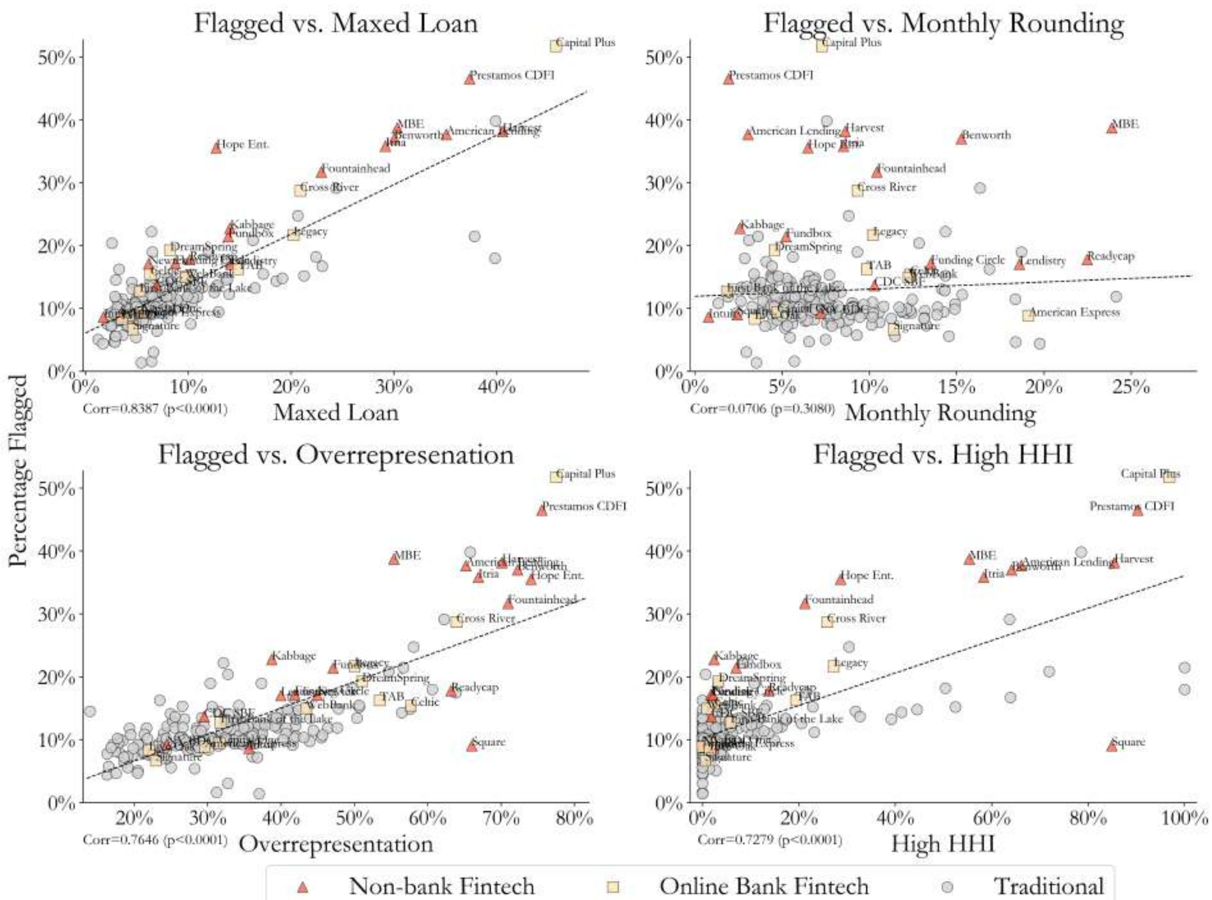
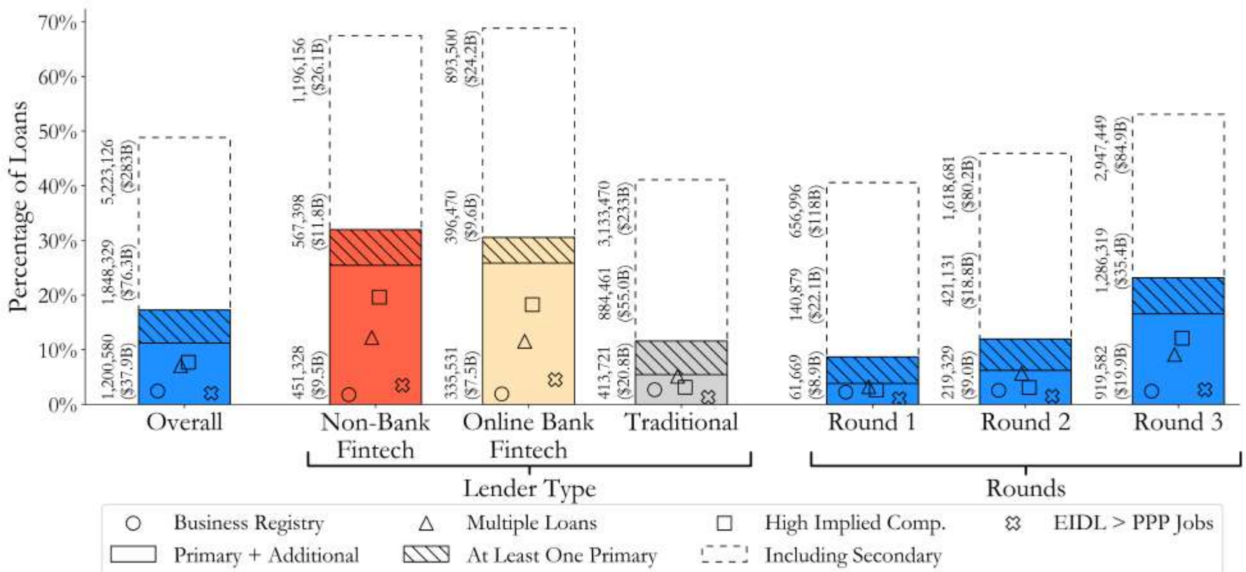


Figure IA.6. Lender Level

This figure shows additional variation in percentage of loans flagged. Panel A replicates Figure 10, Panel A and adds loans flagged by at least one primary or secondary flag as the dashed, non-shaded portions of the bar. In Panel B, each subpanel shows a lender type and each series is the percentage of loans flagged by the given flag across time. The vertical dotted lines split each subpanel into the three PPP lending rounds. The loans used to calculate each series are filtered to the sets for which we can determine each flag (same as in Figures 2-4). Note that mid-August through December 2020 is not shown in Panel B since no PPP loans were originated during this period. In both panels, red represents non-bank fintech lenders, cream represents online bank fintech lenders, and grey represents traditional lenders.

