Using Metrics of Potential Misreporting to Assess the Extent of PPP Fraud:

A Comment on the University of Texas Study

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Abstract

The Paycheck Protection Program (PPP) enabled the distribution of over $800 billion in forgivable loans to small businesses in response to the Covid-19 pandemic. After the initial round of almost $350 billion in funding quickly ran out, concerns were raised about the extent to which PPP loans were being made to small businesses in need. FinTech companies became active in facilitating loans to very small businesses that were not obtaining PPP loans from traditional banks, especially such nonemployer businesses as gig workers, freelancers, and independent contractors. The activities of these FinTechs are the focus of a recent study by researchers from the University of Texas at Austin who develop “metrics related to potential misreporting” and reach the conclusion that “while FinTech lenders likely increase PPP access, this may come at the cost of facilitating fraudulent credit”. However, their methodology is characterized by serious flaws—including the use of inappropriate data and the adverse impact of censoring, measurement error, and statistical noise—that disproportionately raise suspicions about smaller businesses, especially nonemployer businesses listing a residential address. As a result, the metrics are inadequate and especially inappropriate for comparing rates of suspicious activity among FinTech loans relative to traditional bank loans. Moreover, nothing in the study can answer the key questions of how many flagged loans are actually fraudulent and how many fraudulent loans are not flagged.

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1. Introduction

The Paycheck Protection Program (PPP), established by the CARES Act and implemented by the Small Business Administration (SBA), enabled the distribution of over $800 billion in forgivable loans in order to provide "small businesses with the resources they need to maintain their payroll, hire back employees who may have been laid off, and cover applicable overhead" in response to the onset of the Covid-19 pandemic (U.S. Department of the Treasury, 2021). The loan program began after the CARES Act was signed into law in March 2020, entailed three successive rounds of funding, and concluded with a third-round loan application deadline at the end of May 2021.

After the initial round of almost $350 billion in funding quickly ran out, concerns were raised about the extent to which PPP loans were being made to small businesses in need. These concerns were addressed with various programmatic changes, including those described in the whitehouse.gov "Fact Sheet" entitled "Biden-Harris Administration Increases Lending to Small Businesses in Need, Announces Changes to PPP to Further Promote Equitable Access to Relief" (The White House, 2021).

These concerns were also addressed by FinTech companies that "came out of nowhere and, through an astute mix of technology and advertising — and the dogged pursuit of an opportunity that big banks missed — found a way to help those businesses" (*New York Times*, 2021a). The activities of these FinTechs are the focus of a recent study produced by three researchers from the University of Texas at Austin, henceforth "UT study." The authors of the UT study develop "metrics related to potential misreporting" and reach the conclusion that "while FinTech lenders likely increase PPP access, this may come at the cost of facilitating fraudulent credit" (Griffin et al., 2021a).

To support this conclusion in the August 2021 version of the UT study, the authors utilize four primary metrics of potential misreporting to identify "1.8 million questionable loans representing $76 billion in capital," with about half of the identified loans attributed to FinTech lenders. Armed with supplemental data in an October revision of the UT study, the corresponding numbers increase to 2.1 million loans and $81.4 billion (Griffin et al., 2021b) before falling again, after the methodology is revised in December, to 1.5 million questionable loans and $68.9 billion (Griffin et al., 2021c).

While the UT study finds that FinTech loans are more likely than loans made by "traditional banks" to be identified as questionable and to constitute more than half of such loans, the loans made by traditional banks constitute more than two-thirds of the total dollar value of loans identified as questionable. This result arises because FinTech loans tend to be made to smaller businesses and, hence, entail smaller dollar amounts.

In fact, systematic differences in borrower attributes between FinTech lenders and traditional lenders raise important questions about the validity of uniformly applying the metrics of potential misreporting to compare the extent of questionable loans across these lender types. PPP loans approved by FinTech lenders are much more likely than traditional lender loans to be obtained by small, nonemployer businesses with residential addresses, and it is just these attributes that are associated with key methodological problems in the UT study. As a result, measurement and statistical problems with the metrics differentially impact the findings for loans approved by FinTech lenders relative to traditional lender loans. Moreover, much care should be taken before findings based on such metrics of potential misreporting are used to make any inferences about the absolute and relative rates of actual PPP fraud.

The four primary metrics utilized in the UT study are as follows: (1) *business registry flag* - inconsistencies in reporting of business registration, (2) *multiple loan flag* - multiple loans approved for businesses listing identical residential addresses, (3) *high implied compensation flag* - relatively high values of imputed compensation, and (4*) EIDL advance jobs flag* - inconsistency between the number of jobs reported in the PPP loan application and the number reported in an Economic Injury Disaster Loan (EIDL) application to the SBA. In the analysis below, I consider the usefulness of these four primary metrics for assessing potential and actual fraud in the PPP loan program, both in absolute terms and, especially, for making comparisons between FinTech and traditional lenders.

I also consider the usefulness of five secondary metrics. While each of these secondary metrics is introduced along with the primary metrics as creating "an inference that a loan is suspicious,"[1] there should be no question that the headline findings and dollar figures are driven solely by the primary metrics. The secondary metrics are mainly used to corroborate these findings, serving as "external verification" of the primary metrics. Far from serving this purpose, however, these metrics tend to be characterized by similar, related deficiencies to those described for the primary metrics, including a greater propensity to flag loans made to nonemployer businesses regardless of similarities or differences in the actual rates of fraudulent activity.

In this analysis, I pay special attention to businesses (henceforth, "Blueacorn businesses") with loan applications attributed to two lenders ("Blueacorn lenders")[2] that are highlighted in the UT study and are reported to have made most of their loans partnering with the FinTech lender service provider Blueacorn.[3] Analysis of the same SBA data used in the UT study indicates that Blueacorn businesses are systematically different from those that applied for loans via traditional lenders. These differences will lead to observed differences in the metrics of potential misreporting regardless of differences in actual rates of PPP fraud.

Notably, 99.8 percent of Blueacorn businesses report just one job, whereas only about 35 percent of borrowers from traditional lenders do so. The stark difference likely arises from a

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[1] Griffin et al., 2021a, page 1.
[2] The two lenders are Capital Plus Financial and Prestamos CDFI.
[3] Blueacorn funded this research.

Blueacorn marketing effort that reportedly included “marketing blitzes encouraging freelancers, gig workers, sole proprietors and other small merchants to apply for loans through their websites” (*New York Times*, 2021a).[4] Well over half of these smallest of businesses are minority-owned. Thus, they appear to be just the kinds of businesses targeted by programmatic changes in the third round of the PPP intended to increase equitable access for small businesses in need.

Yet they are also just the kinds of businesses that are disproportionately impacted by methodological and statistical flaws in the UT study metrics—especially with respect to the use of inappropriate data and the adverse impact of censoring, measurement error, and statistical noise. As a result, the UT study metrics are inadequate and inappropriate for assessing suspicions of PPP fraud among Blueacorn loans, both in absolute terms and when making comparisons to suspicious activity among traditional bank loans.

I rely on publicly available data for this analysis, including not only the data on nearly 12 million PPP loans posted by SBA in June 2021 and utilized in the two most recent versions of the UT Study (Griffin et al., 2021b, 2021c) but also the revised data posted by SBA in November 2021 and then again in January 2022. These revised databases are notable for the exclusion of almost 295,000 (300,000) loans in November 2021 (January 2022) relative to the UT study data. Importantly, about 40 percent of the excluded loans are attributed to Blueacorn lenders in the June 2021 data, likely reflecting cancelled loans.[5]

The remainder of this paper is organized as follows: Section 2 describes the PPP data used in the analysis. Section 3 describes the four primary metrics of potential misreporting and details key methodological and statistical flaws that yield metrics that are more likely to raise suspicions about loans made by FinTech, especially Blueacorn, lenders. Section 4 highlights concerns with the secondary metrics. Section 5 concludes.

The concluding section notes that nothing in the UT study can be used to assess the specificity or the sensitivity of the metrics with respect to actual fraud. The study tells us nothing about the rate at which one would expect to find actual fraud among either the loans that are flagged by the metrics of potential misreporting or the loans that are not flagged. To make such an assessment of the rates of false positives and false negatives, as well as of the total amount of PPP fraud, would be purely speculative.

[4] The quoted text refers to both Blueacorn and Womply, another FinTech.

[5] This finding is inconsistent with the assertion that “there is no evidence that *[FinTech]* lenders attempted to decrease misreporting over time” (Griffin et al., 2021c, page 3).

2. PPP Loan Data

The UT study analyzes loan-level PPP data made publicly available by SBA, first on May 3, 2021 (Griffin et al., 2021a) and then updated on June 30, 2021 (Griffin et al., 2021b, 2021c). I begin here by discussing the June 2021 data, before turning to updated data made available in November 2021 and further updated in January 2022.[6] Table 1 reports summary statistics from the June 2021 data for variables included in this analysis. Tables 2 and 3 report comparable statistics for the November 2021 data and January 2022 data, respectively.

2.1. The June 2021 Data

The June 2021 data include entries for 11,768,689 loans. The UT study reports that these data "cover all PPP loans issued from the start of the program on April 3, 2020 through the end of the program on June 30, 2021 that had not been repaid as of June 30, 2021."[7] The database includes information on the borrower (e.g., name, address, gender, race, ethnicity, business type, industrial classification, number of reported jobs), the lender (name and address), and the loan (e.g., approval date, approved amount, draw, and status).

I supplement these data in two ways with similar methods to those used in the UT study. First, I utilize the smartystreets.com US address verification system to distinguish residential from commercial addresses. Second, I classify the lenders as either FinTech or traditional based on the list of lenders classified as such in UT study tables and figures and/or in the Erel and Liebersohn (2021) study on which the UT study classifications are based. In both cases, the information is incomplete, so I do not classify some addresses as either residential or commercial and I do not classify some lenders as either FinTech or traditional.

The first two columns in Table 1 describe the distribution of attributes among all loans in the June 2021 data. Each pair of columns to the right describes the same attributes for each lender type: Blueacorn, other FinTechs, traditional, and those not classified. We see here that the 959,145 loans approved by Blueacorn lenders constitute about 8 percent of all loans in this database, while over three million loans approved by FinTech lenders account for over 25 percent of loans, and over four million loans approved by traditional lenders account for nearly 35 percent. The remaining 32 percent of loans are approved by unclassified lenders.

The UT study begins with an analysis of the business registry flag based on reported business type, restricting attention to those businesses described as corporations, S-corporations, and LLCs. Looking first at the June 2021 data for all loans, described in the first two columns of Table 1, we see that about 20 percent of borrowers report "Corporation," another 20 percent report "Limited Liability Company (LLC)," and almost 10 percent report "Subchapter S Corporation."

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[6] The most recent data are available at https://data.sba.gov/dataset/ppp-foia. I began this research after the May 2021 data were replaced by the June 2021 data. I have not had access to the May 2021 data.

[7] Griffin et al., 2021c, page 5.

Thus, about half of all borrowers report one of these three business types. However, this share varies greatly across lender types, as described in the columns to the right. This share reportedly constitutes almost 70 percent of loans made by lenders identified as traditional lenders but is about 7 percent for Blueacorn lenders, over 20 percent for loans made by other FinTechs, and about 60 percent for unclassified lenders.[8] Further, almost all of these Blueacorn businesses are reported to be LLCs. Thus, we see the first evidence that the borrowers from FinTech lenders, especially Blueacorn lenders, are systematically different from those that borrow from traditional lenders.

Relatedly, loans from FinTech lenders, especially Blueacorn lenders, go to much smaller businesses than do loans made by those identified as traditional lenders. Fully 99.8 percent of Blueacorn businesses report just one job, versus 80 percent for other FinTechs, and just 35 percent for traditional lenders.

The frequency with which exactly one job is reported is particularly important when interacted with reported business type. For Blueacorn businesses, almost two out of every three loans with one job also report a business type of sole proprietorship, while one out of every four are reportedly independent contractors and just one of every 25 are reportedly self-employed. All three of these types—sole proprietorships, independent contractors, and self-employed—should be considered to be nonemployer businesses for the purposes of the analysis in the UT study. Autor et al. (2022) classify all three of these types, as well as the infrequently observed single-member LLC, as nonemployer businesses when one job is reported.[9]

Nonemployer businesses are mainly comprised of sole proprietorships that file Schedule C in individual tax returns. Programmatic changes in the third round of the PPP enabled Schedule C filers to apply for loan amounts based on gross income rather than net income on or after March 3, 2021.[10] With 99.6 percent of Blueacorn loans approved on or after this date, this programmatic change likely applies to the overwhelming majority of Blueacorn loans. About 60 percent of other FinTech loans list an approval date on or after March 3, 2021, as do 22 percent of loans approved by both traditional and unclassified lenders.

With smaller businesses come smaller loans amounts, as described in Table 1. Whereas just over half of Blueacorn loans and about 55 percent of loans made by other FinTechs are for less

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[8] Loans made by unclassified lenders, which constitute about one out of every three PPP loans, are an unknown mix of traditional and FinTech lenders. The summary statistics discussed in this section and detailed in Tables 1 through 3 strongly suggest that the majority, if not the great majority, of the loans made by unclassified lenders are made by what the UT study would label as traditional lenders.

