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Did FinTech Lenders Facilitate PPP Fraud?

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ABSTRACT

In the $793 billion Paycheck Protection Program, we examine metrics related to potential misreporting including nonregistered businesses, multiple businesses at residential addresses, abnormally high implied compensation per employee, and large inconsistencies with jobs reported in another government program. These measures consistently concentrate in certain FinTech lenders and are cross-verified by seven additional measures. FinTech market share increased significantly over time, and suspicious lending by FinTechs in 2021 is four times the level at the start of the program. Suspicious loans are being overwhelmingly forgiven at rates similar to other loans.

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 an increase in regulatory burdens for

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traditional banks is the predominant driver in the rise of FinTech lending. A large aspect of the scrutiny and regulation of traditional banking was its perceived role in the financial crisis, which included facilitating widescale mortgage fraud, as partially evidenced by over $137 billion in government fines and settlements (Griffin, Kruger, and Maturana (2019)). FinTech lenders offer a new banking model that replaces traditional lending relationships with online advertisements, application programming interfaces, and loan screening algorithms.

The Paycheck Protection Program (PPP), a historic COVID-19 relief program for businesses, rapidly distributed over $793 billion of funds in three short rounds spread between April 2020 and May 2021. Although FinTech lenders began with a slow start, with less than 5% of loans in round 1, they ramped up to over 80% of loans by May 2021, highlighting their growing importance. FinTech lending was recognized for broadening access to PPP loans, particularly to smaller firms without preexisting lending relationships with traditional banks, and for facilitating quick and efficient lending when many small businesses were in need of funds due to the COVID-19 pandemic. However, the rapid expansion of FinTech lending may have come at the expense of underwriting standards. While traditional banks have established borrower relationships and extensive Bank Secrecy Act (BSA) compliance programs, many FinTech lenders had few established relationships and may have been less diligent when establishing 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 also 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. Did FinTech lenders prevent or facilitate fraud in the PPP? And how does potential fraud and misreporting vary across individual lenders?

To investigate these questions, we perform a big data analysis of loan features on the 11.5 million PPP loans with eight disparate data sets. We introduce four primary and four secondary indicators of whether a loan is potentially misstated, which we then validate with three independent external measures. Each indicator creates an inference that a loan is suspicious but is not proof of misreporting on its own. The four primary measures are nonregistered businesses, multiple loans at a residential address, abnormally high implied compensation relative to industry by core-based statistical area (CBSA) averages, and large inconsistencies (as large as 10-fold) between the jobs reported by borrowers on their PPP application and jobs reported to another contemporaneous government program application with a different incentive structure. FinTech loans are 3.23 times as likely to have at least one primary indicator of misreporting compared to traditional loans and 6.52

times as likely to have a primary indicator that is confirmed by an additional primary, secondary, or external indicator. Suspicious lending rates vary substantially across lenders, with potential misreporting rates in excess of 25% for 10 large FinTech lenders. Suspicious lending is most pronounced for unincorporated businesses, which highlights the challenge of quickly extending widespread aid to small entities with limited documentation.[1] FinTech lenders exhibited consistently higher misreporting rates across all borrower types even after controlling for loan and borrower characteristics.

We assess each of the four primary indicators with multiple discontinuity and comparative analyses. First, there is substantial cross-validation across the four main indicators. For example, loans that report abnormally high compensation relative to the U.S. Census average compensation in the loan's industry and CBSA also have higher incidences of nonregistered businesses, multiple loans at the same address, and inconsistencies in jobs reported. These patterns are substantially elevated in FinTech lenders but are also present for traditional lenders, indicating that misreporting is not just confined to FinTech. Second, someone receiving a fictitious loan might wish to maximize or come close to maximizing their proceeds. We find monotonically increasing levels of indicators when approaching the perceived maximum compensation threshold and a sharp discontinuity at the threshold with lower levels of suspicious lending just above the threshold. These patterns are present for all four main indicators; discontinuities are present both for traditional and FinTech lenders but are much more pronounced for FinTechs with an increase in potential misreporting of over 6.5 times when approaching the threshold from below. Third, even though PPP loan amounts were supposed to be based on historical past compensation with detailed supporting documentation, rounded monthly compensation values are common and coincide with higher levels of each of the four primary misreporting indicators for FinTech lenders.

Fourth, PPP lending at the industry-county level frequently exceeds the number of establishments listed for that industry and county in U.S. Census data. For FinTech lenders, 39.3% of loans exceed industry-county establishment counts, and 32.6% of loans exceed industry-county establishment counts by a factor of more than two.[2] Measures of misreporting monotonically increase as the ratio of PPP loans to businesses documented by the U.S. Census increases, particularly for FinTech lenders. Fifth, because networks in a region may use recurring loan features, we construct a concentration ratio to measure clustering in loan amounts, number of jobs, 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. Sixth, we collect criminal background data for a sample of 150,000 individuals. FinTech borrowers are

[1] Fraud was also widespread in pandemic unemployment insurance programs, potentially for similar reasons (Podkul (2021)).

[2] The corresponding figures for traditional lenders are 14.0% and 8.2%, respectively.

more than 3.4 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. Seventh, the flags strongly correlate with loans flagged in online crowd-sourced data collected from PPP Detective. Finally, the PPP coincides with a surge in regulatory suspicious activity reports (SARs) from banks and other financial institutions related to small business lending, and these reports exhibit strong geographic correlation with our suspicious loan measures.

Overall, we find 1.41 million questionable loans representing $64.2 billion in capital based on our primary measures. These measures inevitably contain some false positives, which would lead to overstatements, and some flagged loans may have been legitimately eligible for smaller loans. However, the measures also miss many forms of suspicious lending, and sensitivity analysis indicates that this total is likely substantially understated. Slightly lowering the threshold on the high implied compensation and considering excess loans in industry-county pairs beyond the number of establishments reported by the U.S. Census results in a total suspicious lending estimate of $117.3 billion. Moreover, this sensitivity analysis is along only two limited dimensions, and most of our metrics are conservative and only apply to subsets of loans, further highlighting that these estimates are ranges that, like most fraud estimates, have considerable uncertainty.

Proponents of the PPP often point to the urgency of getting money out quickly as a potential rationale for tolerating a high level of fraud (e.g., McArdle (2022)). However, this urgency mainly applies to the initial rollout of the program, and potential misreporting increased over time with particularly high rates in the last month of round 3 (25.0%), even after the Office of the Inspector General for the Small Business Administration (SBA) flagged PPP fraud as a concern in October 2020. Several of the FinTech lenders with the highest suspicious loan rates are new lenders who did not start making PPP loans on their own until round 3. There is no evidence that lenders decreased misreporting over time. Instead, second-draw loans to borrowers with suspicious first-draw loans from 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 four largest FinTech lenders, Cross River, Prestamos, Harvest Small Business Finance, and Capital Plus, exhibited high rates of misreporting and large lending volume growth while generating approximately a billion dollars in processing fees each. Finally, FinTech lenders often doubled or tripled their potential misreporting rates in round 3 compared to rounds 1 and 2.

Overall, our findings indicate that misreporting was common in the PPP, especially for FinTech lenders. This result comes with two important caveats. First, not all FinTech lenders have high misreporting rates. In particular, Square and Intuit, which are quintessential FinTech lenders but also benefit from established reputations and broad existing customer relationships before the PPP, have among the lowest rates of potential misreporting. Thus, online lending in and of itself does not appear to be the problem. Second, our findings may not translate to other settings because of unique features of the PPP. In particular, the PPP involved almost no balance sheet risk for lenders. Although many FinTech lenders were susceptible to misreporting in the PPP, this vulnerability may not be a characteristic of FinTech lending under different incentive structures.

Our work is related to four main literatures. First, there is a rapidly emerging literature on FinTech lending that highlights its growing importance and positive economic effects achieved by filling gaps left by traditional banks in both residential (Buchak et al. (2018)) and business lending (Gopal and Schnabl (2022)). 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 (2022) examine FinTech lending in the PPP and find that FinTech lenders increased access to the PPP by lending more in ZIP Codes with fewer traditional banks, lower incomes, and higher minority percentages. Chernenko and Scharfstein (2022) show that Black- and Hispanic-owned firms were less likely to receive PPP loans from traditional lenders. Howell et al. (2022) find that FinTechs were more likely to provide PPP loans to Black-owned businesses.[3] With respect to FinTech lending before the PPP, Gopal and Schnabl (2022) show that FinTech lenders have positive economic effects by filling in gaps in lending to small businesses left by traditional banks following the financial crisis. Although most of the FinTech literature finds benefits to FinTech lending such as increased competition, broader financial access, less discrimination, faster lending speed, and lower defaults, our paper analyzes a potential cost of FinTech expansion and differential practices across FinTechs. These costs are an important consideration when evaluating FinTech PPP lending, but we leave overall welfare analysis to future research.

Second, regarding the efficacy of the PPP, Chetty et al. (2022) show that the PPP increased employment at participating firms by only 2% at a cost of \$377,000 per job saved, and Autor et al. (2022) find costs of \$170,000 to \$257,000 per job retained. Granja et al. (2022) find small employment effects due to the PPP and a low correlation between regional COVID-19 variation and PPP funding allocation. In contrast, Faulkender, Jackman, and Miran (2021) find that the program was much more effective with an estimated 18.6 million jobs saved at an average cost of \$28,000, and Denes, Lagaras, and Tsoutsoura (2021) show that firms with short-term delays in PPP access experienced

[3] Atkins, Cook, and Seamans (2022) find that FinTechs helped close a gap in loan size between Black- and white-owned businesses. In contrast, Bartlett et al. (2022) find that FinTech algorithms charge higher interest rates to minorities in residential mortgage lending but price discriminate less than traditional banks. Begly et al. (2022) show that the SBA disaster-relief home loan program denies more loans to minorities and subprime borrowers due to the program's risk-insensitive pricing. Ben-David, Johnson, and Stulz (2022) find that FinTech lending to small businesses through a major lending platform contracted with the onset of COVID-19 in March 2020 due to financial constraints.

fewer visits and higher shutdown rates. 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 (Rabetti (2022), Bartik et al. (2020), Neilson, Humphries, and Ulyssea (2020), Duchin et al. (2022), Glancy (2022), Li and Strahan (2021)). Our evidence adds an additional concern regarding the PPP's efficacy and fairness. We are the first academic paper to examine widescale potential PPP loan misreporting, but there have been interesting press and investigative reports regarding suspicious PPP loans (e.g., Wieder, Ben and Bobrowsky, Meghan (2020), Willis and DePillis (2021)), some of which feature FinTech lenders.[4]

Third, assessment of the PPP also relates to a broader literature on fraud, waste, and abuse in government programs (e.g., Glaeser and Goldin (2006)), including waste due to poor program design and administration (Bandiera, Prat, and Valletti (2009)). Duflo (2017) emphasizes the importance of program details. In the PPP, the lack of direct tools for validating eligibility and limited incentives for high-quality underwriting by lenders with no skin in the game may have significantly increased fraud and abuse. Chetty, Friedman, and Saez (2013) find that the fraction of people who manipulate self-reported income in the Earned Income Tax Credit program grows over time. A similar mechanism of fraud growing over time seems to be at work here. Hanson et al. (2020) argue that direct relief for small businesses from the Internal Revenue Service could have been more targeted and efficient than the PPP's external lender model.

Finally, our work relates to forensic economics and loan misreporting. Zitzewitz (2012) surveys the literature on forensic economics, noting that a common thread in this literature is quantifying activity about which there was previously only anecdotal evidence, in large part because agents have an incentive to keep it hidden. Widescale mortgage fraud and misreporting in securitized mortgages (Piskorski, Seru, and Witkin (2015), Garmaise (2015), Griffin and Maturana (2016), Mian and Sufi (2017), Kruger and Maturana (2021)) prior to the financial crisis 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 as related regulation increased for traditional banks (Buchak et al. (2018)). Our findings indicate that replacing traditional lending with FinTech lending amplified misreporting problems, at least with respect to the PPP.

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

[4] Concerns about PPP fraud have been flagged by the Office of the Inspector General for the SBA (see report at https://www.sba.gov/sites/default/files/2021-01/SBA%20OIG%20Report-21-07.pdf). Beggs and Harvison (2022) find that among the 2,999 registered investment advisors who took PPP loans, those with a history of financial misconduct received unusually large PPP loan allocations.

deterrence of current policies and enforcement. The implications of these findings are further discussed in the conclusion.

I. Data and Summary Statistics

A. Data Sources

The basis for our sample is loan-level PPP data released on January 2, 2022 by the SBA. This data set covers all PPP loans issued from the start of the program on April 3, 2020 through its end on June 30, 2021 that had not been repaid or canceled as of January 2, 2022. At the loan level, the data include 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 11,469,801 loans originated by 4,809 different lenders and with a total value of $793 billion. We follow Erel and Liebersohn (2022) and classify lenders as either traditional or FinTech (consisting of online banks and nonbank lenders) using the same methodology.[5]

In addition to the PPP data, we use multiple other data sources. Economic Injury Disaster Loans (EIDL) were provided by the SBA to businesses and individuals and included forgivable advances of up to $10,000. EIDL Advance loan-level data were released on December 1, 2020 and cover all EIDL Advances issued in 2020. Data on state business registrations are from OpenCorporates, which collects its data directly from state governments and covers 76 million businesses across all U.S. states except Illinois. The data include incorporation dates, dissolution dates (if applicable), and, implicitly, whether the business has ever been registered. Criminal background data are collected 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] We also utilize data on 147,662 loans reported on PPP Detective (https://www.pppdetective.com), a crowd-sourced platform that allows individuals to search PPP loans and report PPP loans as "potentially being fraudulent." The BSA requires banks and other financial institutions to

[5] We use Erel and Liebersohn's (2022) classifications for lenders who were active in rounds 1 and 2 (the sample period for Erel and Liebersohn (2022)), and we use the same methodology for classifying round 3 lenders who were not active enough to be classified in the earlier rounds. Classification of FinTech lenders can be difficult because traditional banks with multiple branch locations may also originate loans from other lenders or online portals. See the Internet Appendix for additional details. The Internet Appendix is available in the online version of the article on *The Journal of Finance* website. Results are robust to different definitions of FinTech lenders, including restricting FinTechs to online banks or nonbanks and dropping large community development lenders who operated as FinTechs in the PPP (as shown in Table IA.II in the Internet Appendix).

[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 are collected only from round 1 and 2 loans because round 3 data were released after the criminal records data were collected.

report suspicious activities to the Financial Crimes Enforcement Network (FinCEN), a division of the U.S. Treasury Department. We utilize summary data from FinCEN on SARs from 2014 to 2021. Finally, we use several U.S. governmental data sources for address, demographic, and business information. Additional details on all of the data sources are described in the Internet Appendix.

B. Summary Statistics

Summary statistics for the 3.7 million FinTech and 7.7 million traditional bank loans in our sample are reported in Table I. FinTech loans have an average loan amount of \$23,000 compared to \$91,000 for traditional bank loans. Despite these large differences in means, the median loan sizes of \$19,000 and \$21,000 are similar. The average FinTech loan reports supporting 2.3 jobs compared to 10.5 for traditional banks. After normalizing loan size relative to reported jobs, FinTech loans have a higher average (\$63,000) and median (\$68,000) implied compensation than traditional bank loans (\$47,000 average and \$39,000 median). For FinTech loans, 19.5% of borrowers are organized as corporations, S-corporations, or limited liability companies (LLC), compared to 65.8% for traditional bank lenders. FinTech loans were also less likely to be repeat loans, with 27.1% of round 3 FinTech loans going to borrowers with previous PPP loans, compared to 60.8% for round 3 traditional bank loans.