Panel A. Percentage of Loans Flagged with Broader Flags, by Lender



Panel B. Percentage of Loans Flagged Over Time, by Lender Type

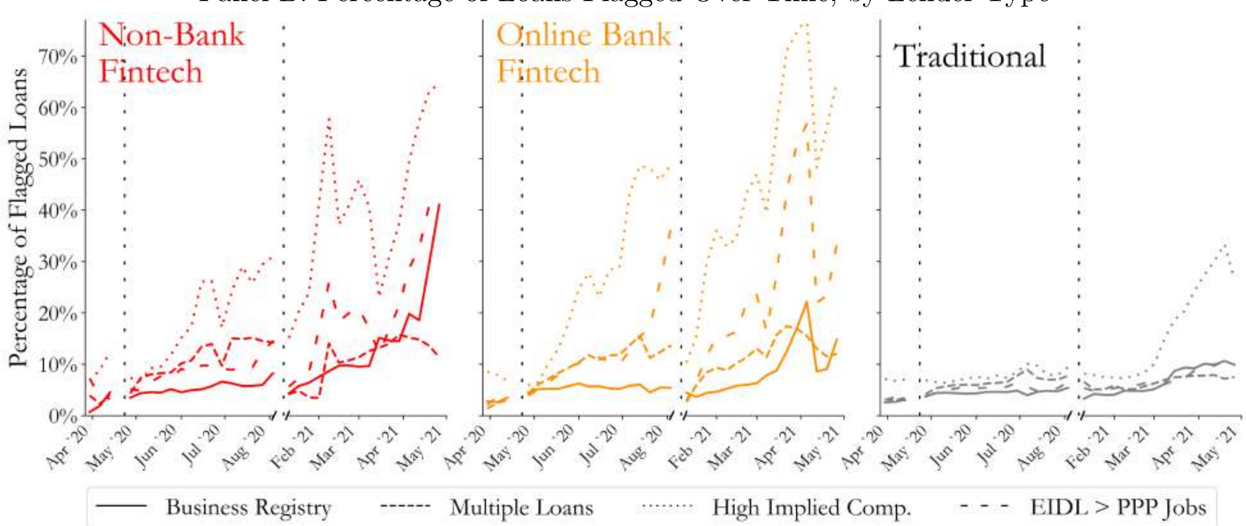
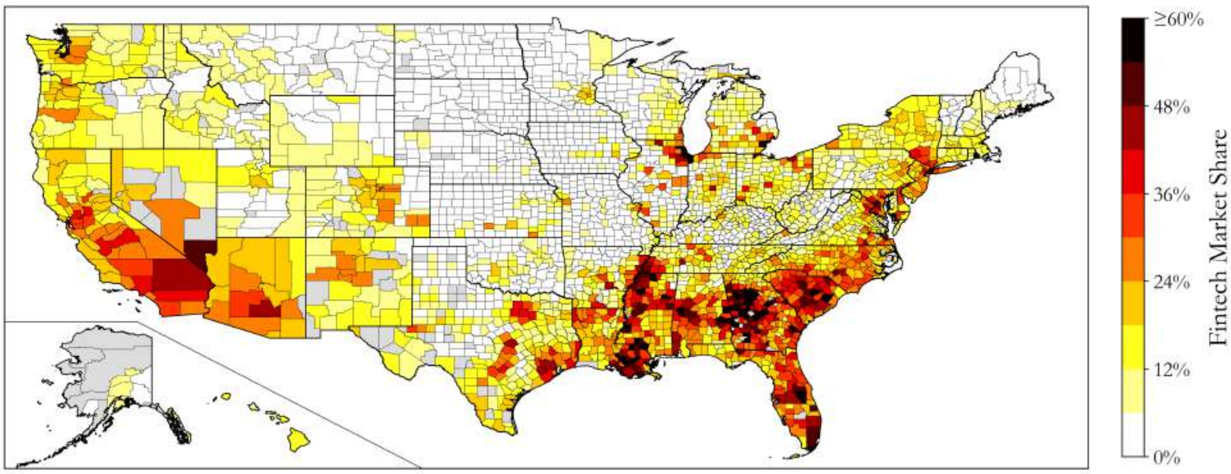


Figure IA.7. Geography

This figure shows additional geographic variation (extending Figure 11). Panel A shows the fintech market share in each county. Panel B shows the growth in lending between rounds 1-2 and round 3 in each county. In both panels, counties are colored based on the color scheme shown in the bar to the right of the maps and counties with fewer than 100 loans are colored grey.

Panel A. Fintech Market Share, by County



Panel B. Lending Growth, by County

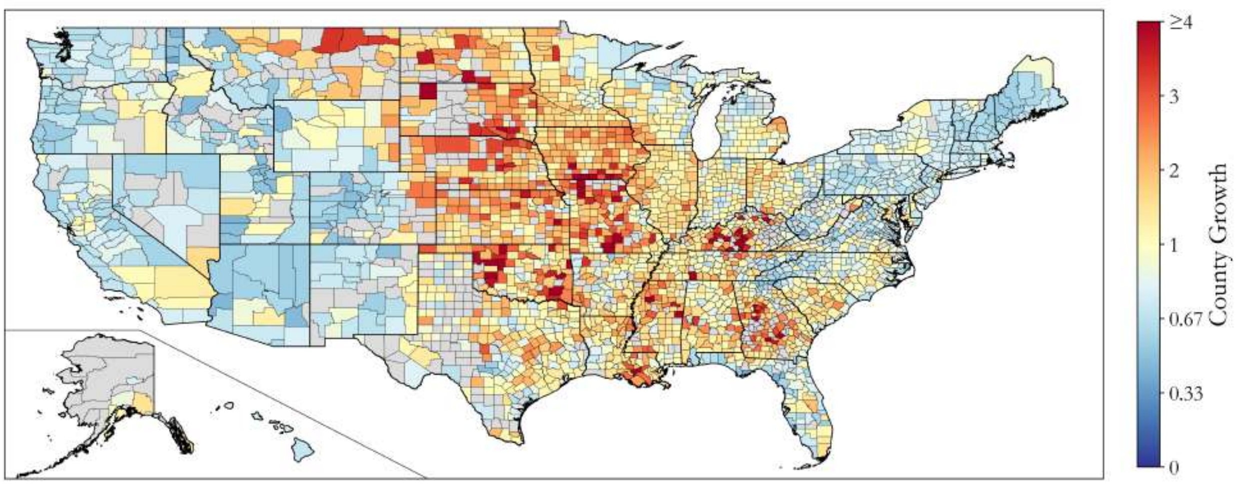


Figure IA.8. Pairwise Lender Correlations

This figure shows pairwise lender correlations using data at the county-lender level. The lower triangular shows correlations between the percentage of loans flagged by at least one primary flag and the upper triangular shows correlations between the lenders' market shares across counties. Lenders are order such that those with the highest percentage of flagged loans (across the entire sample) are at the top on the vertical axis and the left on the horizontal axis. Labels are colored red for non-bank fintechs, orange for online bank fintechs, and black for traditional lenders. Coloring of each square in the matrix is based pairwise correlation and the coloring scheme is shown at the bottom with darker red representing higher positive correlation and darker blue representing higher negative correlation. For each pairwise correlation, counties are filtered to the set that have 25 loans by both lenders. The top 75 lenders (by number of loans) are shown.

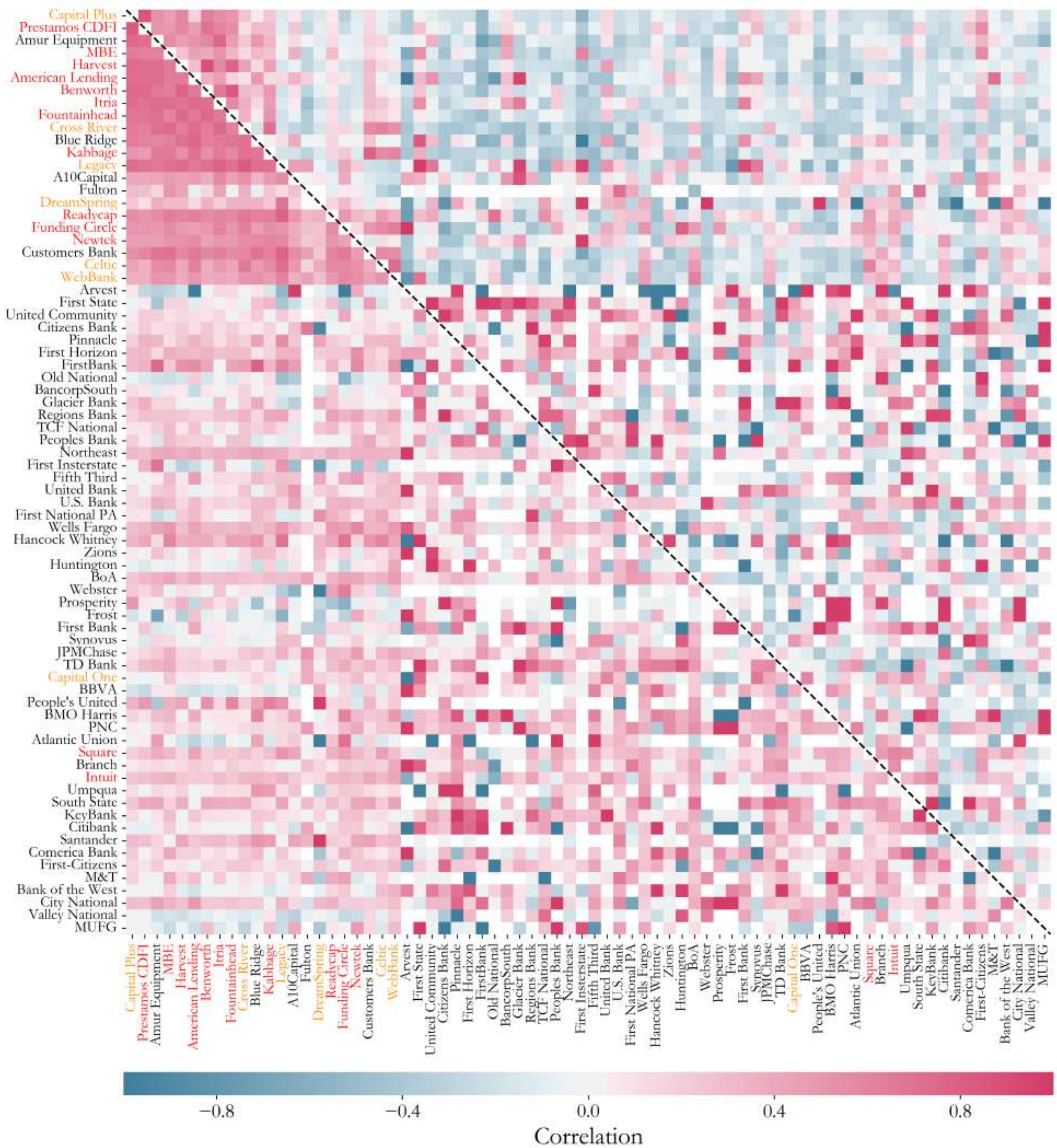


Figure IA.9. Lender Network

This figure replicates Panel B of Figure 12 using all loans where the borrower received a first and second draw loan. Node size is proportional to the number of first draw loans (which also received either a second draw from the same or different lender) and second draw originated by the lender. Edges are directed and have a width proportional to the number of loans moving clockwise from the first draw lender to the second draw lender. Red nodes are fintech lenders and grey nodes are traditional lenders. Pure red edges are between two fintech lenders, pure grey edges are between two traditional lenders, and darker red edges are between a fintech and traditional lender. Top 100 first draw lenders are shown and the remainder are combined into the “Other" nodes (one for other fintech lenders and one for other traditional lenders).

