Misaligned CARES Act: Overcrowding, Selective Verification and Unintended Racial Consequences

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Abstract

I utilize a novel data on proprietary servicer comments to investigate *strategic borrower responses* to the mortgage forbearance program contained in the Coronavirus Aid, Relief, and Economic Security Act. The unique text data allows me to corroborate the *selective verification* of unemployment status (financial hardship) by the servicer. I also discern *unintended distributional implications* for African American and Hispanic borrowers with performing loans to reduce ex-post risk, although the servicer does not have the race information about the borrowers. The *soft information* obtained from servicer call transcripts helps me identify the reasons for these communications and the *incentive compatibility* between the borrower and the servicer. My finding sheds light on the poor-targeting of Government programs, like FHA, VA, USDA, etc., during exacerbated income shocks, such as, COVID-19.

Key words: Strategic Behavior, Forbearance, Machine learning, NLP, Race, COVID-19, CARES

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1 Introduction

Government intervention has been the mechanism to attenuate large unexpected shocks like COVID-19 or housing crashes like the 2008 financial catastrophe. I investigate the effectiveness or lack thereof of such Government interventions selectively applied on Government programs by Housing and Urban Development (HUD). Specifically, I find irrational (opportunistic) behavior among borrowers with Govt.-backed loans vis-a-vis spatial overcrowding and rational (logical and conservative) behavior from borrowers with Conventional loans. Conventional borrowers with lower income and more financial constraints are the hardest hit by the wrath of COVID-19 and hence apply for forbearance and conventional borrowers with relatively higher income and stable jobs do not take up forbearance even though they may be affected in the short-term. On the other hand, the borrowers with Govt-backed loans opportunistically apply for forbearance from almost all income brackets in Figure 1 and I provide evidence in Figure 2 that some of these borrowers avail forbearance even though they are not *unemployed* or have not had any *curtailment of income*. Hence, the Govt.-backed loan borrowers spatially overcrowd forbearance applications. Moreover, I show that servicers are much more lenient towards borrowers with Govt.-backed loans and stringent with borrowers with Conventional loans by verifying the employment status thereby scrutinizing the forbearance applications of the latter. The CARES Act and the uniqueness of the data set allows me to disentangle both of these information asymmetries in the same set up. Specifically, I use the servicer call transcripts to extract *soft* information about the borrower and create a narrative retrieval apparatus via Inbound/Outbound calls [1] capturing the intent of those communications. For marginal borrowers who have missed a couple of payments and whose loans are about to become non-performing, I see a significant spike in Foreclosure Moratorium by the end of March 2020 in Figure 3. In April 2020, the servicers face a crucial choice whether to approve these marginal borrowers in their forbearance applications or advise them to avail the foreclosure moratorium.

[1]Inbound communications are initiated by the borrower and Outbound communications are initiated by the servicer. The dialogue between the borrower and the servicer is recorded in call transcripts, email exchanges and/or physical mails.

I see that, by May 2020, most of these borrowers have been dissuaded and informed about their ineligibility (due to adverse delinquency status) by the servicer. This could have serious implications of a looming housing crisis if there is a massive surge of foreclosure after foreclosure moratorium ends.

The first few cases of the global COVID-19 pandemic in the United States were diagnosed in early March 2020. The global COVID-19 pandemic precipitated a growing public health crisis and necessitated President Trump to sign the Coronavirus Aid, Relief and Economic Security Act ("CARES Act") into law on March 27, 2020. The CARES Act[2] contained numerous fiscal stimulus programs and policy directives designed to aid households and businesses negatively affected by the government mandated shutdown (business closings) and social distancing restrictions imposed after March 15, 2020. Of course, there is a lot heterogeneity in terms of the implementation of the shutdown orders (DLima et al., 2020) and actual implementation of the mask and social-distancing policies across counties and states, but these are not the prerogative of this paper. Instead, I investigate the effect of the CARES Act as a point-in-time Government policy and the implications thereof. In order to protect households from unemployment or income curtailment resulting from government ordered business shutdowns, Title IV of the CARES Act stipulated a foreclosure moratorium and created a payment forbearance program for federally-related mortgage loans.[3] One important feature of the forbearance program is that it does not require that borrowers prove financial hardship or be in a delinquency status before requesting forbearance[4]. Indeed, I show in Tables 1 and 2, that borrowers having performing Govt-backed (PL_Gov) loans strategically take advantage of the CARES Act and apply for forbearance (13.18%) even though they were not unemployed (1.48%) or did not suffer from major financial hardship (4.73%). After a forbearance application is approved, lenders are prohibited from collecting accrued interest, late fees, convenience fees, or other charges associated with

[2]For details, check https://www.govtrack.us/congress/bills/116/s3548.

[3]Section 4022 specifies that lenders must grant a minimum 60-day foreclosure moratorium beginning March 18, 2020 on all Federally backed mortgage loans. The section also requires that lenders create a 180-day forbearance program for borrowers experiencing direct or indirect financial hardship due to the COVID-19 crisis.

[4]See a sample Forbearance 2-page naive application form in (Agarwal et al., 2020a)

the missed payments. The Department of Housing and Urban Development clearly demarcated the rules governing the forbearance program for Federal Housing Administration (FHA) loans on April 1, 2020 and because of this I see most Forbearance applications approved on April 9th by this specific servicer. There is another peak of forbearance applications when the Housing Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac, announced their forbearance plans covering conventional mortgages on April 21, 2020. While the CARES Act specifically targets payment relief to FHA/VA loans and conventional mortgages backed by the GSEs, it does not clearly indicate/delegate specific rules non-government backed (or private-label) mortgages, which leads room for interpretation and discretion by the servicer.

The typical forbearance is approved for 6 months (or two consecutive 3 month blocks). The borrower can choose to preempt the forbearance approval by starting to pay if she regains her financial status and ability to continually pay from a new job or other source of income. The borrower can also choose to use the 6 months forbearance approval, even if she regains her ability pay before the end of 6 months. Beyond the first 6 months, the borrower can be granted another forbearance period of 6 months. The CARES Act stipulates as maximum of one full year from the time a borrower first applied for forbearance relief. In practice, no servicer would require a lumpsum payment afterwards. There will mostly be a partial payment plan after the end of the forbearance spell (similar to a loan modification or an additional refinance loan). The CARES Act mandated that the servicer inform at least the Gov-backed borrowers about their eligibility of availing forbearance if their loans were performing ex-ante. There is a grey area for marginal borrowers who are about to become non-performing in terms of their payment ex-ante. This ambiguity is the crux of the negative amplified outcome of the misaligned CARES Act. Servicers can choose to offer Foreclosure Moratorium to marginal borrowers who are not yet formally in foreclosure and/or bankruptcy proceedings. Servicers can also offer loan modification. This leaves a discretionary room for the servicer. The conflict of interest between the master and special servicer is well-documented in the real estate finance literature. This incentive incompatibility of the special servicer with the investor and the issuer can plausibly lead to a surge of foreclosures in the near future and a vicious cycle thereafter depending on whether the economic recovery is tick-mark shaped or W-shaped.

In this paper, I analyze the differential impact of the CARES Act forbearance provision that specifically targeted government backed loans (FHA/VA and GSE mortgages) but not mortgages originated outside these government agencies. I utilize a novel administrative dataset obtained from a mortgage servicer that comprises a portfolio of FHA/VA and private-label mortgages. First, I manually identify a set of keywords for identifying Inbound/Outbound communications and borrower reported unemployment status in Section 11.1 in the Appendix. Because of unique and real-time nature of this almost-daily administrative transcript of the communication between the borrower and the servicer, I am able to track the borrower-noted unemployment status, which is much more accurate than the aggregated estimates of unemployment from Bureau of Labor Statistics. Also the reason for these communications and the incentive compatibility between the borrower and the servicer can be captured from Inbound-/Outbound communications. I use these indicator variables in my regression specification. There are several aspects of reporting Unemployment status via Inbound/Outbound communications. Also, Inbound/Outbound communications can take place due to different reasons. I do not distinguish these different aspects of Unemployment Status, Inbound/Outbound communications in the regression specification as it would require big data for exploiting such a rich specification. Also, I use logistic regression for number of forbearance applications on several variables including but not limited to Inbound/Outbound communications and borrower reported unemployment status, which is a linear model and hence cannot capture the non-linearity of the different aspects of these indicator variables and their interactions. Instead, I bring to bear an application of natural language processing (NLP) technology in order to identify whether the borrower or servicer initiated the forbearance process. I also identify whether the borrower indicated financial distress (e.g. job loss) as a motivating factor in requesting forbearance. To the best of my knowledge, the use of transcripts of communications between the servicer and borrowers to identify requests for forbearance and financial distress has not been pursued before in academia. In contrast, typical studies in the mortgage literature that examine mortgage default of modification rely on datasets derived from servicer records containing hard coded data (Agarwal et al., 2012) and (Mayer et al., 2014). In other words, access to servicer-borrower communications is not available in most mortgage performance data. As a result, my study provides a unique insight into the initial process of requesting mortgage payment relief that has heretofore been unavailable to researchers.

In line with the design of the CARES Act forbearance program, there is a higher incidence of forbearance with government backed loans in response to communication initiated by the servicer (denoted as "outbound"). The CARES Act required that servicers proactively reach out to borrowers with details about the forbearance program. The Act leaves a grey area and does not stipulate that servicer proactively contact private-label or non-government back loans. A positive increase in forbearance in the private label set follows from a borrower initiated (denoted as "inbound") communication. Unlike government-backed mortgages, the servicer is able to demand that the borrower prove financial hardship before granting forbearance for Non-Gov borrowers. Consequently, I find a lower incidence of forbearance within this set of loans following communication with the servicer. The endogeneity from the strategic overcrowding of forbearance applications by Gov-backed performing loan borrowers and the endogeneity emanating from selective verification by the servicer *undo the CARES Act*. To overcome these endogeneity issues, I implement Differences-in-Differences approach towards the end of the paper. However, the CARES Act does help some financially constrained borrowers and, at the same time, does not bail out the servicers.

Based on the available data, I find evidence for the following research questions. I formulate them as conjectures/claims which *undoes* the CARES Act (not technically hypotheses, as I am not rejecting the null) and corroborate them using logistic regression with and without fixed effects and Differences-in-Differences approaches (for alleviating endogeneity concerns) in the following sections of the paper.