[9] Independent contractor and self-employment are common descriptions of employment status, whereas sole proprietorship is a business structure. Supporting the argument that these sole proprietors should be treated identically to the self-employed and independent contractors, the IRS website for the Self-Employed Individuals Tax Center states that, generally, an individual is self-employed if "You carry on a trade or business as a sole proprietor or an independent contractor." See https://www.irs.gov/businesses/small-businesses-self-employed/self-employed-individuals-tax-center, accessed 1/27/2022.

[10] See footnote 16 in Griffin et al. (2021b).

than $20,000, only about 42 percent of loans made by both traditional and unclassified lenders are less than $20,000.

This differential increases substantially when we consider all loans under $25,000, as the category $20,000-$24,999 includes 48 percent of loans made by Blueacorn lenders, 33 percent for other FinTechs, 13 percent for traditional lenders, and 14 percent for unclassified lenders. The high frequency of loans in the range $20,000-$24,999 is attributable in part to the value $20,833.33 that corresponds to implied annual compensation of $100,000 for businesses reporting one job, as calculated in the UT study and discussed below. Less than one percent of Blueacorn loans exceed $25,000, versus about 12 percent for other FinTechs, and about 45 percent for both traditional and unclassified lenders.

The PPP data also contain information on the borrower's reported industry, as described by the North American Industrial Classification System (NAICS) code. Table 1 describes the share of loans reporting each of the four most prevalent 4-digit NAICS codes among Blueacorn businesses. Almost 20 percent of Blueacorn businesses are reported to provide personal care services (8121), while more than five percent provide services to buildings and dwellings (5617), taxi and limousine service (4853), and residential building construction (2361). Whereas these four NAICS codes account for about 36 percent of loans made by Blueacorn lenders, they account for about 25 percent of loans made by other FinTech lenders and less than 10 percent for traditional lenders. The biggest differences between Blueacorn and traditional lenders are found in the classifications of taxi and limousine service and, especially, personal care services.

Another key systematic difference for the purposes of this study pertains to the share of business addresses that are classified as residential. Over 90 percent of Blueacorn business addresses are found to be residential, while 3 percent are commercial and 5 percent are not classified. The corresponding rates are 42 percent residential, 50 percent commercial, and 8 percent not classified for traditional lenders, and 74, 20, and 7, respectively, for FinTechs.

There appear to be key systematic differences in the demographic distribution of business owners as well. This comparison is complicated by the presence of numerous loans for which no information is reported. For instance, as described in Table 1, no information is provided on race for almost 30 percent of loans made by Blueacorn lenders and almost 85 percent of loans made by other FinTechs, 80 percent among traditional lenders, and over 75 percent among unclassified lenders.

Even with this extent of missing information, the Blueacorn businesses are seen to be disproportionately owned by members of minority groups—in particular, African Americans. Just over 55 percent of Blueacorn businesses report that the owner is Black or African American, while just 13 percent are reported to be White, the aforementioned almost 30 percent have no report, and the remaining share report a different racial group. In contrast, about 7 percent of loans made by other FinTech lenders report Black or African American, along with 2 percent for traditional lenders and 1 percent for unclassified lenders.

2.2. Revisions to the PPP Data over Time

In the original version of the UT study published in August 2021, Griffin et al. (2021a) report results based on data for 10,697,219 loans approved through April 30, 2021. They also note:

> Subsequent to the data used in our analysis, the SBA posted another dataset on June 30, 2021. In addition to including data for loans originated in the closing weeks of the PPP, the new data is missing 95,526 loans that were present in the earlier data, presumably due to cancellations and repayments.[11]

The June 2021 data on 11,768,689 loans approved through June 30, 2021 are analyzed in Griffin et al. (2021b, 2021c) and described in Table 1.

Table 2 describes the PPP data posted in November 2021, and Table 3 describes the data posted in January 2022. In each case, the included loans were approved from the beginning of the PPP through June 30, 2021.

The November data report on 11,475,004 loans, showing a net decline of almost 293,000 loans from the June data. The total in the January 2022 data of 11,469,801 shows a further decline of about 5,200 loans. Thus, the total net decline from June 2021 to January 2022 is almost 300,000 loans.

Loans made by Blueacorn lenders decline from about 960,000 in June 2022 to about 840,000 in January 2022. This decline of nearly 120,000 loans accounts for 40 percent of the net decline in all loans in the PPP data, yet Blueacorn loans account for just 8 percent of the loans in the June 2021 data. Published statements indicate that this disproportionately high rate of decline arises mainly from loans that were cancelled by Blueacorn lenders.[12] These statements and findings suggest that loans cancelled by Blueacorn likely also constitute a disproportionate share of the 95,000 loans that Griffin et al. (2021a) note were removed from the PPP data between April and June of 2021.

But for the decline in the number of loans, the statistics on the distributions of attributes are generally very similar for the November 2021 (Table 2) and January 2022 (Table 3) data to those described for June 2021 (Table 1) above. The one notable, substantive exception is the change in statistics on loan status, with the majority showing a status of "paid in full" by January

[11] See footnote 4 of Griffin et al. (2021a).

[12] For instance, a *New York Times* article describing the UT study reports: "Before the study was released, Blueacorn sent a letter *[to]* Jay Hartzell, the president of the University of Texas at Austin, objecting to the researchers' approach. Blueacorn said that by relying on interim data released by the Small Business Administration before the P.P.P. ended, the study counted loans that its lenders initially approved but later canceled because of suspicious traits. Nearly 157,000 applications — about 16 percent of all of the loans Blueacorn's lenders approved — were canceled by the lenders before they were paid out." (*New* York *Times*, 2021b)

2022.[13] The share of loans classified as “active un-disbursed” declines for Blueacorn lenders and other FinTechs from 15 percent and 8 percent, respectively, in June 2021 to a negligible fraction by January 2022. Inspection of the data reveals that 67 percent of Blueacorn loans classified as active un-disbursed in June 2021 are not included in the January 2022 data and are therefore likely to have been cancelled.

2.3. Loans to Nonemployer Businesses at Residential Addresses after March 3 2021

Blueacorn businesses may generally be characterized as nonemployer businesses that list a residential address and are approved for loans on or after March 3, 2021, the date on which PPP rule changes allow these businesses to base loan amounts off of gross rather than net income. As reported at the bottom of Tables 1 through 3, about 86% of Blueacorn businesses fall into this classification, as opposed to about 47% for other FinTechs, 8% for traditional lenders, and 11% for unclassified lenders. Here, as in Autor et al. (2022), nonemployer businesses are defined as those reporting one job and a business type of sole proprietorship, independent contractor, self-employed, or single-member LLC.

Table 4 describes this subset of 2,827,854 loans included in the January 2022 data. Blueacorn lenders account for about 25 percent of these loans and combine with other FinTechs to account for a total of almost 75 percent. In contrast, as reported in Table 3, Blueacorn accounts for just 7 percent of all 11,469,801 loans in the January 2022 data, while Blueacorn and other FinTechs combine to account for less than 33 percent of all loans. Thus, Blueacorn and other FinTech lenders approve a large majority and a disproportionate share of the loans to these nonemployer businesses.

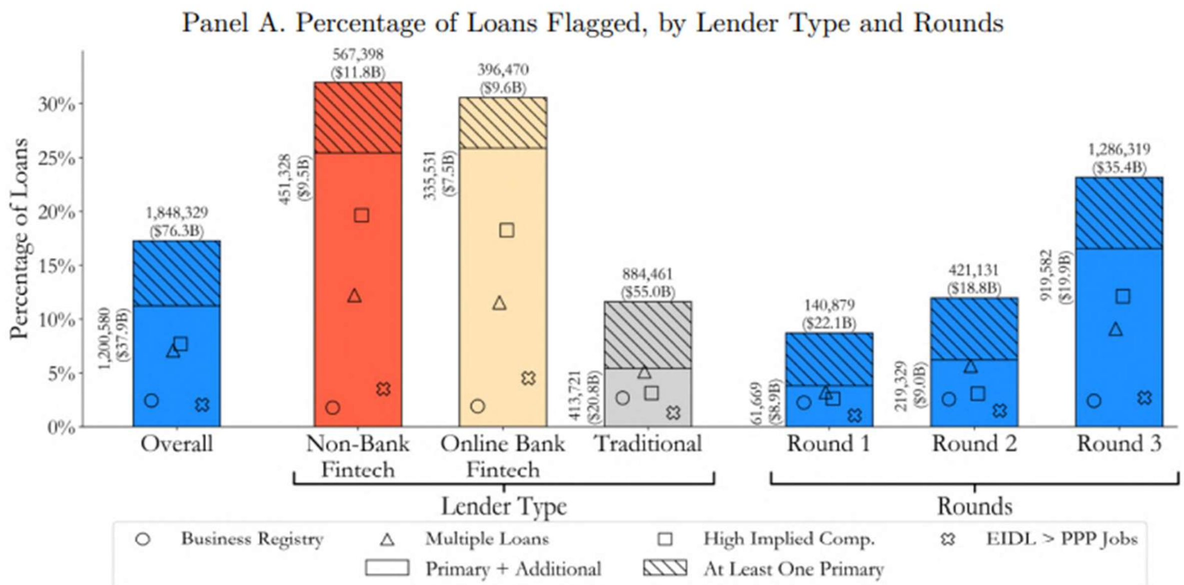
The reported distribution of loan amounts is another key feature of these data with respect to the UT study metrics; in particular, the concentration of loan amounts near the value $20,0833.33 that, for this sample, corresponds to implied gross annual income of $100,000 or more. As displayed in Table 4, about 47 percent of the loans approved by Blueacorn and 44 percent of those approved by other FinTechs fall in the range $20,000-$24,999, versus about 30 percent for both traditional lenders and those not classified. In fact, loan amounts in the 50-dollar-wide range from $20,800 to $20,850 comprise about 34 percent of the loans in Table 4 made by Blueacorn lenders, 33 percent for other FinTech lenders, 26 percent for traditional lenders, and 27 percent for unclassified lenders.[14]

[13] In addition to changes in loan status, the data on reported gender change substantially, with all borrower entries classified as “unanswered” in the January 2022 data. About 61 percent are classified as “unanswered” in the June and November 2021 data.

[14] Within this 50-dollar-wide range, more than 91 percent of Blueacorn loan amounts take the value $20,832 and more than 5 percent are $20,833. The corresponding percentages are about 3 percent and 91 percent, respectively, for other FinTechs, where, unlike Blueacorn, many other loan amounts near these values are not rounded to the nearest dollar, including about 1 percent at $28,033.33. For traditional lenders, the corresponding percentages are about 20 percent and 54 percent, respectively, again with a considerable share at non-rounded values, including 7 percent at $28,033.32 and 7 percent at $28,033.33.

3. Primary Metrics of Potential Misreporting

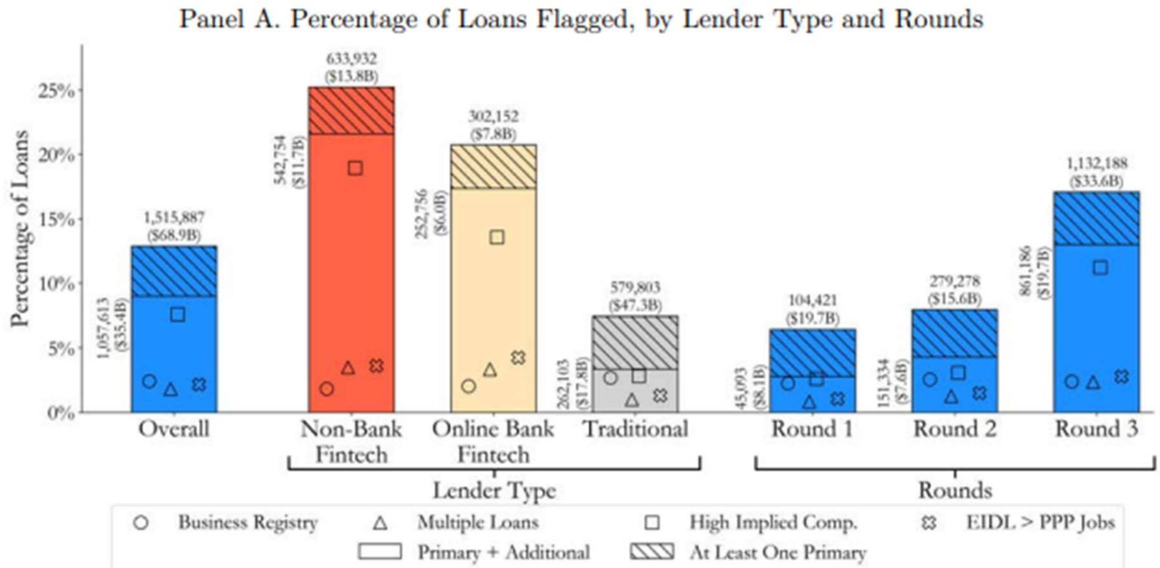
Over the course of its three iterations, the UT study identifies 1.5 to 2.1 million questionable loans representing 68.9 to 81.4 billion dollars in capital. These loans are identified based on being flagged by at least one of four primary metrics of potential misreporting. The summary findings are depicted in Figure 10 of the UT study, as seen in the following extract from the August version:[15]



We see here, based on the height of each bar, that the percentage of flagged loans is much higher for FinTech lenders (about 30 percent) than for traditional lenders (over 10 percent). Looking at the symbols depicted within each bar, we see that the high implied compensation flag (square) is the most prevalent flag among FinTechs, with about 19 percent of FinTech loans flagged, versus about three percent of loans approved by traditional lenders. The multiple loan flag (triangle) is the second most prevalent for FinTech lenders at about 12 percent and the most prevalent for traditional lenders at about 5 percent.