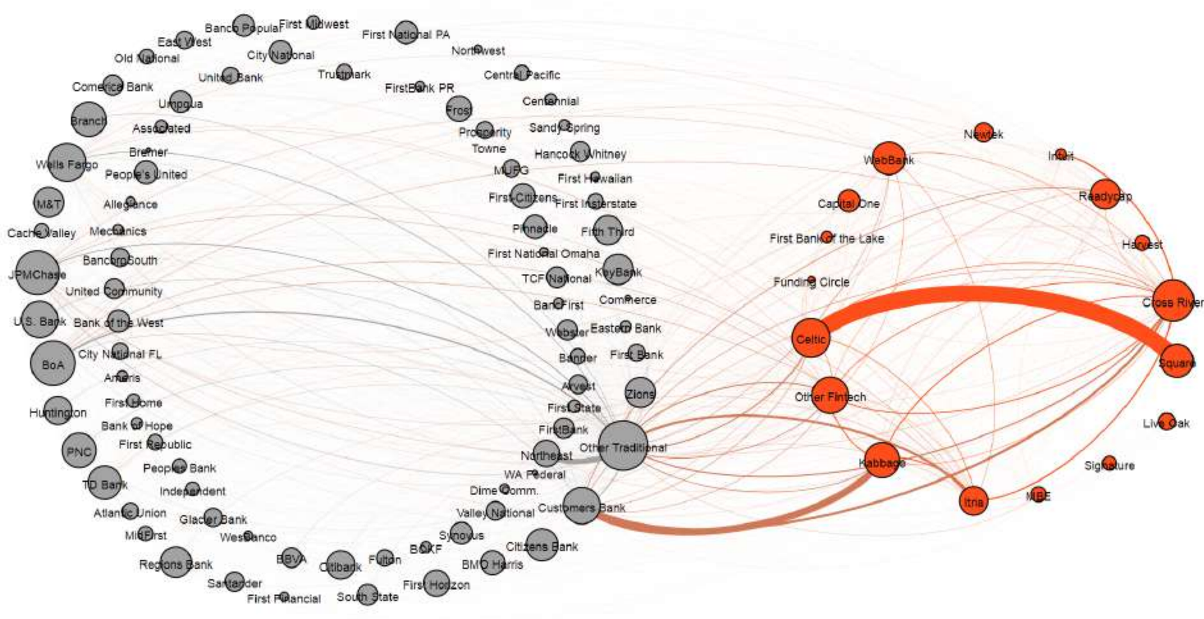
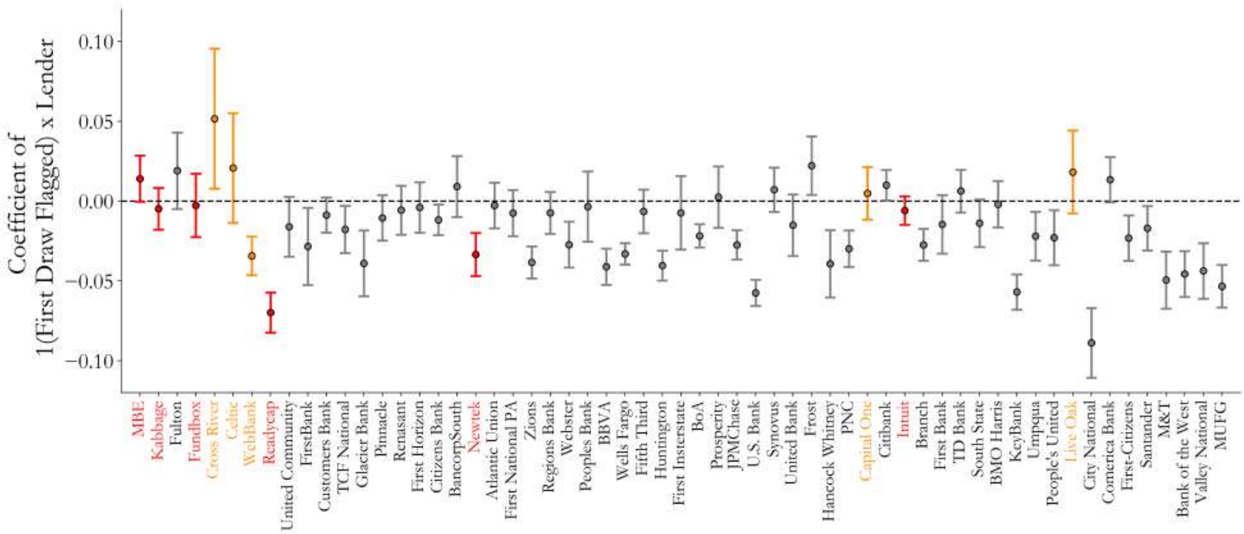


Figure IA.10. Second Draw Loans

This figure examines whether lenders were more/less likely to provide a second draw loan to a borrower who's first draw loan is flagged by at least one of our primary flags. Similar to Table VII, we estimate a OLS regression with a dummy for whether the same lender provided the first and second draw loans as the dependent variable and a dummy for whether the first draw loan was flagged by at least one of the primary flags interacted with an indicator for each lender as the independent variable. The regression includes controls for loan size and jobs and zip code, business type, NAICS × CBSA, and lender fixed effects. For Panel A, if a borrower did not receive a second draw loan, the dependent variable is set to 0, and in Panel B, only borrowers that received both a first and second draw loans are included in the sample. In both panels, the hollow dots show the point estimates from the regression and the error bars show 95% confidence intervals corrected for multiple comparisons using a Bonferroni correction. Lenders with at least 10,000 loans in rounds 1-2 are considered. Red error bars and labels represents non-bank fintech lenders, cream represents online bank fintech lenders, and grey represents traditional lenders.