Conjecture 1: Borrowers having Gov-backed performing loans are **overcrowding** forbearance applications, even if they are not unemployed/have any financial hardship from curtailment of income.

Conjecture 2: Servicers **selectively verify** the employment status of Non-Gov loan borrowers and dissuade marginal borrowers by offering loan modification and/or foreclosure moratorium, to preempt/prevent them from availing forbearance.

Conjecture 3: Servicers' behavior have **unintended distributional implications** towards African American and Hispanic borrowers, their forbearance applications are accepted only in dire financial conditions.

Conjecture 4: **Poorly-targeted** CARES Act helped some borrowers and did not bail out servicers; still some borrowers overcrowded and some servicers prevented certain borrowers from availing forbearance.

There has been a plethora of research following the inception of the CARES Act. Carroll et al. (2020) model responses of households to past consumption stimulus packages and find, during the lockdown, many types of spending are undesirable/impossible. They also opine the jobs that disappear during the lockdown will not reappear when lifted. Humphries et al. (2020) provide evidence on impact of COVID-19 on small business owners and how these effects have evolved since CARES Act. Chetty et al. (2020) track economic activity at a granular level (statistics on consumer spending, business revenues, employment rates, and other key indicators disaggregated by county, industry, and income group) in real time using anonymized data from private companies. Using these data, they study the mechanisms through which COVID-19 affected the economy by analyzing heterogeneity in its impacts across geographic areas and income groups. Boar and Mongey (2020) documented that many unemployed workers received benefits that exceeded wages at their previous job using a dynamic model through 4 different aspects: the temporary nature of the CARES Act, uncertainty that their return-to-work offer might expire, search frictions and wage losses out of unemployment in a recession. Akee et al. (2020) dissect the US Department of the Treasuryâs distribution of first-round CARES Act funds to Indian Country in terms of relief funds based on tribesâ populations. The authors find that Treasury has employed a population data series that produces arbitrary and capricious "over and under-representations" of tribesâ enrolled citizens. Petrosky-Nadeau (2020) investigate the existence a reservation level of benefit payments in this dynamic decision problem at which an individual is indifferent between accepting and refusing an offer under the increased unemployment insurance (UI) payments and extended duration provided by the CARES Act. This reservation benefit is a simple statistic to test the job acceptance deterrence effects of current UI payments, summarizing the decision problem conditional on the believed state of the labor market and the weeks of UI compensation remaining. Coibion et al. (2020) study how the large one-time transfers to individuals from the CARES Act affected their consumption, saving and labor-supply decisions. Individuals report having spent or planning to spend only around 40 percent of the total transfer on average. This relatively low rate of spending out of a one-time transfer is higher for those facing liquidity constraints, who are out of the labor force, who live in larger households, who are less educated and those who received smaller amounts. Neilson et al. (2020) explore information frictions and the "first-come, first-served" design of the Paycheck Protection Program (PPP) which extended 669 billion dollars of forgivable loans in an unprecedented effort to support small businesses affected by the COVID-19 crisis. Baker and Judge (2020) explore the government response with a critical forgivable loan program, which alone will not provide the cash they need to retain workers, pay rent, and help their business come back to life when Americans are no longer sheltering in place. Wilson and Stimpson (2020) claim that the adverse policy environment in the United States (US) has made immigrant communities particularly vulnerable to uncontrolled community spread of COVID-19. Given the importance of immigrants to the US economy and society, and the human toll this pandemic is having on migrants worldwide, federal and state policies should pivot to find ways to improve access to healthcare for immigrants. Capponi et al. (2020) show the existence of a self-reinforcing feedback loop between foreclosures and growth in house prices: an increase in foreclosures puts a downward pressure on house prices, and in turn lower house prices lead to more foreclosures. Bhutta et al. (2020) show that cash assistance included in the CARES Act, namely, unemployment insurance benefit expansions and stimulus payments are instrumental in allowing almost all families to cover their recurring, non-discretionary expenses in the event of long-term unemployment. Adams-Prassl et al. (2020) show that the immediate labor market impacts of Covid-19 differ considerably across countries, e.g., Germany with short-time work scheme less likely to be affected. Women and less educated workers are more affected by the crisis.

Racial implications in Real Estate Literature have been studied from various perspectives in (Cashin, 2008), (Bayer et al., 2016), (Denton, 2017), (Spalding, 2008), (Jackson, 1980), (Pace et al., 1998), (Schafran and Wegmann, 2012). To the best of my knowledge, the unintended racial implications of selective verification of the unemployment status (financial hardship) has not been studied previously in this literature.

2 Data

I utilize a proprietary administrative dataset containing detailed information on residential mortgage performance that was collected from daily mortgage servicing logs.[5] The data consists of the servicing records spanning the period from January to May 2020 for 19,418 loans that were active as of January 2020. The data contains a rich set of variables that provide information about the borrowers and their loans. For example, the data records the loan-to-value ratio (LTV) at origination, the loan's current interest rate, balance and appraisal, whether the loan is a fixed-rate or adjustable-rate mortgage, the loan purpose (cash out refinance, home improvement, rate-term/vanilla refinance, or purchase), the property type (modular home, single family, multi-family, condominium, townhouse, or planned unit development (PUD)) and occupancy status (owner-occupied, second home, or investment property), the borrower's credit (FICO) score at origination, loan modification flag, and amount of any corporate advances paid by the servicer on behalf of the borrower.[6] For a subset of the data, I have the employment

[5]This dataset was provided by a private equity firm that focuses on real estate investments.

[6]The borrower makes monthly payments comprising principal, interest, taxes, and insurance (PITI). The TI part is usually put into an escrow account. The servicer then draws down that escrow account to pay the taxes and insurance premium on behalf of the borrower. That account can typically hold up to 2-yrs of TI funds. The servicer can earn a float on those funds. There is a separate reserve fund set-up where the servicer deposits part of the PI to hold in reserve in case the borrower misses a payment. This reserve is funded out of the monthly servicing fee that the servicer deducts from the PI before passing it to the investor.
Corporate advances are expenses paid by the servicer and recoverable from the borrower. Typical corporate advances include attorney or court fees associated with a foreclosure or required insurance premiums paid on behalf of the borrower. The servicer passes all these costs through to the investor. Each month, the advances they make are netted out of the remittance that goes to the investor. If the pool doesn't generate enough cash to cover the advances (rare), then the investor has to write a check to cover the advances. On a particular loan, advances balances get paid down from the cash that comes in – either if the borrower makes a payment or the loan liquidates when the borrower is delinquent and there are advance balances which get paid down first before

industry (mostly Small and Medium Enterprise for the borrowers in this portfolio) and credit tradeline information, which provides a proxy for the household liability (mortgage, credit card, auto loan, student loan, etc.).

As typical in mortgage servicing data, my dataset contains detailed *hard* information on each loan's payment status. Using this information, I define loans as being performing (PL) or non-performing (NPL). I classify loans as performing if their payments are less than 60-days delinquent and non-performing if payments are 60-days or more delinquent. The data indicates whether the loan was originated as part of a federal government-backed insurance program (Federal Housing Administration (FHA), Veterans Administration (VA), or US Department of Agriculture (USDA)) or if the loan was originated as a conventional or non-conforming mortgage.[7]

In addition to the typical information collected from mortgage servicing tapes used in prior studies (e.g. Cordell et al., 2015; Kruger, 2018; Buchak et al., 2018; Agarwal et al., 2018; Conklin et al., 2019), the unique feature of this dataset is that it contains transcripts documenting the communication between the borrowers and the servicer call centers. These transcripts contain real-time (almost daily) loan status updates and thus provide a preview of the loan status variables contained in typical mortgage servicing records. Thus, using these servicer comments, I create a time series of several important indicator variables to capture the borrower's payment intention or financial stress. For example, I search the transcripts for the keywords "COVID" and "forbearance" to identify if and when a borrower had a conversation with the servicer regarding forbearance options emanating from CARES Act (enacted in March 2020).[8] To capture financial stress arising from plausible employment interruption, I use natural language processing (NLP) techniques (Agarwal et al. (2020b)) to identify whether a borrower is unemployed in Appendix 11.1. I also identify borrowers who are experiencing income disruption

any cash is applied to PI.

[7]Conventional mortgages refer to loans eligible for purchase by Fannie Mae or Freddie Mac while non-conforming refers to jumbo mortgages or subprime mortgages that are not eligible for purchase by the government sponsored enterprises (GSEs).

[8]See the Appendix for a complete list of key words used to denote various aspects of the mortgage servicing calls.

via the keywords "curtailment of income". This is a stronger indicator than unemployment for a COVID based forbearance application and, more importantly, is a proxy for the borrower's inability to pay. I also scan for the words "foreclosure" and "moratorium" to identify borrowers who are currently in a foreclosure moratorium status, a relief channel for non-performing loans. Finally, I identify whether the servicer comments originated with the borrower (inbound) or from the servicer (outbound), detailed in Appendix 11.1. My regression specification is very rich and I use Forbearance Applications as my dependent variable and Inbound/Outbound Communications and Borrower noted Unemployment as explanatory variables. However, I do not use interactions of Borrower noted Unemployment and Inbound/Outbound Communications in the regression specification. Similarly, there are several aspects of Inbound/Outbound Communications which captur the rationale and the incentives of those communications. I showcase these details via NLP separately instead of directly invoking them in the regression. I provide the t-SNE diagrams[9], which are 2-dimensional projections of word clouds similar to the words "Unemployed", "Inbound" (IB) and "Outbound" (OB) in Figure 4. The strategic element of the forbearance applications is higher for the inbound comments. The creation of these flags (dummies) is uniquely able to determine the delinquency status of the borrower and her propensity to apply for forbearance.