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 (nonbank FinTech lenders) and cream (online banks). Six of the 10 top lenders by number of loans are FinTechs, with Cross River, Prestamos, and Harvest in the top five alongside Bank of America and JPMorgan Chase.[7] Due to their larger average loan size (Erel and Liebersohn (2022)), dollar lending volume is higher for most 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 1.1% of loans in the first week of round 1 to 5.9% in the last week of round 1. Round 2 continued the PPP after a short break of 10 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 50.1% of loans over the last two weeks, for an overall market share of 4.2% in round 1 and 20.1% in round 2. Round 3 of the PPP started in January 2021 with a low FinTech market share of 12.3% in the first three weeks, but reached over 86% of loans for the second half of May 2021, for an overall round 3 market share of 46.4%.[8]

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

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

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 on April 3, 2020 through its end on June 30, 2021 that had not been repaid or canceled as of January 2, 2022. FinTech lenders are determined following Erel and Liebersohn (2022). *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 the average compensation in the loan's industry-CBSA based on the U.S. Census CBP data. *CBSA/NAICS Avg. Receipts* is the average receipts (for business types that were able to use gross income to calculate loan size) to nonemployer businesses in the loan's industry-CBSA based on the U.S. Census NES data. *Normalized Comp*. is the ratio of *Implied Comp*. and either *CBSA/NAICS Avg. Comp*. or, if the business was able to use gross income to calculate its loan amount, the larger of *CBSA/NAICS Avg. Comp*. and *CBSA/NAICS Avg. Receipts*. *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, and *Frac. Matched EIDL Advance* is the percentage of loans with a matching EIDL Advance. *Frac. FinTech (Either Type)*, *Frac. Nonbank 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]	3,732,133 [32.54%]			7,737,668 [67.46%]		
Loan Amount	23,200	84,470	18,500	91,211	305,665	20,833
Jobs Reported	2.322	9.000	1.000	10.493	29.547	3.000
Implied Comp.	62,984	37,357	67,594	46,633	46,321	38,743
CBSA/NAICS Avg. Comp	46,921	38,895	36,942	49,798	37,459	42,849
CBSA/NAICS Avg. Receipts	46,141	31,432	35,732	59,458	37,254	53,291
Normalized Comp.	1.676	1.377	1.227	1.091	1.221	0.897
Num. Loans (Within Draw) at Address	1.321	0.794	1.000	1.193	0.801	1.000
Frac. Corp, S Corp, LLC	0.195			0.658		
Frac. Second Draw (Round 3 Loans)	0.271			0.608		
Frac. Matched EIDL Advance	0.182			0.269		

	Round 1	Round 2	Round 3
Num. Loans [Pct. Loans]	1,618,989 [14.1%]	3,517,397 [30.7%]	6,333,415 [55.2%]
Loan Amount	197,351	57,424	42,766
Jobs Reported	20.468	7.915	4.561
Implied Comp.	47,173	43,364	57,945
CBSA/NAICS Avg. Comp	49,339	51,830	46,935
CBSA/NAICS Avg. Receipts	–	–	50,003
Normalized Comp.	1.156	1.040	1.477
Num. Loans (Within Draw) at Address	1.277	1.212	1.261
Frac. FinTech (Either Type)	0.0424	0.201	0.467
Frac. Nonbank FinTech	0.0265	0.0789	0.410
Frac. Online Bank FinTech	0.0159	0.122	0.0574
Frac. Corp, S Corp, LLC	0.829	0.657	0.342
Frac. Second Draw	–	–	0.451
Frac. Matched EIDL Advance	0.292	0.301	0.195

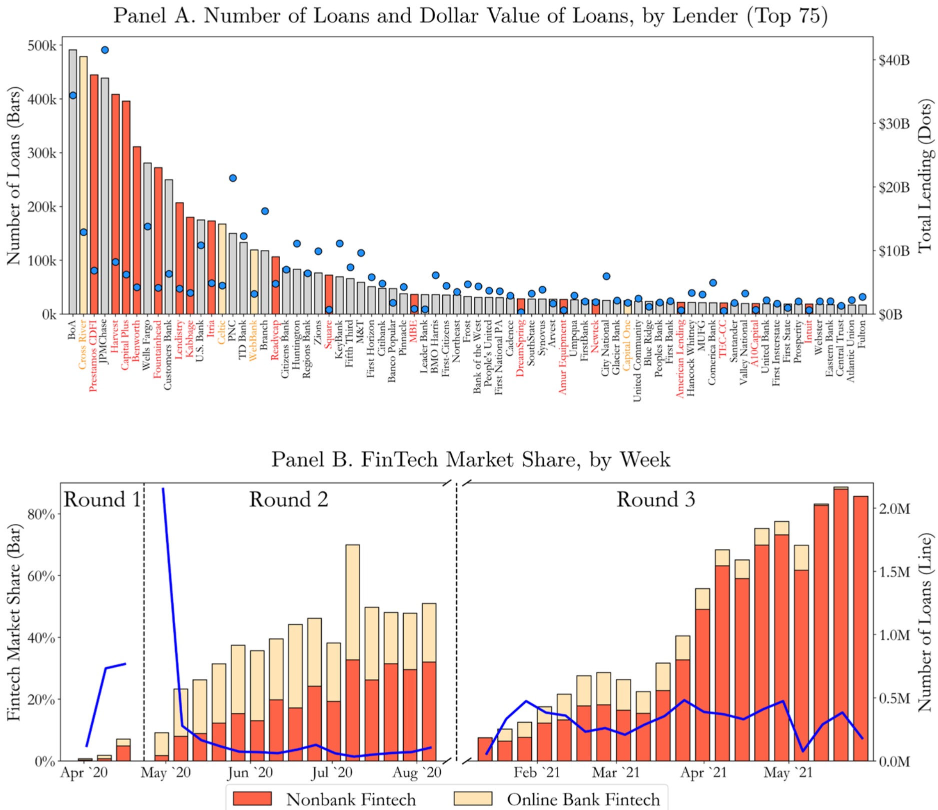

Figure 1. FinTech market share. This figure shows the role that FinTech lenders played in the PPP. Panel A shows the number of loans (bars) and dollar value of loans (dots) originated by the top 75 lenders (by number of loans). Panel B shows the percentage of loans originated by FinTech lenders during each week of rounds 1, 2, and 3 of the PPP on the left axis and the total number of loans originated each week on the right axis. In both panels, red represents nonbank FinTech lenders, cream represents online bank FinTech lenders, and gray 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. (Color figure can be viewed at wileyonlinelibrary.com)

II. Primary 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 may also contain false positives. In subsequent sections, we validate the measures and explore how they relate to one another and other misreporting indicators.

A. 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:

(i) Is there a matching business in the business registry data? ("Missing Business")[10]
(ii) Was the business dissolved and inactive before being approved for a PPP loan? ("Dissolved Business")[11]
(iii) Is the earliest incorporation or initial filing date for the business after February 15, 2020? ("Late Incorporation/Filing")

These three subflags are combined to form an overall business registry flag.[12] Additional details are described in the Internet Appendix.

B. Multiple Loan Flag

Although a business owner may have multiple businesses registered to the same address, the presence of multiple loans at an individual residential address during the same draw is also a potential sign of fictitious operations. We first standardize addresses and identify those 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. We identify residential (i.e., nonbusiness, noncentral) standardized addresses with multiple loans within the same draw. To be conservative, we only flag addresses with three or more loans.

As an example, a modest suburban home north of Chicago with an estimated home value of $170,000 per Zillow received 14 loans at a single address, all with colorful business names, almost all in the same industry, most with the

[9] See loan application at https://www.sba.gov/sites/default/files/2021-03/Borrower-Application2483ARPrevisions%20%28final%203-18-21%29-508.pdf.

[10] We take a conservative approach to quantifying missing businesses by considering all businesses registered to do business in the state of the PPP loan as well as all businesses in other states that list a registration address in the state of the PPP loan. We are also conservative in our name matching and count any business name with a match ratio of 75% or more as a potential match.

[11] 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. To be conservative, this flag is only applied when the dissolved business registration matches the PPP borrower with a higher level of confidence (with at least a 90% match ratio as opposed to the 75% ratio cutoff used for the existence of a registration). If multiple business registrations match with ratios of at least 90%, the flag is only applied if they have all been dissolved. The late incorporation flag also employs the same conservative methodology.

[12] As external validation of this flag for a smaller sample, we also compare PPP borrower names to data from the Florida Department of Business and Professional Regulation, following Chernenko and Scharfstein (2022) (see Figure IA.2 in the Internet Appendix). Loans flagged as a missing business based on the overall business registry are over 6.8 times less likely to have a potential match in the restaurant data as compared to loans that are not flagged. Loans flagged as having missing business registrations that also have another flag (primary or secondary) are over 13.9 times less likely to have a potential match in the restaurant data.

same loan amount, and all backing 10 jobs (as shown in Panel A of Exhibit IA.1 in the Internet Appendix).[13] Another multiple-loan example involves 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 (as shown in Panel B of Exhibit IA.1 in the Internet Appendix).[14] Random loan-level inspections of the data reveal numerous other examples of multiple suspicious loans flowing to addresses that do not seem to be the locations of identifiable businesses. The multiple loan flag functions as a way to systematically analyze these loans.

C. 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. PPP loan applications report how many employees the business has based on the same time period used to calculate average payroll expenses (2019 in most cases). Using loan size and number of reported employees, we can impute implied average annual compensation. Implied compensation at the borrower level is strongly related to average compensation in the borrower's industry (North American Industry Classification System (NAICS) four-digit) and CBSA (e.g., see Figure IA.3 in the Internet Appendix).[15]

For our main measure of high implied compensation, we conservatively only flag loans for which the implied compensation per job reported is more than three times the industry-CBSA average compensation/receipts ("high implied compensation"). Because compensation is censored at \$100,000 for

[13] The first loan is to an LLC that was registered in 2018, but the 13 subsequent loans during July and August 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 13 of the business names or any indication of employees other than the owner.

[14] This income is high for the indicated industries, which have average compensation of \$25,000 to \$46,000 in the Chicago CBSA according to the U.S. Census County Business Patterns (CBP). All four individuals also received second-draw loans for the same amount. SBA guidelines ask the borrower for their business address. The industries themselves are also suspicious in that one of the loans is for an auto repair business and two are for equipment manufacturing despite no evidence of these businesses in photos of the property. The borrower in another loan for a nail salon does not appear to have an Illinois nail technician license. Another borrower at the address changed industries from equipment manufacturing to the nail salon industry during round 3 despite also not having a nail technician license.

[15] Schedule C filers also had the option of using gross income instead of net income for owner compensation after March 3, 2021. To conservatively account for the option, we compare implied compensation for sole proprietor, independent contractor, self-employed, and single member LLC loans after March 3, 2021 to the greater of industry/CBSA average compensation and industry/CBSA average receipts for single-employee firms. This adjustment is also used in calculating the high implied compensation measure below.

most borrowers, this flag is only possible in industry-CBSA pairs with average annual compensation/receipts below \$33,333.33.[16]

D. EIDL Advance Jobs > PPP Jobs Flag

Concurrently with the PPP, the SBA provided businesses and individuals with the ability to receive a forgivable EIDL Advance of up to \$10,000.[17] For all EIDL Advances issued in 2020, the advance amount was calculated as \$1,000 per employee (up to the \$10,000 maximum).[18] Thus, there was an incentive for borrowers to inflate the number of jobs reported on their EIDL applications.[19] We focus on cases in which EIDL jobs exceed PPP jobs because the job inflation incentive is provided by the EIDL Advance program; there is no direct incentive to inflate the number of jobs on the PPP application since PPP loans are based on total payroll as opposed to the number of jobs reported. To make it less likely that differences are driven by reporting or timing differences in the number of employees reported, we only consider differences of three or more jobs. Most of the flagged loans are even more egregious than this. As discussed further below, 14.1% of matched FinTech loans have an EIDL-PPP jobs difference of a full nine jobs, indicating that the borrower reported one job to the PPP but maxed out the EIDL Advance with at least 10 reported jobs.

E. FinTech Differences?

In Panel A of Figure 2, we plot suspicious loan rates by lender for the top 75 lenders. FinTech lenders tend to cluster at the left of the graph and traditional

[16] Some loans are also outside of a CBSA or in an industry-CBSA pair that is too small to be included in the U.S. Census CBP or Nonemployer Statistics (NES) data. In total, 3,313,359 loans (28.9% of the sample) are in industry-CBSA pairs with average annual compensation/receipts below \$33,333.33. Because this compositional construction censors loans in higher compensation industry-CBSAs, we analyze this flag within the subset of industry-CBSAs with compensation/receipts below \$33,333.33.

[17] Although the EIDL Advance program was billed as a forgivable advance with the potential for a larger nonforgivable loan, 65.8% of EIDL Advances involved no additional EIDL loan. EIDL Advances were immediately forgiven by the SBA.

[18] The EIDL Advance rules changed for 2021 to: (i) provide the entire \$10,000 regardless of employee count, and (ii) target the advances to low-income communities and those with a demonstrated decrease in revenue.

[19] Note that the misreporting identified by this flag is committed on the EIDL Advance application. The flag does not directly imply misreporting on the PPP loan; however, individuals who engaged in financial misconduct in one area are five times as likely to commit subsequent misconduct (Egan, Matvos, and Seru (2019)). For borrowers who take out the maximum EIDL Advance of \$10,000, we can infer that the borrower claimed at least 10 employees on their EIDL Advance application. Subsequent to the release of the first public version of this paper, an October 7, 2021 report by the SBA OIG found that over 700,000 EIDL recipients applied for and received advances for multiple employees even though they only had a single employee, resulting in \$4.5 billion of improper EIDL Advance payments (see report at https://www.sba.gov/sites/default/files/2021-10/SBA%20OIG%20Report%2022-01%20.pdf).