Striking changes are evident in the third and final iteration of the UT study, depicted in this extract from the December version: [16]

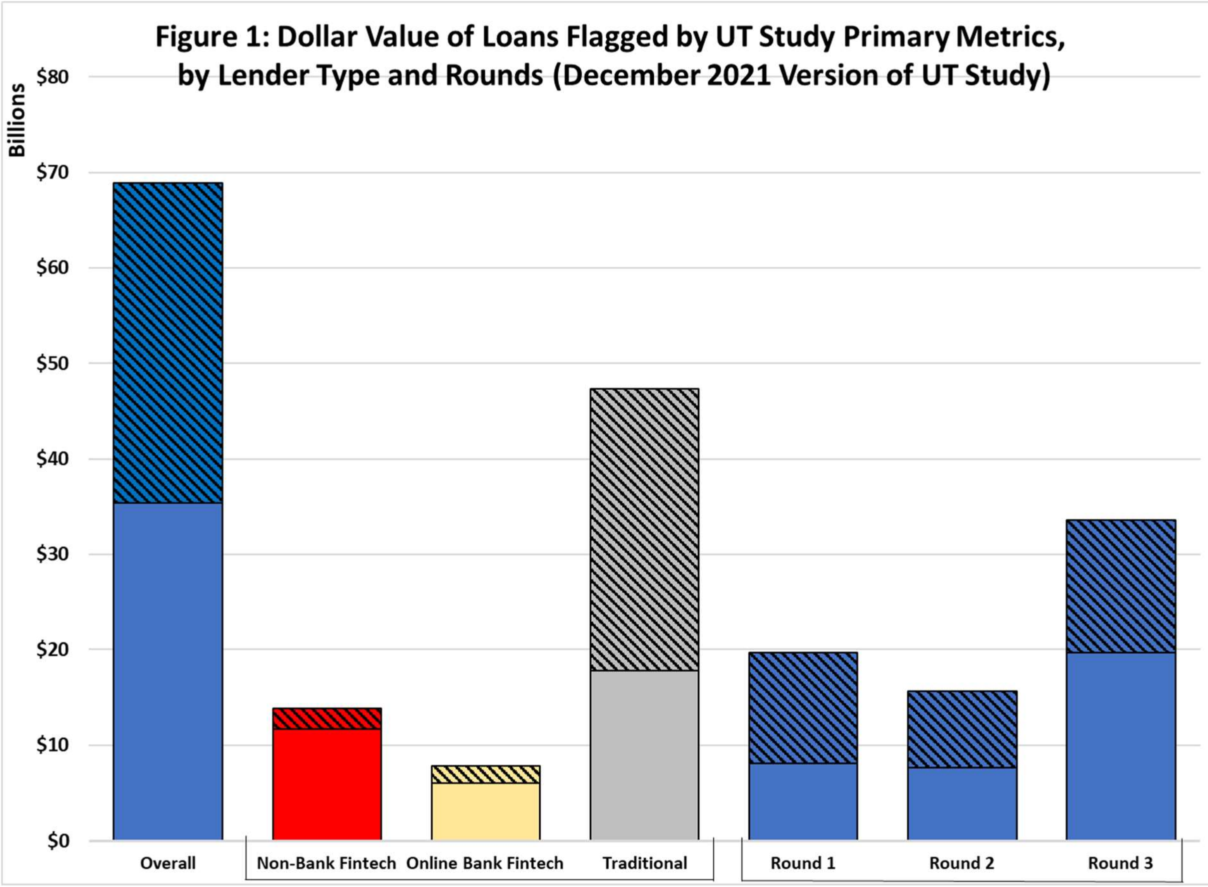
[15] Source: Panel A of Figure 10 in Griffin et al. (2021a).
[16] Source: Panel A of Figure 10 in Griffin et al. (2021c).



We see here that the overall decline in the share of loans identified as questionable may be mainly attributed to a decline in the multiple loan flag rate depicted by triangles. As a result, variation in the high implied compensation flag rate drives variation in the identified share of questionable loans across lender types. In particular, about four out of every five identified non-bank FinTech loans, and about two out of every three identified online bank FinTech loans, are flagged for high implied compensation.

The entries in Figure 10 of the UT study also point to another important feature of the main findings. That is, while the percentage of loans flagged by the primary metrics is notably greater for FinTechs than for traditional lenders, the dollar value of the traditional loans is much greater. The reversal is seen in Figure 1 below, which takes the entries from Figure 10 above and changes the units on the vertical axis from percentage of loans to billions of dollars in loan amounts.[17]

[17] Source: Panel A of Figure 10 in Griffin et al. (2021c).



These summary findings should be kept in mind as one considers the data and calculations on which they are based. The sections below describe details of the four primary metrics of potential misreporting—business registry flag, multiple loan flag, high implied compensation flag, and EIDL advance jobs flag—presented in the order in which they appear in the UT study. The discussion draws attention to concerns about misclassifications of and systematic biases in these flags arising from reporting issues, statistical issues, data and sample censoring, and reliance on inappropriate data. These problems differentially impact the observed flag rates for traditional lenders relative to FinTech lenders, especially Blueacorn lenders.

3.1. Business Registry Flag

The business registry flag identifies borrowers outside the state of Illinois that report a business type of corporation, S-corporation, or LLC, but for which no matching active business is found in an OpenCorporates database of state registrations as of February 15, 2020.[18] This date threshold is used because "the SBA required businesses to be 'in operation on February 15, 2020… [and] not permanently closed.'"[19]

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[18] The OpenCorporates database does not cover business registrations in Illinois.
[19] Griffin et al., 2021c, page 8.

As reported in Table 1, about 7 percent of Blueacorn businesses report a business type of corporation, S-corporation, or LLC. The UT study finds that about one out of every four of these types of Blueacorn businesses has a reporting inconsistency, thereby generating a flag rate of about 2 percent across all loans approved by Blueacorn lenders. This rate appears to be lower than the rate for loans approved by traditional lenders.[20]

Rather than comparing the business registry flag rates among all borrowers, however, the UT study focuses on the potential misreporting rate only among those businesses reported to be a corporation, S-corporation, or LLC, which they find to be higher for FinTechs than for traditional lenders. In so doing, the authors acknowledge a major concern with the metric:

> It is possible that there are errors in the data or that some businesses have names that are difficult to match; which may explain why all of the lenders have at least some missing registrations, with business registry flag rates of one to five percent common across many lenders.[21]

They immediately rebut this concern with the claim that "there is not an obvious explanation" for why some lenders "would have disproportionately high matching issues." One explanation is that, when the smallest of businesses—i.e., those reporting one job—are reported to be some form of corporation, then this reported business type is more likely to be erroneous than is the comparable report made by a larger business. With 99.8 percent of Blueacorn businesses reporting just one job, business-type reporting errors are a plausible source of disproportionately high matching issues.[22]

Further, it is also plausible that these small, primarily nonemployer, businesses lack standardization with respect to the reporting of business names on which to be matched across databases. For instance, within a random sample of 500 Blueacorn businesses reported to be a corporation, S-corporation, or LLC, I find that about 17 percent report only the name of an individual person for the borrower name in the June 2021 PPP data.[23] In contrast, a comparable random sample of loans made by traditional lenders includes just over 1 percent reporting only the name of an individual person for the borrower name.

3.2. Multiple Loan Flag

The section of the UT study on multiple loans begins with the following statement:

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[20] The rate for traditional lenders appears to be about 3 percent, as depicted in Figure 10 of Griffin et al. (2021c).
[21] Griffin et al., 2021c, page 9.
[22] Business-type reporting issues may also cause some loans to be mistakenly excluded from the analysis. For example, there are numerous businesses in the June 2021 data, especially among non-Blueacorn businesses, with "LLC" in the borrower name that have reported business type of sole proprietorship (77,037), partnership (31,732), Limited Liability Partnership (26,444) or self-employed individual (19,519), among other types, and are therefore apparently excluded.
[23] These cases exclude reported borrower names that list both an individual's name and a business structure identifier, such as LLC or PC.

> While it is possible that a business owner may have multiple businesses registered to the same address, the presence of multiple loans at a residential address during the same draw is also a potential sign of fictitious operations.[24]

This statement is true by construction, given the reference to a *potential* sign, rather than an *actual* sign, of fictitious operations.

The first two versions of the UT study flag about seven or eight percent of loans as multiple loans, with the rate falling to about two percent in the most recent version.[25] The published rate falls from about 16 or 17 percent to about 4.5 percent for Blueacorn loans.[26] This steep decline occurs because the most recent version of the UT study requires finding three loans at the same address, rather than just two, for these loans to be flagged as suspicious.

In this section, I discuss why two loans at a residential address should not have been flagged as suspicious in the first two versions of the UT study. I also ask why the bulk of the remaining flagged loans, those with three loans at a residential address, would be suspicious and, moreover, why no effort appears to have been made to flag multiple loans at commercial addresses. As noted above, loans approved by traditional lenders are much more likely to report commercial addresses than are loans approved by FinTech lenders, especially Blueacorn lenders.

3.2.1. Multiple loan flag in Griffin et al. (2021a, 2021b)

To motivate interest in the chosen metric of potential misreporting—that is, multiple loans at a residential address during the same draw—the UT study authors point first to an example of a residential address associated with 14 PPP loans, each of which reports 10 jobs. They follow this example with another one in which an address is associated with four loans made to four different individuals each reporting one job and implied annual income or gross receipts in excess of $100,000. Finally, they assert:

> Loan level inspections of the data reveal numerous other suspicious loans flowing to addresses that do not seem to be the locations of identifiable businesses despite applications claiming to employ multiple workers. The multiple loan flag functions as a way to systematically analyze these loans.[27]

Upon reading the supporting evidence for adopting this metric, one may therefore expect the multiple loan flag to identify residential addresses associated with many loans reporting multiple jobs at each business, in which case it should be clear that this flag would then only potentially apply to the 0.2 percent of Blueacorn businesses reporting multiple jobs.

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[24] Griffin et al., 2021a, page 8.
[25] See Panel A of Figure 10 in each version of the study.
[26] See Panel B of Figure 2 in each version of the study.
[27] Griffin et al., 2021a, page 8.

Or, upon reading the supporting evidence, one may expect the multiple loan flag to identify residential addresses associated with many loans that also have some other specific attributes, such as high levels of income or gross receipts. Instead, this metric simply requires that a residential address be associated with more than one loan in the same draw, despite the opening statement that "it is possible that a business owner may have multiple businesses registered to the same address" paired with supporting evidence that relies on the presence of additional attributes to create suspicion.

How common is it for a business owner to operate multiple businesses? With respect to Blueacorn businesses, the appropriate benchmark may be found in federal statistics on nonemployer businesses. According to data from the Internal Revenue Service, there were approximately 27.1 million individual income tax returns that reported nonfarm sole proprietorship activity in tax year 2018 (Dungan, 2021). These returns accounted for approximately 30.8 million separate nonfarm businesses.

Thus, on average, each individual reported 1.135 businesses, indicating that up to 13.5 percent of sole proprietors filed returns for more than one business.[28] Griffin et al. (2021a) report a multiple loan rate of approximately 16 percent for Blueacorn lenders.[29] Based solely on the IRS data describing the frequency of multiple nonemployer businesses operated by an individual, this multiple loan flag rate may not be surprising in the absence of fraud.

Moreover, the IRS study concerns individual taxpayers, not individual addresses. It must be the case that many Blueacorn applicants live at the same residential address as other adults and it is reasonable to expect many of those other adults to also operate businesses, such as gig work, and to have applied for PPP loans.

To assess the extent to which the reported rate of multiple loans may be attributable to single individuals as opposed to multiple individuals listing the same residential address, I report here on two random samples of residential addresses associated with two loans—one sample where each pair of loans includes a Blueacorn lender loan and a second sample where each pair of loans includes a traditional lender loan.[30] The results from the Blueacorn sample indicate that loans to two different individuals constitute the great majority—almost 80 percent in this

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[28] This rate is an upper bound, calculated under the hypothetical that all individuals with multiple businesses filed returns for exactly two businesses. To the extent that some individuals filed returns for more than two businesses, the rate would fall accordingly.

[29] See Panel B of Figure 2 (Griffin et al., 2021a). The rate increases to about 17 percent in Griffin et al. (2021b).

[30] One random sample includes 500 pairs of loans from among the residential addresses in the January 2022 data associated with exactly two loans where at least one of those two loans is approved by a Blueacorn lender. The other random sample includes a comparable 500 pairs of loans where at least one of the two loans is approved by a traditional lender. The address validation system I utilize does not distinguish central addresses (e.g., apartment buildings) from non-central residential addresses. However, many borrowers at central addresses report an apartment or unit number, or the like. I attempt to exclude central addresses (e.g., apartment buildings) from these random samples by finding corresponding residential addresses in the PPP data that match on street number and name, as well as city and zip code, and also include a listed apartment, unit, or suite number.

sample—of pairs listing the same residential address, with about three percent appearing to be the same individual and the remaining 17 percent indeterminate (i.e., at least one borrower name does not include the name of an identifiable person). In contrast, only about one out of every three pairs in the traditional lender sample appear to be comprised of two different individuals, with about 5 percent appearing to be the same individual, and over 60 percent indeterminate. Thus, at least for the Blueacorn sample, most of the pairs of businesses reporting the same residential address are operated by different individuals.