Panel A. Unconditional of Receiving Second Draw



Panel B. Conditional on Receiving Second Draw

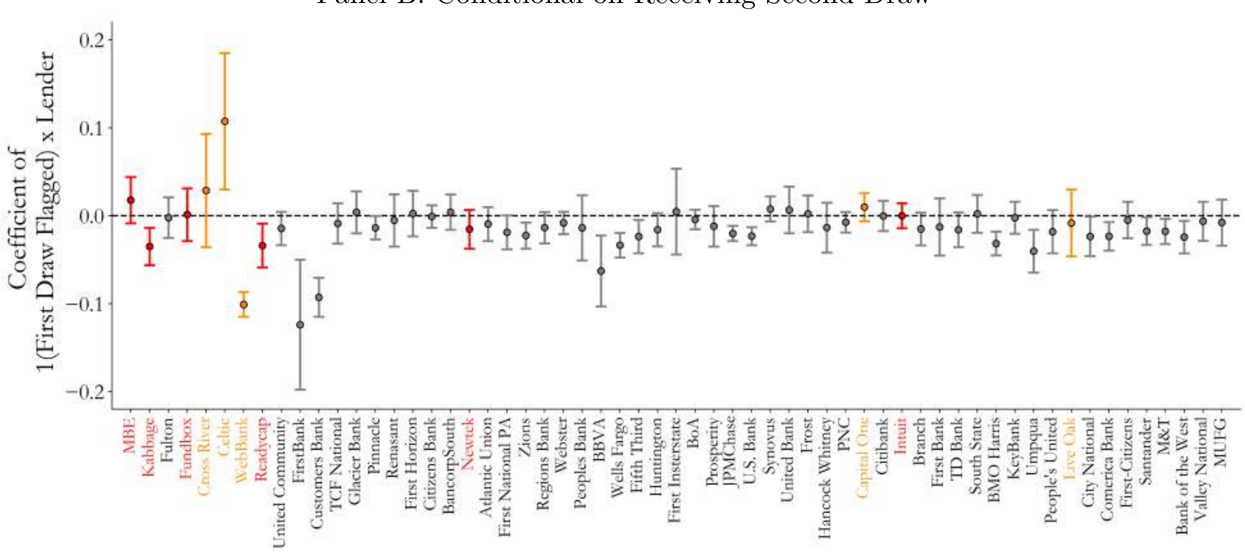
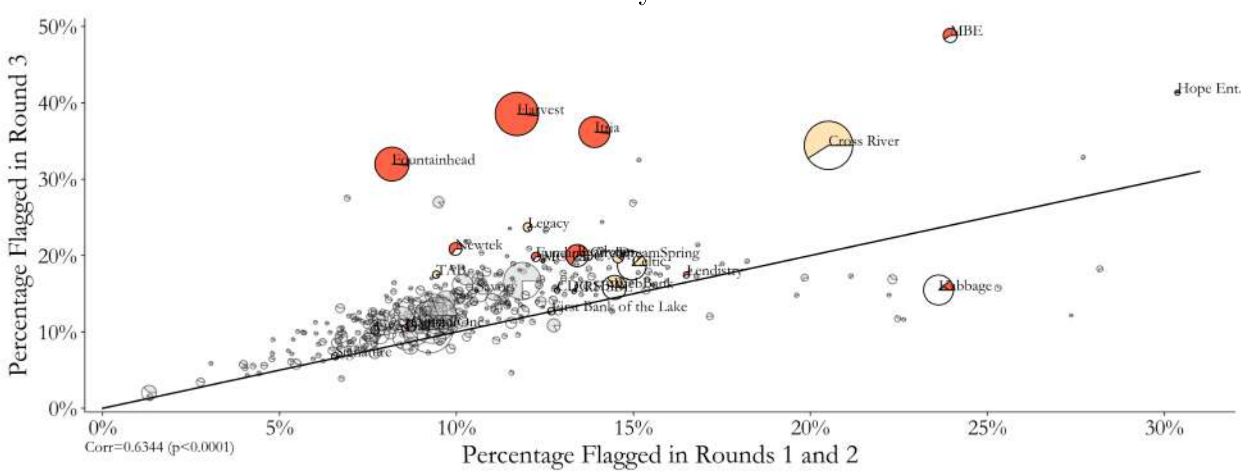


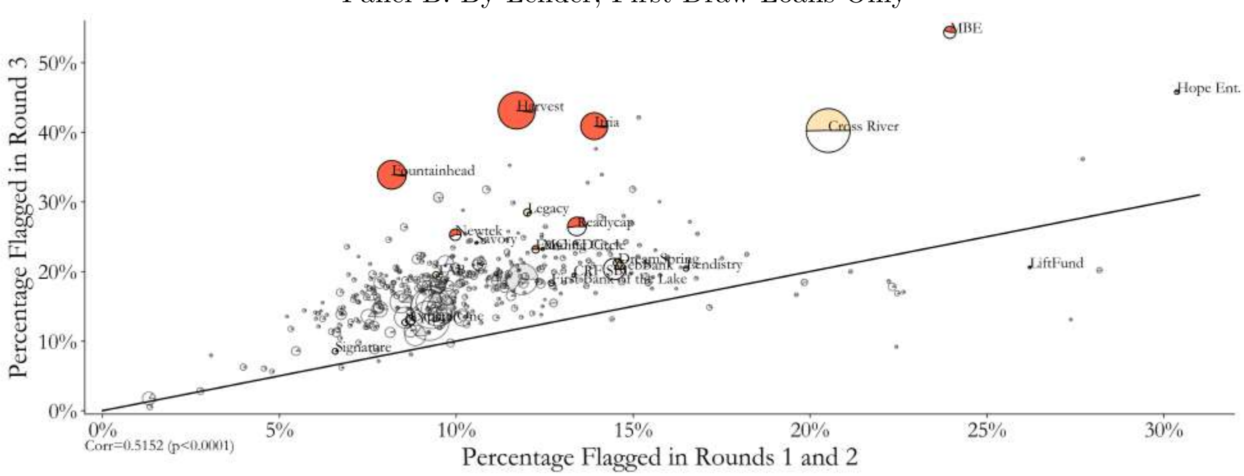
Figure IA.11. Persistence and Growth Across Rounds

This figure shows the persistence and growth of flagged loans across the PPP lending rounds. Panel A shows this by lender using all loans and Panel B by lender using first draw loans only. Panel C and D shows this by county and state (by zip code is shown as Panel B of Figure 13). For all panels, the percentage of loans flagged in rounds 1 and 2 are shown on the horizontal axis and round 3 on the vertical axis. For Panel A, lenders with at least 1,000 loans in rounds 1 and 2 combined and in round 3 are shown. For Panel B, lenders with at least 1,000 loans in rounds 1 and 2 combined and 250 first draw loans in round 3 are shown. In Panel C, counties with at least 100 loans in round 1 and 2 combined and in round 3 are shown. In all panels, the circle size corresponds to the total number of loans, the black line is a 45-degree line, and the correlation is presented in the bottom of each panel. For Panels A and B, the percentage of the circle that is shaded represents the proportion of loans that each lender provided/in each state in round 3 relative to in round 1 and 2. For Panel C and D, the circles are colored based lending growth in the county/state with the color scheme shown in the bar to the right of each panel.

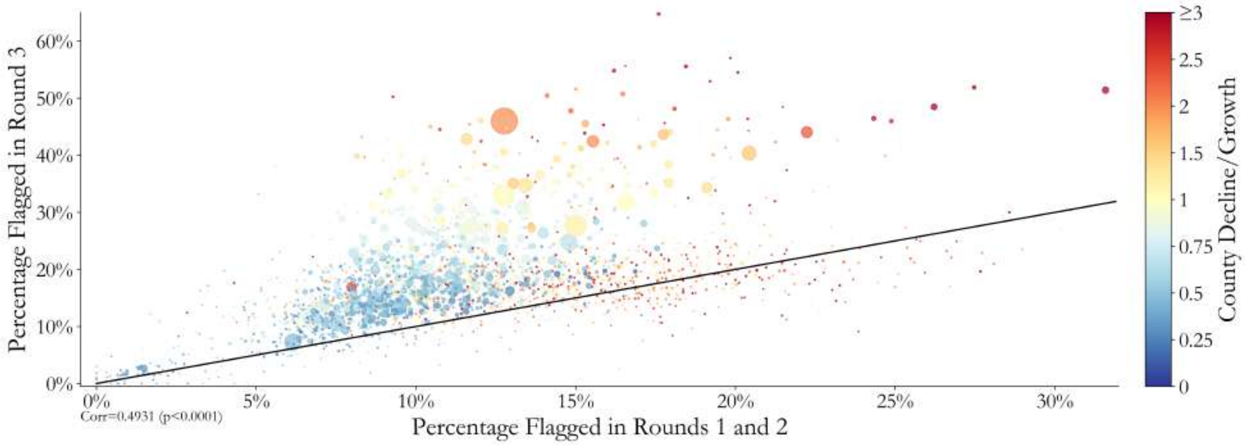
Panel A. By Lender



Panel B. By Lender, First Draw Loans Only



Panel C. By County



Panel D. By State

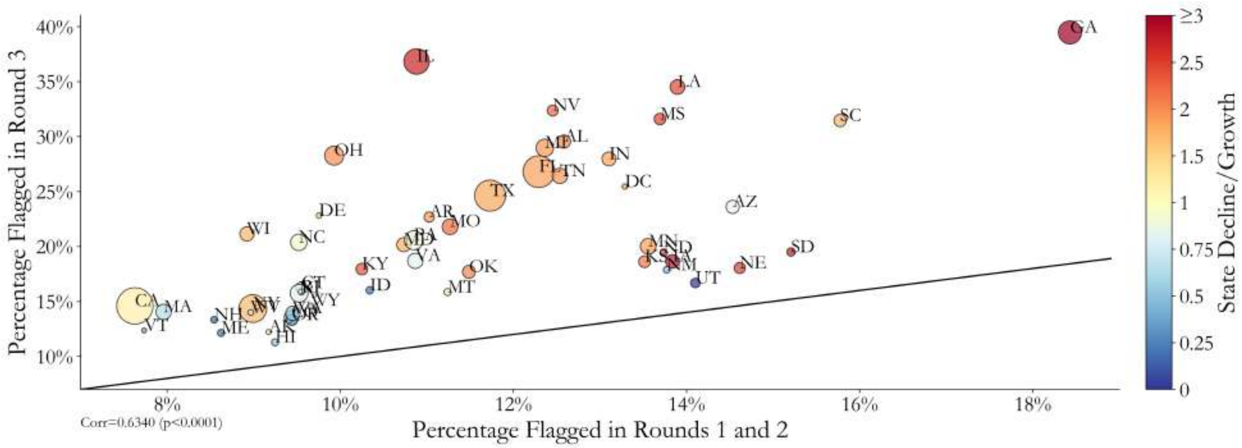


Figure IA.12. Repayment

This figure shows the percentage of first draw loans that have been repaid between December 1, 2020 and June 30, 2021 (left axis, blue bars) and that are part of a DOJ enforcement action (right axis, purple bars). The first draw sample is filtered based on the criteria at the bottom of each set of bars. In total, this figure is based on 16,930 loans that were repaid between December 1, 2020 and June 30, 2021 and 279 loans that are part of DOJ enforcement actions.