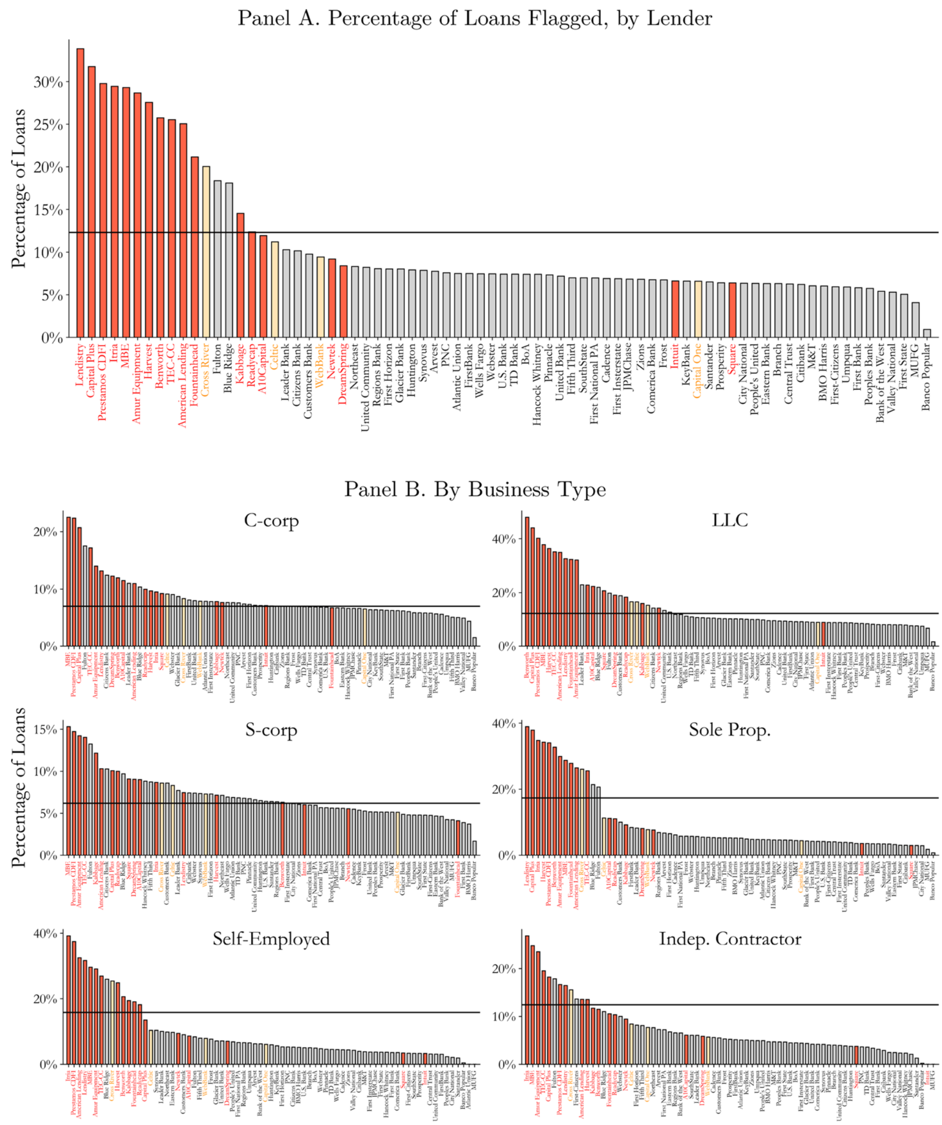

Figure 2. Misreporting rates. This figure shows the variation in the percentage of loans flagged across lenders. In both panels, the bars show the percentage of loans originated by each lender that are flagged by at least one of the primary flags and the horizontal line represents the percentage of loans originated by any lender that are flagged by at least one primary flag. The top 75 lenders by number of loans (across the entire sample) are shown. Panel A is based on all loans by each lender and Panel B is based on loans by each lender to specific business types (as denoted by each subpanel title). (Color figure can be viewed at wileyonlinelibrary.com)

lenders cluster in the middle and to the right. The 10 lenders with the most suspicious loans are all FinTechs and have at least a quarter of their loans implicated, compared to the overall average of 12.3%. In the extreme, Lendistry, Capital Plus, Prestamos, Itria, and MBE have primary flag rates of 33.8%, 31.8%, 29.8%, 29.4%, and 29.3%, respectively. Although most of the FinTech lenders cluster among the lenders with the most suspicious loans, there are a few exceptions. In particular, Capital One, Intuit, and Square have misreporting rates that are well under the average misreporting rates across all lenders.

Panel B of Figure 2 plots the suspicious lending rates by lender separately for different business types. FinTech lenders consistently cluster to the left in each plot, indicating that the patterns of suspicious lending are not isolated to only a few business types. Suspicious lending to unincorporated entities is consistently higher, reaching near or over 40% for some lenders' LLC, self-employed, and sole proprietorship loans. However, for corporate entities (C-Corp and S-Corp), the levels are not trivial, as they reach as high as 20% and 15%, respectively. It is important to note that most of the suspicious loan indicators only apply to subsets of loans. To confirm that selection along these dimensions is not driving the results, we examine lender fixed effects from regressions with business type fixed effects and indicators for loans with matching EIDL loans and loans in industry-CBSAs with compensation/receipts below \$33,333.33 and find similar dispersion across lenders.[20]

Figure 3 plots lender-level flag rates separately for each indicator. Each plot shows how two of the individual flags relate to one another at the lender level. For example, the plot on the top left shows the relation between the business registry and multiple loan flags, and the plot on the bottom right shows the high implied compensation and EIDL > PPP jobs flags. All of the flags are plotted as a percentage of loans that could potentially be flagged by the measure (corporate and LLC loans for the business registry flag, all loans for the multiple loan flag, loans in industry-CBSAs with compensation/receipts below \$33,333.33 for the high implied compensation flag, and loans with matching EIDL Advances for the EIDL > PPP jobs flag). Three related patterns are apparent in the plots. First, FinTech lenders are consistently near the top end of each individual flag measure. Second, a similar set of FinTech lenders clusters near the top for each of the individual measures. Third, the flag rates

[20] As shown in Panel A of Figure IA.4 in the Internet Appendix, regressions with these controls result in large and significant lender fixed effects (with Bonferroni corrections for multiple testing and for standard errors double clustered by lender and ZIP Code) with a dispersion of 30.5 percentage points (ppt) across the top 75 lenders, which is only slightly below the unconditional dispersion of 32.9 ppt shown in Panel A of Figure 2. We also calculate lender fixed effects in more saturated regressions with all of the control variables and fixed effects used in column (4) of Table II. Although fixed effects in these regressions remain large and significant, the additional control variables decrease their dispersion to 14.6 ppt across lenders. To the extent that fraud clusters heavily in certain ZIP Codes and industry-CBSA pairs as displayed later in the paper, this fully saturated regression with industry × CBSA and ZIP Code fixed effects may understate differences across lenders.

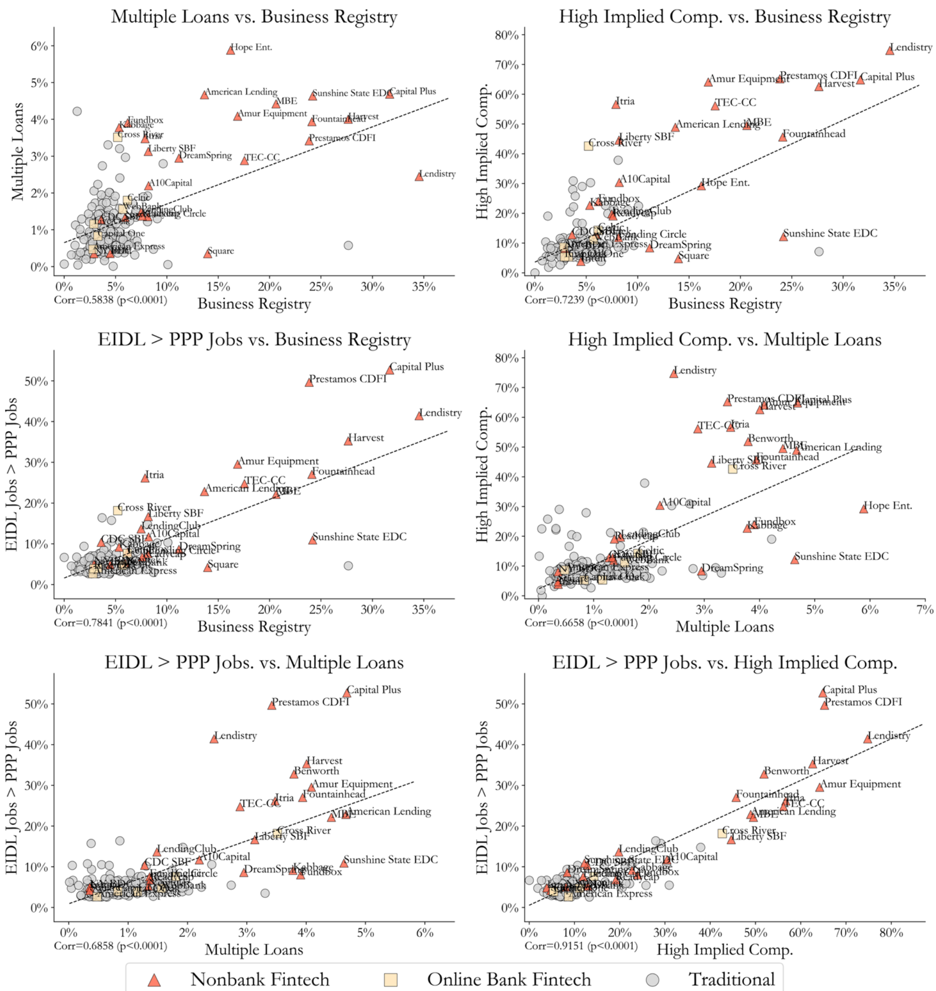

Figure 3. Relation between primary flags. This figure shows the relation between the primary flags (business registry, multiple loans, high implied compensation, or EIDL > PPP jobs flags) at the lender level. Each subpanel is a scatterplot with the percentage of loans flagged by one of the flags on each axis. Loans are filtered to the sets for which we can determine each flag for each axis separately (i.e., we do not require that both flags can 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. (Color figure can be viewed at wileyonlinelibrary.com)

are significantly correlated with one another across lenders. In particular, FinTech lenders Capital Plus, Lendistry, Prestamous, and Harvest are consistently at the top of each graph, and several other FinTech lenders are not

Table II

Prevalence of Flags by Lender Type

This table presents the percentage of loans flagged by the four main flags, at least one of the 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; 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 controlling for number of jobs reported, loan size, and whether we can match the loan to an EIDL Advance; and column (5) shows the differences between matched pairs of FinTech and traditional loans. The N values show 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 and adjusted differences are reported in Panels A and B, respectively, of Table IA.I in the Internet Appendix. t-statistics are in parentheses. Significance levels are indicated by $^{***}p < 0.010$.

	(1) FinTech	(2) Traditional	(3) Unadjusted Difference	(4) Adjusted Difference	(5) Matched Difference
Business Registry	0.103	0.0429	0.0605***	0.0372***	0.0296***
	$N = 697{,}283$	$N = 4{,}838{,}905$	(3.12)	(3.76)	(3.19)
Multiple Loans	0.0330	0.00961	0.0234***	0.0111***	0.0199***
	$N = 3{,}723{,}133$	$N = 7{,}737{,}668$	(9.96)	(6.33)	(5.29)
High Implied Comp.	0.474	0.0857	0.388***	0.100***	0.134***
	$N = 1{,}285{,}292$	$N = 2{,}028{,}067$	(8.14)	(7.97)	(5.35)
EIDL > PPP Jobs	0.213	0.0473	0.166***	0.0672***	0.0956***
	$N = 677{,}896$	$N = 2{,}084{,}437$	(4.57)	(4.22)	(4.52)
At Least One Primary Flag	0.230	0.0713	0.159***	0.0602***	0.0754***
	$N = 3{,}723{,}133$	$N = 7{,}737{,}668$	(8.62)	(8.25)	(7.95)
At Least Two Primary Flags	0.0239	0.00329	0.0206***	0.00744***	0.0137***
	$N = 3{,}723{,}133$	$N = 7{,}737{,}668$	(8.00)	(5.76)	(7.92)

far behind. In contrast, no traditional lender is in the top 10 for more than one flag.[21]

Table II summarizes the percentage of loans with each of the four flags separately for FinTech and traditional lenders. The table also summarizes the percentage of all loans with at least one flag and with two or more flags. For each individual measure, the denominator is the number of loans that could have the flag. 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 loans. Differences between FinTech and traditional flag percentages are reported in column (3). For all four individual

[21] Graphical rankings of lenders for each separate measure similar to Panel A of Figure 2 are shown in Figure IA.5 in the Internet Appendix. Additional details and supplemental analysis regarding how the individual flags vary across lenders are further discussed in the Internet Appendix.

measures, FinTech lenders have flag rates that are 2.40 to 5.53 times as high as traditional lenders, with particularly large differences for the high implied compensation and EIDL > PPP jobs flags. Overall, 23.0% of FinTech loans have at least one of the flags, compared to 7.1% 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 lenders, column (4) reports adjusted differences based on regressions that control for loan size and number of jobs and include ZIP Code, business type, and industry × CBSA fixed effects.[22] After accounting for these effects, the adjusted difference between FinTech and traditional flag rates is 3.7 ppt for the business registry flag (which is 85% of the rate for traditional loans), 1.1 ppt (116%) for the multiple loan flag, 10.0 ppt (117%) for the high implied compensation flag, and 6.7 ppt (142%) 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. To further control for potentially nonlinear loan characteristic effects, we match FinTech loans with traditional loans based on loan size, industry, county, and business type in column (5) with similar results.[23] Despite the extensive matching, control variables, and fixed effects, it remains possible that other omitted variables or unobserved loan characteristics could explain some of the differences between FinTech and traditional loans, but these effects would have to be large to explain the results. To control for any unobserved differences across households, Table IA.III in the Internet Appendix considers a restricted sample of residential addresses with multiple loans within the same draw. Consistent with results in Table II, flag rates are elevated for FinTech loans across all of the potential misreporting measures, with highly statistically significant differences in all specifications. Tests in the next section, including grouping around discontinuities and clustering, also help to address omitted variable concerns.

F. 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 indicators to occur randomly across loans and lenders. Therefore, multiple flags for the same loan create a heightened misreporting inference, and high lender flag rates

[22] The differences and standard errors reported in columns (3) and (4) are based on regressions with and without control variables and fixed effects. Results for these regressions are reported in more detail in Table IA.I in the Internet Appendix. Table IA.II in the Internet Appendix shows how these results change with the inclusion of different fixed effects, different standard error clustering, and different definitions of FinTech lenders.

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

across multiple indicators may be due to policies and practices that facilitate more misreporting.

In addition to their relations to one another, the granularity of the flags establishes patterns that would be difficult to explain based on errors or honest mistakes. This is particularly true for differences for the EIDL > PPP jobs flag. Panel A of Figure 4 shows the frequency of particular differences between EIDL Advance and PPP jobs. The asymmetry of the plot is consistent with an incentive to inflate EIDL Advance to increase EIDL Advance payments, which were $1,000 per employee, up to $10,000. Even more strikingly, the most common discrepancy between the programs is a difference of nine jobs, which implies that the borrower claimed 10 or more jobs and took out the maximum EIDL Advance of $10,000 despite only reporting one PPP job. In particular, EIDL jobs exceed PPP jobs by nine 14.3% of the time for FinTech loans compared to 0.5% for traditional loans.