Finally, one must ask why the UT study restricts attention to residential addresses, or, more precisely, non-central residential addresses.[31] After all, suppose the opening statement of the section on multiple loans had stricken the word "residential," as follows:

> While it is possible that a business owner may have multiple businesses registered to the same address, the presence of multiple loans at a*[n]* ~~residential~~ address during the same draw is also a potential sign of fictitious operations.

Would the statement be any less true or noteworthy than the original statement? Restricting attention to non-central residential addresses greatly limits the number of loans made by traditional lenders that are subject to being flagged. As previously noted and detailed in Table 1, I find that no more than 42 percent of loans made by traditional lenders are associated with a non-central residential address in the June 2021 database, whereas the corresponding share is 92 percent for Blueacorn lenders and 74 percent for other FinTech lenders.[32] Thus, this metric is particularly inappropriate for assessing the multiplicity of loans made by traditional lenders and, in turn, for making comparisons of multiplicity rates between traditional and FinTech lenders, especially Blueacorn.[33]

Without an explanation, it is hard to understand why multiple loans with the same commercial address are excluded from the analysis. After all, many examples can be found where the loan details create an inference of suspicious activity.

For instance, three suspicious first-draw loans list the same commercial address in Charlotte, North Carolina, and are each approved between April 15 and May 1 of 2020. The borrowers—two sole proprietorships and a partnership—report job totals of 16, 8, and 11, and loan

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[31] The UT study excludes residential addresses that are found to be "central addresses (e.g., office and apartment buildings)" (Griffin et al., 2021a, page 9).

[32] As previously noted, the address validation system I utilize does not distinguish central addresses (e.g., apartment buildings) from non-central residential addresses. Thus, the percent of addresses found to be residential represents an upper bound on the percent that are non-central residential addresses.

[33] Note that this same concern applies to the business registry flag but in the opposite direction—that is, only a small fraction of Blueacorn businesses are subject to being flagged. However, in that case, the UT study reports results in Panel A of Figure 2 only for this restricted set of businesses (corporations, S-corporations, and LLCs), thereby increasing the depicted rate for Blueacorn and other FinTechs relative to traditional lenders. In contrast, Panel B of Figure 2 reports results for all businesses (residential or otherwise), whereas restricting it to businesses with residential addresses would have increased the depicted rate for traditional lenders much more than for Blueacorn lenders and other FinTechs.

amounts of $150,000, $300,000, and $300,000, respectively. A criminal indictment from December 2020 describes these three suspicious loans along with a $1,000,000 first-draw loan approved on May 10 of 2020 for an LLC listing a commercial address on the same street in Charlotte.[34]

As another example, six suspicious loans list the same commercial address in Las Vegas, Nevada, and another three list the same Las Vegas street address along with a suite number of 130. Five of the loans report a borrower name of National Investment Group Corporation (two in suite 130), two report a name of National Legal Advisors, and the other two borrower names begin with "National Legal Advisors" but add the words "In Care Of " in one case and "In Care Corp." in the other case in suite 130. Six of the nine loans report the same NAICS code of 541110 (offices of lawyers), whereas two report 451120 (Hobby, Toy, and Game Stores) and one reports 452319 (All Other General Merchandise Stores). All nine of these first-draw loans are approved between April 27 and June 4 of 2020, with the number of listed jobs ranging from 16 to 49 and loan amounts ranging from $93,403 (with 35 jobs) to $215, 624 (with 31 jobs). According to information in the OpenCorporates database used elsewhere in the UT study, the same individual serves as president of both National Investment Group Corporation and National Legal Advisors Corp in the state of Nevada. Five of these nine loans are also described in the first five counts of a criminal indictment from January 2021.[35]

3.2.2. Multiple loan flag in Griffin et al. (2021c)

The UT study reports on a substantially revised methodology in its third iteration. In particular, now this metric only flags loans at residential addresses associated with at least three, rather than two, loans during the same draw. This restriction brings the multiple loan flag rate for all loans down from about 8 percent to about 2 percent.[36] Thus, the reported rate of suspicious loans decreases by a factor of four when the presence of two loans at the same residential address is no longer considered to be worth flagging. The reported results for Blueacorn loans are perhaps even more striking, falling from about 16 percent to about 4.5 percent.[37]

If two loans at the same address are not worth flagging, then what about three loans? The address validation data I have obtained indicate that about three out of every four residential addresses with more than two first-draw loans have exactly three first-draw loans.[38] This finding holds for addresses of loans made by Blueacorn lenders, as well as more generally for loans made by any lender. Thus, were the next revision of the UT study to require more than

[34] See, for example, the press release at https://www.justice.gov/opa/pr/north-carolina-restaurant-owner-and-son-charged-covid-relief-fraud. The indictment is available at https://www.justice.gov/criminal-fraud/file/1354346/download, accessed 2/3/22

[35] The indictment is available at https://www.justice.gov/criminal-fraud/file/1366541/download, accessed 2/3/22.

[36] See Figure 10 in Griffin et al. (2021b) and in Griffin et al. (2021c), respectively.

[37] See Panel B of Figure 2 in Griffin et al. (2021b) and in Griffin et al. (2021c), respectively.

[38] With first-draw loans accounting for more than 90 percent of Blueacorn loans, it makes sense to restrict attention here to first-draw loans. In addition, I attempt to exclude central addresses (e.g., apartment buildings) from the analysis, as described above for the random samples.

three loans at the same address to create an inference of suspicion, then three out of every four loans flagged in the most recent revision would no longer be flagged.

3.3. High Implied Compensation Flag

In the most recent version of the UT study, the high implied compensation flag is, by far, the most prevalent of the four primary metrics of potential misreporting.[39] About eight percent of all loans are flagged as having implied compensation that exceeds an estimate of expected compensation by a factor of at least three.

The calculation of this metric is complicated, relying in part on a PPP rule that ties the loan amount to employee compensation, with individual annual compensation capped at $100,000. The method begins with an effort to impute implied average compensation at the business based on the loan amount and the reported number of jobs. Then, this imputed amount is compared to an estimate of average compensation at similarly situated businesses (i.e., same industry and same geographic region), but only if this estimated average compensation is less than $33,333.33. Finally, the loan is flagged for high implied compensation if imputed compensation is at least three times as large as estimated average compensation at similarly situated businesses.

The original methodology for calculating the high implied compensation flag contains a number of systematic problems. These problems are detailed below, followed by a discussion of the revised methodology that was adopted to address some of these concerns.

While the calculation of this metric is complicated and subject to flaws that disproportionately impact nonemployer businesses, one notable feature of the data on these businesses should not be overlooked. That is, as detailed in Table 4 for nonemployer businesses listing residential addresses, a disproportionate share of loans made by Blueacorn and other FinTech lenders include loan amounts of just over $20,000 that imply gross income in excess of $100,000. It is likely that these loans would generate a discrepancy in high implied compensation flag rates by lender type even if one were to restrict attention to nonemployer businesses.[40]

3.3.1. High implied compensation flag in Griffin et al. (2021a)

The high implied compensation flag methodology is particularly problematic when applied to Blueacorn businesses and, further, when comparisons are made between Blueacorn businesses and larger businesses with employees. First, the original UT study estimates average compensation at similarly situated businesses using County Business Patterns (CBP) payroll data pertaining only to businesses with employees, thereby excluding the nonemployer businesses that constitute the great majority of Blueacorn businesses. Second, compensation for self-employed workers tends to be systematically different from pay for employees, making this extrapolation from employee pay to nonemployer compensation more tenuous. Third,

[39] See Figure 10 of Griffin et al. (2021c).

[40] For related evidence, see Panel B of Figure IA.4 in Griffin et al. (2021c).

programmatic changes in the PPP enabled the great majority of Blueacorn businesses to seek loan amounts based on gross income rather than net income, thereby making the comparison between imputed compensation and CBP payroll data even more inappropriate. I now discuss these three issues in turn before describing some technical concerns that arise from the way the metric is constructed and the way the data on which it is based are generated.

CBP data exclude nonemployer businesses

To estimate expected average compensation at a business, the UT study uses CBP data on payrolls reported by all businesses in the same industry and geographic area, as indicated by the reported 4-digit NAICS code and core-based statistical area (CBSA) or county. The CBP data from the U.S. Census pertain only to businesses with employees. According to the 2018 County Business Patterns & Nonemployer Statistics Combined Report, the CBP data cover 7,912,405 employer business establishments and exclude 26,485,532 nonemployer business establishments (U.S. Census Bureau, 2021).[41]

Any attempt to extrapolate findings from the population of employer businesses to the population of nonemployer businesses deserves, at a minimum, an explanation as to why this extrapolation would be appropriate. Further, the methodology ignores the likelihood that average pay at a business establishment is sensitive to the number of employees at the establishment, even within industrial classification and geographic region, making the extrapolation from CBP payroll data to compensation at Blueacorn businesses more problematic.

Self-employed versus employee compensation

Compensation for self-employed workers tends to be more variable and, according to economic theory, higher than wages paid to otherwise similarly situated employees, thereby exacerbating the problem of extrapolation from CBP data. The income variability is particularly important for this metric of potential misreporting, as those with unusually high income in a given year will be flagged as high compensation because they happen to be reporting on a particularly good year.

PPP change to income basis for loan amounts

Changes in the PPP enabled Schedule C filers to apply for loan amounts based on gross income rather than net income on or after March 3, 2021.[42] Not only are the great majority of Blueacorn businesses likely to be Schedule C filers, but also 99.6 percent of all Blueacorn loans are listed as approved on or after that March 3, 2021. Thus, the great majority of Blueacorn

[41] For a U.S. Census Bureau definition of nonemployer businesses, see, for example, the description at https://www.census.gov/programs-surveys/abs/technical-documentation/NESDmethodology.html, accessed 1/20/2022: "The nonemployer universe is comprised of businesses with no paid employment or payroll, annual receipts of $1,000 or more ($1 or more in the construction industries), and filing IRS tax forms for sole proprietorships (Form 1040, Schedule C), partnerships (Form 1065), or corporations (the Form 1120 series)". Note that the owner of a single-member LLC may choose not to file a corporate tax return and instead file Schedule C.
[42] See footnote 16 in Griffin et al. (2021b).

businesses are likely eligible to seek loan amounts based on gross income that, depending on costs, can be substantially higher than net income, making the comparison between imputed compensation and CBP payroll data even more inappropriate.

For example, consider one of the most common Blueacorn businesses: taxi and limousine service. Mishel (2018) reports that Uber takes fees accounting for about one-third of passenger fares—that is, gross income—and then driving costs and other expenses must also be deducted in order to calculate net income that is perhaps just half of gross income.

Censored compensation

For businesses with employees, allowable PPP loan amounts are based in part on 2.5 months of average monthly payroll expenses, with individual compensation capped at a maximum annual rate of $100,000. Where annual compensation for each employee falls short of $100,000, the UT study imputation method of dividing the loan amount by the number of reported jobs may be appropriate. However, when one or more employees earns six figures, the method breaks down as the implicitly reported compensation is censored at $100,000.

This problem is easiest to observe when there is just one job reported and the individual earns six-figure compensation, as the loan amount would be $20,833.33—that is, 2.5 x $100,000/12. When there is more than one job, however, it is not possible to know how much censoring is occurring unless every employee has six-figure compensation.[43]

This statistical issue creates yet another problem when attempting to compare findings for Blueacorn businesses to findings for larger businesses. For example, a business with two employees earning $60,000 and, say, $150,000 (or even $250,000 or $350,000) will be found to have lower imputed average compensation—the average of $60,000 and $100,000—than every nonemployer business with more than $80,000 in gross income.

Excluded loans

The censoring at $100,000 also creates a sample censoring problem for this metric that flags loans when imputed compensation exceeds estimated expected compensation by a factor of three. With implicit compensation censored at $100,000, the UT study chooses to exclude any loan where similarly situated businesses are estimated to have average compensation in excess of $33,333.33. Additional loans are excluded whenever the CBP data do not include reports for the relevant industry-geography pair. In total, only 3,297,068 out of the 10,697,219 loans analyzed in the first version of the UT study, or just over 30 percent of the loans, are reportedly included in the calculations.[44] Thus, almost 70 percent of loans are not subject to being flagged

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[43] For example, if a loan reports two jobs and a loan amount of $41,666.66 (2 x $20,833.33), then both jobs may be inferred to have six-figure compensation. However, if the amount were instead $41,500 or even, say, $25,000, then either one or neither of the two jobs may have six-figure compensation.

[44] See footnote 18 of Griffin et al. (2021a).

as high compensation, including about 73 percent of loans approved by traditional lenders versus just 60 percent of loans approved by FinTech lenders.[45]

Measurement error and misclassification

A loan is flagged for high compensation based on the ratio of the estimate of the value of one random variable—average compensation at the business—to the estimate of the value of another random variable—expected average compensation at businesses similar to the business that took the loan. The estimates in both the numerator and the denominator of the ratio are subject to measurement error.

Whenever the error is positive for the numerator or negative for the denominator, then the ratio may erroneously increase past the threshold value of three for the loan to be misclassified as high compensation. Conversely, negative errors in the numerator and positive errors in the denominator may lead to misclassifications in which the loan is not flagged as high compensation.