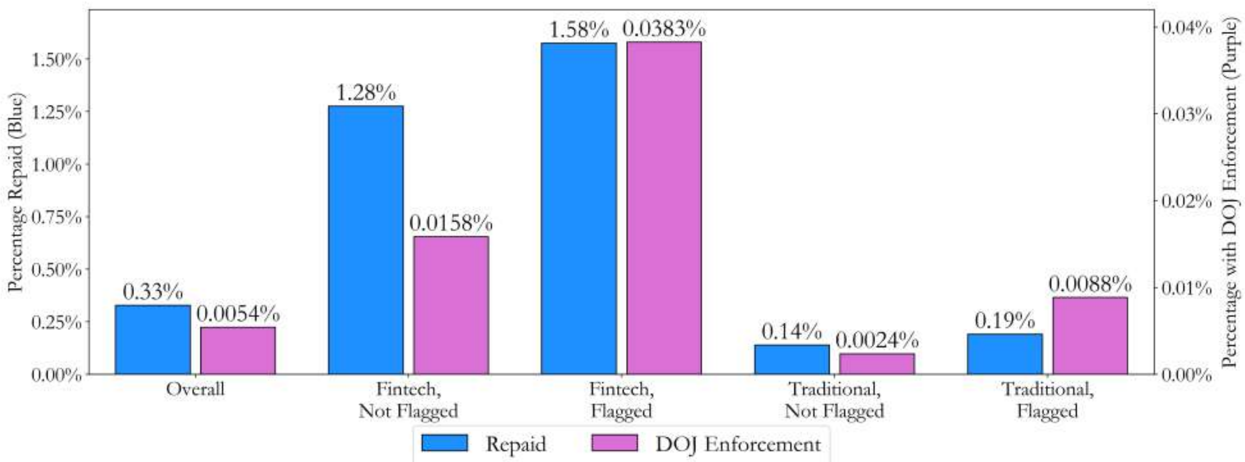


Table IA.I. Cross Verification of Flags

In this table, we examine the relationships between our four main flags. We estimate OLS regressions with dummies for each of our main flags as dependent variables and dummies for the other three flags as independent variables. Panel A shows the relationships without lender fixed effects and Panel B shows the relationship within lenders by adding lender fixed effects. In both panels, specification (1) uses business registry as the dependent variable, (2) uses multiple loans, (3) uses high implied compensation, and (4) uses EIDL > PPP jobs. Loans are filtered to the sets for which we can determine the flag being used as the dependent variable (same as in Figures 2-4). Fixed effects are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Panel A. Without Lender Fixed Effect

Dep. Variable:	(1) Business Registry	(2) Multiple Loans	(3) High Implied Comp.	(4) EIDL > PPP Jobs
Business Registry		0.00872***	0.0211***	0.00281*
		(4.81)	(9.17)	(1.89)
Multiple Loans	0.0138***		0.0293***	0.0307***
	(5.47)		(6.54)	(11.32)
High Implied Comp.	0.0363***	0.0243***		0.215***
	(6.87)	(8.65)		(16.30)
EIDL > PPP Jobs	-0.00545***	0.0217***	0.0701***	
	(-4.34)	(11.65)	(18.96)	
ln(Jobs Reported)	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes
1(EIDL Adv. Matched)	Yes	Yes	Yes	No
Lender FE	No	No	No	No
Observations	5,192,997	10,043,880	3,291,095	2,545,320
Num. Lenders	4,731	4,885	4,779	4,736
R^2	0.086	0.088	0.597	0.261
Mean of Dep. Variable	0.048	0.069	0.241	0.083

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Panel B. With Lender Fixed Effect

Dep. Variable:	(1) Business Registry	(2) Multiple Loans	(3) High Implied Comp.	(4) EIDL > PPP Jobs
Business Registry		0.00762***	0.0117***	-0.000433
		(5.52)	(3.86)	(-0.26)
Multiple Loans	0.00960***		0.0192***	0.0192***
	(6.94)		(5.46)	(6.78)
High Implied Comp.	0.0281***	0.0166***		0.175***
	(8.67)	(7.31)		(17.52)
EIDL > PPP Jobs	-0.00559***	0.0182***	0.0589***	
	(-4.30)	(10.05)	(14.13)	
ln(Jobs Reported)	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
NAICS $\times$ CBSA FE	Yes	Yes	Yes	Yes
1(EIDL Adv. Matched)	Yes	Yes	Yes	No
Lender FE	Yes	Yes	Yes	Yes
Observations	5,192,915	10,043,853	3,291,009	2,545,208
Num. Lenders	4,654	4,860	4,695	4,631
R^2	0.099	0.095	0.615	0.290
Mean of Dep. Variable	0.048	0.069	0.241	0.083

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.II. Prevalence of Flags by Lender Types

Panel A shows the full results for the unadjusted and adjusted differences provided in Table III. Fixed effects are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Panel A. Unadjusted Percentages

Dep. Variable:	(1) Business Registry	(2) Multiple Loans	(3) High Comp.	(4) EIDL > PPP Jobs	(5) At Least One	(6) At Least Two
Fintech	0.0409***	0.0681***	0.376***	0.146***	0.198***	0.0442***
	(3.12)	(7.16)	(6.27)	(3.80)	(6.19)	(5.42)
Observations	5,448,466	10,697,211	3,297,020	2,679,396	10,697,211	10,697,211
Num. Lenders	4,771	4,902	4,779	4,837	4,902	4,902
R^2	0.004	0.014	0.180	0.051	0.056	0.022
Mean of Dep. Var.	0.048	0.071	0.241	0.082	0.173	0.019

Panel B. Adjusted Percentages

Dep. Variable:	(1) Business Registry	(2) Multiple Loans	(3) High Comp.	(4) EIDL > PPP Jobs	(5) At Least One	(6) At Least Two
Fintech	0.0276***	0.0290***	0.0943***	0.0590***	0.0733***	0.0164***
	(3.47)	(3.85)	(5.74)	(3.76)	(6.31)	(5.90)
ln(Jobs Reported)	Yes	Yes	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,192,997	10,043,880	3,291,095	2,545,320	10,043,880	10,043,880
Num. Lenders	4,731	4,885	4,779	4,736	4,885	4,885
R^2	0.083	0.089	0.601	0.250	0.260	0.122
Mean of Dep. Var.	0.048	0.069	0.241	0.083	0.173	0.019

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.III. Discontinuity at $100k

In this table, we examine the relationship between our four main flags and implied compensation. We estimate OLS regressions with dummies for each of our main flags as dependent variables and dummies for $5k wide bins (i.e., ($0k, $5k], ..., ($95k, $100k], ..., ($125k, $130k]) of implied compensation as independent variables. The dummy variable for the ($0k, $5k] bin is used as the baseline. Panel A shows the results for fintech loans and Panel B for traditional loans. In both panels, specification (1) uses business registry as the dependent variable, (2) uses multiple loans, (3) uses high implied compensation, and (4) uses EIDL > PPP jobs. Loans are filtered to corporation, S-corporation, and LLC loans for specification (1), all loans for (2), loans for which we can determine CBSA/NAICS average compensation for (3), and loans with a matched EIDL Advance for (4). Fixed effects and control variables are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Panel A. Fintech Loans