We next examine the distribution of normalized compensation in more detail and assess how it relates to our other three suspicious loan flags. To capture abnormally high compensation, we examine the distribution of implied average compensation for the borrower normalized by mean compensation or receipts across all firms in the borrower's industry and CBSA based on U.S. Census Bureau CBP data. The distribution is shown separately for FinTech and traditional loans in the top left plot in Panel B of Figure 4. FinTech borrowers have a much fatter right tail of the abnormal compensation distribution within CBSA-industry pairs; 16.4% of FinTech borrowers have normalized compensation above 3, compared to 2.5% of traditional borrowers.[24]

The remaining three plots in Panel B of Figure 4 show the percentage of loans with the business registry, multiple loans, and EIDL > PPP loan flags, respectively, separately for FinTech and traditional lenders.[25] All flags increase significantly as normalized compensation increases for loans made by FinTech lenders. While 7.9% of corporate and LLC FinTech loans with normalized compensation below one have the business registry flag, 27.0% of loans with normalized compensation above three have the flag. Similarly, the multiple loan flag increases from 2.3% for FinTech loans with normalized compensation below one to 4.9% when normalized compensation is above three. An even larger increase from 8.1% to 63.6% is observed for the EIDL > PPP flag. Importantly, while FinTech loans exhibit a stronger relation between normalized compensation and the other loan flags, this pattern is not limited

[24] Most of this is due to round 3 FinTech loans, as is evident in Figure IA.3, Panel A, in the Internet Appendix. FinTech implied compensation is much higher in round 3 and appears to be almost completely disconnected from average industry-CBSA compensation and receipts. Panel B of Figure IA.3 in the Internet Appendix shows that this differential pattern for FinTech and traditional lenders in round 3 is also evident even when the sample is restricted to Schedule C borrowers, both before and after Schedule C borrowers were permitted to use gross income, starting on March 3, 2021.

[25] The plots, as well as subsequent analysis. are calculated based on loans for which data to calculate each flag 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).

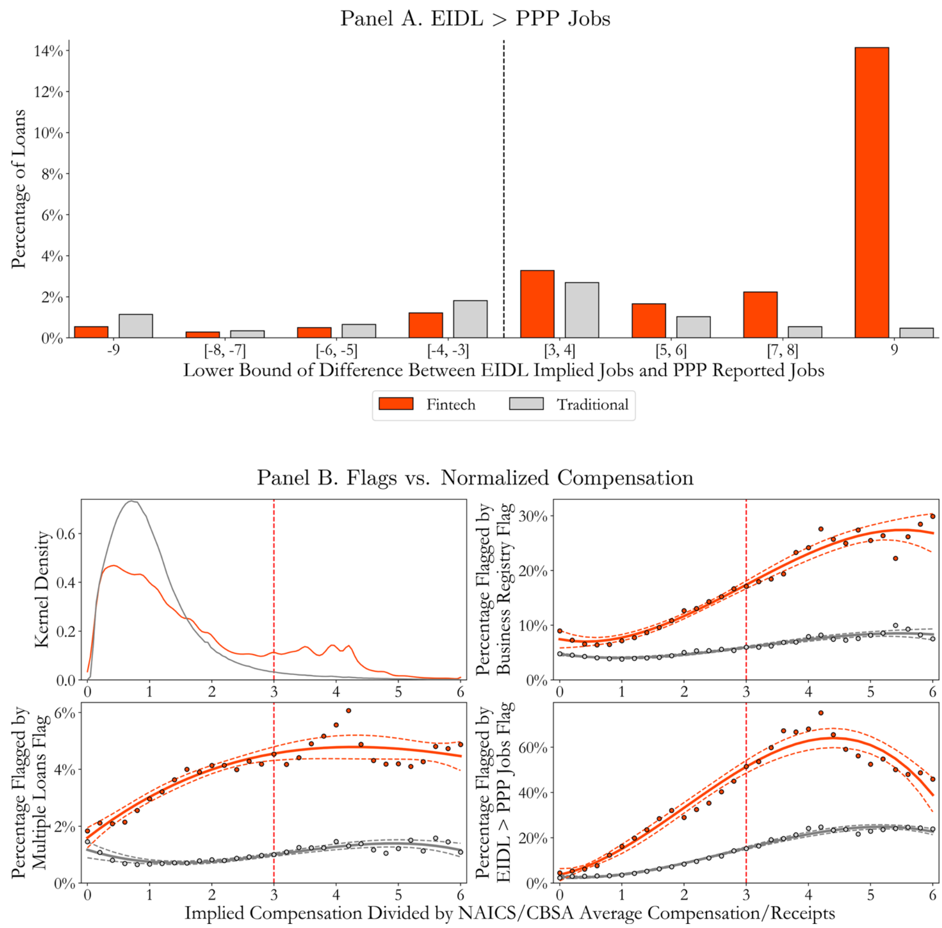

Figure 4. Additional features of primary flags. This figure shows additional features of the primary flags. Panel A shows the difference between the number of employees implied by a business's EIDL Advance amount ("EIDL Implied Jobs") and the number of jobs reported by the business on its PPP application ("PPP Reported Jobs") by lender type. Panel B shows the distribution of normalized compensation and the relation between it and the other primary flags. We define normalized compensation as the implied compensation of the loan divided by the average compensation/receipts in the loan's industry-CBSA. In the top left subpanel of Panel B, the kernel density of loans is shown, and in the other three subpanels, the percentage of loans flagged by the given flag in each bin is shown, 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 95% confidence intervals. In both panels, only loans for which the given flag can be determined are considered. (Color figure can be viewed at wileyonlinelibrary.com)

to FinTechs. Traditional bank loans also have more flags when normalized compensation is higher, suggesting that at least some traditional bank loans also have misreporting, 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.

To assess loan-level relations between the flags, we calculate odds ratios between each pair of flags. For each odds ratio, z-statistics calculated based on standard errors double-clustered by ZIP Code and lender are in parentheses. The odds ratios for the full sample are all above 1.48 and highly significant (as shown in Panel A of Table IA.IV in the Internet Appendix). In particular, the odds ratio between the high implied compensation and EIDL $>$ PPP jobs flags is 14.43 and has a z-statistic of 20.46, indicating that loans flagged by the high implied compensation flag are over 14 times as likely to be flagged by the EIDL $>$ PPP jobs flag as well and vice versa. To examine whether these relations can be explained by observed loan characteristics, we regress 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, with and without lender fixed effects (as shown in Table IA.V in the Internet Appendix). Except for the relation between the business registry flag and EIDL $>$ PPP jobs flags, the coefficients between the flags are all positive, economically large relative to the mean flag rates, and highly statistically significant.

As an additional examination of the primary flags, we also compare them to direct evidence of loan size inflation for nonprofits based on comparing loan sizes to nonprofit compensation disclosed on IRS Form 990. Loan size inflation by nonprofits is increasing and highly related to the primary flags (see Figure IA.7 and the Internet Appendix for details on this analysis).

III. Secondary Suspicious Loan Measures

In addition to misreporting, the primary indicators introduced in the previous section also have potentially innocent explanations. In this section, we develop and analyze four additional measures as added validation. The additional measures involve discontinuities, rounded compensation levels, abnormal numbers of loans in industry-county pairs, and clustering of loan features within lender-county pairs. We also examine how these measures relate to the primary measures and the differences between FinTech and traditional lenders.

A. 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, with the ability to also include nonwage benefits and payroll expenses in excess of $100,000.[26] A borrower might want to maximize their loan amount by submitting payroll

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

expenses at or close to the $100,000 per employee limit without the additional expenses that are eligible with proper payroll details.

Panel A of 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. FinTech loans stand out as having more loans with implied compensation right at and slightly under $100,000, and traditional banks have more loans with implied compensation between $10,000 and $75,000. The percentage of loans with one of the four primary flags 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 increases from $40,000 to $100,000, the prevalence of the primary flags for FinTech loans increases from 6.5% to 43.5%. For traditional lenders, the increase is also present but much smaller. For FinTech loans with implied compensation above $100,000, there is a sharp drop-off in the flag rate, which indicates that businesses that followed the detailed SBA guidelines for including nonwage payroll expenses for employees with wages above $100,000 are less likely to have one of the primary misreporting flags. Similar patterns exist for each of the flags individually (see Panel A of Figure IA.8 in the Internet Appendix).[27]

Additionally, the SBA used a loan amount cutoff of $150,000 for more streamlined processing (fewer calculations and less documentation) of loan forgiveness applications.[28] Consistent with applicants or lenders being aware of the threshold and trying to avoid scrutiny, the percentage of flagged loans is high for loans up to $150,000 and decreases after the threshold. This is true for both traditional and FinTech lenders, but much more pronounced for FinTech lenders (see Figure IA.9 in the Internet Appendix).

B. 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.[29] It is unlikely that actual monthly payroll would be a round

[27] In Table IA.VI in the Internet Appendix, we formally test for discontinuities at $100,000 of compensation using a fully saturated regression and find large and highly economically significant discontinuities for FinTech loans for three of the four measures and for the combined measure. The discontinuities are much smaller for traditional loans.

[28] The shorter form and reduced requirements for loans of $150,000 or below to receive forgiveness are outlined at https://www.sba.gov/sites/default/files/2021-07/PPP%20–%20Forgiveness%20Application%20and%20Instructions%20–%203508S%20%287.30.2021%29-508.pdf.

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

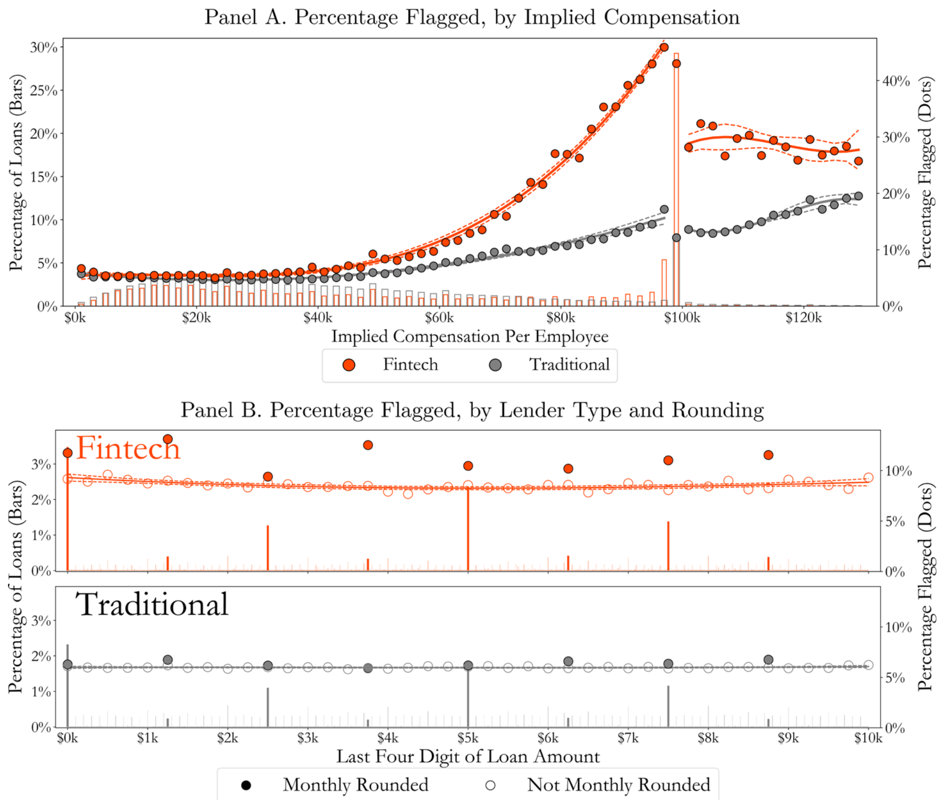

Figure 5. Discontinuities at $100,000 and rounding. This figure shows the prevalence of the primary flags across implied compensation and loan amounts. Panel A shows the relation between implied compensation per employee and being flagged by at least one of the four main flags. Loans are binned into $2,000-wide bins (i.e., ($0k, $2k], … , ($98k, $100k], … ,($128, $130k]). The left axis shows the percentage of loans in each bin (bars) and the right axis shows the percentage of loans in each bin that are flagged (dots). The solid lines are third-degree polynomial fits (weighted based on the number of loans in each bin), which are separately fitted for loans below $98,000 and loans above $100,000, and the dashed lines are 95% confidence intervals. Panel B shows the prevalence of loans being flagged by at least one of the four main flags by whether the total monthly implied compensation of a loan is rounded to an interval of $500 (i.e., the loan amount is within ± 50 cents of an interval of $1,250) and lender type. Specifically, the last four digits of the loan amount are considered (i.e., $123,456.78 → $3,456.78). The top subpanel shows FinTech loans and the bottom shows traditional loans. Further, 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-bin for monthly rounded (solid dots) and $250-wide bin for nonrounded (hollow dots). 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. The solid lines are third-degree polynomial fits for the percentage flagged in the nonrounded bins and the dashed lines are 95% confidence intervals. (Color figure can be viewed at wileyonlinelibrary.com)

number, especially after including unemployment insurance, employer insurance, and retirement contributions. Thus, rounded loan amounts may suggest that the loans lack actual documentation and may be more likely to involve misreporting, as shown in other contexts (Eid, Maltby, and Talavera (2017), Nigrini (2018)). 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.

In Panel B of Figure 5, we first examine the distribution of the last four digits of loan amounts, excluding EIDL refinancing, for FinTech and traditional loans.[30] Both FinTech and traditional loans exhibit rounding at \$1,250 increments, particularly at increments of \$2,500 (corresponding to \$500 and \$1,000 increments of implied monthly payroll). FinTech lenders have moderately more rounding, with 9.7% of loans rounded to \$1,250 increments compared to 7.4% for traditional lenders.

The right axis of Panel B of Figure 5 examines the prevalence of the primary misreporting flags. The percentage of loans with a primary flag is plotted as a solid dot at the \$1,250 loan increments and as a hollow dot at other loan amounts (shown in \$250-wide bins). If rounded loans are more likely to be misreported, one would expect an elevated flag rate at round number thresholds. For FinTech loans, this is exactly what we observe. At rounded increments, the flag rates are consistently higher, by 2.14 ppt on average. This difference is highly significant, which can be seen by comparison to the dotted lines plotting a 95% confidence interval estimated with a third-degree polynomial estimated based on the nonrounded loans. For traditional lenders, there is economically small and statistically weak evidence of elevated flags in some of the rounded bins. Results for each flag individually show that rounded loans by FinTech lenders have elevated levels of all four primary misreporting flags (see Panel B of Figure IA.8 in the Internet Appendix). 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.

C. Loan Overrepresentation

If there is an organized effort to obtain funds for nonexistent 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 IA.2 in the Internet Appendix shows an example that appears to fit this

[30] Loan amounts within 50 cents of a \$1,250 increment (which corresponds to \$500 of implied monthly payroll) 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 total implied compensation within ± \$1,000 of an interval of \$100,000 are excluded to make sure these results are distinct from the maximum compensation result shown in Panel A of Figure 5.

pattern: a group of 4,299 $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 (discussed further in the Internet Appendix). These are followed by examples from 938 $20,000 first-draw loans by Cross River to businesses engaged in "All Other Miscellaneous Crop Farming" primarily located in urban areas of Chicago, most of which have exactly one or eight employees. In addition to having the same loan amount and similar industries, these $20,000 loans cluster in the last two weeks of round 2 and in round 3.