Censoring at $100,000 of reported compensation at firms with some employees earning more than this amount and some earning less is a measurement problem that results in negative errors in the numerator, making loans less likely to be classified as high compensation. This aspect of censoring does not impact the flag rate for businesses with one job, but it will impact —that is, reduce—the flag rate for larger businesses, thereby invalidating comparisons of high compensation flag rates across these groups of businesses.

The CBP data are a source of measurement error in the denominator that may cause misclassification. In order to avoid disclosing data for individual companies when, for instance, few companies are in the same industry-geography pair, the Census may suppress data from publication, as alluded to above regarding excluded businesses. In other cases, however, CBP will actually infuse the data with noise and describe the published data as including low, medium, or high "noise infusion."[46] This noise is a source of measurement error in the denominator that leads to classification errors in the high compensation flag.

3.3.2. High implied compensation flag in Griffin et al. (2021b, 2021c)

In its second iteration, the UT study notes that "Schedule C filers also had the option to use gross income instead of net income for owner compensation after March 3, 2021."[47] To address this concern about PPP changes to the income basis for loan amounts, the UT study revises the methodology for flagging loans as high implied compensation when the borrower is reported to be sole proprietor, independent contractor, self-employed, or single-member LLC with a loan date after March 3, 2021.

[45] See the sample sizes reported in Table III of Griffin et al. (2021a).
[46] See, for example, U.S. Census Bureau (2017).
[47] See footnote 16 of Griffin et al. (2021b).

In particular, the estimate of the benchmark (denominator) against which to compare the estimate of implied compensation (numerator) is now based on the greater of (i) the previously utilized CBP data estimate of average compensation at similarly situated businesses with employees and (ii) "industry/CBSA average receipts for single-employee firms."[48] No data source is reported in Griffin et al. (2021b) for average receipts of single-employee firms, and it is not clear that any such federal statistics have been published on firms with one employee. The second revision of the UT study reports the source to be "Nonemployer Statistics (NES) data from the US Census" (Griffin et al., 2021c).

This methodological revision appears intended to address two of the six main areas of concern listed above: the exclusion of nonemployer businesses from CBP data and the PPP change to the income basis for loan amounts. However, the other concerns remain and may be heightened by the use of NES data, especially with respect to measurement error and misclassification because of this metric's crucial reliance on data for specific industry-geography pairs.

Variability in NES data on average receipts based on geographic definition

Consider, for example, the data for the most prevalent NAICS code for Blueacorn businesses: 8121 personal care services. According to the most recent CSA-level data posted on the Census website, average receipts in 2018 for such nonemployer businesses range from $14,446 (CSA 185,Cleveland-Indianola, MS)[49] to $36,564 (CSA 488, San Jose-San Francisco-Oakland, CA)[50] over the 172 CSAs reported.[51] In contrast, county-level data for 2018 receipts range from an average of $4,000 in Foard County, Texas to $97,000 in McPherson County, Nebraska.

It is not clear whether the UT study uses the county-level data or the CSA-level data or a different unit of observation. It is clear, however, that this choice is important. For instance, consider a personal care services business with gross income of $83,000 or more in San Joaquin County, California in the San Jose-San Francisco-Oakland CSA. The NES data on 2,543 such businesses in this county have average receipts of $27,570. In contrast, the 28,119 such businesses in this CSA have average receipts of $36,564. If the county average were used for the denominator, then the calculated ratio for a business with income of $83,000 would be 3.01 and the loan would be flagged as high implied compensation. In contrast, if the CSA average were used, then the denominator would increase by about one-third and the calculated ratio would fall to 2.27, below the threshold value of 3.0 to be flagged as high compensation.

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[48] See footnote 17 of Griffin et al. (2021b).

[49] CSA 185 includes two counties in Mississippi: Bolivar and Sunflower.

[50] CSA 488 includes 12 counties in California: Alameda, Contra Costa, Marin, Napa, San Benito, San Francisco, San Joaquin, San Mateo, Santa Clara, Santa Cruz, Solano, and Sonoma.

[51] See https://www.census.gov/data/datasets/2018/econ/nonemployer-statistics/2018-ns.html accessed 1/24/2021.

In fact, this hypothetical business would be excluded from the analysis if the CSA average were used, because, as noted above, loans are excluded whenever the estimate for the denominator exceeds $33,333.33 or is not available. In the final version of the analysis, 3,416,620 loans are reported to be included in the analysis of high implied compensation.[52] Thus, 8,352,069 loans, or more than 70 percent of all loans in the June 2021 data, are excluded from being flagged by this metric of potential misreporting. Once again, loans approved by traditional lenders are excluded at a higher rate (73 percent) than loans approved by FinTech lenders (60 percent).[53]

Heterogeneity and self-selection of nonemployer businesses within industry-geography pairs

Finally, one must again consider the variability of gross income for nonemployer businesses, not only for a given business over time but also across businesses in a given year. Garin and Koustas (2021) highlight the heterogeneity of these businesses, ranging from those that engage in the work as a supplement for paid work to those that rely on it as the main source of income. The NES data cover all nonemployer businesses with receipts in excess of $1000 ($1 for construction). Thus, average receipts will likely be a downward-biased estimate of expected gross income (denominator) for any nonemployer business that devotes more time to the activity than the average nonemployer business in that industry-geography pair.

It is plausible that more active nonemployer business owners are more likely to apply for PPP loans than less active ones. If this form of self-selection is present in the PPP data, then this metric of misreporting would be systematically biased in favor of flagging nonemployer businesses for high implied compensation.

3.4. EIDL Advance Jobs Flag

The fourth and final primary metric of potential misreporting concerns discrepancies between the number jobs reported in the PPP loan application and the number of jobs that may be inferred from data on Economic Injury Disaster Loan (EIDL) Advances of up to $10,000 made in 2020. In particular, with EIDL amounts of $1,000 per employee, the UT study calculates the implied number of employees as one for every $1,000, up to a maximum of 10 employees.[54]

This metric flags loans for only one type of discrepancy; that is, loans are flagged when the number of jobs implied by the EIDL data exceeds the number of jobs reported in the PPP data. Cases where the number of jobs reported in the PPP data exceeds the number implied by the EIDL data are not flagged.

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[52] See footnote 19 of Griffin et al. (2021c).
[53] See sample sizes reported in Table III of Griffin et al. (2021c).
[54] The EIDL rules changed in 2021, as described in footnote 20 of Griffin et al. (2021a): "The EIDL Advance rules changed for 2021 to: A) provide the entire $10,000 regardless of employee count, and B) to target the advances to low-income communities and those with a demonstrated decrease in revenue." Thus, EIDL amounts in 2021 are unrelated to employee counts. The UT study restricts attention to the 2020 EIDL data.

Moreover, loans are only flagged when the number of EIDL jobs exceeds PPP jobs by at least three. Therefore, with a maximum of 10 jobs imputed based on the EIDL data, only loans reporting seven or fewer jobs in the PPP data are subject to being flagged. As discussed above and detailed in Tables 1 through 3, loans to such small businesses are much more likely to have been made by FinTech lenders, especially Blueacorn lenders, than by traditional lenders. For instance, Table 1 shows that, in the June 2021 data, 99.9 percent of loans made by Blueacorn lenders report seven or fewer jobs versus 73 percent of loans found to have been made by traditional lenders. More than one out of every four of these traditional lender loans, therefore, are not subject to being flagged by this metric of misreporting.

The UT study does not report on the share of loans that are subject to being flagged. In addition to not flagging loans with more than seven reported jobs, loans are excluded from the analysis unless the PPP borrower is also found in the EIDL data from 2020. The UT study reports: "we match borrowers in the PPP and EIDL loan-level datasets based on business name and zip code."[55] It appears that about one out of every four loans is matched to EIDL data,[56] but no information is provided on the efforts made to ensure that such matches are valid. Further, the study does not address the question of whether the number of jobs inferred from 2020 EIDL data should be expected to equal the number of jobs reported perhaps many months later in the PPP, such as on or after March 3, 2021 as would be the case for more than 99 percent of loans made by Blueacorn lenders.

Finally, one must question why this metric is used to flag potential misreporting *in the PPP data*. Even the authors of the UT study acknowledge, "The EIDL > PPP jobs flag is primarily an indicator of misreporting on the EIDL application."[57] They immediately rebut this concern with the conjecture that "applicants who misreport in one area are likely willing to misreport in other areas too."

4. Secondary Metrics of Potential Misreporting

The UT study reports on five secondary metrics of potential misreporting. While these metrics are introduced with a claim to creating "an inference that a loan is suspicious," they have no direct impact on headline numbers reported regarding the extent of potential misreporting, the relative rates of potential misreporting by borrowers from FinTech lenders versus traditional lenders, nor the total dollar amount of loans that are flagged as suspicious. Instead, the analysis of the secondary metrics mainly utilizes the measures as "external verification" for the primary metrics.

[55] Griffin et al., 2021a, page 5.
[56] See sample sizes reported in Table III in each version of the UT study.
[57] Griffin et al., 2021a, page 12.

The five secondary metrics are as follows: (1) *discontinuities at $100,000 compensation*, (2) *rounded loan amounts*, (3) *loan overrepresentation*, (4) *loan clustering*, and (5) *criminal records*. In the discussion below, I highlight key concerns regarding the usefulness of these five secondary metrics for assessing potential and actual fraud in the PPP loan program. Far from serving as some sort of external verification for the four primary metrics, these metrics tend to suffer from the same problems described in the previous section, including calculation methods that rely on inappropriate data and that seem more likely to flag loans made to nonemployer businesses regardless of similarities or differences in the actual rates of fraudulent activity.

4.1. Discontinuities at $100,000 Compensation

The analysis of secondary metrics begins by reporting on the rates of flagged loans at and around implied compensation of $100,000. The section begin as follows:

> PPP loan size is calculated as 2.5 times a borrower's average monthly payroll, including up to $100,000 in wages per employee. This $100,000 cutoff is a hard maximum for self-employment compensation. For other employees, payroll expenses also include employer insurance and retirement contributions and unemployment taxes, which can push included payroll expenses above $100,000 per employee. Someone filling out a fraudulent PPP application and who may not have carefully read the PPP rules, might want to maximize their loan amount by submitting payroll expenses at or close to the $100,000 per employee limit without the additional expenses that are eligible with proper payroll details.[58]

This description and conjecture about fraudulent applications ignores the PPP changes to the income basis for loan amounts to nonemployer businesses after March 3, 2021, as discussed above and in footnotes of the most recent revision of the UT study. It is therefore my understanding that this description, which draws attention to the cutoff for self-employment compensation, has no relevance for the self-employed after March 3, 2021—i.e., the great majority of Blueacorn businesses—because they may seek loan amounts based on gross income rather than net income.

Further, as also discussed above, the censoring of compensation at $100,000 has a different effect on businesses with one job, such as over 99 percent of Blueacorn businesses, than it has on larger businesses. That is, when these larger business have some or many employees with six-figure compensation but at least one employee with lesser compensation, then the average of censored compensation will necessarily be less than $100,000, thereby smoothing out the data and reducing related discontinuities, even if average uncensored compensation exceeds this amount. Therefore, as in the case of the high implied compensation flag rates, comparison of discontinuities at $100,000 for nonemployer businesses and larger businesses is not appropriate.

[58] Griffin et al., 2021c, page 15.

Moreover, with the same underlying statistical issue causing related problems, one should not view findings based on this discontinuity metric as external verification of the high implied compensation metric. The two metrics rely on the same information and tell related stories.

4.2. Rounded Loan Amounts

Next, the UT study looks for elevated flag rates at rounded loan amounts, based on the following assertion:

> Rounded loan amounts suggest that the numbers are potentially fictitious as opposed to being based on actual documented data.[59]

This assertion presents a false dichotomy between fictitious data and documented data. It is well understood that rounding may convey imprecision or uncertainty. See, for example, the discussion by Binder (2017). To the extent that loan applications were not completed while sitting with fully audited financial results for the year in question, then one should expect some imprecision and uncertainty. Further, the applicant may be expected to round somewhat when reporting on, for instance, 2.5 x Average Monthly Payroll.

The extent to which rounding occurs may be indicative of something about the business. While fictitious data is one possibility, other possibilities include variability of income and variability in record-keeping habits prior to filing reports based on audited results. Once again, these sources of rounding seem more likely to be associated with nonemployer businesses, including gig work, than with larger businesses. This rounding may then, in turn, be correlated with the primary metrics based on underlying statistical reporting issues rather than fraudulent activity. That is, this secondary metric may be spuriously correlated with the primary metrics rather than providing external verification.

4.3. Loan Overrepresentation

The UT study seeks to identify "networks of illegitimate borrowers" by searching for concentrations of PPP borrowers in the same industry-geography pair in excess of the total number of businesses believed to exist in that industry-geography pair. CBP data are used to estimate this total number of businesses. Many cases are found where the number of PPP borrowers exceeds the estimated total number of businesses by a factor of two or more, especially for FinTech lenders.

As detailed above, the CBP data exclude nonemployer businesses. U.S. Census data indicate that the number of nonemployer business establishments exceeds the number of employer business establishments by a factor of more than three to one (U.S. Census Bureau, 2021). While the UT study acknowledges that "the CBP data does not include self-employed and independent contractors as establishments," it chooses to exclude only those PPP borrowers listed as self-employed or independent contractor from the counts of PPP borrowers in an

[59] Griffin et al., 2021c, page 17.

industry-geography pair. Sole proprietors with one reported job, including nearly two out of every three Blueacorn businesses, should be excluded as well. The recent Autor et al. (2022) analysis of the PPP data, for example, does just that, classifying as nonemployer businesses the borrowers reporting one job and a business type of sole proprietor, self-employed, independent contractor, or single-member LLC.[60]

Rather than providing external verification, the UT study decision to include sole proprietorships in the counts of PPP borrowers invalidates the findings on loan overrepresentation. This problem disproportionately impacts the results for FinTech lenders, especially Blueacorn lenders.