Dep. Variable:	(1) Business Registry	(2) Multiple Loans	(3) High Implied Comp.	(4) EIDL > PPP Jobs
($0k, $5k]	Used as Baseline			
($5k, $10k]	-0.00786** (-2.30)	0.0112*** (3.25)	0.0189** (2.56)	-0.0106** (-2.56)
($10k, $15k]	-0.0154*** (-2.88)	0.0156*** (3.24)	0.0252** (2.20)	-0.0125** (-2.44)
($15k, $20k]	-0.0133** (-2.34)	0.0199*** (3.10)	0.0384*** (2.72)	-0.00352 (-0.55)
($20k, $25k]	-0.0162** (-2.25)	0.0228*** (3.19)	0.0651*** (3.71)	0.000367 (0.05)
($25k, $30k]	-0.0108 (-1.38)	0.0237*** (3.03)	0.0829*** (4.10)	0.00670 (0.82)
($30k, $35k]	-0.0122 (-1.53)	0.0267*** (3.16)	0.0953*** (4.45)	0.0164** (2.20)
($35k, $40k]	-0.0111 (-1.27)	0.0297*** (3.42)	0.104*** (4.50)	0.0298*** (3.54)
($40k, $45k]	-0.00806 (-0.92)	0.0314*** (3.56)	0.126*** (4.95)	0.0286*** (3.24)
($45k, $50k]	-0.00562 (-0.59)	0.0384*** (4.06)	0.123*** (4.75)	0.0544*** (4.93)
($50k, $55k]	-0.000251 (-0.02)	0.0363*** (3.78)	0.149*** (5.33)	0.0476*** (4.71)
($55k, $60k]	-0.00344 (-0.34)	0.0387*** (3.97)	0.171*** (5.86)	0.0587*** (5.35)
($60k, $65k]	0.00184 (0.18)	0.0441*** (4.14)	0.200*** (6.47)	0.0737*** (5.59)
($65k, $70k]	0.00314 (0.28)	0.0463*** (4.20)	0.250*** (7.02)	0.0900*** (6.46)
($70k, $75k]	0.00107 (0.11)	0.0470*** (4.45)	0.310*** (7.92)	0.0987*** (5.67)
($75k, $80k]	0.0116 (1.21)	0.0535*** (5.04)	0.385*** (8.32)	0.127*** (6.28)
($80k, $85k]	0.0139 (1.42)	0.0519*** (4.93)	0.422*** (8.39)	0.146*** (6.77)
($85k, $90k]	0.0112 (1.08)	0.0580*** (5.75)	0.471*** (9.71)	0.177*** (8.01)
($90k, $95k]	0.0178 (1.57)	0.0615*** (6.05)	0.516*** (10.74)	0.246*** (9.93)
($95k, $100k]	0.0433*** (3.07)	0.0638*** (6.00)	0.540*** (11.20)	0.307*** (16.80)
($100k, $105k]	-0.00553 (-0.37)	0.0639*** (2.88)	0.455*** (10.94)	0.115*** (6.20)
($105k, $110k]	-0.00488 (-0.39)	0.0605*** (3.49)	0.445*** (10.57)	0.121*** (6.07)
($110k, $115k]	-0.00838 (-0.64)	0.0562*** (4.85)	0.443*** (9.52)	0.0940*** (5.98)
($115k, $120k]	-0.0134 (-1.00)	0.0526*** (3.50)	0.466*** (10.19)	0.103*** (6.22)
($120k, $125k]	-0.00159 (-0.10)	0.0500*** (3.39)	0.489*** (9.84)	0.0809*** (5.13)
($125k, $130k]	-0.00347 (-0.20)	0.0403*** (3.39)	0.463*** (10.06)	0.0672*** (3.18)
ln(Jobs Reported)	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes
Observations	628,213	2,983,832	2,692,483	590,845
Num. Lenders	77	77	77	77
R^2	0.208	0.093	0.681	0.443
Mean of Dep. Var.	0.0831	0.121	0.214	0.197

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Panel B. Traditional Loans

Dep. Variable:	(1) Business Registry	(2) Multiple Loans	(3) High Implied Comp.	(4) EIDL > PPP Jobs
(\$0k, \$5k]	Used as Baseline			
(\$5k, \$10k]	-0.00758*** (-4.28)	-0.00459** (-2.51)	-0.00645 (-1.56)	-0.0110** (-2.39)
(\$10k, \$15k]	-0.0119*** (-4.88)	-0.00832*** (-3.43)	-0.00349 (-0.63)	-0.0120** (-2.22)
(\$15k, \$20k]	-0.0137*** (-4.82)	-0.0103*** (-3.63)	0.00511 (0.85)	-0.00718 (-1.39)
(\$20k, \$25k]	-0.0152*** (-4.76)	-0.0129*** (-4.07)	0.0162** (2.50)	-0.00161 (-0.29)
(\$25k, \$30k]	-0.0150*** (-4.12)	-0.0144*** (-4.06)	0.0277*** (3.90)	0.00399 (0.71)
(\$30k, \$35k]	-0.0143*** (-3.68)	-0.0149*** (-4.11)	0.0401*** (5.21)	0.00947 (1.53)
(\$35k, \$40k]	-0.0153*** (-3.61)	-0.0165*** (-4.01)	0.0513*** (6.18)	0.0127** (2.11)
(\$40k, \$45k]	-0.0145*** (-3.27)	-0.0170*** (-4.04)	0.0643*** (7.20)	0.0178*** (2.72)
(\$45k, \$50k]	-0.0137*** (-3.02)	-0.0159*** (-3.62)	0.0771*** (8.11)	0.0196*** (2.93)
(\$50k, \$55k]	-0.0132*** (-2.68)	-0.0178*** (-3.72)	0.0915*** (9.06)	0.0241*** (3.34)
(\$55k, \$60k]	-0.0121** (-2.47)	-0.0175*** (-3.68)	0.108*** (10.13)	0.0314*** (3.98)
(\$60k, \$65k]	-0.0129** (-2.50)	-0.0161*** (-3.34)	0.123*** (10.87)	0.0374*** (4.02)
(\$65k, \$70k]	-0.0128** (-2.40)	-0.0160*** (-3.15)	0.144*** (11.99)	0.0452*** (4.90)
(\$70k, \$75k]	-0.0110** (-2.05)	-0.0160*** (-2.95)	0.160*** (12.81)	0.0393*** (4.92)
(\$75k, \$80k]	-0.0104* (-1.87)	-0.0153*** (-2.73)	0.170*** (13.01)	0.0333*** (4.19)
(\$80k, \$85k]	-0.0109* (-1.94)	-0.0150*** (-2.71)	0.184*** (12.93)	0.0383*** (4.63)
(\$85k, \$90k]	-0.00975* (-1.73)	-0.0133** (-2.25)	0.203*** (12.85)	0.0456*** (5.46)
(\$90k, \$95k]	-0.00757 (-1.33)	-0.0110* (-1.80)	0.218*** (11.78)	0.0531*** (4.89)
(\$95k, \$100k]	0.0148** (2.42)	-0.0149** (-2.39)	0.248*** (10.78)	0.0694*** (3.97)
(\$100k, \$105k]	-0.0128* (-1.83)	-0.0155*** (-2.59)	0.210*** (12.20)	0.0555*** (5.03)
(\$105k, \$110k]	-0.0151** (-2.43)	-0.0142** (-2.20)	0.216*** (14.42)	0.0545*** (6.08)
(\$110k, \$115k]	-0.0130** (-2.01)	-0.0172*** (-2.61)	0.234*** (14.91)	0.0627*** (6.96)
(\$115k, \$120k]	-0.0150** (-2.29)	-0.0150** (-2.32)	0.255*** (16.93)	0.0674*** (6.37)
(\$120k, \$125k]	-0.0151** (-2.25)	-0.0151** (-2.35)	0.271*** (16.44)	0.0629*** (6.45)
(\$125k, \$130k]	-0.0161** (-2.30)	-0.0162** (-2.57)	0.292*** (18.48)	0.0694*** (6.91)
ln(Jobs Reported)	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes
Observations	4,466,915	6,922,683	5,735,350	1,907,883
Num. Lenders	4,652	4,805	4,774	4,659
R^2	0.073	0.088	0.295	0.105
Mean of Dep. Var.	0.0426	0.0465	0.0360	0.0464

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.IV. Criminal Records (Fintech)

In this table, we examine the relationship between each of our flags and the borrower's criminal records for loans by fintech lenders. We estimate OLS regressions with a dummy for whether the borrower has a felony from 2000 or after on their record as the dependent variable and dummies for whether the loan is flagged by each of our flags individually as the independent variable. Panel A shows the relationship for fintech loans and Panel B for traditional loans. Loans are filtered to the sets for which we can determine the flag (same as in Figures 2-9). Note that the business registry flag is not included since we can only determine criminal records for loans to individuals while the business registry flag can only be determined for corporations and LLCs. Fixed effects are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Panel A. Fintech Loans