Panel A of Figure 6 plots histograms of FinTech (red bars) and traditional (gray bars) lender loans by the ratio of first-draw PPP loans to Census CBP establishments counts in the loan's industry-county pair. For FinTech lenders, 39.3% of loans exceed industry-county establishment counts, and this occurs 14.0% of the time for traditional lenders. For loans in the right tail, the differences are even more extreme, with 32.6% of loans exceeding industry-county establishment counts by a factor of more than two for FinTech lenders and 8.2% for traditional lenders. Even further in the right tail, 7.4% of FinTech loans exceed industry-county establishment counts by a factor of more than 10 as compared to 0.8% of traditional loans.[31] This analysis excludes loans to self-employed individuals and individual contractors because these business types are not included in CBP establishment counts. Abnormal levels of loans relative to CBP establishment counts are largely driven by sole proprietorships, highlighting potential issues with lending to nonregistered entities.[32] Some excess PPP loans may be due to 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 6 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 substantially as the loan-to-establishment ratio increases, particularly for FinTech lenders. While 13.9% of FinTech and 6.7% of traditional loans in industry-county pairs with a loan-to-establishment ratio at or below one are flagged, the flag rate is 41.9% for FinTech and 10.7% for traditional loans when the loan-to-establishment ratio is above two.

Panel B of Figure 6 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 pair than listed in the

[31] 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 $r > 1$. The interval limits are changed to 2 (10) instead of 1 for the 32.6% (7.4%) and 8.2% (0.8%) figures.

[32] The majority of loans in overrepresented industry-county pairs are generated by elevated levels of sole proprietorships, particularly as one reaches increasing levels of abnormal establishments (as shown in Figure IA.10 in the Internet Appendix).

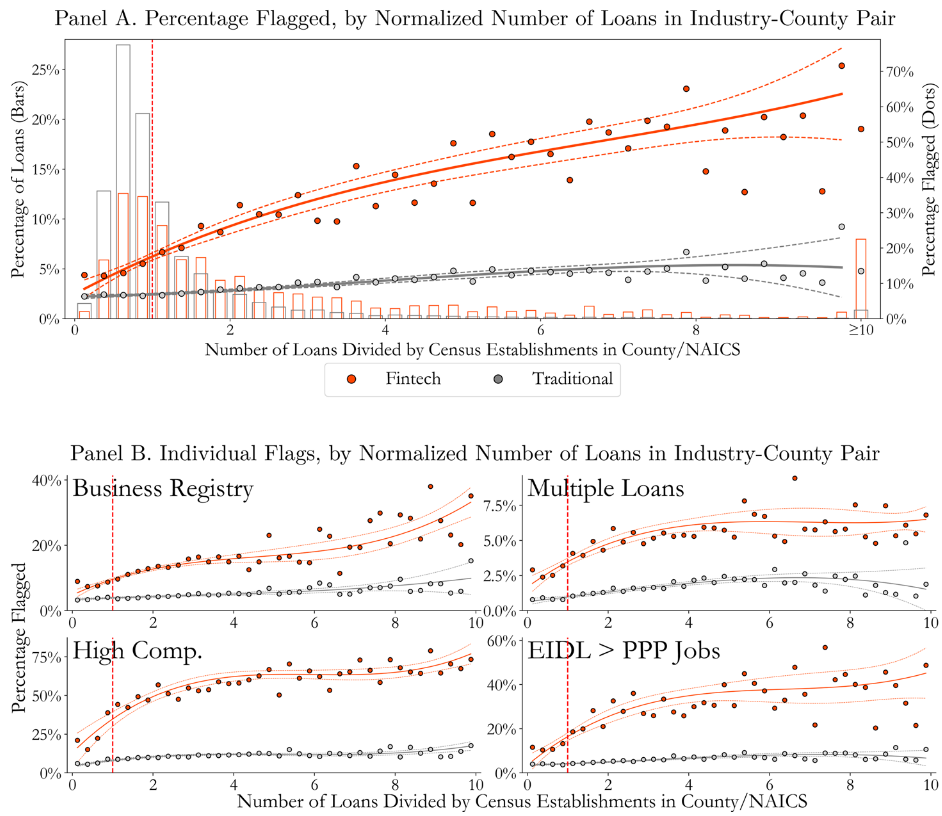

Figure 6. Overrepresentation of industries in counties. This figure shows overrepresentation of loans within industry-county pairs. We define the normalized number of loans as the number of first-draw loans divided by the number of establishments (per the 2019 U.S. Census County Business Patterns data set) in an industry (represented by NAICS code) and county pair. Panel A shows the relation between the normalized number of loans and our four main flags combined together as at least one flag and Panel B shows the relation 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. (Color figure can be viewed at wileyonlinelibrary.com)

CBP, the number of suspicious loans flagged increases substantially 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 a high loan-to-establishment ratio being particularly suspicious.

D. Loan Clustering

In addition to exhibiting geographic and industry clustering, many of the 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.[33] There will clearly be some loan similarities by chance and due to lender specialization, but it is instructive to quantify how frequently 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). The concentration ratios are based on the sum of squared shares of loans with a characteristic.[34] Then, we rescale each of the concentration ratios to have a median of 1,000 and an interquartile range of 300 so that the three concentration ratios have similar impacts on the overall concentration measure. Finally, we average the three concentration ratios for each lender-county pair.

The bars in Panel A of Figure 7 plot the distribution of scaled concentration ratios separately for FinTech and traditional loans. High concentration ratios are much more common for FinTech loans: 88.6% of FinTech loans in lender-county pairs with a scaled concentration ratio above 1,000, compared to 20.3% of loans for traditional banks. The dots in Panel A of Figure 7 plot how the incidence of loans being flagged by at least one of the four primary suspicious loan flags changes with the concentration ratio. When the scaled concentration ratio is below 1,000, 10.2% of FinTech loans and 6.6% of traditional loans are flagged by at least one flag. When the scaled concentration ratio is above 1,300, this grows to 35.7% for FinTech loans and is similar (6.7%) for traditional loans. Panel B of Figure 7 shows that similar patterns hold for each of the four suspicious loan flags individually. The overall pattern is similar to the previous secondary measures: FinTech lenders have much higher loan concentration ratios, and high concentration ratios are highly related to the suspicious loan flags, particularly for FinTech loans. This pattern is 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.

IV. External Validation

The primary and secondary measures developed in the previous two sections allow us to systematically flag individual loans as suspicious. In this

[33] It is not clear why fictitious loan applications frequently repeat the same information, but the pattern is clear in the examples, and there is no other obvious explanation for this clustering.

[34] For example, let $i = 1, 2, \ldots, n$ 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.

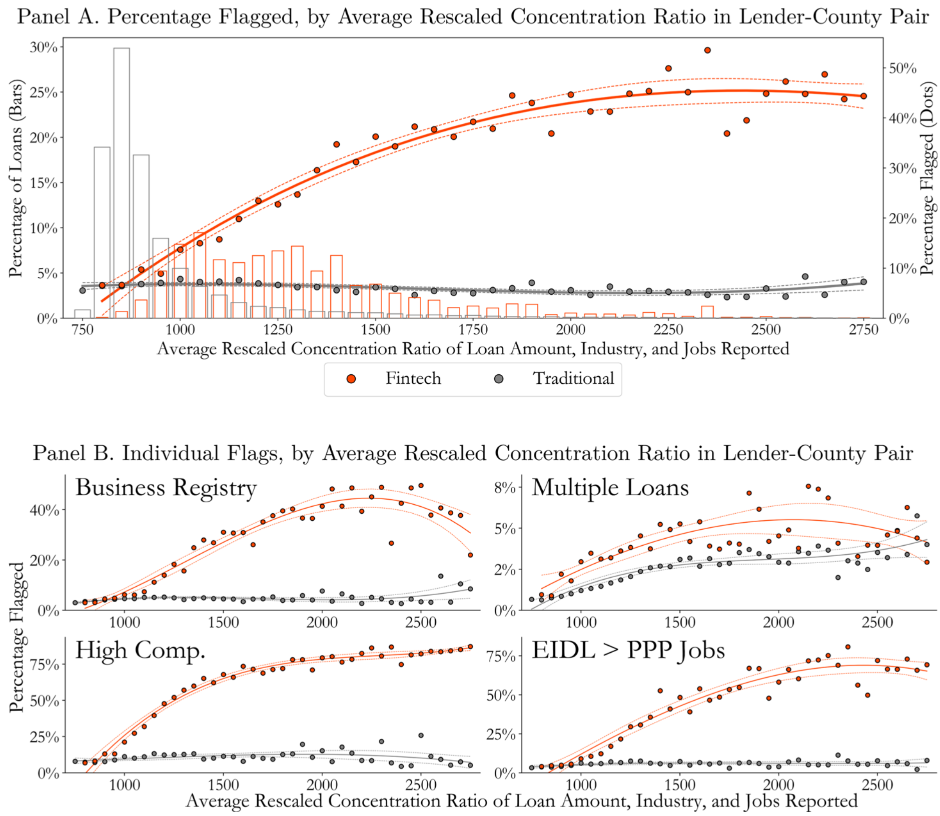

Figure 7. Clustering within lenders and counties. This figure shows clustering of loans within lender-county pairs. We calculate the concentration ratios of industries, loan amount (rounded to \$100), and jobs reported (excluding 1) for first-draw loans in each lender-county pair, rescale each concentration 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 $i = 1, 2, \ldots, n$ represent the n industries in a given lender-county pair, then $Concentration_{industry} = \sum_{i=1}^{n} s_i^2$, 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, $Rescaled\,Concentration_{industry} = \frac{Concentration_{industry} - \text{Median}[Concentration_{industry}]}{75^{\text{th}}\text{Percentile}[Concentration_{industry}] - 25^{\text{th}}\text{Percentile}[Concentration_{industry}]} \times 300 + 1,000$. Panel A shows the relation between the average rescaled concentration ratio and our four main flags combined together as at least one flag and Panel B shows the relation 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% of traditional loans are outside the range of the average rescaled concentration ratio 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 which 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. (Color figure can be viewed at wileyonlinelibrary.com)

section, we validate these measures based on comparisons with detailed subsets of data for three external measures of suspicious lending: criminal records data, crowd-sourced data on PPP fraud, and official SARs filed by financial institutions.

A. Criminal Records

Recidivism statistics show that individuals with past criminal histories are highly likely to commit crimes in the future (Alper, Durose, and Markman (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 years. 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 in the past.[35] We do not evaluate the design and efficacy of this aspect of the program or lenders' compliance with its specific prohibitions. Instead, our analysis uses criminal records as a potential additional validation and risk factor. To assess the prevalence of criminal records among PPP borrowers, we collect 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.

The left subpanel of Panel A of Figure 8 plots the percentage of borrowers with felony charges on their criminal records between 2000 and 2020 within the sample of 150,000 individual borrowers for whom we collected background information.[36] Felony charges are present for 4.7% of FinTech borrowers compared to 1.4% of traditional borrowers. There is also a strong relation between criminal records and both the primary and secondary indicators. A loan that is flagged by at least one primary flag is 2.2 times as likely to be to a borrower with a felony charge for FinTech lenders and 1.4 times for traditional lenders. The EIDL misreporting indicator seems to capture the highest percentage of felony charges. We confirm that these relations are robust and statistically significant by regressing an indicator for having a felony charge on the other primary and secondary risk flags for loans originated by FinTech lenders.[37]

[35] 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.

[36] Ninety-five percent confidence intervals based on standard errors clustered by ZIP Code and lender are plotted on top of the bars. Panel A of Figure IA.11 in the Internet Appendix shows robustness to using convictions rather than charges; charges are used for the main analysis since convictions are more difficult to identify in the data. Panel B of Figure IA.11 in the Internet Appendix shows how felony rates vary across loans flagged by each flag individually, and Panel C of Figure IA.11 in the Internet Appendix replicates Panel B using felony charges from 2015 to 2020. We find significant results for FinTech based on nearly all of the flags, and while the percentage of borrowers with felonies is lower across the board in Panel C, the relative results remain.

[37] Results are reported in Table IA.VII in the Internet Appendix. 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, the coefficients are positive,

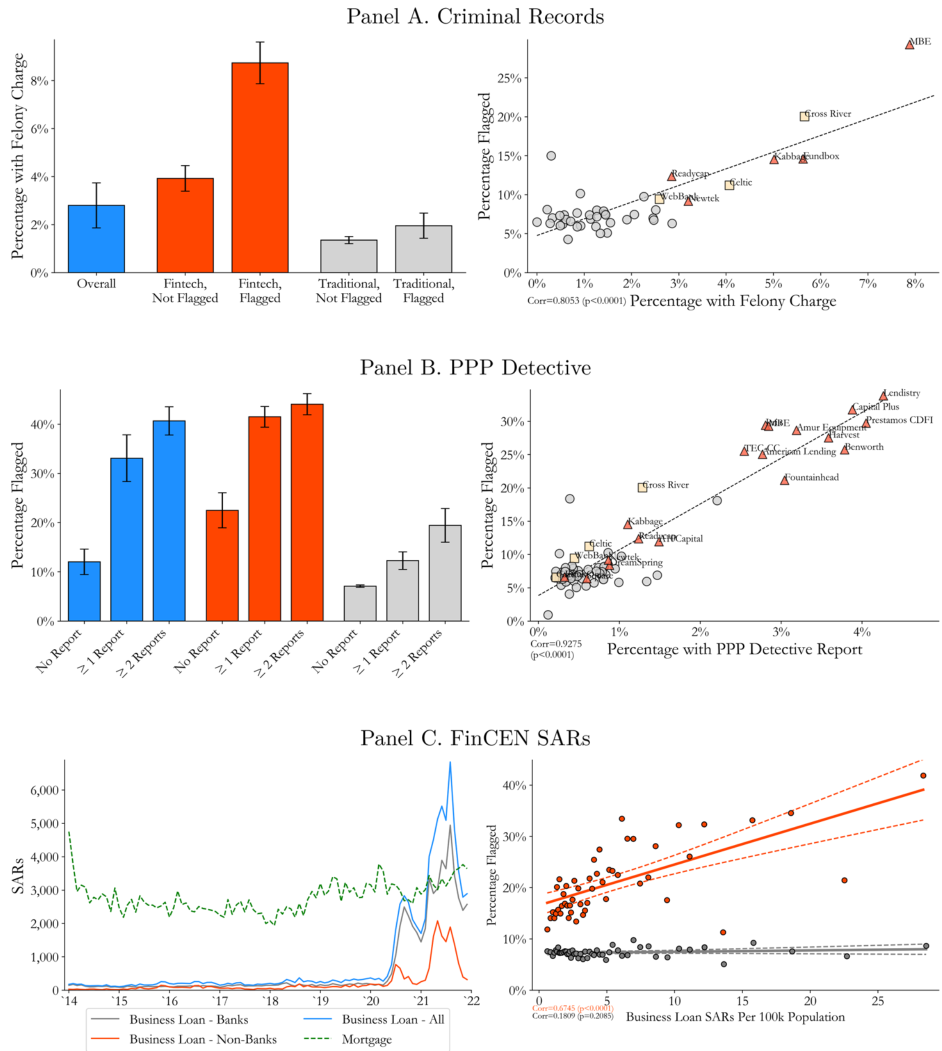

Figure 8. External validation. This figure shows relations between the external validation measures and whether the loan is flagged by at least one primary flag. Panel A shows the relation between the borrower having a felony charge from between 2000 and 2020 on their record and their loan being flagged. This is based on a sample of 150,000 round 1 and 2 loans to self-employed individuals, independent contractors, and sole-proprietors. Panel B shows the relation between the loan being reported on PPP Detective and the loan being flagged. The left panel of Panel C shows the number of SARs from banks and other financial institutions to FinCEN per month from 2014 to 2021, and the right subpanel shows the relation between the percentage flagged (separately for FinTech and traditional borrowers) and the average number of business loan SARs in 2020 and 2021 per 100,000 population (truncated at the 95th percentile) across counties. In the left subpanels of Panels A and B, the error bars denote 95% confidence intervals (standard errors double-clustered by ZIP Code and lender). In the right subpanels of Panels A and B, lenders with at least 0.2% of the sample and the top 75 lenders by number of loans, respectively, are shown. In all right subpanels, the lines are linear fits and correlations are shown in the bottom left. In the right subpanel of Panel C, the dashed lines are 95% confidence intervals. (Color figure can be viewed at wileyonlinelibrary.com)

The right subpanel of Panel A of Figure 8 examines how felony charges vary across lenders with a clear positive relation between the percentage of a lender's sampled borrowers with felony charges and the percentage of its overall loans with at least one of the primary suspicious loan flags. In particular, the four lenders with the highest felony charge percentages (MBE, Cross River, Fundbox, and Kabbage, all of which are FinTech) also have the highest primary flag rates.[38]

B. PPP Detective

We utilize data from the PPP Detective, a crowd-sourced platform that allows users to report loans as "potentially being fraudulent." In total, 147,662 loans have at least one PPP Detective report as of the end of February 2022, which represents 1.2% of PPP loans overall. Although it is unclear what information is used to report loans on PPP Detective and the number of loans reported on PPP Detective is relatively small compared to what our flags identify, the measure provides an external, crowd-sourced qualitative measure to compare our more systematic quantitative approach against.