4.4. Loan Clustering

The UT study seeks to identify other such "clustering," beyond clustering within industry-geography pairs. This alternative method includes the loan amount and the number of reported jobs in the definition of the concentration ratio used to characterize the extent of clustering. However, "because it is common across all lenders," a report of exactly one job is excluded from this concentration ratio.[61] Thus, all but 0.2 percent of Blueacorn loans are apparently excluded. Findings regarding this metric should therefore have no bearing on findings regarding potential misreporting for Blueacorn lenders.

4.5. Criminal Records

The UT study reports that the PPP began with strong restrictions on loans to individuals with criminal records or facing criminal changes, but these restrictions were substantially weakened in June 2020 for non-financial crimes. Citing recidivism statistics on criminal behavior, the authors of the UT study posit that individuals with past criminal histories, including and perhaps exclusively non-financial crimes, will be more likely to commit PPP fraud.

To assess the prevalence of criminal records among PPP borrowers, the study relies on criminal background data from a LexisNexis search based on the borrower's name and address for a random sample of PPP borrowers in rounds 1 and 2. This analysis is problematic in many ways, especially with respect to Blueacorn borrowers.

Anyone considering performing such an analysis of non-financial criminal records should be aware of the disparate impact this analysis would likely have with respect to members of racial and ethnic minority groups. As discussed above, these individuals are much more likely to be found among Blueacorn borrowers than among borrowers from other lenders. Perhaps that is reason enough to disregard this secondary metric.

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[60] See, for example, the note at the bottom of Table 1 in Autor et al. (2022): "Note. Panels A and B reflect data on employer businesses. The main panels exclude loans to the self-employed, sole proprietors, independent contractors, and single-member LLCs with only one reported job because non-employers are excluded from the SUSB data used to calculate the denominator of the takeup rates displayed in column (5)."

[61] Griffin et al., 2021c, page 20.

It is worth noting, however, that this metric is yet another case that disproportionately impacts, by design, nonemployer businesses relative to larger businesses. As noted in footnote 7 of Griffin et al. (2021c), the random sample of 150,000 individuals for the LexisNexis search is restricted to loans where the businesses type is listed as self-employed, independent contractor, or sole proprietor, and where the reported borrower name appears to be the name of an individual. Loans made by FinTech lenders, especially Blueacorn lenders, are much more likely to be included in this analysis than loans made by traditional lenders.

5. Concluding Remarks

The UT study attempts to perform a big data analysis of PPP loans to identify potentially fraudulent activity. The authors of the study note that each metric of potential misreporting "creates an inference that a loan is suspicious but is not proof of misreporting on its own."[62] My analysis of the UT study raises serious concerns about the links between these metrics and this inference of suspicion, noting how problems with the metrics differentially impact the findings for loans approved by FinTech lenders, especially Blueacorn lenders, relative to the findings for loans approved by traditional lenders.

Even if we were to accept the published numbers at face value, we would be left wondering how the published rates of potential misreporting relate to such actual misreporting as overstated incomes or even fictitious businesses. For instance, relative to traditional lenders, it is evident that a disproportionate share of nonemployer business loans approved by Blueacorn and other FinTech lenders are for amounts of just over $20,000 that imply annual gross income in excess of $100,0000. What is not clear is what one should infer and what actions should be taken based on this one piece of information that likely has an outsized impact on UT study findings of discrepancies in potential rates of fraud between FinTech lenders and traditional lenders.

Nothing in the UT study can answer the key question of how many flagged loans are actually fraudulent loans as opposed to what may be thought of as false positives. Similarly, the UT study tells us nothing about the rate of fraudulent activity among loans that were not flagged—that is, false negatives. Instead, the UT study offers this assessment:

> While some of the loans flagged as suspicious by the primary measures may be sincere mistakes or errors in the data, these four measures surely miss many fraudulent loans.[63]

The unknown rates of false positives and false negatives are related to the specificity and the sensitivity of the test, which are two terms that are now much more familiar to us all than in pre-Covid times. As in the case of Covid testing, without some understanding of the specificity

[62] Griffin et al., 2021a, page 1.
[63] Griffin et al., 2021c, page 23.

and the sensitivity of the test, it is difficult to know whether to recommend strong actions in response to a positive test and take comfort in a negative test, to ignore the test result in the absence of additional supporting evidence, or to perhaps abandon this form of testing because of the potentially harmful impacts of actions taken in response to false positives and false negatives.

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Table 1. PPP Loan Attributes, by Lender Type: June 2021 Data

			All Loans		Lender Type							
					Blueacorn		Other FinTech		Traditional		Not Classified	
		Attribute	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans
Borrower Attributes	Business Type	Corporation	2,300,675	19.6%	1,164	0.1%	231,230	7.7%	1,199,661	29.8%	868,620	23.0%
		Independent Contractors	896,361	7.6%	245,199	25.6%	444,632	14.8%	123,585	3.1%	82,945	2.2%
		Limited Liability Company(LLC)	2,393,853	20.3%	62,471	6.5%	291,393	9.7%	1,087,251	27.0%	952,738	25.3%
		Self-Employed Individuals	921,329	7.8%	38,348	4.0%	554,018	18.4%	135,721	3.4%	193,242	5.1%
		Single Member LLC	75,233	0.6%	4,674	0.5%	33,136	1.1%	16,253	0.4%	21,170	0.6%
		Sole Proprietorship	3,601,594	30.6%	606,342	63.2%	1,265,208	42.1%	767,490	19.1%	962,554	25.5%
		Subchapter S Corporation	1,072,388	9.1%	378	0.0%	148,812	5.0%	480,455	11.9%	442,743	11.7%
		Other	504,937	4.3%	569	0.0%	39,728	1.3%	215,871	5.4%	248,769	6.6%
		Missing	2,319	0.0%	0	0.0%	18	0.0%	2,282	0.1%	19	0.0%
	Number of Reported Jobs	0	209	0.0%	0	0.0%	15	0.0%	35	0.0%	159	0.0%
		1	6,309,558	53.6%	957,305	99.8%	2,409,521	80.1%	1,446,993	35.9%	1,495,739	39.7%
		2-4	2,061,859	17.5%	763	0.1%	269,639	9.0%	992,979	24.7%	798,478	21.2%
		5-7	1,059,804	9.0%	336	0.0%	122,309	4.1%	508,293	12.6%	428,866	11.4%
		8-10	622,211	5.3%	258	0.0%	69,340	2.3%	292,998	7.3%	259,615	6.9%
		11-20	846,544	7.2%	271	0.0%	79,009	2.6%	387,458	9.6%	379,806	10.1%
		21-50	578,937	4.9%	114	0.0%	42,011	1.4%	259,991	6.5%	276,821	7.3%
		51-100	172,268	1.5%	61	0.0%	10,270	0.3%	79,537	2.0%	82,400	2.2%
		101-500	117,291	1.0%	37	0.0%	6,061	0.2%	60,284	1.5%	50,909	1.4%
		501+	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Missing	7	0.0%	0	0.0%	0	0.0%	1	0.0%	6	0.0%
	NAICS Code	Residential Building Construction (2361)	328,879	2.8%	50,503	5.3%	83,962	2.8%	95,145	2.4%	99,269	2.6%
		Taxi and Limousine Service (4853)	292,438	2.5%	53,251	5.6%	183,751	6.1%	39,972	1.0%	15,464	0.4%
		Services to Buildings and Dwellings (5617)	348,166	3.0%	55,130	5.8%	120,232	4.0%	88,101	2.2%	84,703	2.3%
		Personal Care Services (8121)	815,452	6.9%	186,890	19.5%	342,531	11.4%	153,121	3.8%	132,910	3.5%
		Other NAICS classification	9,851,351	83.7%	613,371	64.0%	2,265,395	75.3%	3,532,197	87.7%	3,440,388	91.2%
		Missing	132,403	1.1%	0	0.0%	12,304	0.4%	120,033	3.0%	66	0.0%
	Address	Residential	6,515,239	55.4%	885,142	92.3%	2,212,480	73.6%	1,695,786	42.1%	1,721,831	45.6%
		Commerical	4,465,441	37.9%	27,907	2.9%	591,265	19.7%	2,029,658	50.4%	1,816,611	48.2%
		Not classidfied	788,009	6.7%	46,096	4.8%	204,430	6.8%	303,125	7.5%	234,358	6.2%
	Gender	Female Owned	1,593,125	13.5%	396,062	41.3%	397,129	13.2%	366,247	9.1%	433,687	11.5%
		Male Owned	2,971,769	25.3%	373,405	38.9%	546,701	18.2%	893,003	22.2%	1,158,660	30.7%
		Unanswered	7,203,795	61.2%	189,678	19.8%	2,064,345	68.6%	2,769,319	68.7%	2,180,453	57.8%
	Race	American Indian or Alaska Native	85,517	0.7%	6,494	0.7%	5,777	0.2%	61,272	1.5%	11,974	0.3%
		Asian	295,936	2.5%	12,138	1.3%	68,775	2.3%	124,497	3.1%	90,526	2.4%
		Black or African American	892,722	7.6%	531,519	55.4%	221,537	7.4%	88,454	2.2%	51,212	1.4%
		Eskimo & Aleut	22	0.0%	0	0.0%	3	0.0%	8	0.0%	11	0.0%
		Multi Group	57	0.0%	1	0.0%	7	0.0%	43	0.0%	6	0.0%
		Native Hawaiian or Other Pacific Islander	10,759	0.1%	3,736	0.4%	1,800	0.1%	2,485	0.1%	2,738	0.1%
		Puerto Rican	705	0.0%	4	0.0%	33	0.0%	595	0.0%	73	0.0%
		Unanswered	8,912,783	75.7%	277,593	28.9%	2,534,284	84.3%	3,206,295	79.6%	2,894,611	76.7%
		White	1,570,188	13.3%	127,660	13.3%	175,959	5.9%	544,920	13.5%	721,649	19.1%
	Ethnicity	Hispanic or Latino	371,670	3.2%	66,952	7.0%	84,423	2.8%	138,198	3.4%	82,097	2.2%
		Not Hispanic or Latino	2,986,511	25.4%	628,350	65.5%	425,983	14.2%	820,083	20.4%	1,112,095	29.5%
		Unknown/NotStated	8,410,508	71.5%	263,843	27.5%	2,497,769	83.0%	3,070,288	76.2%	2,578,608	68.4%
Lender Attributes	Type	Blueacorn	959,145	8.2%	959,145	100.0%	0	0.0%	0	0.0%	0	0.0%
		Other FinTech	3,008,175	25.6%	0	0.0%	3,008,175	100.0%	0	0.0%	0	0.0%
		Traditional	4,028,569	34.2%	0	0.0%	0	0.0%	4,028,569	100.0%	0	0.0%
		Not classified	3,772,800	32.1%	0	0.0%	0	0.0%	0	0.0%	3,772,800	100.0%
Loan Attributes	Approval Date	Before March 3, 2021	7,295,211	62.0%	3,574	0.4%	1,207,612	40.1%	3,133,429	77.8%	2,950,596	78.2%
		On or after March 3, 2021	4,473,478	38.0%	955,571	99.6%	1,800,563	59.9%	895,140	22.2%	822,204	21.8%
	Draw	First Draw	8,863,652	75.3%	880,379	91.8%	2,235,932	74.3%	2,932,565	72.8%	2,814,776	74.6%
		Second Draw	2,905,037	24.7%	78,766	8.2%	772,243	25.7%	1,096,004	27.2%	958,024	25.4%
	Current Approval Amount	Less than $5,000	1,434,527	12.2%	114,016	11.9%	492,847	16.4%	404,372	10.0%	423,292	11.2%
		$5,000-$9,999	1,596,904	13.6%	120,136	12.5%	451,311	15.0%	530,831	13.2%	494,626	13.1%
		$10,000-$14,999	1,256,437	10.7%	106,380	11.1%	335,784	11.2%	433,478	10.8%	380,795	10.1%
		$15,000-$19,999	1,139,594	9.7%	152,744	15.9%	349,358	11.6%	345,618	8.6%	291,874	7.7%
		$20,000-$24,999	2,517,535	21.4%	463,394	48.3%	1,003,101	33.4%	519,485	12.9%	531,555	14.1%
		$25,000-$29,999	375,369	3.2%	1,271	0.1%	57,067	1.9%	172,416	4.3%	144,615	3.8%
		$30,000-$39,999	539,429	4.6%	213	0.0%	59,014	2.0%	260,602	6.5%	219,600	5.8%
		$40,000-$49,999	407,145	3.5%	118	0.0%	43,337	1.4%	196,160	4.9%	167,530	4.4%
		$50,000-$99,999	1,056,858	9.0%	303	0.0%	103,966	3.5%	503,864	12.5%	448,725	11.9%
		$100,000-$249,999	866,267	7.4%	389	0.0%	76,488	2.5%	398,253	9.9%	391,137	10.4%
		$250,000 or more	578,624	4.9%	181	0.0%	35,902	1.2%	263,490	6.5%	279,051	7.4%
	Status	Active Un-Disbursed	465,769	4.0%	148,798	15.5%	227,711	7.6%	63,647	1.6%	25,613	0.7%
		Exemption 4	8,214,245	69.8%	810,347	84.5%	2,508,097	83.4%	2,621,822	65.1%	2,273,979	60.3%
		Paid in Full	3,088,675	26.2%	0	0.0%	272,367	9.1%	1,343,100	33.3%	1,473,208	39.1%
Nonemployer Business, Residential, on or after March 3, 2021		Yes	3,067,283	26.1%	828,407	86.4%	1,466,339	48.8%	347,450	8.6%	425,087	11.3%
		No	8,701,406	73.9%	130,738	13.6%	1,541,836	51.3%	3,681,119	91.4%	3,347,713	88.7%
TOTAL			11,768,689	100.0%	959,145	100.0%	3,008,175	100.0%	4,028,569	100.0%	3,772,800	100.0%