As evident in Figure 4, there are several clusters in the t-SNE, which necessitates a deeper dive into interaction of unemployment with IB in Figure 5, unemployment with OB in Figure 6 and unemployment per se (without IB and OB) in Figure 7. In Figure 4, one can notice 4 clusters. On the South-East corner, words related to "ob" (in violet) which are not so much related to unemployment per se but *continual renegotiation* between the borrower and the servicer. On the North-East corner, the cluster represents words related to "ib" and "inbound" (in sea-green) where the borrower seems to be making the case for loan modification and other *offers* that

[9] A popular method for exploring high-dimensional data is t-SNE, introduced by van der Maaten and Hinton (2008), which has the ability to create two-dimensional âmapsâ from data with hundreds or even thousands of dimensions. The goal is to take a set of points in a high-dimensional space and find a faithful representation of those points in a lower-dimensional space, typically the 2D plane. The algorithm is non-linear and adapts to the underlying data, performing different transformations on different regions. A second feature of t-SNE is a tuneable parameter, âperplexity,â which tracks how to balance attention between local and global aspects of your data. The parameter is, in a sense, a guess about the number of close neighbors each point has.

they can avail from the servicer. In the North-West corner, the two subclusters are entangled, one of them highlights the *occupancy* and related issues emanating from unemployment and the other specifically relates curtailment of income with the *intent* of the borrower. The use of these keywords in defining the "Unemployment", "Inbound" and "Outbound" flags (dummy variables) helps me tease out the tension among these aspects of borrower and servicer behavior, which have not been explored previously in academia, to the best of my knowledge. Figure 5 details 3 of the 4 clusters in Figure 4 on the facets of "Inbound" and "Unemployment". The *partial adjustment* and *payment disputes* in the North-East corner point out aspects of financial hardship and renegotiation related to Inbound calls from the borrower. The other entangled cluster captures several borrower aspects related to *intent* and servicer response to *offer* the borrower more favorable terms for the loans. The *refusal* of forbearance for certain borrowers is also captured in the South-West corner of Figure 5. Figure 6 captures the selective *verification* of the unemployment status of certain borrowers by the servicer. The southern part of Figure 6 underscores the typical outbound conversations related to borrower financial health and dire personal circumstances and the ensuing renegotiations. Finally, Figure 7 encapsulates all words related to "Unemployement" in a giant cluster.

I also find clear indications of multiple facets of IB and OB which can capture the reason for the communication between the borrower and the servicer and also their incentive compatibility. I create 3 sub-clusters of IB t-SNE for: (1) IB and Financial Hardship in Figure 8, (2) IB and Family, Property, Loss in Figure 9, (3) IB and Legal Issues in Figure 10. In the same chain of thought, I create 3 sub-clusters of OB t-SNE for: (1) OB and Loan Modification in Figure 11, (2) OB and COVID in Figure 12, (3) OB and Legal Issues in Figure 13. Figure 8 captures several aspects of the Inbound communications related to financial hardship, e.g., liquidating Vs keeping property by the borrower, change in owner occupancy due to employment transfer and distance of the property from the new job, inability to sell the property, borrower illness, etc. Not all of the above are verified for borrowers with Gov-backed loans and hence this category of Inbound communications heavily contributes towards the opportunistic/strategic elements of borrower forbearance applications. Figure 9 points out Inbound communications related to marital matters like marriage/divorce/death of spouse, excessive obligations, casualty loss, etc. Figure 10 is more comprehensive and nuanced to the legal aspects of Inbound communications, e.g., prior bankruptcy, ownership transfer, business failure, leniency from military service, non-payment by the tenant, payment disputes, etc. Figure 11 captures the keywords related to selective verification by the servicer, e.g., decline, payment dispute, disposition, suspense, reapply, ineligible, denial, flag, intermittent, etc. Figure 12 directly captures Outbound communications related to COVID-19 and as one can see there are not many words related to forbearance, since the servicers approve forbearance applications from the borrowers who fall under the purview of the CARES Act and try to dissuade other borrowers when the borrowers initiate conversations related to forbearance and/or foreclosure moratorium. Figure 13 details the Outbound communications related to the specific servicer attributes such as performance, borrower indication, involuntary, representation, temporary, title, signal, silence, commitment, satisfaction, judicial, document, identification, etc.

Table 1 reports the descriptive statistics for the mortgages as of the April 2020 servicer reporting date. Panel A summarizes the statistics for all loans while Panels B and C summarize the data based on whether the mortgages are government-back loans (Panel B) or non-government program loans (Panel C). The average loan had an origination amount of approximately \$96,700 on a property with an appraised value of approximately \$120,000. The average loan-to-value ratio at origination was approximately 80%. Since the data consists of first-mortgages, second mortgages, and home-equity loans/lines of credit, the average loan amount is lower than samples comprising exclusively first-mortgages. The mean borrower credit score at origination was 613, reflecting the higher proportion of subprime borrowers in the portfolio (65% of the sample). Panels B and C reveal significant differences in the government (FHA/VA) and conventional (non-government) loans. For example, FHA/VA mortgages had higher origination loan-to-vale ratios than conventional loans (96% versus 72%) and higher average current balances (\$122,308 versus \$56,648, respectively). The geographic distribution FHA/VA loans in the dataset in Figure 14 is consistent with the distribution of FHA market shares reported in Ambrose and Pennington-Cross (2000) and Ambrose et al. (2002). Across all loans in the sample in Panel A, the call center logs indicate that 7% of the loans were flagged for a Covid-19 related forbearance. In addition, approximately 3% of the borrowers indicated an employment problem and 5% reported having a serious income issue (curtailment of income). During April, 29% of all borrowers were contacted by the servicer (outbound) while 22% of the borrowers initiated contact with the servicer (inbound). Panel B reveals significant differences in call center activity for government and non-government loans. I see that 42% of government loan borrowers experienced a call center initiated contact (outbound) with the servicer and 32% initiated (inbound) contact with the servicer. In contrast, 23% of the non-government borrowers experienced a call center initiated contact and 17% initiated a contact with the servicer. Consistent with the FHA being more aggressive and faster in responding to the Covid-19 crisis, I see that 11% of these borrowers had a Covid-19 related discussion with the servicer as compared to 4% of the non-government loan borrowers.

Table 2 goes one step further on Panels B and C in Table 1, by creating separate buckets form Performing (PL) and Non-Perfoming (NPL) loans among Govt-backed (Gov) and Non-Gov-backed (Non-Gov) loans. In Panel A, PL and Gov is highest group applying for COVID-19 compared to unemployed borrowers in the group. Number of incoming calls is also very high for this group. For Gov-backed PL loans, COVID-19 Forbearance applicants (11%) is much higher than unemployed (3.9%) and Curtailment of Income (4.7%). So, at least 6% of these borrowers are definitely strategic. The number of Inbound calls is also much higher for Gov-backed loans, leading to the possibility of strategic behavior. The original LTV is much higher for Gov-backed PL loans, still the current mortgage rate for Gov-backed loans is much lower and their FICO scores are relatively higher. In Panel B, PL and Non-Gov still has higher COVID-19 Forbearance applicants than the number of unemployed borrowers in the same group, but much less than PL and Gov, although their current delinquency status is much better. For Non-Gov PL loans, only the unemployed borrowers are applying for COVID-19 Forbearance. This happens to be same as Curtailment of income, which means the only source of income for these borrowers is from employment. In Panel C, NPL and Gov takes advantage of Foreclosure Moratorium, as they are mostly ineligible for Forbearance applications. DLQ for NLP is 4 .37

(in Panel C) and 4.39 (in Panel D), meaning 120+ day delinquent, hence they are ineligible for Forbearance. The servicer may be letting the borrower know their ineligibility for Forbearance since the servicer has corporate advances in place. In particular, the servicer increases their call volume and frequency for NPL non-GOV cases since corporate advances are the highest in that bucket.

The spatial distribution of key variables in this paper provide stronger evidence of the strategic behavior of borrowers in PL_Gov group. There are plenty of Non-Gov loans in Las Vegas in Figure 14 depicted by yellow color and Las Vegas was one of the major fatalities of the COVID-19 pandemic as the entire state runs on gambling and tourism revenue which were shut down abruptly. However, the forbearance applications of residents of Las Vegas were overcrowded (in Figure 15) by residents from the northern mountain states who arguably were affected much less severely by the first major hit of the COVID-19 during March - April. The geographical distribution of the curtailment of income in Figure 16 also paints a similar picture in April 2020 data, where the residents of only a few pockets were facing severe financial hardship, but forbearance applications were rampant from all over the United States by the opportunistic/strategic PL_Gov borrowers. The distribution of Inbound calls and Outbound Calls provide preliminary evidence of strategic behavior by the borrowers and the selective verification by the servicer respectively in my data.

3 Servicer Perspective and Institutional details

If the forbearance is extended for another 3 months after June 2020, this could have serious cash flow implications for the investor (bond-holder). This is crucial since after 4 months of Forbearance, the servicer is not required to make any advances to the investor. So, essentially, after 4 months, the investors would have to take the hit, if the borrower decides to be delinquent and not make timely payments after 6 months of Forbearance. It is a high Cash flow risk whose downside is not protected. If the borrower was 2 payments down or in foreclosure, they are still being reported to the Credit Bureau as 2 payments down or in foreclosure, and they cannot refinance until they become current. They would qualify to be considered for a modification. From the servicer's perspective, all of the non-government insured loans will need to demonstrate that they have been impacted by the pandemic (i.e. borrowers are unemployed). The purpose of the loan does not avid the CARES Act. Certain loans would not be covered, such as second homes and second liens. However, second liens undergo an analysis on whether there is enough equity to initiate foreclosure, and second homes would require full workout submissions. All of this is somewhat moot since there most states have moratoriums on referral to foreclosure, foreclosure sale, and eviction (excluding vacant properties).

Another key question for Non-Gov loans (e.g., Conventional Loans) in this portfolio is if the servicer is indifferent to the outcome: Foreclosure Vs Forbearance, since the advancing costs are taken care of by the investor. It is fair to say the the servicer has no exposure to either PI (principal interest) advances or corporate advances once the loans are acquired by the PE firm (provider of this data). On the government portfolio, the guarantors (HUD, VA and USDA) have insisted on forbearance being a preferred decision before foreclosure. On the conventional portfolios, although there is no guarantor dictating decision paths, the CFPB (Consumer Financial Protection Bureau), the CARES Act, and many states (such as NY and CA) do provide regulatory guidance over offering workout opportunities (forbearance) over foreclosure. They also indicate that the borrower owns certain responsibilities in requesting that help that is more expansive then what the GSEs require, which has allowed the servicer to be more insistent on documentation of financial hardship instead of wanting to take time off from making payments. The servicer does insist on documentation of a lost income rather than a just a phone call request for a forebearance plan. Also, from a business perspective, the servicer earns service fee income on both a loan in foreclosure or on forbearance, so the servicer is indifferent on the path based on similar income and similar expenses. However, if they can ultimately cure the default with a forbearance that turns into a modification, then the servicer would prefer that solution, i.e., they will ultimately make more income. The servicer would also incur additional staffing costs for loans that go through the Foreclosure/REO process than a loan that goes through the forbearance reinstatement process, again slightly favoring the forbearance, where the servicer will ultimately incur less staffing expenses.