Panel B of Figure 8 compares PPP Detective to our primary suspicious lending flags. The left plot first compares primary flag rates for loans with and without PPP Detective reports. Loans with no PPP Detective reports have a flag rate of 12.0%, compared to 33.1% for loans with at least one PPP Detective Report and 40.7% for loans with two or more PPP Detective reports. The plot also repeats the same comparison separately for FinTech and traditional loans. In both cases, flag rates are considerably higher for loans with PPP Detective reports, with particularly large differences for FinTech loans. This pattern indicates that our flags are strongly correlated with PPP Detective at the loan level, particularly for FinTech loans. The right plot in Panel A assesses correlations across lenders by plotting lender-level flag rates and PPP Detective report rates. The two measures have a highly significant correlation coefficient of 0.9275, and the same cluster of FinTech lenders who have high flag rates also have high PPP Detective report rates, again providing strong validation for our suspicious loan flags.[39] A potential concern with this validation is that PPP Detective users could flag loans based on measures that are similar to the flags in this paper, particularly if they read or saw media coverage of early versions of the paper. This concern is mitigated by the PPP Detective interface's

statistically significant, and economically large for FinTech loans with almost no relation between the misreporting indicators and criminal records for traditional loans.

[38] Panel D of Figure IA.11 in the Internet Appendix replicates this figure using felonies post-2005, post-2010, and post-2015. Although the percentage of borrowers with felony charges decreases as the time period is decreased, the relative results remain. Additionally, Panel E of Figure IA.11 in the Internet Appendix replicates this figure using bankruptcy filings post-2015 and finds similar results. The rate of felony charges also increases with implied compensation for FinTech loans but not for traditional loans, adding to the evidence of inflated compensation within FinTech loans (Panel F of Figure IA.11 in the Internet Appendix).

[39] Table IA.VIII in the Internet Appendix shows that these patterns hold in a fully saturated regression framework and for each primary flag.

focus on flagging individual loans and by the consistent results we find across flags, some of which would be difficult to replicate (as shown in Figure IA.VIII in the Internet Appendix). Nevertheless, it is possible that the PPP Detective estimates are not an entirely independent verification.

C. Suspicious Activity Reports

We next examine summaries of SARs to the Financial Crimes Enforcement Network. Panel C of Figure 8 plots SARs over time and across different geographical areas. The left side plots the number of SARs per month over time from 2014 to 2021. The dashed green line plots the number of SARs that are related to mortgage loans, which has been relatively stable over time with between 3,000 and 4,000 reports per month. By contrast, SARs associated with business loans were relatively rare until April 2020 and then jump to over 2,500 per month from August to October 2020 with another large jump to over 5,000 per month from May to August 2021. These jumps follow shortly after the initial launch of the PPP in April 2020 and its further expansion starting in January 2021, with small lags likely due to delays in reporting. Interestingly, most of these SARs are from banks as opposed to nonbanks, potentially suggesting that banks were more rigorous in identifying and reporting suspicious PPP loan applications.[40]

On the right side of Panel C, we examine how business loan SARs correlate geographically with our flag rates at the county level, which is the lowest level of aggregation for SARs reported by FinCEN. For FinTech loans, the binscatter shows a relation between the geography of SARs and the percentage of loans flagged, with flag rates of around 15% in counties with low business SAR rates compared to flag rates in excess of 30% in counties with the highest SAR rates. By contrast, there is little, if any, geographic correlation for traditional loans, suggesting that the SAR reports are likely regarding FinTech loans. This pattern is consistent with many of our other measures and provides another strong external validation for the flagged FinTech loans.

D. Relation between Primary and Secondary Flags and External Validation

We have already seen that the primary flags are strongly predictive of one another, and the evidence in Figures 5 to 8 shows strong relations between the primary and secondary flags and external validation. In Table III, we more formally assess these relations with a regression analysis that controls for loan size and number of jobs reported and includes ZIP Code, business type, industry × CBSA, and lender fixed effects. The dependent variable is an

[40] We thank Mark Egan for pointing out this pattern in the SARs data. The FinCEN SAR data do not distinguish between traditional and online banks, so some of the bank SARs could be from online bank FinTechs. A conversation with a senior employee in the Financial Intelligence Unit of a major traditional bank indicated that the unit filed many SAR reports with the FinCEN regarding customers receiving and depositing apparently fraudulent PPP loans initiated through other lenders.

Table III

Secondary Flags and External Validation

In this table, we examine the relation 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 six secondary/external flags as independent variables. Each specification also includes an interaction between the secondary/external flag and an indicator for whether the loan was originated by a FinTech lender. *$100k Implied Comp. / Receipts* is a dummy variable equal to 1 if the implied compensation/receipts per job is within ± $1,000 of $100,000. *Monthly Rounding* is a dummy variable equal to 1 if the loan amount is within ± 50 cents of an interval of $1,250. *Overrepresentation* is a dummy variable equal to 1 if the number of first-draw loans to businesses not listed as self-employed and independent contractors in a loan's industry-county pair exceeds the number of establishments in the industry-county pair according to the U.S. Census CBP data. *High Concentration* is a dummy variable equal to 1 if the average rescaled concentration ratio in the loan's lender-county pair is above the 75th percentile. *Felony Post-2000* is a dummy variable equal to 1 if the borrower has a felony charge on their criminal record from between 2000 and 2020. *PPP Detective* is a dummy variable equal to 1 if the loan has at least one report on PPP Detective. 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 the bottom of each column. Robust standard errors are double clustered by ZIP Code and lender. t-statistics are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.010$.

Dep. Variable: *1(At Least One Primary Flag)*						
	(1)	(2)	(3)	(4)	(5)	(6)
1($100k Implied Comp.)	0.0192**					
	(2.45)					
1(Monthly Rounding)		0.00274***				
		(4.27)				
1(Overrepresentation)			−0.00609**			
			(−1.98)			
1(High Concentration)				0.0116***		
				(3.68)		
1(Felony Post-2000)					0.0165*	
					(1.82)	
1(PPP Detective)						0.0316***
						(7.89)
× *1(FinTech)*	0.123***	0.0103**	0.0592***	0.0189***	0.0507***	0.0557***
	(16.21)	(2.08)	(9.32)	(3.21)	(4.15)	(6.91)
ln(Jobs Reported)	Yes	Yes	Yes	Yes	Yes	Yes
ln(Loan Amount)	Yes	Yes	Yes	Yes	Yes	Yes
ZIP Code FE	Yes	Yes	Yes	Yes	No	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,792,833	5,152,691	6,060,817	7,382,631	123,651	10,794,163
Num. Lenders	4,769	4,687	4,719	4,146	2,557	4,769
R^2	0.310	0.102	0.332	0.333	0.383	0.294
Mean of Dep. Var.	0.128	0.0663	0.137	0.136	0.105	0.128

indicator variable for the loan having at least one of the primary flags. The secondary flags are all interacted with an indicator variable for FinTech loans, so the direct coefficients represent effects for traditional loans. Five of these six effects for traditional loans are positive and significant, with magnitudes ranging from 4.1% to 24.6% of the mean misreporting rate. Further, all of the interactions between the secondary flags and the indicator for FinTech loans are large and positive, and all are significant. As a result, all of the secondary flags strongly relate to the primary flags for FinTech loans, with relations that are much stronger than for traditional loans. For compensation near $100,000 and rounded compensation, the effects for FinTech loans are 7.41 and 4.76 times as high as those for traditional loans, respectively. For criminal records, PPP Detective, and high loan concentration, the effects for FinTech loans are 4.07, 2.76, and 2.63 times as large as the traditional loan effects, respectively. Finally, for industry overrepresentation, there is a strong effect for FinTechs despite essentially no relation for traditional loans. We also examine relations between the primary and secondary flags at the lender level (see Figure IA.13 in the Internet Appendix) and find that, except for monthly rounding, lenders with high levels of each secondary flag tend to be the same lenders who have high levels of the primary flags.

V. 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. There are two competing issues: (i) despite all the validation, the flag indicators likely contain some false positives, but (ii) the indicators only apply to subsets of loans and are incomplete. We seek to obtain a sense of both of these issues while also caveating that quantifying the extent of fraud often involves large estimate ranges.[41] Panel A of Figure 9 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, 1,410,193 loans representing 12.3% of the PPP and totaling $64.2 billion are suspicious.[42] This valuation of suspicious loans includes the full value of flagged loans, including borrowers who may have been eligible for smaller loans.[43]

[41] For example, despite a large and rigorous academic literature and many government investigations and settlements, there is still no consensus on the exact quantification of mortgage and other fraud leading up to the financial crisis (Griffin (2021)).

[42] Unincorporated sole proprietorships, self-employed individuals, and independent contractors account for 838,830 of these flagged loans, representing $16.7 billion. In addition, the EIDL > PPP flag also provides an indication of misreporting in the EIDL and EIDL Advance program. In particular, 199,019 EIDL Advances (10.1% of those matched to a PPP loan), totaling $1.71 billion, have potential misreporting. Importantly, this does not include other types of misreporting in the EIDL Advance program.

[43] For loans that are flagged by the high implied compensation flag without another primary, secondary, or external flag, Figure IA.14 in the Internet Appendix considers alternative compensa-

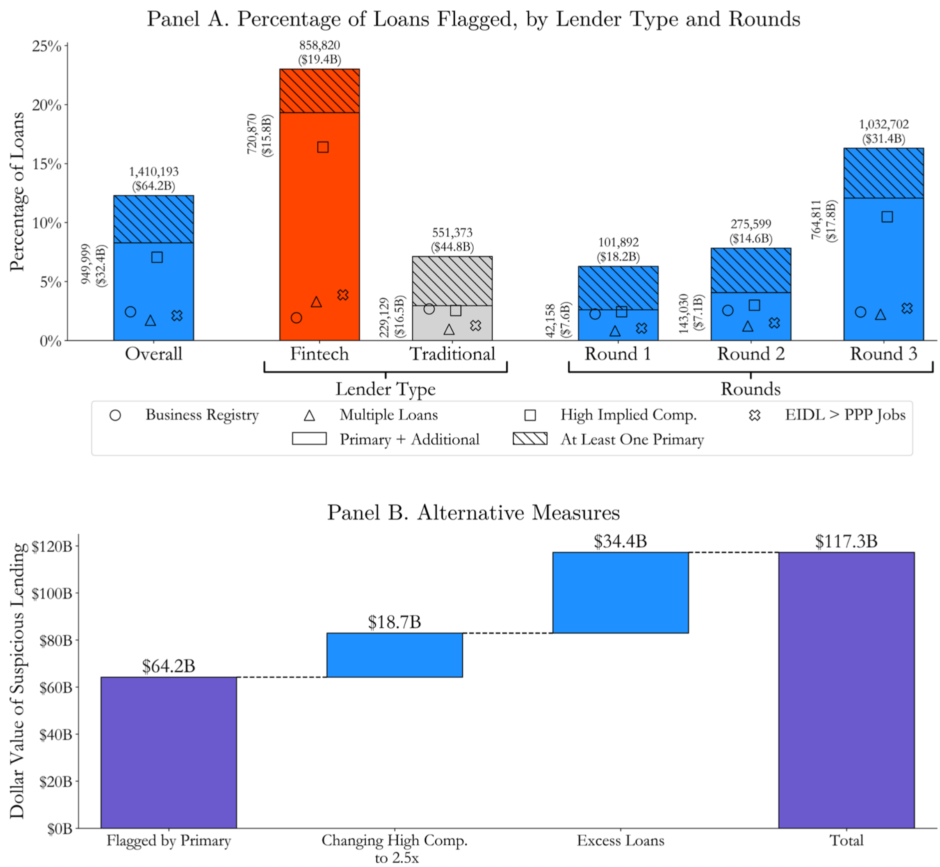

Figure 9. Overall misreporting flag rates. This figure shows the variation in the percentage of loans flagged. Panel A shows the percentage and dollar amounts of flagged loans overall, by lender type, and by round. The plain section of each bar represents the percentage of loans flagged by one primary flag and an additional flag (either another primary flag, secondary flag, or external validation) and the entire bar (plain and stripped sections combined) represents loans flagged by at least one primary flag. The set of numbers to the left of each bar represent the number of loans and dollar value of loans flagged by one primary flag and an additional flag and the set on top of each bar by at least one primary flag. The markers within each bar represent the percentage of loans flagged by each of the primary flags (unconditional of whether a flag can be determined for a given loan). Panel B shows the dollar value of suspicious lending using alternative measures. The leftmost bar is the dollar value flagged by at least one primary flag, the second bar is the incremental dollar value of suspicious lending when the high compensation flag is changed from 3 to 2.5 times the industry-CBSA average compensation/receipts, the third bar is the incremental dollar value of suspicious lending based on excess loans when the loans previously flagged are considered excess first and the dollar value of any additional excess is the average of the flagged loans in the industry-county, and the fourth bar is sum of the first three bars. (Color figure can be viewed at wileyonlinelibrary.com)

FinTech lenders are responsible for a disproportionate share of suspicious loans. FinTech lenders originated 858,820 suspicious loans totaling $19.4 billion. This means that FinTech lenders originated 60.9% of flagged loans, substantially outpacing their 32.5% loan market share.[44] As a share of loans originated by each lender type, 7.1% of traditional loans have at least one of the primary suspicious loan flags compared to 23.0% for Fintech loans.