Table 2. PPP Loan Attributes, by Lender Type: November 2021 Data

					Lender Type							
			All Loans		Blueacorn		Other FinTech		Traditional		Not Classified	
		Attribute	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans
Borrower Attributes	Business Type	Corporation	2,310,158	20.1%	1,152	0.1%	232,712	8.1%	1,199,132	30.3%	877,162	23.2%
		Independent Contractors	833,427	7.3%	221,192	26.2%	417,220	14.5%	112,973	2.9%	82,042	2.2%
		Limited Liability Company(LLC)	2,381,423	20.8%	58,403	6.9%	287,007	10.0%	1,078,016	27.2%	957,997	25.3%
		Self-Employed Individuals	888,240	7.7%	33,585	4.0%	530,617	18.4%	132,079	3.3%	191,959	5.1%
		Single Member LLC	69,335	0.6%	4,244	0.5%	29,974	1.0%	14,209	0.4%	20,908	0.6%
		Sole Proprietorship	3,431,096	29.9%	523,887	62.1%	1,201,804	41.7%	736,438	18.6%	968,967	25.6%
		Subchapter S Corporation	1,055,263	9.2%	359	0.0%	142,866	5.0%	474,053	12.0%	437,985	11.6%
		Other	503,767	4.4%	549	0.0%	38,863	1.4%	214,100	5.4%	250,255	6.6%
		Missing	2,295	0.0%	0	0.0%	17	0.0%	2,260	0.1%	18	0.0%
	Number of Reported Jobs	0	209	0.0%	0	0.0%	15	0.0%	35	0.0%	159	0.0%
		1	6,030,056	52.6%	841,542	99.8%	2,290,390	79.5%	1,397,031	35.3%	1,501,093	39.6%
		2-4	2,055,128	17.9%	759	0.1%	265,739	9.2%	986,807	24.9%	801,823	21.2%
		5-7	1,056,878	9.2%	334	0.0%	120,598	4.2%	505,226	12.8%	430,720	11.4%
		8-10	620,480	5.4%	256	0.0%	68,375	2.4%	291,111	7.4%	260,738	6.9%
		11-20	844,819	7.4%	271	0.0%	78,092	2.7%	385,160	9.7%	381,296	10.1%
		21-50	578,187	5.0%	113	0.0%	41,667	1.5%	258,586	6.5%	277,821	7.3%
		51-100	172,065	1.5%	61	0.0%	10,184	0.4%	79,211	2.0%	82,609	2.2%
		101-500	117,174	1.0%	35	0.0%	6,020	0.2%	60,092	1.5%	51,027	1.4%
		501+	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Missing	7	0.0%	0	0.0%	0	0.0%	1	0.0%	6	0.0%
	NAICS Code	Residential Building Construction (2361)	318,012	2.8%	44,420	5.3%	80,801	2.8%	93,276	2.4%	99,515	2.6%
		Taxi and Limousine Service (4853)	278,203	2.4%	48,945	5.8%	176,297	6.1%	37,546	1.0%	15,415	0.4%
		Services to Buildings and Dwellings (5617)	331,775	2.9%	48,098	5.7%	113,292	3.9%	85,360	2.2%	85,025	2.3%
		Personal Care Services (8121)	766,611	6.7%	160,854	19.1%	324,541	11.3%	147,339	3.7%	133,877	3.5%
		Other NAICS classification	9,648,062	84.1%	541,054	64.2%	2,173,852	75.5%	3,479,761	87.8%	3,453,395	91.2%
		Missing	132,341	1.2%	0	0.0%	12,297	0.4%	119,978	3.0%	66	0.0%
	Address	Residential	6,264,384	54.6%	777,152	92.2%	2,105,559	73.1%	1,654,670	41.8%	1,727,003	45.6%
		Commerical	4,446,404	38.8%	25,326	3.0%	581,555	20.2%	2,014,747	50.8%	1,824,776	48.2%
		Not classifdied	764,216	6.7%	40,893	4.9%	193,966	6.7%	293,843	7.4%	235,514	6.2%
	Gender	Female Owned	1,533,903	13.4%	349,072	41.4%	385,616	13.4%	364,362	9.2%	434,853	11.5%
		Male Owned	2,918,015	25.4%	330,550	39.2%	533,468	18.5%	890,960	22.5%	1,163,037	30.7%
		Unanswered	7,023,086	61.2%	163,749	19.4%	1,961,996	68.1%	2,707,938	68.3%	2,189,403	57.8%
	Race	American Indian or Alaska Native	84,703	0.7%	5,892	0.7%	5,650	0.2%	61,107	1.5%	12,054	0.3%
		Asian	297,649	2.6%	11,369	1.4%	68,548	2.4%	125,076	3.2%	92,656	2.5%
		Black or African American	821,554	7.2%	466,767	55.4%	216,849	7.5%	86,441	2.2%	51,497	1.4%
		Eskimo & Aleut	21	0.0%	0	0.0%	2	0.0%	8	0.0%	11	0.0%
		Multi Group	54	0.0%	1	0.0%	6	0.0%	41	0.0%	6	0.0%
		Native Hawaiian or Other Pacific Islander	10,388	0.1%	3,362	0.4%	1,773	0.1%	2,507	0.1%	2,746	0.1%
		Puerto Rican	680	0.0%	4	0.0%	30	0.0%	576	0.0%	70	0.0%
		Unanswered	8,698,735	75.8%	242,044	28.7%	2,414,012	83.8%	3,141,316	79.3%	2,901,363	76.6%
		White	1,561,220	13.6%	113,932	13.5%	174,210	6.1%	546,188	13.8%	726,890	19.2%
	Ethnicity	Hispanic or Latino	364,202	3.2%	60,715	7.2%	83,285	2.9%	137,877	3.5%	82,325	2.2%
		Not Hispanic or Latino	2,908,796	25.4%	553,734	65.7%	419,675	14.6%	818,603	20.7%	1,116,784	29.5%
		Unknown/NotStated	8,202,006	71.5%	228,922	27.1%	2,378,120	82.5%	3,006,780	75.9%	2,588,184	68.3%
Lender Attributes	Type	Blueacorn	843,371	7.4%	843,371	100.0%	0	0.0%	0	0.0%	0	0.0%
		Other FinTech	2,881,080	25.1%	0	0.0%	2,881,080	100.0%	0	0.0%	0	0.0%
		Traditional	3,963,260	34.5%	0	0.0%	0	0.0%	3,963,260	100.0%	0	0.0%
		Not classified	3,787,293	33.0%	0	0.0%	0	0.0%	0	0.0%	3,787,293	100.0%
Loan Attributes	Approval Date	Before March 3, 2021	7,289,511	63.5%	3,522	0.4%	1,204,460	41.8%	3,117,280	78.7%	2,964,249	78.3%
		On or after March 3, 2021	4,185,493	36.5%	839,849	99.6%	1,676,620	58.2%	845,980	21.4%	823,044	21.7%
	Draw	First Draw	8,619,597	75.1%	772,906	91.6%	2,141,023	74.3%	2,880,153	72.7%	2,825,515	74.6%
		Second Draw	2,855,407	24.9%	70,465	8.4%	740,057	25.7%	1,083,107	27.3%	961,778	25.4%
	Current Approval Amount	Less than $5,000	1,405,804	12.3%	104,531	12.4%	480,918	16.7%	395,688	10.0%	424,667	11.2%
		$5,000-$9,999	1,570,819	13.7%	111,716	13.3%	439,387	15.3%	522,893	13.2%	496,823	13.1%
		$10,000-$14,999	1,232,391	10.7%	97,364	11.5%	325,730	11.3%	426,992	10.8%	382,305	10.1%
		$15,000-$19,999	1,100,439	9.6%	136,330	16.2%	334,127	11.6%	337,008	8.5%	292,974	7.7%
		$20,000-$24,999	2,354,728	20.5%	391,028	46.4%	932,641	32.4%	497,607	12.6%	533,452	14.1%
		$25,000-$29,999	371,902	3.2%	1,213	0.1%	54,531	1.9%	170,911	4.3%	145,247	3.8%
		$30,000-$39,999	537,489	4.7%	208	0.0%	57,905	2.0%	258,809	6.5%	220,567	5.8%
		$40,000-$49,999	405,765	3.5%	116	0.0%	42,589	1.5%	194,804	4.9%	168,256	4.4%
		$50,000-$99,999	1,054,012	9.2%	302	0.0%	102,490	3.6%	500,618	12.6%	450,602	11.9%
		$100,000-$249,999	863,783	7.5%	385	0.1%	75,206	2.6%	395,587	10.0%	392,605	10.4%
		$250,000 or more	577,872	5.0%	178	0.0%	35,556	1.2%	262,343	6.6%	279,795	7.4%
	Status	Active Un-Disbursed	3,883	0.0%	3,628	0.4%	5	0.0%	32	0.0%	218	0.0%
		Exemption 4	4,293,493	37.4%	767,647	91.0%	1,439,377	50.0%	1,212,164	30.6%	874,305	23.1%
		Paid in Full	7,177,628	62.6%	0	0.0%	1,441,698	50.0%	2,751,064	69.4%	2,912,770	76.9%
Nonemployer Business, Residential, on or after March 3, 2021		Yes	2,832,912	24.7%	724,112	85.9%	1,367,181	47.5%	316,713	8.0%	424,906	11.2%
		No	8,642,092	75.3%	119,259	14.1%	1,513,899	52.6%	3,646,547	92.0%	3,362,387	88.8%
TOTAL			11,475,004	100.0%	843,371	100.0%	2,881,080	100.0%	3,963,260	100.0%	3,787,293	100.0%