Related to the above aspects, how the servicer is incentivized/contracted may lead to making more financial gains in one choice Vs the other. Of course, the servicer has to consider the local jurisdictions/rules in place for offering loss mitigation options before starting foreclosure. This becomes crucial, since 70-75% of the borrowers who had applied for Forbearance are extending their non-Payment from being in Forbearance. So, there is a clear choice to be made by the servicer for Non-Gov loans (which are not directly under the purview of the CARES Act). The incentives of the servicer for Foreclosure Vs Forbearance paths from being a performing loan, need not be aligned with the interest of the PE firm acquiring these loans. Although the guarantors have no authority over the PE firm portfolio, the government and state agencies/regulators do, and their preference leans towards the borrower (voter). The servicer is definitely risk adverse with picking a fight with a regulator. Even if a request for an extended forbearance is denied, there is a limit to moving forward with the foreclosure process. Properties that are vacant can usually proceed with foreclosure (referral or sale), but not in all states, and in some counties, the Courts have not reopened to allow movement.

4 Univariate Analysis & Empirical Model Specification

The comparison of differences in Covid-19 forbearance responses and call center activity across various loan types is captured in Table 2 in (Agarwal et al., 2020a), which shows that significant differences exist between performing and non-performing loans for government-back and non-government back mortgages. Government-backed performing loans (columns 2-4), had approximately the same rate of in-bound and out-bound communication (15% versus 17%) and for the non-performing government-backed loans, outbound rate (51%) is significantly higher versus inbound (29%). The difference is not surprising since servicers are required to attempt to contact borrowers who have missed monthly payments in an effort to mitigate potential losses associated with default. It is interesting to note that only 9% of non-performing borrower communications mention Covid-19 forbearance relief in contrast to the 13% rate observed in performing borrowers. I also find several interesting insights from Columns (5) through (7) that compare performing and non-performing non-government loans. First, similar to the government loans, I see that outbound communication is significantly higher in the non-performing set than in the performing set (54% vs 10%). Again, this is to be expected since non-performing loans require direct servicer intervention whereas servicers typically respond to borrower requests for some action in the performing loan group. In comparing the differences between government and non-government mortgage portfolios, I see that borrowers with performing loans in the FHA/VA and conventional portfolios have approximately the same unemployment indicator, which is again consistent with borrowers who are current on their mortgage payments having low employment problems. However, the Covid-19 forbearance rates are significantly higher in the government backed loan group than in the non-government portfolio. Thus, given that employment issues are roughly equal between government and non-government borrowers, the higher Covid-19 forbearance rates in the government portfolio is evidence of strategic forbearance requests coming from the borrowers who are current on their government insured mortgages.

I test for evidence of strategic forbearance, controlling for differences across borrowers and mortgages, with the following logistic regression framework (Agarwal et al., 2020a):

$$\begin{aligned} Pr(F_i) &= \Phi(\delta_1 IB_i + \delta_2 OB_i + \delta_3 G_i + \delta_4 P_i + \delta_5 IB_i \times G_i \\ &\quad + \delta_6 OB_i \times G_i + \delta_7 IB_i \times G_i + \delta_8 OB_i \times P_i + \gamma U_i' + X_i'\beta + \kappa_c) \end{aligned} \tag{1}$$

The parameters δ_1 through δ_8 are the primary coefficients of interest and capture the differential effects on the probability of the borrower entering forbearance based on whether the borrower (δ_1) or servicer (δ_2) initiated contact during April 2020. The interaction terms (δ_5 through δ_8) thus capture the differential servicer incentive effects based on the type of loan (government insured or non-government) and the loan payment status (performing versus non-performing).

5 Multivariate Analysis

Table 3 reports the regression results for early forbearance. Columns (1) and (2) report the results for all loans with and without county fixed effects, respectively. Not surprisingly, the positive and statistically coefficients (at the 1% level) in all columns 1-4 in Table 3 for inbound and outbound confirm that the probability of forbearance increases with any communication with the servicer, whether initiated by the borrower or servicer. This is to be expected since forbearance requires an active request on the part of the borrower and thus necessitates communication with the servicer. The estimated coefficients for inbound and outbound in my preferred specification that includes county fixed effects (column 2) reveal that the probability of forbearance is essentially the same regardless of whether the servicer or borrower initiated the contact.

Turning to the differential between FHA/VA in column (3) or private-label mortgages in column (4), the estimated coefficient is not statistically significant indicating no difference in the incidence of requesting forbearance between these borrower groups (all else being equal). However, it is interesting to see that the coefficient for the variable indicating whether the loan is currently performing is also not statistically significant. Thus, I do not find evidence that borrowers who were already in financial difficulty and were delinquent on their loan prior to the pandemic are taking advantage of the forbearance option. In fact, the interaction of inbound with performing is statistically significant and indicates that requests for forbearance are most likely arising from borrowers who were current on their loans at the onset of the pandemic.

Columns 1-2 in Table 3 show that Inbound calls for Performing loans (IB_PL) is positive and significant with and without county fixed effects. Same is true for Outbound Calls for Performing Loans (OB_PL) in Columns 1-2. Essentially, both the borrower and the servicer makes more communications if the loan is performing. I test this with triple interaction too and find the same results as a robustness check. IB_PL is insignificant in Gov-only case in Column 3, since there borrowers get Forbearance by default from CARES Act. In the Non-Gov case, however, IB_PL is significant in Column 4, i.e., the borrowers have to actively communicate with the servicer to apply and be considered for forbearance. Similarly for OB_PL, columns 1-2 are significant. For Gov-only loans, OB_PL is significant as the servicer has to let the borrower know about the availability of forbearance option and have to ask the borrower if they want to enjoy the benefits delaying the payments in the future via forbearance. The servicers also respond to the borrower inquisitions in the situation where the borrower initiates the forbearance conversation. For Non-Gov loans, OB_PL is insignificant, however, I feel that this behavior can also be strategic/selective from the servicer's perspective based on the loan-type, i.e., Cash-Out Refinance or Purchase only loans. Cash-out loans comprise of almost all of the PL foreberance cases for non-Gov loans - 409 out of 461 in April 2020. This is why I separate the sample to only cash-out and no-cash-out in Table 4. IB_GOV and OB_GOV are insignificant without the interaction with the delinquency status of the loans. Curtailment of Income is an important determinant of Forbearance applications for the Liquidity-constrained borrowers. Unemployment Status per se is not as good of an indicator for Forbearance like Curtailment of Income.

Cash Out loans in this PE firm portfolio are distressed loans, which they bought at a significant discount in 2017. No promissory notes are attached to these Cash Out loans. These borrowers have lower FICO scores and are subprime. But from the time, they were acquired by the PE firm, they have mostly remained performing loans. Because the cash-out loans were bought at such discount and they comprise of subprime borrowers which mostly have been making payments, the focus has been less on re-couping corporate advances, since the servicer and the PE firm both share the profit in a liquidation/exit event. Because most Cash Out loans are non-Gov, the borrowers have to provide evidence to the servicer to get Forbearance approved. This is corroborated by positive significance of IB_PL. Both the OB_PL and OB_GOV are positive significant, indicating the servicer calls are significant for GOV PL borrower. On the other hand, the borrower calls significant when they have GOV loan.

Both the IB_GOV and IB_PL are positive but insignificant in Columns 2-4 with County fixed effects. This means, the borrower makes less calls when they have GOV and PL, as they are provisioned for forbearance under the CARES Act. OB_PL is positive significant in Column

2-3, since servicer makes mandatory calls in GOV loan case if the Borrower is PL. OB_PL is negative highly significant for Non-Gov loans (which are not Cash-Out), i.e., the servicer makes more calls for non-GOV borrowers to let them know they have to verify their unemployment status and financial hardship, otherwise they are ineligible for forbearance. For Govt.-backed loans, the CARES act legally binds the servicer to approve those borrowers and continue making advances. The servicer is legally obliged to advance for 4 months into Forbearance. From the data, I find that 70-75% are extending Forbearance. Hence, the servicer will have no incentive to reject Forbearance extensions as they have no skin in the game beyond 1 more month (first Forbearance was approved for 3 months).

6 Race Implications of Forbearance

I find evidence that African American and Hispanic borrowers have been able to avail the leniency from Forbearance, but much less than the white borrowers. This is especially important in the current socio-economic and political climate charged with racial tension. The servicers have sophisticated Machine Learning models to profile the borrowers and hence, even without the race information, the Machine Learning models uncover structural relationships among Loan performance variables and/or triangulate from otherwise excluded characteristics Fuster et al. (2017). Among conventional loans, the percentage of Forbearance applications is higher for White and Hispanics compared to the African American (henceforth Black) borrowers in Figure 17. For Gov-backed loans, the difference is more stark. The white borrowers have a much higher Forbearance application rate than Black and Hispanic, both for PL and NPL loans in Figure 17. In Table 5, I add an indicator whether a borrower is Black (African American) and interact the dummy variable with IB, OB, IB_PL and OB_PL to make further inferences beyond Table 4. Firstly, for Non-Gov Black borrowers, there is a huge negative significance towards forbearance, with and without county fixed effect in Table 5. This clearly shows, all else equal, Black borrowers are prevented (unintendedly dissuaded) against availing forbearance applications because of adverse loan performance behavior, since the servicer does not have the race information of the borrowers. Also, for Non-Gov Black borrowers, IB_PL_Black is positive and significant with no fixed effects. With county fixed effects, the result is also economically significant, however the statistical significance is not bourne out in the county fixed effect due to small sample size when grouped by county.