As a more conservative estimate, we consider loans that have at least one primary flag plus an additional primary flag, secondary flag, or external validation, plotted as the solid part of the bars in Panel A of Figure 9. Although this measure almost certainly misses considerable misreporting, it has the benefit of dropping sincere mistakes or errors in the data that are isolated to a single measure. Under this more conservative measure, 949,999 loans totaling $32.4 billion are suspicious. Of these loans, 720,870 ($15.8 billion) are FinTech. This is an even larger FinTech share than for the primary measure because 83.9% of FinTech loans with a primary flag are further confirmed by an additional flag while the corresponding figure is only 41.6% for traditional loans. The higher confirmation rate for FinTech loans is consistent with flagged FinTech loans being far more likely to be fraudulent as opposed to simply reflecting honest explanations or errors in the data. Lender-level differences with the conservative measure (see Panel A of Figure IA.15 in the Internet Appendix) are also even more pronounced than with the baseline measure. In particular, similar lenders cluster at the top of the graph, and the five FinTech lenders with the highest percentages of loans flagged by at least one flag have flag rates of 29.4%, 29.8%, 28.1%, 25.0%, and 23.5%, respectively, under this more conservative measure. Prestamos is particularly striking because it is the third largest lender overall, with 444,789 loans. Cross River (largest FinTech lender and second largest overall lender, with 478,866 loans) and Harvest (third largest FinTech lender and fifth largest overall lender, with 408,450 loans) are also well above the average flag rate with primary flag rates of 20.0% and 27.6%, respectively.

The last three bars of Panel A plot suspicious lending rates by rounds of the program with the clear pattern that suspicious lending increased over time. In round 1, 6.3% are suspicious, compared to 7.8% in round 2 and 16.3% in round 3. Differences across rounds are even more pronounced with the conservative measure, which is 2.6% in round 1, 4.1% in round 2, and 12.1% in round 3.

Although some of the loans flagged as suspicious by the primary measures may be sincere mistakes or errors in the data, the four primary measures also surely miss many fraudulent loans. For example, because the high implied compensation flag only flags loans with implied compensation that is

tion thresholds and calculates dollar valuations using only loan value attributed to compensation above the flag thresholds. Using this approach decreases the overall suspicious lending estimate from $64.2 billion to $52.1 billion.

[44] Additionally, FinTech lenders originated 30.2% of the dollar volume of flagged loans, substantially outpacing their 10.9% dollar market share. 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 market share.

over three times the mean compensation or receipts in the loan's industry and CBSA and the PPP has a maximum eligible compensation of $100,000, the indicator is only applicable in industry-counties with mean annual compensation/receipts of $33,333 or less. These industries and counties represent 28.9% of PPP loans, suggesting that there is probably substantial exaggerated compensation in other loans that we cannot detect. Similarly, the business registry and EIDL > PPP jobs flags apply to 48.3% and 24.1% of loans, respectively. These limitations are particularly important for estimating FinTech suspicious lending because FinTech loans were less common for corporate/LLC borrowers and borrowers with matching EIDL Advances.[45] In Panel B of Figure 9, we evaluate potential undercounting of suspicious lending with sensitivity analysis to adding other suspicious loans that we might be missing. We first consider changing the threshold for high implied compensation from 3 times to 2.5 times the mean compensation in the loan's industry-CBSA pair. This enables us to potentially detect inflated compensation in another 7.3% of loans that are in industries and counties with mean compensation between $33,333 and $40,000. This change flags another 265,849 loans, totaling $18.7 billion, as suspicious.

Another indication of potential undercounting is the magnitude of excess loans beyond the number of business entities in an industry-county pair as per counts from the U.S. Census CBP data. Unlike the primary suspicious loan flags, this measure does not directly identify individual loans. Its magnitude is also inherently limited because loans can be suspicious even if they do not exceed Census establishment counts. The excess loan measure requires us to exclude loans to self-employed individuals and independent contractors because they are not included in Census establishment counts, and we also omit second-draw loans to prevent double counting. Due to these restrictions, the excess loan measure only applies to 54.6% of loans, representing 65.0% of total dollars lent. Nonetheless, excess lending is independent of our primary measures and can be used as a separate quantification of the total amount of suspicious loans even though it is also likely an underestimate. In the third bar of Panel B of Figure 9, we calculate how many additional loans would have to be suspicious in each industry-county pair to explain the magnitude of excess lending. For example, if an industry-county pair has 100 excess loans (e.g., 200 PPP first-draw business loans compared to 100 Census business entities), and our primary measures flag 75 loans as suspicious in that industry-county, we infer that at least 25 other loans are also suspicious. To estimate the size of these excess loans, we use the average loan amount of the flagged loans in the industry-county pair.[46] When subtracting flagged loans, we use the 2.5 times

[45] The business registry flag only applies to corporate/LLC loans and the EIDL > PPP jobs flag only applies to loans with matched EIDL Advances. The business registry flag is applicable to 18.6% of FinTech loans (compared to 62.5% of traditional loans), and the EIDL > PPP jobs flag is applicable to 18.2% of FinTech loans (compared to 26.9% of traditional loans). The high implied compensation flag is more applicable to FinTech loans than traditional loans, but the difference is moderate (34.4% of FinTech loans are applicable, compared to 26.2% of traditional loans).

[46] In industry-counties where there are no flagged loans, we use the average of all loans.

mean compensation version of the high compensation flag so that the excess loan measure is additive with the additional loans identified with the 2.5 times version of the high compensation flag. Based on this process, we estimate that excess loans represent another $34.4 billion of suspicious lending. Combined with the 2.5 times version of the high compensation flag, this results in a total suspicious lending estimate of $117.3 billion. It is worth noting that this sensitivity analysis is along only two limited dimensions that do not apply to all loans and thus likely still misses significant suspicious lending.

VI. Why Might Suspicious Lending Concentrate in FinTech?

FinTech lenders on average have much higher suspicious lending rates than traditional lenders, and Tables II, IA.1, and IA.IX show that their elevated suspicious lending is not explained by observable facets of loan composition. Did FinTech lending improve over time? What could be driving the elevated flag rates for FinTech lenders? And what are the consequences in terms of loan forgiveness and enforcement?

A. Did FinTech Lenders Improve Standards over Time?

In the early stages of the COVID pandemic, getting money out quickly was a primary focus, and it is possible that FinTech lenders making SBA loans for the first time may have lacked some of the capabilities necessary to review loan applications for signs of fraud. As the program progressed, the urgency of processing loans quickly likely diminished, and lenders and the SBA had more time to develop fraud-detection programs. Additionally, the Office of Inspector General for the SBA issued a report in October 2020 warning that fraud may be widespread in the PPP. All else equal, if lenders and the SBA improved standards over time, we should expect fraud to decrease. On the other hand, people exploiting the system may have also learned over time.

To assess these competing forces, 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 there is little downside for the lender. This may be particularly true for lenders with little reputation or other business to protect.

Under scenario A, 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, the amount of suspicious lending could grow over time as lenders develop a reputation for rapid and unquestioning approval.

Scenario A predicts:

(i) Loan misreporting will decrease over time as lenders become more aware and develop systems to screen out suspicious loans.
(ii) Suspicious first-draw borrowers will be less likely to receive a second-draw loan from the same lender than nonsuspicious borrowers.
(iii) Regions with high misreporting in rounds 1 and 2 will face extra scrutiny from lenders, which will decrease misreporting in round 3.

Scenario B predicts:

(i) Loan misreporting will grow over time as borrowers learn about the potential for fraud.
(ii) Borrowers with suspicious first-draw loan will be able to obtain second-draw loans from the same lender.
(iii) Regions with high misreporting in rounds 1 and 2 will have the same or more misreporting in round 3.

Did lenders improve their loan screening over time? Although we do not observe denied applications or specific lender practices, we can observe how loans that were approved and funded changed 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 10 plots more granular suspicious loan rates on a weekly basis separately for 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 to around 30% of loans flagged as suspicious during April and early May of 2021. PPP funds for most loans were exhausted on May 4, 2021 (Cowley (2021)). The suspicious loan rate fell toward the end of May 2021, but this could be due to loan composition since funding after May 4 was only available for prioritized community financial institutions and some loans that were already under review prior to May 4. 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 less than 10%, but by the end of the program the FinTech suspicious loan rate was close to 30%, more consistent with scenario B.[47]

We also examine lending growth and changes in suspicious loan rates across rounds at the lender level. Most FinTech lenders had higher suspicious lending rates in round 3 than in rounds 1 and 2 (Panel A of Figure IA.16 in the

[47] Panel B of Figure IA.15 in the Internet Appendix shows similar trends for each primary flag individually.

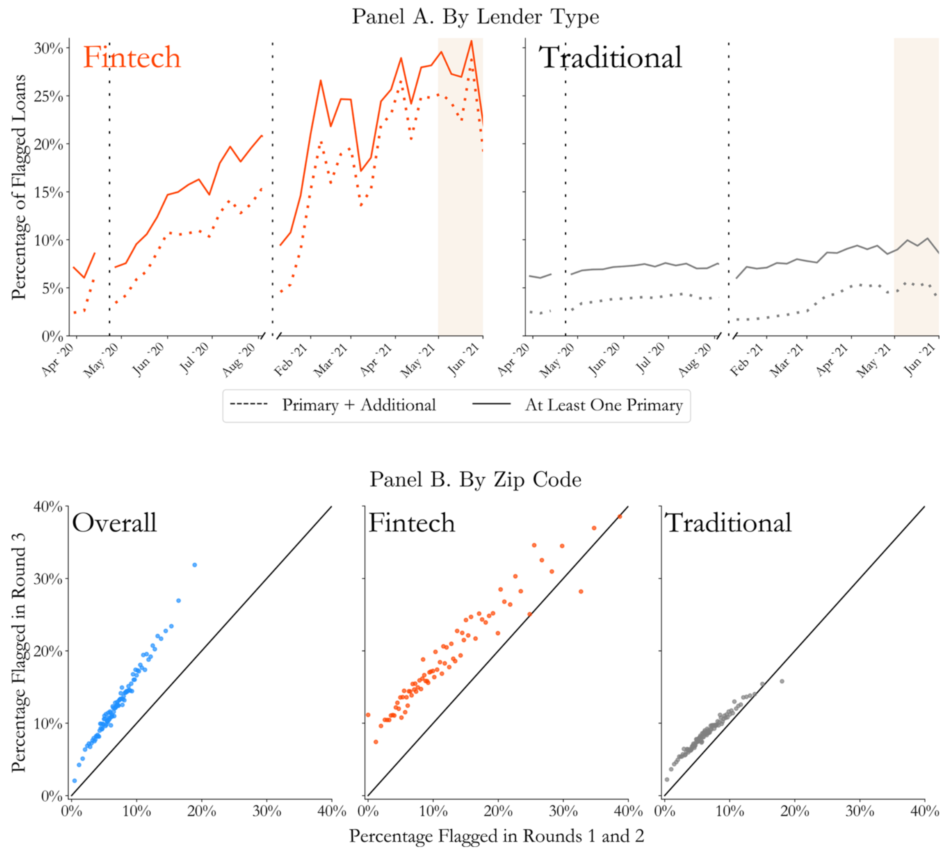

Figure 10. Persistence and growth across rounds. This figure shows the persistence and growth of flagged loans across lending rounds. Panel A shows this by lender type and Panel B by ZIP Code. In Panel A, each subpanel shows a lender type and each series is the percentage of loans flagged by the given measure across time. In Panel B, the percentage of loans flagged in rounds 1 and 2 is shown on the horizontal axis and in round 3 on the vertical axis. For Panel A, the vertical dotted lines split each subpanel into the three 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 (another primary, secondary, or external). For Panel B, the left subpanel uses all loans, the middle uses FinTech loans, and the right uses traditional loans. ZIP Codes with at least 100 loans in rounds 1 and 2 combined are shown. The black line is a 45° line. (Color figure can be viewed at wileyonlinelibrary.com)

Internet Appendix). Additionally, many of the FinTech lenders with the highest suspicious loan rates in rounds 1 and 2 also had the most growth in lending and the most growth in suspicious loans in round 3. In Table IV, we ask whether lenders appear to be learning by regressing indicators for the four primary flags in round 3, individually and combined, on lenders' rounds 1 and 2 misreporting rates for the same flags. For FinTech lenders, we find large and statistically significant positive relations across the board with largely

Table IV

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) to (4)) and at least one of them (specification (5)) as the dependent variable 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 loan was originated by a FinTech or traditional lender are included in all specifications. For specifications (1) to (4), loans are filtered to the sets for which we can determine the flag. Further, to ensure that we have accurate measures of past behavior, we require that each lender have at least 100 loans in rounds 1 and 2 (combined) for which we can determine the given flag. Fixed effects are as indicated at the bottom of each column. Robust standard errors are double clustered by ZIP Code and lender. t-statistics are in parentheses. Significance levels are indicated by $^{**}p < 0.05$, $^{***}p < 0.010$.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable:	*1(Business Registry)*	*1(Multiple Loans)*	*1(High Implied Comp.)*	*1(EIDL > PPP Jobs)*	*1(At Least One Flag)*
Past Pct. This Flag					
× *1(FinTech)*	0.905***	0.627***	0.361***	0.861***	0.456***
	(4.67)	(3.69)	(2.72)	(2.97)	(4.50)
× *1(Traditional)*	0.167	0.211**	−0.453***	−0.173	−0.185
	(0.73)	(2.20)	(−3.83)	(−1.26)	(−1.55)
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	1,830,109	5,280,796	1,574,978	1,010,713	5,280,796
Num. Lenders	2,432	3,078	1,547	1,409	3,078
R^2	0.141	0.0512	0.630	0.346	0.366
Mean of Dep. Variable	0.0705	0.0208	0.341	0.135	0.164

insignificant and several negative relations for traditional lenders. For traditional lenders, there is overall no relation between their flag rates in rounds 1 and 2 and the likelihood of their loans being flagged in round 3. By contrast, FinTech lenders have persistent and increasing levels of suspicious loans over time, consistent with scenario B above.

To assess prediction 2, we estimate regressions to test whether a first-draw borrower is more or less likely to receive a second-draw loan from the same lender if their first-draw loan is flagged by at least one of the primary misreporting indicators. Table V shows that borrowers of traditional loans that 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 3.09 ppt (with t-statistics of 11.41) and FinTechs have a smaller and statistically insignificant decrease of 1.02 ppt (with t-statistics of −0.84).[48] This indicates

[48] These results are based on $SameLender_i$ being set to 0 if the borrower did not get a second draw at all.

Table V

Likelihood of Receiving a Second-Draw Loan

In this table, we examine whether lenders were more/less likely to provide a second-draw loan to a borrower whose 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 who received both a first- and second-draw loans are included in the sample. In the even specifications, interactions for whether the first-draw loan was originated by a FinTech or a traditional lender are included. Fixed effects are as indicated at the bottom of each column. Robust standard errors are double clustered by ZIP Code and lender. *t*-Statistics are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{***}p < 0.010$.