Dep. Variable: Felony Post-2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Multiple Loans at Address	0.00669**						
	(2.14)						
High Implied Comp.		0.0198***					
		(3.18)					
EIDL Jobs > PPP Jobs			0.0675***				
			(9.66)				
$100k Implied. Comp.				0.0132***			
				(5.11)			
Monthly Rounding					0.00735		
					(1.46)		
Overrep. in County/NAICS						0.0105***	
						(3.14)	
High Concentration							0.00588*
							(1.70)
ln(Jobs Reported)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	No	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,372	17,479	10,626	54,372	54,372	23,737	52,486
Num. Lenders	70	45	47	70	70	68	63
R^2	0.127	0.112	0.185	0.126	0.126	0.150	0.123
Mean of Dep. Var.	0.047	0.056	0.047	0.047	0.047	0.047	0.048

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Panel B. Traditional Loans

Dep. Variable: Felony Post-2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Multiple Loans at Address	0.00269						
	(1.54)						
High Implied Comp.		0.00712					
		(1.21)					
EIDL Jobs > PPP Jobs			0.0352*				
			(1.74)				
$100k Implied Comp.				-0.00167			
				(-1.32)			
Monthly Rounding					0.00205		
					(0.73)		
Overrep. in County/NAICS						0.00393	
						(1.25)	
High Concentration							0.00366
							(0.92)
ln(Jobs Reported)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	No	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,297	11,345	7,095	64,297	64,297	32,924	57,872
Num. Lenders	2,470	1,054	603	2,470	2,470	1,649	2,187
R^2	0.222	0.307	0.358	0.222	0.222	0.252	0.216
Mean of Dep. Var.	0.014	0.017	0.016	0.014	0.014	0.014	0.013

t-statistics in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.010$

Table IA.V. Prevalence of Secondary Flags by Lender Types

In this table, we examine the propensity of the secondary flags by lender type. We estimate OLS regressions with each of the secondary flags as the dependent variable and a dummy for whether the lender is a fintech as the independent variable. Loans are filtered to the sets for which we can determine each flag (same as in Figures 5-9). Fixed effects and additional controls are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Panel A. Unadjusted Differences

	(1)	(2)	(3)	(4)	(5)
Dep. Variable:	\$100k Comp.	Monthly Rounding	Overrep. in County/NAICS	High Concentration	Felony
Fintech	0.172***	0.0297**	0.294***	0.400***	0.0334***
	(4.62)	(2.02)	(9.22)	(3.58)	(8.64)
Observations	10,697,211	5,365,570	5,981,065	7,351,176	150,000
Num. Lenders	4,902	4,883	4,887	4,397	3,657
R^2	0.054	0.001	0.070	0.210	0.010
Mean of Dep. Var.	0.129	0.080	0.415	0.205	0.027

Panel B. Adjusted Differences

	(1)	(2)	(3)	(4)	(5)
Dep. Variable:	\$100k Comp.	Monthly Rounding	Overrep. in County/NAICS	High Concentration	Felony
Fintech	0.0568***	0.0197	0.123***	0.293***	0.0179***
	(3.65)	(1.39)	(8.74)	(3.83)	(8.50)
ln(Jobs Reported)	Yes	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	No
Business Type FE	Yes	Yes	Yes	Yes	Yes
NAICS $\times$ CBSA FE	Yes	Yes	No	Yes	Yes
Observations	10,043,880	5,077,162	5,975,404	6,939,796	124,476
Num. Lenders	4,885	4,839	4,886	4,232	3,194
R^2	0.297	0.041	0.208	0.525	0.128
Mean of Dep. Var.	0.127	0.080	0.415	0.192	0.027

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.VI. Within State/County Variation

This table examines the degree to which geographic variation in flagged loans can be explained by fintech market share. We estimate OLS regressions with the percentages of flagged loans in each zip code as the dependent variable and the fintech markey share in each zip code as the independent variable. Specification (1) examines the relationship across all zip codes, (2) examines the relationship within states, and (3) examines the relationship with counties. Zip codes with at least 100 loans are considered. Fixed effects are indicated at the bottom of each column. Robust standard errors are clustered at the county level.

Dep. Variable: Percentage Flagged in Zip Code

	(1)	(2)	(3)
Fintech Market Share	0.272***	0.351***	0.427***
	(13.82)	(23.95)	(19.71)
State FE	No	Yes	No
County FE	No	No	Yes
Observations	15,457	15,457	14,599
Num. Counties	2,880	2,880	2,022
R^2	0.350	0.600	0.771
Mean of Dep. Var.	0.161	0.161	0.163

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.VII. County Cultural Features

This table replicates Table V at the county level rather than the loan-level. The variables are as defined in Table V. All variables (independent and dependent) are rescaled to have a mean of 0 and standard deviation of 1. Counties with at least 100 loans are considered. Fixed effects are indicated at the bottom of each column. Robust standard errors are clustered at the state level.

Dep. Variable: At Least One Flag

	(1)	(2)	(3)
Public Corruption	0.106	0.0767	0.00313
	(1.48)	(1.21)	(0.10)
Religious Affiliation	0.0206	0.00994	0.0464**
	(0.72)	(0.40)	(2.41)
Ashley Madison Usage	0.0703***	0.0422	-0.0665**
	(2.88)	(1.35)	(-2.65)
Population Density		-0.0179*	-0.0487***
		(-1.85)	(-4.40)
Median Income		-0.0275	-0.0431
		(-0.83)	(-1.87)
Pct. Non-White		0.389***	0.101***
		(6.52)	(2.80)
College Educated		0.00571	0.00430
		(0.20)	(0.18)
2019 Unemployment		-0.169***	-0.185***
		(-2.95)	(-3.99)
Pct. Fintech			0.586***
			(7.00)
State FE	Yes	Yes	Yes
Observations	3,002	3,001	3,001
R^2	0.381	0.469	0.577

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.VIII. Previous SBA Lending

In this table, we examine lender level relationship between suspicious lending in the PPP and previous SBA lending. *ln(Num. 7(a) Loans Pre-2020 + 1)* is the natural log of the number of SBA 7(a) loans originated by the lender pre-2020. *Num. Year Since First 7(a) Loan* is the number of years between when the lender originated its first SBA 7(a) loan and 2020 (we have data going back to 1990, so this variable can take a maximum value of 30). *New Lender* is a dummy that takes one a value of 1 if the lender had not originated any SBA 7(a) loans pre-2020. *1(Fintech)* and *1(Traditional)* are indicator functions for whether the lenders is a fintech or traditional lender, respectively. Lenders with at least 1,000 PPP loans are considered. Robust standard errors are used.

Dep. Variable: Percentage Flagged

	(1)	(2)	(3)	(4)
ln(Num. 7(a) Loans Pre-2020 + 1)	-0.00730***			
	(-8.32)			
Num. Year Since First 7(a) Loan		-0.00125***		
		(-4.93)		
New Lender			0.0514***	
			(4.41)	
× 1(Fintech)				0.0733**
				(2.03)
× 1(Traditional)				0.0373***
				(3.64)
1(Fintech)				0.0307**
				(2.43)
Observations	1,111	1,111	1,111	1,111
R^2	0.099	0.050	0.061	0.095
Mean of Dep. Var.	0.125	0.125	0.125	0.125

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.IX. Fees

In this table, we show the dollars value of loans originated, number of loans originated, and the estimated fees received by the top 75 PPP lenders (by number of loans). The list is sorted in descending order by estimated fees. The first forty lender are on this page and the remaining 35 are on the next page.