OB_PL is still negative for Non-Gov loans with race in the specification, providing robustness of the selective behavior by the servicer, as detailed in the previous section Table 4. OB_Black for Non-Gov loans is highly positive and significant, with and without county fixed effects. This implies the servicers verify the Unemployment status or financial hardship for Black borrowers and then and then only are those Black borrowers are approved on their forbearance applications. OB_PL_Black is negative and significant without county fixed effects, which means Black borrowers who have performing loans are dissuaded by the servicers with their forbearance applications. Typically a borrower who has a performing loan ex-ante should not be in financial distress ex-ante. Essentially, the servicer is trying to reduce the ex-post risk for Black borrowers. If the Black borrowers are really in financial distress, they need to provide hard evidence to get their forbearance approved. On the flip side, these borrowers are not encouraged by the servicer to apply for forbearance and are mostly pre-empted by adding an income verification clause.

In it important to point out some nuances of columns (5), (6) in Table 5. Column (5) is without county fixed effect and I see warnings that some fitted probabilities of forbearance are numerically 0 or 1. This implies perfect predictability for a whole lot of people, specially in counties from which I have lower number of loans and hence lower forbearance application rates. This is plausibly related to the commonalities in a small county, i.e., if one person applies for forbearance, there everyone in the vicinity also does and vice versa. Also, the supply chains in smaller counties are heavily affected by the economic activities from big cities, which are mostly coastal in USA and hence affect heavily by COVID-19. The African American community amplifies these small county commonalities further more and hence their behavior is uniform and predictable from the same county. Also, smaller counties presumably have fewer industries and fewer number of jobs available, which skews the forbearance application behavior one way or the other. This is the reason, I evaluate forbearance rate with county fixed effect in column (6). This enables me to observe forbearance application and acceptance for African American people across county level heterogeneity, before and after CARES Act.

7 Diff-in-Diff for Borrower & Servicer behaviors

To address the endogeneity concerns from the strategic overcrowding of forbearance applications by Gov-backed performing loan borrowers and the endogeneity emanating from selective verification by the servicer, I use Difference-in-Differences approach. The treatment group comprises of the Govt.-backed loans and the control group contains the Conventional/Private Label Non-Govt. backed loans. The treatment time is end of March 2020, when the effect of CARES Act is internalized. In Table 6, the first variable is the interaction between treatment group and treatment time. In all columns (1)-(6), the interaction is statistically significant, implying significant causal impact of CARES Act on the treatment group. This clearly addresses the endogeneity concerns.

Columns (1) (without county fixed effect) and (2) (with county fixed effect) in Table 6 capture the Diff-in-Diff estimates for all loans, controlling for Inbound/Outbound calls and their interactions with Performing Loans and Gov dummies. The unique feature of this specification is the real-time "Borrower Noted Unemployment" and "Borrower Noted Income Curtailment" which gives me a unique chance to capture the borrower financial health. The strong positive significance of the interaction term provides evidence of the average positive treatment effect on the treated. Then I delve deeper to confirm the narrative of the paper. In columns (3) and (4), I explore the Diff-in-Diff approach to capture the strategic forbearance applications of the borrowers from their Inbound communications. The volume of Inbound communications after CARES Act increases the likelihood of forbearance applications. This overcrowds several worthy borrowers who really need the forbearance because of their financial hardship, e.g., borrowers in Las Vegas who are heavily impacted by the shutdown of the gaming industry cannot all avail forbearance, whereas, borrowers in mountain zone in Montana and other areas are applying for forbearance although the local economy was not affected by COVID-19 immediately in March/April.

Similarly, I conduct a Diff-in-Diff analysis in columns (5) (without county fixed effect) and (6) (with county fixed effect) to capture the selective verification of of borrowers by the servicers vis-a-vis Outbound communications. The robust positive significance of the interaction term again provides sound evidence to the narrative that the servicers try to pre-empt certain borrowers with Non-performing loans and other marginal borrowers from availing the forbearance options. Instead, the servicers encourage them for loan modification or foreclosure moratorium options.

For robustness checks, I also create Non-Gov dummy in Table 7 as the Outbound communications of the servicers for selective verification of unemployment status mostly targets the Non-Gov borrowers. I still find strong positive statistical significance for the interaction of term of the Treatment time and the treated (here treatment group in Non-Gov). Finally, because of multi-collinearity issues discusses in Section 6, I exclude those counties which have one or less loans for the whole time horizon of 5 months. Table 8 again shows strong statistical significance among counties with more than one loans for the interaction term. These results prove beyond any doubt the causal impact of strategic/opportunistic behavior on the borrower's part on forbearance selective verification by servicer on dissuading (denial with provision of alternatives like foreclosure moratorium or loan modification) forbearance applications.

8 Cost-benefit analysis of CARES Act

I conduct a simple Back-of-Envelope Calculation to give an estimate of the cost and benefit of the CARES Act. As of the end of May 2020, the US Residential Mortgage Debt was **\$ 11.1 Trillion**[10]. Around 4 million Gov borrowers availed Forbearance by the end of May 2020[11]. Forbearances are approved for 6 months at a time. So the, next cost of forbearance for Gov-

[10]Source:https://www.housingwire.com/articles/u-s-mortgage-debt-hits-a-record-15-8-trillion/: :text=Outstanding%20U.S.%20mortgage%20debt%20rose,according%20to%20the%20Federal%20Reserve

[11]Source:https://www.cnbc.com/2020/05/07/4-million-homeowners-in-cares-act-mortgage-forbearance-program.html

backed borrowers nationally is:

(Availed Forbearance) * (P&I) * (Forbearance period)/ (Principal Payment)
= 4,000,000 * $721.18 * 6 / 3 = **$ 5.76 Trillion**

Here, I use a mortgage calculator and use the terms of Gov-backed of mortgage from the Summary Statistics Table 1 detailed in Figure 18 in Black Knight August 2020 report.

9 Looming Plausible Housing Crisis

United States is still in the middle of the COVID-19 pandemic and no one can say for certain what the future holds. The national elections are right around the corner. In these highly uncertain circumstances, the possibility of an upcoming housing crisis cannot be overlooked. I take recourse to a recent article by Black Knight August Research[12]. Although the number of Forbearance applications have gone down in Figure 19 and weekly new forbearance plans have declined and flatted in Figure 20, there is still a sizable amount of forbearance plans extended in Figure 21. Moreover, the evictions of non-paying renters/homeowners is temporarily halted by President Trump at least till the election. As evident in Figure 22, the status of loans leaving COVID-related Forbearance plans are not current. After the forbearance period ends, they become delinquent loans, which can subsequently be offered foreclosure moratorium or loan modification to cure them. There could be a significant surge in foreclosure in the near future if these borrowers are able to avail foreclosure moratorium and get temporary relief from ban in eviction for renter and homeowners alike. FHA and VA have worse delinquency than other GSE and Private label loans. So, the marginal borrowers whose loans are about to become Non-performing can eventually end up in a vicious cycle of foreclosure and lack of employment which in turn increases foreclosure. So, a misaligned CARES Act to provide economic relief to the borrowers due to a public health crisis could be amplified into a much bigger housing crisis

[12] Black Knight's August Report on Forbearance is provided here: https://cdn.blackknightinc.com/wp-content/uploads/2020/10/BKI$_M M_A ug2020_R eport.pdf$

in the near future. Also, the loss of 5.76 Trillion USD, as explained in the previous section could become permanent and it may take years, if not a decade, of slow economic recovery to reduce this national debt.

10 Conclusion

In this paper, I provide insights on the lack of effectiveness of the mortgage forbearance program contained in the CARES Act. Utilizing a novel administrative dataset coming from a mortgage servicer, I examine the communications between borrower and servicer in order to shed light on the probability that a borrower will request forbearance. In line with studies looking at mortgage modifications during the Great Financial Crisis period (Demyanyk and Van Hemert, 2011), (Mayer et al., 2014), I provide evidence to suggest that borrowers are strategically taking advantage of the CARES Act to request mortgage forbearance, the servicers are selectively verifying the unemployment status/financial hardship for Non-Gov borrowers. I find that this selective verification by the servicer precludes unintended distributional implications based on race for African American and Hispanic borrowers. My results document strategic behavior in response to CARES Act policy which was an ad-hoc response during the advent of COVID-19 in the United States. The economic costs of strategic behavior/selective verification are significantly large relative to the potential gains to borrowers, lenders, and servicers from these policies. My results highlight the misalignment of ad-hoc policies on Government programs such FHA, VA, USDA of the HUD, due to the non-verification (for Gov borrowers) and selective verification (Non-Gov borrowers) of unemployment status/financial hardship. I am able to conduct this research due to the narrative retrieval apparatus I have created from the novel administrative data on the communication between the borrower and the servicer. The flawed interpretations and the erroneous inference thereof of the special servicers can be mitigated using Machine Learning/Natural Language Processing techniques. More work must be done to assess the overall costs/benefits of such forbearance policies and their effectiveness in preventing foreclosures. Otherwise, surge in foreclosure will inevitably lead to the next housing crisis.

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11 Appendix

11.1 Key words chosen manually

Keywords for identifying **employment** issues are: “unemployed”, ”out of work”, ”laid off”, ”furlough”, ”unable to achieve”, “collactivitie” and “suspended”, “insufficient” and “conditional liquidation”, “ADV” and “late charge”, “not available” and “payment”, “loss” and “request”, “lost job”, and “didn’t” and “work”.

Keywords for identifying **Inbound** communications are: ”Inbound”, ”IB”, ”reached out to” and not ”borrower”, ”received”, ”Borrower is writing”, ”was contacted”, ”borrower” and ”informed” or ”indicated”, ”request”, ”marital difficulties”, ”death of family member”, ”excessive obligations”, ”casualty loss”, ”payment dispute”, ”tenant not paying”, ”prior bk” and not ”OB” and not ”Outbound”.

Keywords for identifying **Outbound** communications are: ”OB”, ”Outbound”, ”COVID19 Forbearance Letter 712 Requested from vendor”, ”Asked”, ”Replied”, ”msg in dmm portal to da”, ”Called borrower”, ”LMStatus:”, ”No Contact”, ”email reply back”, ”Good Morning”, ”CMS encourages”, ”Carrington Mortgage Services authorizes”, ”next due”, ”response”, ”responded”, ”decline”, ”CMS representative”, ”will be asked”, ”CMS is committed”, ”was contacted”, ”LM Program”, ”payment dispute”, ”prior bk”, ”illness”, ”Offered Borrower” and not ”IB” and not ”Inbound”.