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

	(1)	(2)	(3)	(4)
	Unconditional of Receiving Second Draw		Conditional on Receiving Second Draw	
1(First Draw Flagged)	-0.0261^{***}		-0.00878^{*}	
	(−6.54)		(−1.84)	
× *1(FinTech)*		−0.0102		0.0122
		(−0.84)		(0.55)
× *1(Traditional)*		-0.0309^{***}		-0.0156^{***}
		(−11.41)		(−4.86)
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
Lender FE	Yes	Yes	Yes	Yes
Observations	4,847,988	4,847,988	1,579,897	1,579,897
Num. Lenders	4,647	4,647	4,446	4,446
R^2	0.121	0.121	0.415	0.415
Mean of Dep. Var.	0.278	0.278	0.836	0.836

that traditional banks were less likely to continue lending to borrowers with previous suspicious borrowing, but FinTechs are not actively learning in a similar manner. Columns (3) and (4) of Table V condition on the borrower receiving a second draw (either from the same or different lender) with similar results.[49]

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 of Figure 10 plots ZIP Code level binscatters of the percentage of loans flagged in rounds 1 and 2 on the horizontal axis and the percentage of flagged loans

[49] In Figure IA.17 in the Internet Appendix, 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 toward flagged and nonflagged loans rather than systematic changes in the lender's behavior.

in round 3 on the vertical axis. The left subpanel uses all loans, the middle uses FinTech loans, and the right uses traditional loans. The figure displays three interesting findings. First, all of the binscatter dots in the left plot are above the 45° line, indicating that misreporting rates increased in round 3 almost everywhere. Second, the ZIP Codes with the highest suspicious loan rates in rounds 1 and 2 also had the highest suspicious loan rates in round 3. Third, growth in potential misreporting rates was particularly pronounced for FinTech lenders. Instead of scrutinizing areas with high suspicious lending in rounds 1 and 2, FinTech lenders facilitated even more suspicious lending in these areas in round 3.[50] We also test these results at the ZIP Code-lender level 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 a 5.2-ppt increase in round 3 flagged loans for FinTech lenders, with a much weaker relation for traditional lenders and similar results at the county-lender level (see Table IA.X in the Internet Appendix).

B. FinTech Lender Background, Fluidity, and Incentives

The largest FinTech lender, Cross River, is a small community bank in New Jersey that acts as a conduit for partner FinTechs. The second largest FinTech PPP lender, Prestamos, is a Community Development Financial Institution with locations in Arizona, Nevada, and New Mexico. Harvest Small Business Finance, Capital Plus Financial, Benworth, and Fountainhead, the other FinTech lenders in the top 10 by number of PPP loans originated, follow a similar pattern of limited business outside of PPP lending (see Table IA.XI in the Internet Appendix for background information on the largest FinTech lenders).[51] We systematically examine this relation more formally and find that 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 (as shown in Table IA.XII in the Internet Appendix). FinTech lenders also relied more heavily on liquidity support from the Federal Reserve than traditional lenders.[52]

[50] Results are similar at the county and state levels. See Panels C and D of Figure IA.16 in the Internet Appendix.

[51] MBE Capital Partners, the fourteenth largest FinTech lender with the fifth highest suspicious loan rate, is another interesting example. MBE scaled up to fund PPP loans with a combination of financing from an insurance company affiliated with Magic Johnson and loans from the Federal Reserve. Its CEO is now being criminally charged for fraud in MBE's application to become an approved PPP lender (Omeokwe (2022)).

[52] Financing for FinTech PPP loans was in part provided with a credit facility, the Paycheck Protection Program Liquidity Facility (PPPLF), in which the Federal Reserve extended credit to lenders using PPP loans as collateral. While most traditional lenders did not use the PPPLF at all, it was a major source of funding for some of the largest FinTech lenders (Figure IA.18 in the Internet Appendix).

B.1. FinTech Fluidity

The six largest FinTech lenders primarily originated loans that were sourced from 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 (Cowley (2020)). The other large FinTech lenders originated loans sourced by two start-ups that did not do any PPP lending until round 3, Womply and BlueAcorn (Cowley and Koeze (2021)).[53]

To further understand the network of relationships between lenders we first consider the use of multiple lenders for loans in the same draw to the same noncommercial address as identified by the multiple loan flag. For FinTech borrowers with multiple loans to the same address, 60.2% of loans are split across multiple lenders, with connections between lenders seemingly explained by FinTech portals sourcing loans for multiple lenders (as shown in Panel A, Figure IA.19 in the Internet Appendix). For example, there is a strong relationship between Prestamos and Capital Plus, the two lenders who partnered with BlueAcorn. There are also strong relationships between Harvest, Benworth, Capital Plus, and Fountainhead, all of which are Womply partners. By contrast, 82.7% of traditional borrowers who took out multiple loans received all their loans from the same lender.

For a borrower that already received a first-draw loan, obtaining a second-draw loan from the same lender only required refreshing the application with some additional information. This provided a strong incentive for borrowers to use the same lender. Nonetheless, there are large movements between FinTech lenders that likely reflect online lending portals switching lenders (Panel B, Figure IA.19 in the Internet Appendix), which again highlights the fluid nature of the FinTech space. The lack of relationship banking within FinTech may be advantageous for expanding access to capital (Erel and Liebersohn (2022)), but it may also increase dubious lending.

B.2. 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.[54] Based on this fee schedule, we estimate that PPP lending generated $38.0 billion of lender processing fees, $8.6 billion of which went to FinTech lenders (see Table IA.XIII

[53] 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.

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

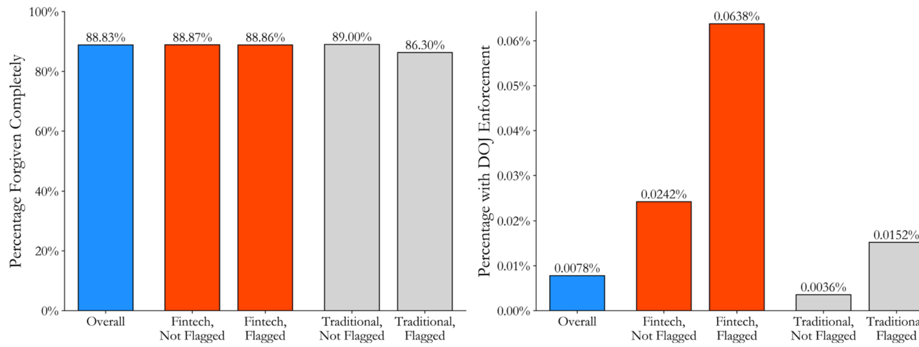

Figure 11. Enforcement and forgiveness. This figure shows the forgiveness of and DOJ enforcement actions regarding PPP loans. The left subpanel shows the percentage of round 1 loans that have been completely forgiven as of January 3, 2022. The right subpanel shows the percentage of round 1 and 2 loans that are part of DOJ enforcement actions as of March 1, 2022. In both panels, the overall percentage and the percentage by lender type and whether the loan is flagged by at least one primary measure are shown. (Color figure can be viewed at wileyonlinelibrary.com)

in the Internet Appendix). The top four FinTech lenders alone likely generated \$4.03 billion in processing fees, including \$1.06 billion to Prestamos, \$1.03 billion to Cross River, \$1.02 billion to Harvest, and \$938 million to Capital Plus. The average processing fee for FinTech PPP loans was 18.5% of the loan balance, largely driven by the high processing fees for small loans in round 3.[55] We lack data on cost structure and lender fee sharing with partner organizations used to source the loans such as Womply and BlueAcorn.[56]

C. Forgiveness and Enforcement Actions

PPP loans were designed to be fully forgiven in most cases. The left plot of Figure 11 shows the percent of round 1 loans that have been fully forgiven as of January 2, 2022. Approximately 90% of loans have already been forgiven, even those that are flagged as suspicious. Loans in rounds 2 and 3 are also on track for high levels of forgiveness (Figure IA.20 in the Internet Appendix). These high forgiveness levels make it doubtful that most dubious loans will ever be paid back.

[55] The average FinTech processing fee for rounds 1 and 2 was 4.97%. This dramatically increased to 22.1% in round 3.

[56] Crossroads Systems, the owner of Capital Plus (the fourth largest FinTech lender and sixth largest lender overall), reported \$932.7 million of revenue in 2021, \$897.8 million of which was due to PPP lending fees, compared to \$36.6 million of total revenue in 2020, before Capital Plus starting originating PPP loans on a widespread basis (see press release at https://www.prnewswire.com/news-releases/crossroads-systems-reports-fiscal-fourth-quarter-and-fiscal-year-2021-financial-results-301443835). Earlier in the pandemic, Capital Plus received a PPP loan of \$376,800, reportedly to cover payroll for its 28 employees. Similarly, Benworth Capital Partners (the fifth largest FinTech and seventh 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.

The economics of crime depend crucially on a crime's expected penalty and probability of detection (Becker (1968)). The U.S. Department of Justice (DOJ) is pursuing criminal complaints alleging PPP fraud, and some borrowers have voluntarily repaid their loans without applying for loan forgiveness or had their loan canceled. However, the magnitude of these enforcement actions is tiny. Compared to the 1.41 million loans we identify as suspicious, as of March 1, 2022, the DOJ has publicized 258 criminal complaints regarding only 502 loans. The right plot in Figure 11 shows the percent of loans with DOJ enforcement actions by lender type and whether or not the loan is flagged as suspicious by at least one of the four primary measures. Consistent with our flags identifying fraud, enforcement actions are more common for FinTech loans and loans that have been flagged, but the enforcement rate is well under 0.1% in all cases.[57]

An earlier version of this paper based on the May 3, 2021 SBA data release was strongly criticized by several PPP lenders for including loans that were in the SBA data but were eventually canceled. Lenders indicated that many loans were approved by the SBA but later denied due to their internal fraud detection process. It is important to note that the current version of the paper is entirely based on the January 2, 2022 SBA data release and thus does not include these earlier loans that were approved but later canceled.[58] Overall, we detect 234,727 canceled loans between the May 3, 2021 and January 3, 2022 data releases. Of these canceled loans, 30.7% are flagged by at least one primary suspicious loan measure. This again implies that the true amount of fraud is likely substantially greater than our indicators can identify. Overall, enforcement action, repayment, and cancellation rates are all rare but somewhat elevated for flagged loans (see Table IA.XIV and Figure IA.21 in the Internet Appendix). Although more enforcement actions may be forthcoming, there appears to be little penalty for most suspicious lending thus far.

D. Economic Discussion

What have we learned that may speak to why suspicious lending concentrated so heavily in FinTech lenders? There were clearly large financial incentives for loan origination, and many FinTech lenders with small pre-pandemic operations generated substantial processing fees. There seems to have been

[57] See the Internet Appendix for additional details on enforcement actions, repayments, and cancelations. Of the DOJ enforcement action loans with enough data to be matched to the PPP loan-level data, 216 loans were originated by FinTech lenders and 185 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. We focus on loans from rounds 1 and 2 for this analysis to allow more time for repayments and enforcement actions. SBA data indicate that only 16,930 round 1 and 2 loans were repaid between December 1, 2020 and June 30, 2021.

[58] Interestingly, dropping the canceled loans led to only minuscule reductions in suspicious loan rates, even for the lenders who raised the issue as a major concern.

little cost for bad lending practices since all credit risk was borne by the government, and financial penalties for lenders with poor lending practices, at least currently, seem very low. Although most FinTech lenders have high suspicious loan rates, Square and Intuit have among the lowest suspicious loan rates of all lenders, indicating that online lending does not appear to be the problem in and of itself. Square and Intuit had reputational capital to protect and established relationships with customers. Since Square, Intuit, and traditional lenders likely had access to additional information from applicants (e.g., customer payments, payroll, and bank account details), the lack of customer relationships may have also made other FinTechs more attractive targets for fraudulent applications.

The fact that new FinTechs and lenders who have fewer SBA loans prepandemic and have lent in SBA programs for fewer years all have higher rates of suspicious lending points to poor lending practices playing a larger role when there is a lack of reputational capital at stake. Traditional lenders may have followed standard, pre-pandemic SBA lending standards, in which the government only partially reimbursed lenders for losses. The one-time nature of the PPP with immediate profits in the present and a low likelihood of future repeat business also removed a natural market disciplinary force. Interestingly, in the buildup to the mortgage crisis, considerable fraudulent origination was similarly concentrated in small originators with little prior histories (Piskorski, Seru, and Witkin (2015), Griffin and Maturana (2016)).[59]

The fact that suspicious lending through FinTechs substantially increased from 2020 to 2021 suggests that poor practices cannot be solely attributed to the urgency of distributing funds or the lack of existing lending processes at the onset of the PPP. Although it may not be possible to precisely pin down which factors led to poor FinTech lending practices, the growing magnitudes of fraud throughout the program highlight that the lack of immediate ramifications for borrowers or lenders encouraged growth in fraudulent practices. Policymakers should carefully consider the effects of government programs that remove traditional market-based disciplinary forces and rely solely on discipline from reputational concerns and potential future law enforcement.

[59] There is some evidence that ZIP Codes with mortgage fraud preceding the financial crisis also have higher levels of PPP fraud, though the relation is weaker with the inclusion of demographic controls and county fixed effects (as shown in Table IA.XV in the Internet Appendix). Interestingly, in the 2003 to 2007 period, the largest and most reputable banks created some of the worst performing structured products (mortgage-backed securities and collateralized debt obligations), indicating that the financial incentives for short-term profits were seemingly large enough that even these banks were willing to tarnish their reputation (Griffin, Lowery, and Saretto (2014)). With the PPP, the fact that traditional banks had low levels of suspicious lending better fits the traditional reputation model (Chemmanur and Fulghieri (1994)).

VII. Conclusion

We examine four primary and four secondary measures related to potentially misreported loans with further validation from three additional external measures. FinTech loans are highly suspicious at a rate of over six times that of traditional loans. The top 12 lenders with the highest rates of suspicious loans are all FinTech lenders. Our analysis of the four primary suspicious loan indicators estimates the total amount of potential misreporting as 1.41 million loans with a balance of $64.2 billion, and these flags only apply to subsets of loans. Supplemental analysis indicates that likely misreporting may be twice as large, and suspicious lending more than quadrupled from the early to later stages of the PPP. Round 1 suspicious loans have already been overwhelmingly forgiven at a rate similar to nonsuspicious loans, and extremely few have been prosecuted.

Our findings have important policy implications. First, the PPP did not include robust verification requirements, and traditional banks may have been more apt to follow standard lending practices than new FinTech PPP lenders. The lack of rigorous verification for PPP loans seems to have led to substantial costs to taxpayers, especially in 2021 when there was likely also less urgency to the loans. Second, FinTech lending, though found in other papers to be successful at adapting to new environments and quickly disbursing funds, seemingly 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 findings, along with evidence that the PPP saved relatively few jobs at a high cost (Autor et al. (2022), Chetty et al. (2022), Granja et al. (2022)), provide growing evidence that the PPP may not have been an efficient source of capital allocation. Fourth, incentives in the PPP appear misaligned in that FinTech lenders with widespread indicators of misreporting made billions of dollars dispersing loans with apparently lax oversight procedures.

Finally, the increasing scale of misreporting through time indicates that current penalty and enforcement systems are not effective. If the system is not changed for future programs, the most likely outcome is even more of the same. This paper is also an example of how forensic research can more fully investigate the rent-seeking dimension of finance (Zingales (2015)). Government agencies can assist with 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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Appendix S1: Internet Appendix.
Replication Code.
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