Table 3. PPP Loan Attributes, by Lender Type: January 2022 Data

			All Loans		Lender Type							
					Blueacorn		Other FinTech		Traditional		Not Classified	
		Attribute	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans
Borrower Attributes	Business Type	Corporation	2,313,635	20.2%	1,157	0.1%	233,499	8.1%	1,190,511	30.2%	888,468	23.3%
		Independent Contractors	828,545	7.2%	220,363	26.2%	413,952	14.4%	112,253	2.9%	81,977	2.2%
		Limited Liability Company(LLC)	2,381,777	20.8%	58,368	6.9%	287,349	10.0%	1,069,465	27.2%	966,595	25.3%
		Self-Employed Individuals	885,319	7.7%	33,391	4.0%	528,488	18.4%	131,669	3.3%	191,771	5.0%
		Single Member LLC	69,144	0.6%	4,236	0.5%	29,883	1.0%	14,145	0.4%	20,880	0.6%
		Sole Proprietorship	3,433,161	29.9%	522,187	62.1%	1,204,579	41.8%	734,969	18.7%	971,426	25.5%
		Subchapter S Corporation	1,051,918	9.2%	356	0.0%	142,102	4.9%	469,825	11.9%	439,635	11.5%
		Other	504,013	4.4%	548	0.0%	38,898	1.4%	211,503	5.4%	253,064	6.6%
		Missing	2,289	0.0%	0	0.0%	17	0.0%	2,254	0.1%	18	0.0%
	Number of Reported Jobs	0	209	0.0%	0	0.0%	15	0.0%	35	0.0%	159	0.0%
		1	6,024,918	52.5%	838,779	99.8%	2,288,101	79.5%	1,392,174	35.4%	1,505,864	39.5%
		2-4	2,055,108	17.9%	758	0.1%	265,730	9.2%	980,686	24.9%	807,934	21.2%
		5-7	1,056,873	9.2%	334	0.0%	120,595	4.2%	501,166	12.7%	434,778	11.4%
		8-10	620,471	5.4%	255	0.0%	68,372	2.4%	288,378	7.3%	263,466	6.9%
		11-20	844,807	7.4%	271	0.0%	78,088	2.7%	380,977	9.7%	385,471	10.1%
		21-50	578,181	5.0%	113	0.0%	41,663	1.5%	255,314	6.5%	281,091	7.4%
		51-100	172,060	1.5%	61	0.0%	10,184	0.4%	78,245	2.0%	83,570	2.2%
		101-500	117,166	1.0%	35	0.0%	6,019	0.2%	59,618	1.5%	51,494	1.4%
		501+	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Missing	7	0.0%	0	0.0%	0	0.0%	1	0.0%	6	0.0%
	NAICS Code	Residential Building Construction (2361)	317,734	2.8%	44,280	5.3%	80,668	2.8%	92,494	2.4%	100,292	2.6%
		Taxi and Limousine Service (4853)	278,082	2.4%	48,900	5.8%	176,227	6.1%	37,503	1.0%	15,452	0.4%
		Services to Buildings and Dwellings (5617)	331,528	2.9%	47,954	5.7%	113,192	3.9%	84,746	2.2%	85,636	2.3%
		Personal Care Services (8121)	765,515	6.7%	160,072	19.0%	324,236	11.3%	146,820	3.7%	134,387	3.5%
		Other NAICS classification	9,644,608	84.1%	539,400	64.2%	2,172,147	75.5%	3,455,062	87.8%	3,477,999	91.2%
		Missing	132,334	1.2%	0	0.0%	12,297	0.4%	119,969	3.1%	68	0.0%
	Address	Residential	6,259,668	54.6%	774,556	92.1%	2,103,510	73.1%	1,648,294	41.9%	1,733,308	45.5%
		Commerical	4,446,232	38.8%	25,280	3.0%	581,468	20.2%	1,996,724	50.7%	1,842,760	48.3%
		Not classified	763,901	6.7%	40,770	4.9%	193,789	6.7%	291,576	7.4%	237,766	6.2%
	Gender	Female Owned	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Male Owned	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Unanswered	11,469,801	100.0%	840,606	100.0%	2,878,767	100.0%	3,936,594	100.0%	3,813,834	100.0%
	Race	American Indian or Alaska Native	84,700	0.7%	5,886	0.7%	5,651	0.2%	61,049	1.6%	12,114	0.3%
		Asian	298,075	2.6%	11,358	1.4%	68,597	2.4%	125,124	3.2%	92,996	2.4%
		Black or African American	819,789	7.2%	464,904	55.3%	216,859	7.5%	86,449	2.2%	51,577	1.4%
		Eskimo & Aleut	21	0.0%	0	0.0%	2	0.0%	8	0.0%	11	0.0%
		Multi Group	54	0.0%	1	0.0%	6	0.0%	41	0.0%	6	0.0%
		Native Hawaiian or Other Pacific Islander	10,383	0.1%	3,353	0.4%	1,777	0.1%	2,506	0.1%	2,747	0.1%
		Puerto Rican	667	0.0%	4	0.0%	30	0.0%	563	0.0%	70	0.0%
		Unanswered	8,693,435	75.8%	241,318	28.7%	2,411,476	83.8%	3,115,046	79.1%	2,925,595	76.7%
		White	1,562,677	13.6%	113,782	13.5%	174,369	6.1%	545,808	13.9%	728,718	19.1%
	Ethnicity	Hispanic or Latino	364,229	3.2%	60,607	7.2%	83,319	2.9%	137,662	3.5%	82,641	2.2%
		Not Hispanic or Latino	2,908,127	25.4%	551,819	65.7%	419,808	14.6%	814,828	20.7%	1,121,672	29.4%
		Unknown/NotStated	8,197,445	71.5%	228,180	27.1%	2,375,640	82.5%	2,984,104	75.8%	2,609,521	68.4%
Lender Attributes	Type	Blueacorn	840,606	7.3%	840,606	100.0%	0	0.0%	0	0.0%	0	0.0%
		Other FinTech	2,878,767	25.1%	0	0.0%	2,878,767	100.0%	0	0.0%	0	0.0%
		Traditional	3,936,594	34.3%	0	0.0%	0	0.0%	3,936,594	100.0%	0	0.0%
		Not classified	3,813,834	33.3%	0	0.0%	0	0.0%	0	0.0%	3,813,834	100.0%
Loan Attributes	Approval Date	Before March 3, 2021	7,289,488	63.6%	3,514	0.4%	1,204,485	41.8%	3,093,012	78.6%	2,988,477	78.4%
		On or after March 3, 2021	4,180,313	36.5%	837,092	99.6%	1,674,282	58.2%	843,582	21.4%	825,357	21.6%
	Draw	First Draw	8,614,374	75.1%	770,193	91.6%	2,138,638	74.3%	2,860,063	72.7%	2,845,480	74.6%
		Second Draw	2,855,427	24.9%	70,413	8.4%	740,129	25.7%	1,076,531	27.4%	968,354	25.4%
	Current Approval Amount	Less than $5,000	1,405,780	12.3%	104,508	12.4%	480,946	16.7%	394,376	10.0%	425,950	11.2%
		$5,000-$9,999	1,570,677	13.7%	111,657	13.3%	439,323	15.3%	520,710	13.2%	498,987	13.1%
		$10,000-$14,999	1,232,262	10.7%	97,321	11.6%	325,655	11.3%	425,079	10.8%	384,207	10.1%
		$15,000-$19,999	1,100,101	9.6%	136,116	16.2%	334,017	11.6%	335,384	8.5%	294,584	7.7%
		$20,000-$24,999	2,350,211	20.5%	388,609	46.2%	930,571	32.3%	495,483	12.6%	535,548	14.0%
		$25,000-$29,999	371,895	3.2%	1,206	0.1%	54,530	1.9%	169,692	4.3%	146,467	3.8%
		$30,000-$39,999	537,483	4.7%	208	0.0%	57,900	2.0%	256,564	6.5%	222,811	5.8%
		$40,000-$49,999	405,762	3.5%	116	0.0%	42,588	1.5%	193,117	4.9%	169,941	4.5%
		$50,000-$99,999	1,053,996	9.2%	302	0.0%	102,484	3.6%	495,606	12.6%	455,604	12.0%
		$100,000-$249,999	863,777	7.5%	385	0.1%	75,202	2.6%	390,997	9.9%	397,193	10.4%
		$250,000 or more	577,857	5.0%	178	0.0%	35,551	1.2%	259,586	6.6%	282,542	7.4%
	Status	Active Un-Disbursed	619	0.0%	464	0.1%	23	0.0%	23	0.0%	109	0.0%
		Exemption 4	3,691,765	32.2%	768,038	91.4%	1,245,950	43.3%	944,536	24.0%	733,241	19.2%
		Paid in Full	7,777,417	67.8%	0	0.0%	1,632,794	56.7%	2,992,035	76.0%	3,080,484	80.8%
Nonemployer Business, Residential, on or after March 3, 2021		Yes	2,827,854	24.7%	721,545	85.8%	1,364,929	47.4%	316,177	8.0%	425,203	11.2%
		No	8,641,947	75.4%	119,061	14.2%	1,513,838	52.6%	3,620,417	92.0%	3,388,631	88.9%
TOTAL			11,469,801	100.0%	840,606	100.0%	2,878,767	100.0%	3,936,594	100.0%	3,813,834	100.0%

Table 4. Attributes of PPP Loans to Nonemployer Businesses at Residential Addresses after March 3 2021: January 2022 Data

					Lender Type							
			All Loans		Blueacorn		Other FinTech		Traditional		Not Classified	
		Attribute	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans	Number of Loans	Percent of Loans
Borrower Attributes	Business Type	Corporation	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Independent Contractors	566,728	20.0%	203,664	28.2%	287,530	21.1%	49,472	15.7%	26,062	6.1%
		Limited Liability Company(LLC)	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Self-Employed Individuals	489,182	17.3%	30,910	4.3%	332,769	24.4%	46,394	14.7%	79,109	18.6%
		Single Member LLC	50,635	1.8%	3,861	0.5%	24,096	1.8%	8,856	2.8%	13,822	3.3%
		Sole Proprietorship	1,721,309	60.9%	483,110	67.0%	720,534	52.8%	211,455	66.9%	306,210	72.0%
		Subchapter S Corporation	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Other	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Missing	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
	Number of Reported Jobs	0	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		1	2,827,854	100.0%	721,545	100.0%	1,364,929	100.0%	316,177	100.0%	425,203	100.0%
		2-4	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		5-7	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		8-10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		11-20	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		21-50	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		51-100	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		101-500	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		501+	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Missing	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
	NAICS Code	Residential Building Construction (2361)	92,838	3.3%	37,605	5.2%	31,318	2.3%	9,707	3.1%	14,208	0.0%
		Taxi and Limousine Service (4853)	211,078	7.5%	44,693	6.2%	135,765	10.0%	22,183	7.0%	8,437	2.0%
		Services to Buildings and Dwellings (5617)	150,333	5.3%	41,941	5.8%	78,218	5.7%	14,228	4.5%	15,946	3.8%
		Personal Care Services (8121)	383,548	13.6%	143,708	19.9%	195,886	14.4%	21,428	6.8%	22,526	5.3%
		Other NAICS classification	1,990,057	70.4%	453,598	62.9%	923,742	67.7%	248,631	78.6%	364,086	85.6%
		Missing	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
	Address	Residential	2,827,854	100.0%	721,545	100.0%	1,364,929	100.0%	316,177	100.0%	425,203	100.0%
		Commerical	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Not classidfied	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
	Gender	Female Owned	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Male Owned	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		Unanswered	2,827,854	100.0%	721,545	100.0%	1,364,929	100.0%	316,177	100.0%	425,203	100.0%
	Race	American Indian or Alaska Native	13,516	0.5%	4,776	0.7%	1,459	0.1%	4,861	1.5%	2,420	0.6%
		Asian	32,207	1.1%	9,487	1.3%	12,741	0.9%	4,248	1.3%	5,731	1.4%
		Black or African American	520,413	18.4%	399,738	55.4%	83,125	6.1%	22,819	7.2%	14,731	3.5%
		Eskimo & Aleut	4	0.0%	0	0.0%	0	0.0%	2	0.0%	2	0.0%
		Multi Group	4	0.0%	1	0.0%	3	0.0%	0	0.0%	0	0.0%
		Native Hawaiian or Other Pacific Islander	3,762	0.1%	2,862	0.4%	415	0.0%	200	0.1%	285	0.1%
		Puerto Rican	29	0.0%	3	0.0%	6	0.0%	15	0.0%	5	0.0%
		Unanswered	1,964,130	69.5%	211,983	29.4%	1,232,159	90.3%	236,405	74.8%	283,583	66.7%
		White	293,789	10.4%	92,695	12.9%	35,021	2.6%	47,627	15.1%	118,446	27.9%
	Ethnicity	Hispanic or Latino	99,511	3.5%	51,165	7.1%	23,292	1.7%	13,811	4.4%	11,243	2.6%
		Not Hispanic or Latino	797,576	28.2%	469,410	65.1%	112,612	8.3%	73,253	23.2%	142,301	33.5%
		Unknown/NotStated	1,930,767	68.3%	200,970	27.9%	1,229,025	90.0%	229,113	72.5%	271,659	63.9%
Lender Attributes	Type	Blueacorn	721,545	25.5%	721,545	100.0%	0	0.0%	0	0.0%	0	0.0%
		Other FinTech	1,364,929	48.3%	0	0.0%	1,364,929	100.0%	0	0.0%	0	0.0%
		Traditional	316,177	11.2%	0	0.0%	0	0.0%	316,177	100.0%	0	0.0%
		Not classified	425,203	15.0%	0	0.0%	0	0.0%	0	0.0%	425,203	100.0%
Loan Attributes	Approval Date	Before March 3, 2021	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
		On or after March 3, 2021	2,827,854	100.0%	721,545	100.0%	1,364,929	100.0%	316,177	100.0%	425,203	100.0%
	Draw	First Draw	2,198,822	77.8%	659,912	91.5%	981,131	71.9%	230,770	73.0%	327,009	76.9%
		Second Draw	629,032	22.2%	61,633	8.5%	383,798	28.1%	85,407	27.0%	98,194	23.1%
	Current Approval Amount	Less than $5,000	496,256	17.6%	88,538	12.3%	226,503	16.6%	71,708	22.7%	109,507	25.8%
		$5,000-$9,999	450,672	15.9%	92,741	12.9%	201,835	14.8%	64,241	20.3%	91,855	21.6%
		$10,000-$14,999	334,498	11.8%	80,772	11.2%	151,983	11.1%	44,319	14.0%	57,424	13.5%
		$15,000-$19,999	365,201	12.9%	117,236	16.3%	172,018	12.6%	36,919	11.7%	39,028	9.2%
		$20,000-$24,999	1,162,546	41.1%	341,216	47.3%	599,718	43.9%	96,780	30.6%	124,832	29.4%
		$25,000-$29,999	16,356	0.6%	976	0.1%	12,646	0.9%	1,380	0.4%	1,354	0.3%
		$30,000-$39,999	1,432	0.1%	42	0.0%	119	0.0%	490	0.2%	781	0.2%
		$40,000-$49,999	428	0.0%	9	0.0%	44	0.0%	163	0.1%	212	0.1%
		$50,000-$99,999	399	0.0%	9	0.0%	60	0.0%	147	0.1%	183	0.0%
		$100,000-$249,999	66	0.0%	6	0.0%	3	0.0%	30	0.0%	27	0.0%
		$250,000 or more	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
	Status	Active Un-Disbursed	461	0.0%	431	0.1%	620,104	45.4%	4	0.0%	26	0.0%
		Exemption 4	1,521,089	53.8%	656,625	91.0%	744,825	54.6%	126,290	39.9%	118,070	27.8%
		Paid in Full	1,306,304	46.2%	64,489	8.9%	1,364,929	100.0%	189,883	60.1%	307,107	72.2%
Nonemployer Business, Residential, on or after		Yes	2,827,854	100.0%	721,545	100.0%	1,364,929	100.0%	316,177	100.0%	425,203	100.0%
		No	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
TOTAL			2,827,854	100.0%	721,545	100.0%	1,364,929	100.0%	316,177	100.0%	425,203	100.0%