11.2 Differential Borrower Behavior

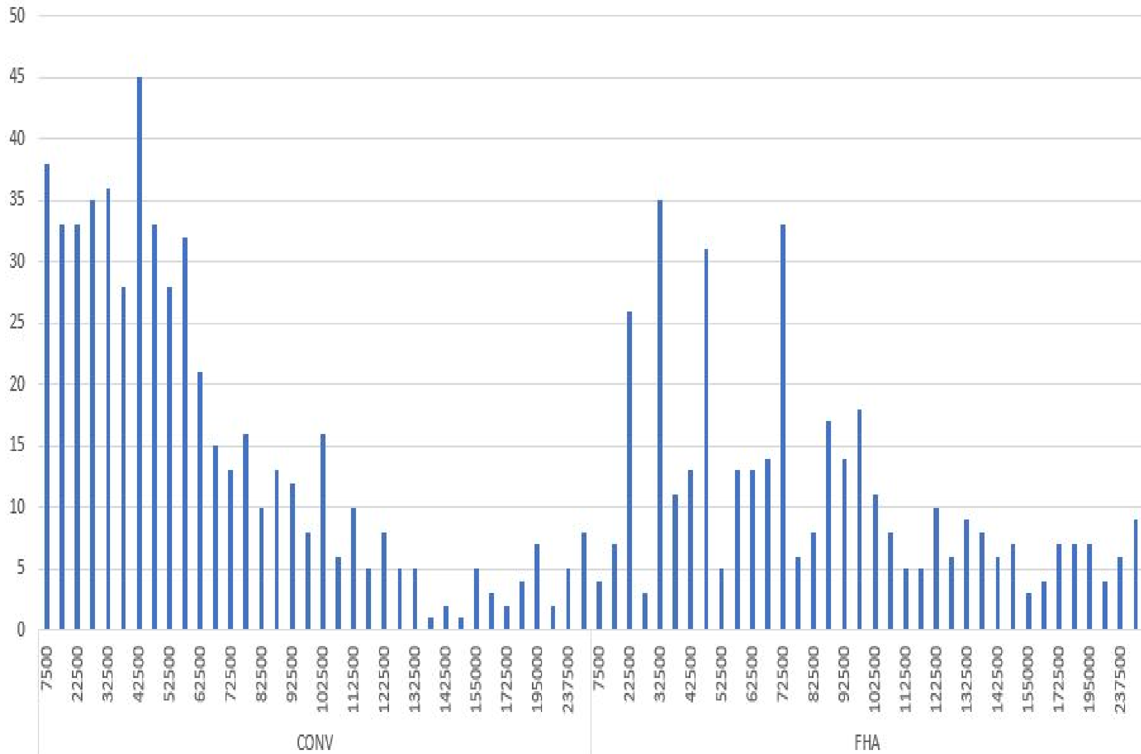

Figure 1: Forbearance applications and Loan Count across different median incomes in US Dollars

I find irrational (opportunistic) behavior among borrowers with Govt.-backed loans and rational (logical and conservative) behavior from borrowers with Conventional loans. Conventional borrowers with lower income and more financial constraints are the hardest hit by the wrath of COVID-19 and hence apply for forbearance and conventional borrowers with relatively higher income and stable jobs do not take up forbearance even though they may be affected in the short-term. The borrowers with Govt-backed loans opportunistically apply for forbearance from almost all income brackets in Figure 1

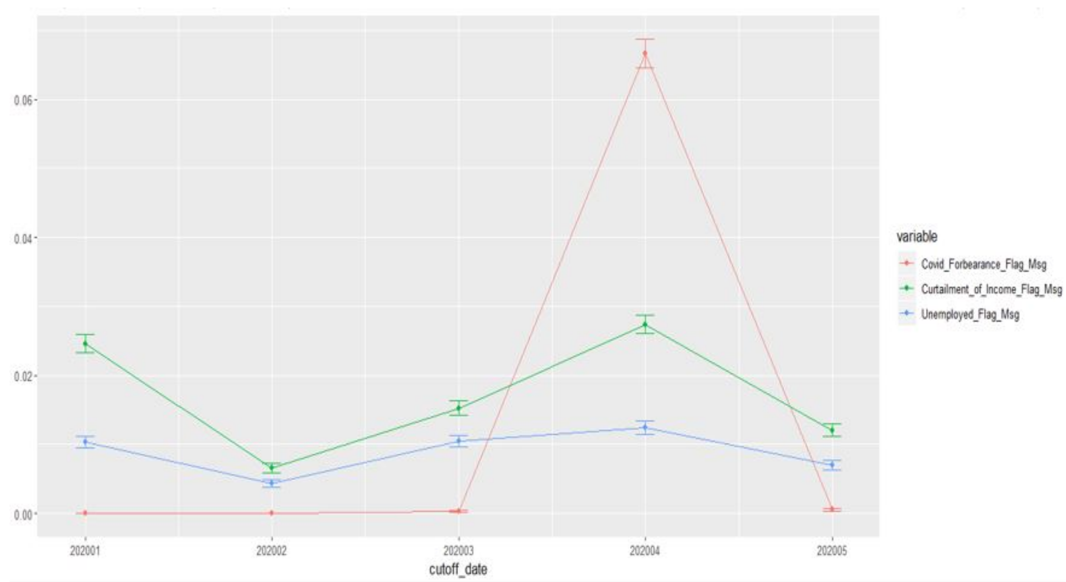

Figure 2: Performing Loans: Time Trend of COVID, Unemployed Curtailment of Income Flags

I provide evidence in Figure 2 that some of these borrowers avail forbearance even though they are not *unemployed* or have had any *curtailment of income*. Moreover, I show that servicers are much more lenient towards borrowers with Govt.-backed loans and stringent with borrowers with Conventional loans by verifying the employment status thereby scrutinizing the forbearance applications of the latter.

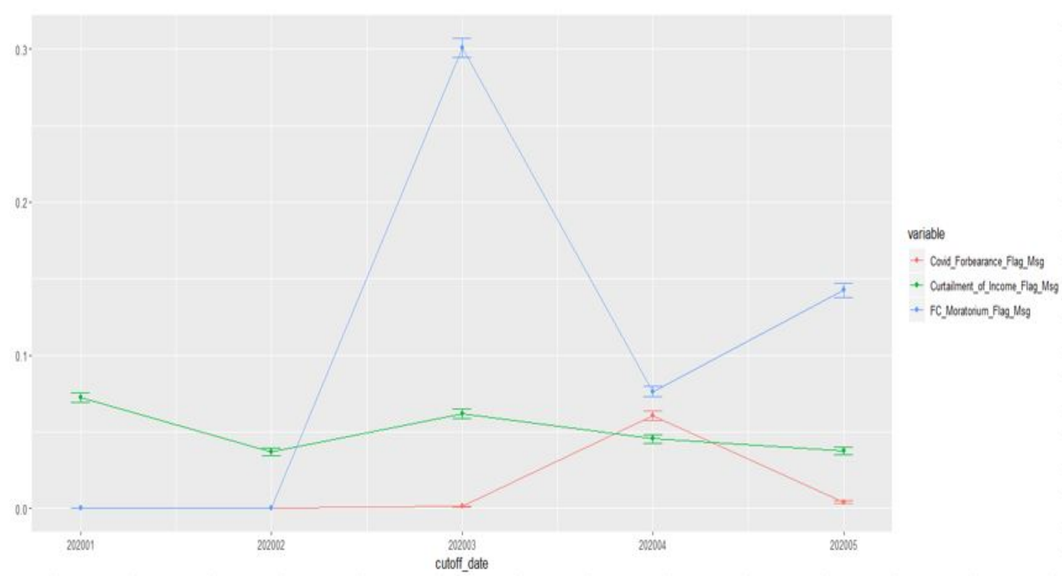

Figure 3: Non-Performing Loans: Time Trend of COVID, Unemployed Curtailment of Income Flags

For NPL borrowers, I see a significant spike in Foreclosure Moratorium by the end of March 2020 in Figure 3. In April, the servicers face a choice whether to approve these marginal borrowers in their forbearance applications or advise them to avail foreclosure moratorium. I see that, by May 2020, most of these borrowers have been dissuaded and informed about their ineligibility (due to adverse delinquency status) by the servicer.