Lender	Lender Type	Dollars Lent	Number of Loans	Estimated Fees
JPMChase	Traditional	$41,443,991,367	435,357	$1,678,309,528
BoA	Traditional	$34,237,075,966	489,325	$1,465,504,191
Cross River	Fintech	$12,771,048,507	471,609	$1,016,828,757
Capital Plus	Fintech	$6,600,599,313	380,377	$926,869,448
Harvest	Fintech	$7,604,665,609	377,620	$925,992,546
Wells Fargo	Traditional	$13,767,834,276	277,949	$682,814,302
Customers Bank	Traditional	$7,052,505,022	279,880	$633,299,177
Benworth	Fintech	$3,766,809,946	275,920	$620,067,286
PNC	Traditional	$17,347,783,902	118,639	$599,553,379
Branch	Traditional	$16,632,176,414	118,281	$587,181,993
Fountainhead	Fintech	$3,461,750,875	233,226	$544,969,507
Itria	Fintech	$5,476,551,657	193,336	$529,482,556
U.S. Bank	Traditional	$10,774,383,938	173,024	$500,996,114
TD Bank	Traditional	$12,181,766,237	131,879	$489,897,697
KeyBank	Traditional	$11,064,228,582	68,580	$373,012,393
Zions	Traditional	$9,838,138,445	75,854	$354,088,405
Prestamos CDFI	Fintech	$2,388,759,974	145,583	$350,692,221
M&T	Traditional	$9,586,986,927	58,211	$331,490,976
Readycap	Fintech	$4,834,860,801	101,710	$299,981,250
Huntington	Traditional	$8,572,031,801	58,298	$298,254,178
Citizens Bank	Traditional	$7,165,123,714	85,246	$292,990,290
Fifth Third	Traditional	$7,351,389,855	65,094	$267,637,340
Regions Bank	Traditional	$6,406,068,642	77,868	$265,140,975
Celtic	Fintech	$4,624,587,686	167,098	$235,465,688
First Horizon	Traditional	$5,775,813,972	50,462	$216,970,355
WebBank	Fintech	$3,155,253,163	117,110	$208,997,502
Citibank	Traditional	$4,750,119,052	47,572	$189,980,270
Kabbage	Fintech	$3,327,154,152	180,291	$188,787,526
BMO Harris	Traditional	$6,098,989,540	35,902	$185,406,250
City National	Traditional	$5,937,998,585	25,476	$185,259,885
First-Citizens	Traditional	$4,421,177,219	35,364	$176,372,145
Frost	Traditional	$4,679,275,623	32,186	$170,165,268
Pinnacle	Traditional	$4,252,036,436	37,628	$169,374,487
Bank of the West	Traditional	$4,373,311,173	30,779	$163,264,968
Northeast	Traditional	$3,398,482,352	34,462	$160,045,643
Comerica Bank	Traditional	$4,930,860,923	20,897	$141,288,472
Synovus	Traditional	$3,809,538,913	27,526	$140,926,651
BBVA	Traditional	$4,047,201,081	30,545	$139,796,313
Square	Fintech	$645,832,846	68,747	$137,441,297
First National PA	Traditional	$3,658,484,414	30,227	$136,728,828

Lender	Lender Type	Dollars Lent	Number of Loans	Estimated Fees
People's United	Traditional	$3,684,138,310	30,575	$134,384,063
South State	Traditional	$3,231,854,545	27,892	$131,439,149
Hancock Whitney	Traditional	$3,323,651,191	21,416	$116,900,675
Umpqua	Traditional	$2,896,383,321	26,302	$111,438,561
Valley National	Traditional	$3,235,550,835	19,736	$110,968,604
MUFG	Traditional	$3,110,280,065	21,215	$110,220,137
Newtek	Fintech	$2,251,798,067	33,191	$109,857,021
TCF National	Traditional	$2,672,060,267	24,329	$101,875,992
Fulton	Traditional	$2,732,197,822	16,698	$94,982,595
Banco Popular	Traditional	$1,715,514,179	43,916	$91,221,028
United Community	Traditional	$2,218,846,800	22,125	$90,448,450
Glacier Bank	Traditional	$2,005,785,629	24,401	$87,708,029
FirstBank	Traditional	$1,979,278,631	26,087	$86,396,463
MBE	Fintech	$977,705,708	40,531	$81,168,106
Prosperity	Traditional	$2,006,818,115	18,692	$80,413,268
Atlantic Union	Traditional	$2,205,251,421	16,858	$80,411,666
First Bank	Traditional	$1,855,736,212	19,820	$80,129,789
BancorpSouth	Traditional	$1,755,438,034	24,031	$79,769,179
Arvest	Traditional	$1,650,380,829	27,387	$79,327,337
United Bank	Traditional	$2,033,793,736	17,572	$77,850,182
Blue Ridge	Traditional	$1,160,073,893	24,490	$77,795,525
Webster	Traditional	$1,981,355,729	18,371	$76,955,064
Capital One	Fintech	$1,755,412,442	24,534	$76,891,585
Old National	Traditional	$2,103,975,416	15,844	$76,149,828
Santander	Traditional	$1,766,843,960	19,897	$73,154,956
Peoples Bank	Traditional	$1,621,567,864	18,908	$71,227,793
First Insterstate	Traditional	$1,635,315,725	18,733	$71,199,493
Amur Equipment	Traditional	$638,236,364	26,517	$69,401,078
First State	Traditional	$987,800,593	18,992	$54,941,435
A10Capital	Traditional	$627,843,832	18,099	$53,636,427
Legacy	Fintech	$884,489,617	15,938	$53,078,274
American Lending	Fintech	$536,325,746	19,875	$52,714,858
DreamSpring	Fintech	$270,698,683	24,707	$47,508,876
Funding Circle	Fintech	$583,939,117	17,072	$44,210,843
Intuit	Fintech	$639,524,177	18,561	$30,670,444

Table IA.X. Persistence and Growth by Lender-Region Pairs

In this table, we examine persistence and growth of suspicious lending by lender-region pairs. Panel A looks at lender-zip code pairs and Panel B looks at lender-county pairs. We estimate OLS regressions with the percentage of flagged loans during rounds 1-2 within each lender-region pair interacted with whether the lender is a fintech or traditional lender as the independent variables. In specification (1), the dependent variable is whether the lender increased its lending within the region (as a percentage of its overall lending) between rounds 1-2 and round 3; in specification (2), the dependent variable is the percentage change in the percentage of the lender's loans that are in the region between rounds 1-2 and round 3; in specification (3), the dependent variable is the percentage of flagged loans during round 3 within each lender-region pair. In both panels. lender-region pars with at least 25 loans in rounds 1-2 (combined) are considered. Fixed effects are as indicated at bottom of each column. Robust standard errors are double clustered by region (zip code in Panel A and county in Panel B) and lender.

Panel A. By Lender-Zip Code

Dep. Variable:	(1) 1(Lending Growth)	(2) Lending Pct. Change	(3) Pct. Flagged in Round 3
Pct. Flagged in Rounds 1-2			
× 1(Fintech)	1.124***	1.890***	0.549***
	(4.41)	(5.65)	(7.83)
× 1(Traditional)	0.113	0.148	0.155***
	(1.34)	(1.33)	(5.89)
Zip Code FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
Observations	37,091	37,091	37,091
Num. Lenders	1,632	1,632	1,632
R^2	0.409	0.571	0.342
Mean of Dep. Var.	0.352	-0.068	0.158

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Panel B. By Lender-County

Dep. Variable:	(1) 1(Lending Growth)	(2) Lending Pct. Change	(3) Pct. Flagged in Round 3
Pct. Flagged in Rounds 1-2			
× 1(Fintech)	1.291***	2.104***	0.490***
	(4.89)	(3.50)	(4.51)
× 1(Traditional)	0.369***	0.804***	0.206***
	(4.10)	(4.88)	(5.83)
County FE	Yes	YesYes	
Lender FE	Yes	Yes	Yes
Observations	20,031	20,031	20,031
Num. Lenders	2,347	2,347	2,347
R^2	0.371	0.541	0.356
Mean of Dep. Var.	0.430	0.102	0.181

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.XI. Repayment and Enforcement

In this table, we examine elevated repayment and enforcement actions for flagged loans. We estimate OLS regressions with a dummy for whether the loan is flagged by at least one primary flag as the dependent variable and a dummy for whether the loan is repaid (Panel A) or part of a DOJ enforcement action (Panel B) as the independent variable. Even columns include lender fixed effects and odd columns do not. Since loans originated by MBE Capital Partners makes up 42% of the repaid loans, Panel A includes specifications across all loans and excluding loans by MBE Capital Partners. Fixed effects and additional controls are as indicated at bottom of each column. Robust standard errors are double clustered by zip code and lender.

Panel A. Repayment

Dep. Variable: 1(Repaid)

	(1)	(2)	(3)	(4)
	All Loans		Ex. MBE Capital Partners	
Flagged	0.00122**	0.0000469	0.000680***	0.000905***
	(2.08)	(0.05)	(3.19)	(4.37)
ln(Jobs Reported)	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes
Lender FE	No	Yes	No	Yes
Observations	4,866,890	4,866,836	4,843,296	4,843,296
Num. Lenders	4,823	4,769	4,822	4,768
R^2	0.031	0.159	0.027	0.049
Mean of Dep. Variable	0.00328	0.00328	0.00192	0.00192

Panel B. DOJ Enforcement

Dep. Variable: 1(DOJ Enforcement Action)

	(1)	(2)
Flagged	0.0000989***	0.0000961***
	(3.17)	(3.08)
ln(Jobs Reported)	Yes	Yes
ln(Loan Amount)	Yes	Yes
Zip FE	Yes	Yes
Business Type FE	Yes	Yes
NAICS × CBSA FE	Yes	Yes
Lender FE	No	Yes
Observations	4,866,890	4,866,836
Num. Lenders	4,823	4,769
R^2	0.025	0.026
Mean of Dep. Variable	0.0000541	0.0000541

t-statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010