11.3 Keywords from NLP on data

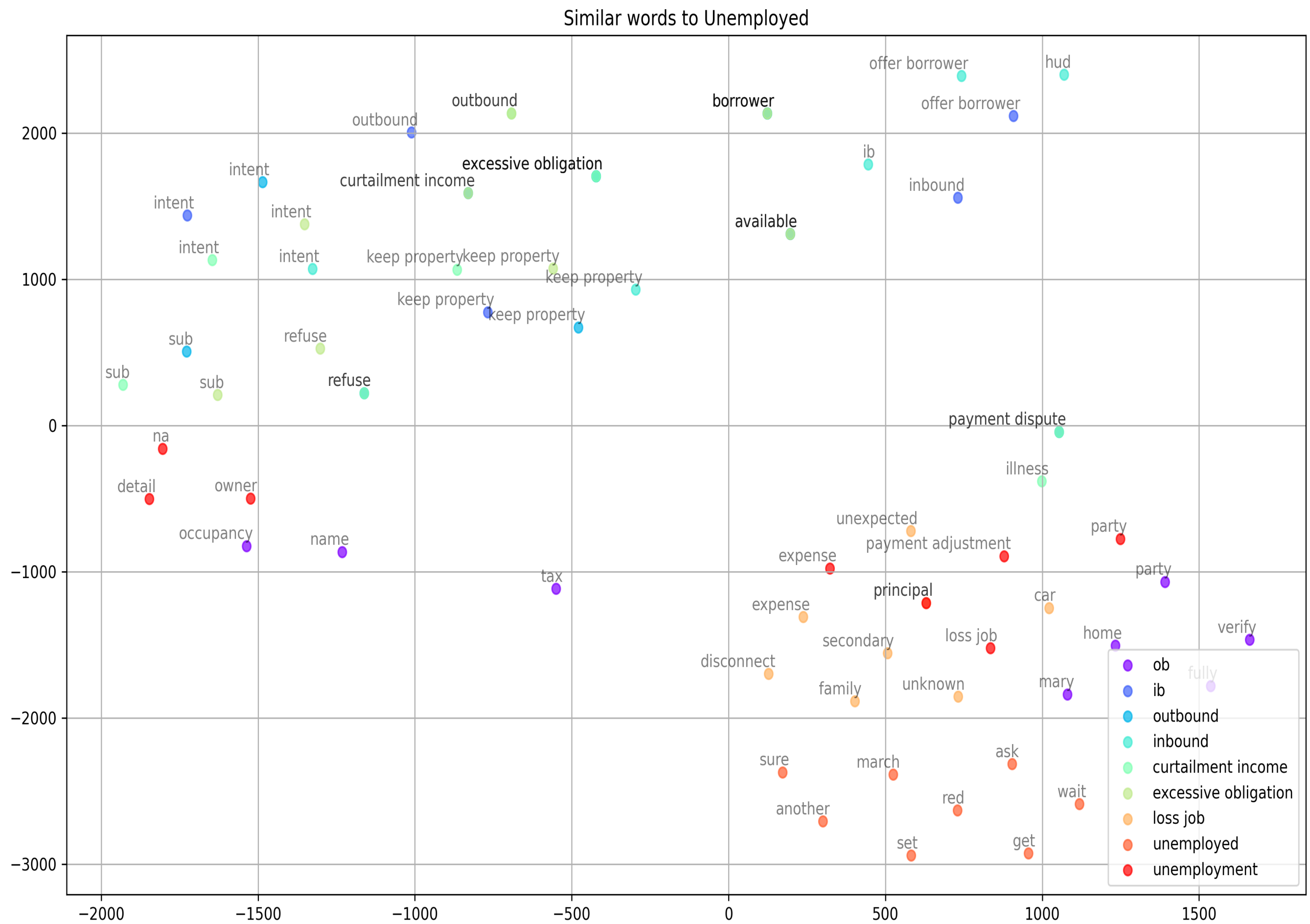

Figure 4: Words related to Unemployment, Inbound and Outbound

In Figure 4, one can notice 4 clusters. On the South-East corner, words related to "ob" (in violet) which are not so much related to unemployment per se but *continual renegotiation* between the borrower and the servicer. On the North-East corner, the cluster represents words related to "ib" and "inbound" (in sea-green) where the borrower seems to be making the case for loan modification and other *offers* that they can avail from the servicer. In the North-West corner, the two subclusters are entangled, one of them highlights the *occupancy* and related issues emanating from unemployment and the other specifically relates curtailment of income with the *intent* of the borrower. The use of these keywords in defining the "Unemployment", "Inbound" and "Outbound" flags (dummy variables) helps me tease out the tension among these aspects of borrower and servicer behavior, which have not been explored previously in academia, to the best of my knowledge.

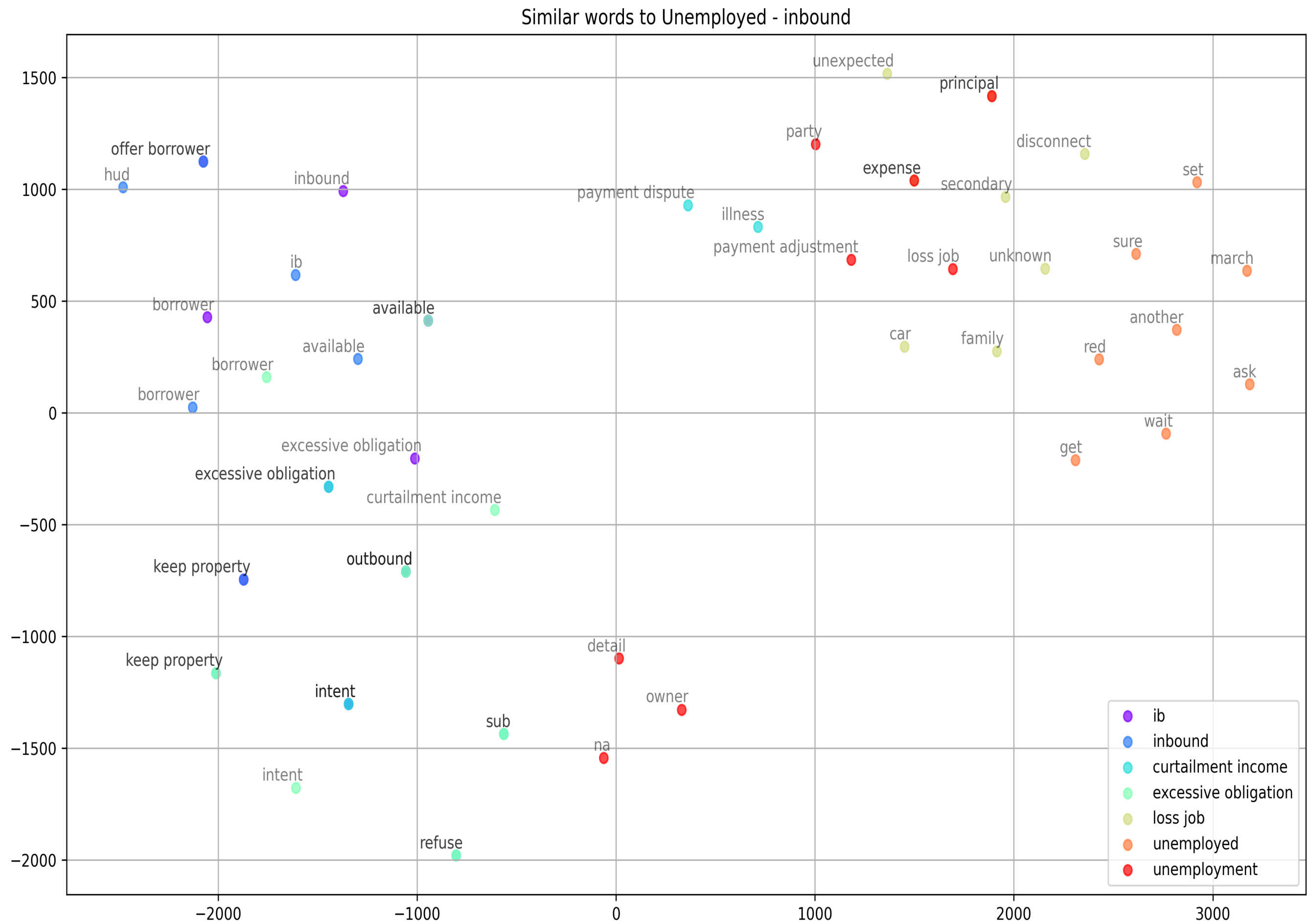

Figure 5: Words related to Unemployment and Inbound

Figure 5 details 3 of the 4 clusters in Figure 4 on the facets of "Inbound" and "Unemployment". The *partial adjustment* and *payment disputes* in the North-East corner point out aspects of financial hardship and renegotiation related to Inbound calls from the borrower. The other entangled cluster captures several borrower aspects related to *intent* and servicer response to *offer* the borrower more favorable terms for the loans. The *refusal* of forbearance for certain borrowers is also captured in the South-West corner of Figure 5.

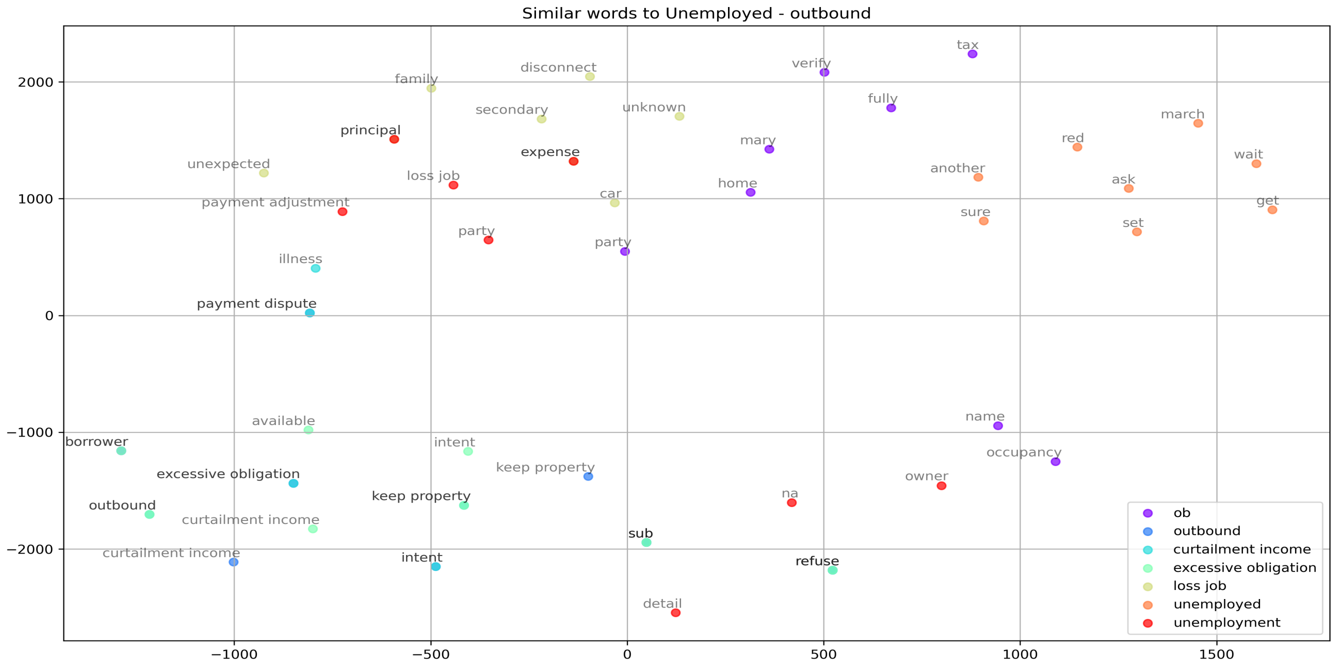

Figure 6: Words related to Unemployment and Outbound

Figure 6 captures the selective *verification* of the unemployment status of certain borrowers by the servicer. The southern part of Figure 6 underscores the typical outbound conversations related to borrower financial health and dire personal circumstances and the ensuing renegotiations.

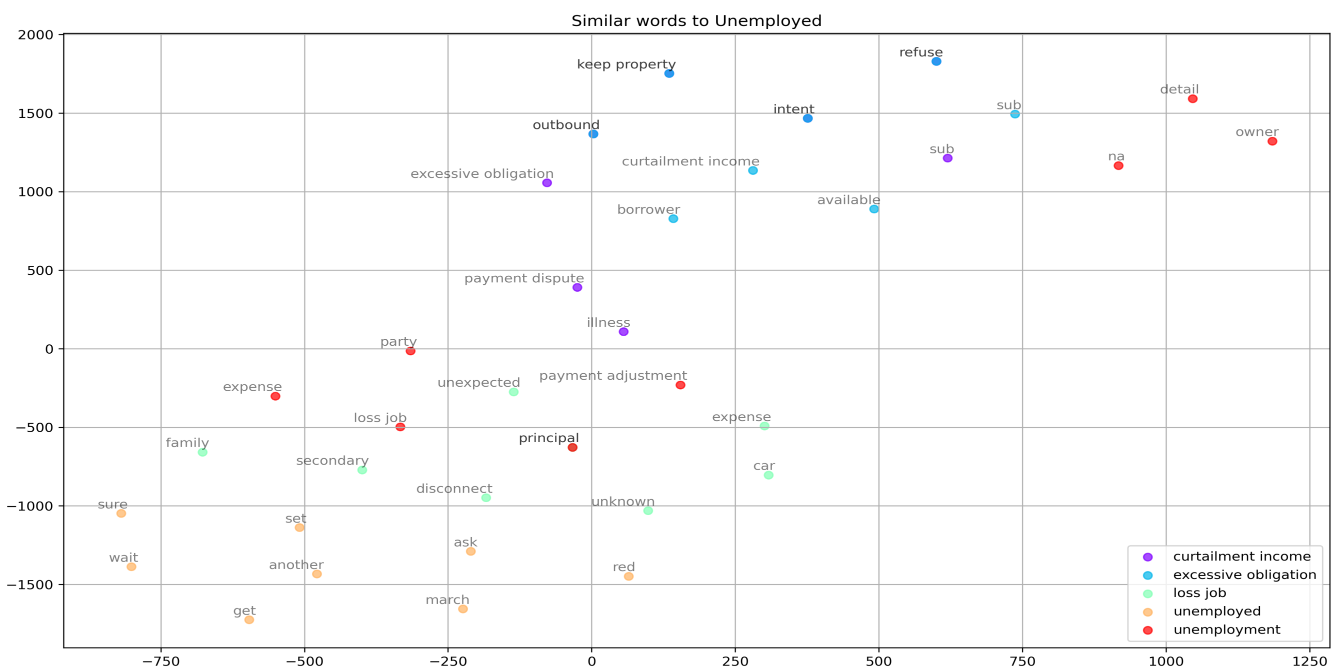

Figure 7: Words related to Unemployment only (without Inbound and Outbound)

Figure 7 encapsulates all words related to ”Unemployement” in a giant cluster.

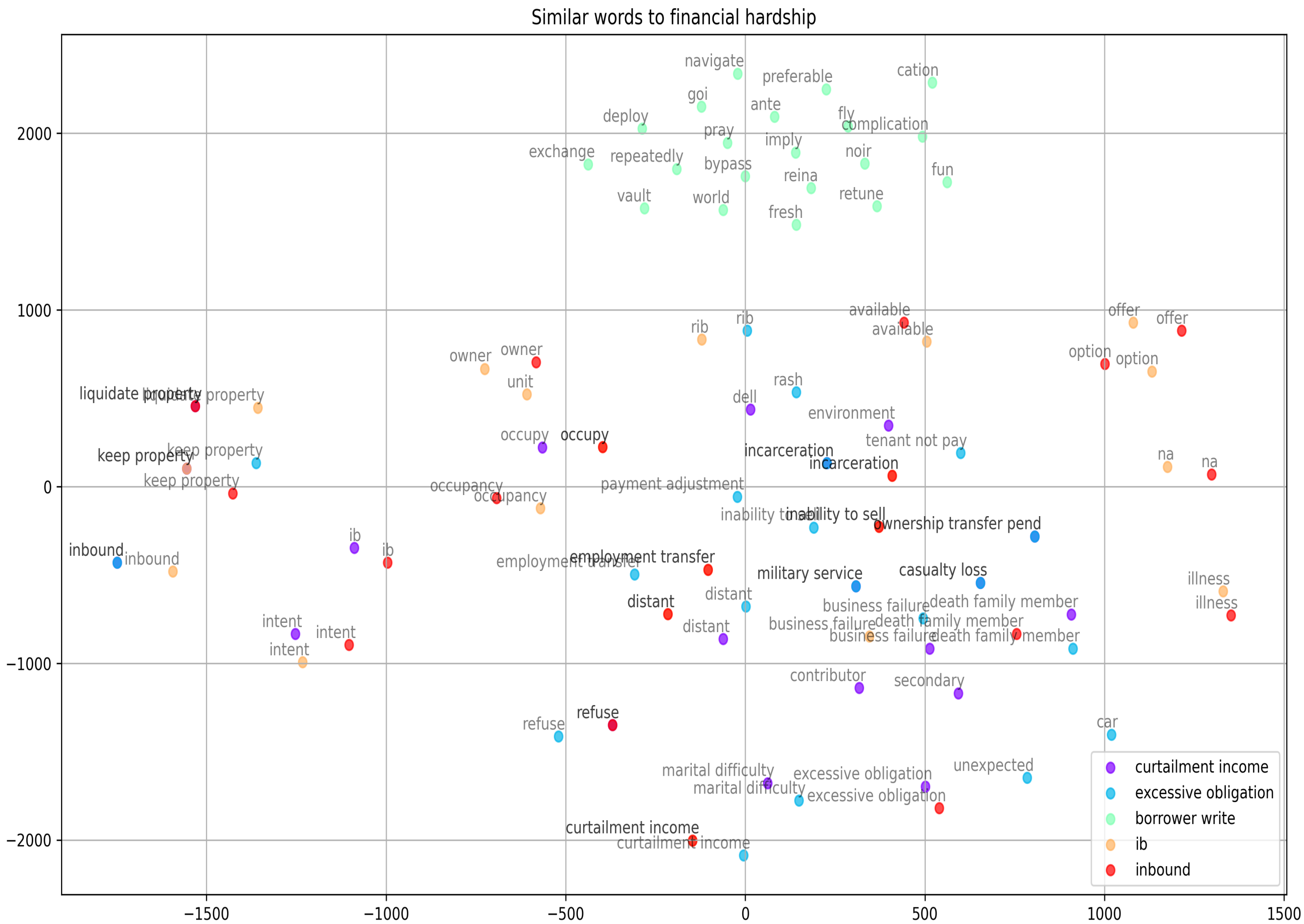

Figure 8: Inbound Communications and Financial Hardship
Figure 8 captures several aspects of the Inbound communications related to financial hardship, e.g., liquidating Vs keeping property by the borrower, change in owner occupancy due to employment transfer and distance of the property from the new job, inability to sell the property, borrower illness, etc. Not all of the above are verified for borrowers with Gov-backed loans and hence this category of Inbound communications heavily contributes towards the opportunistic/strategic elements of borrower forbearance applications.

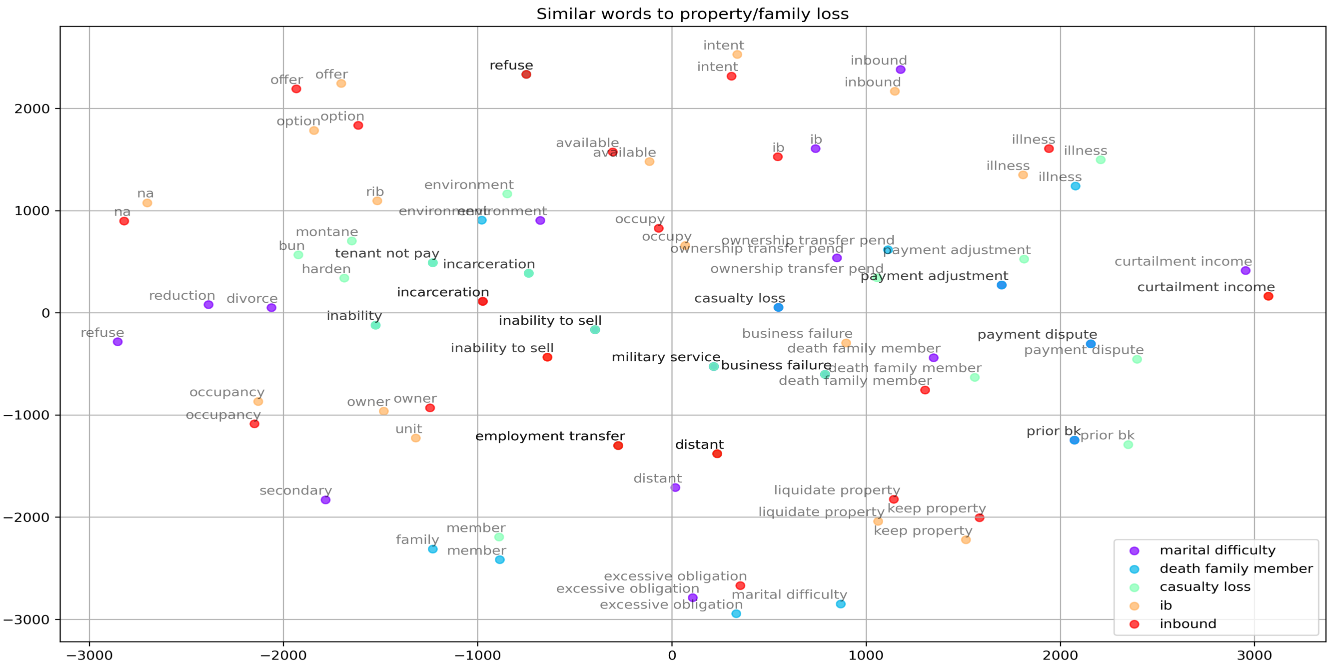

Figure 9: Inbound Communications, Family, Property and Loss
Figure 9 points out Inbound communications related to marital matters like marriage/divorce/death of spouse, excessive obligations, casualty loss, etc.

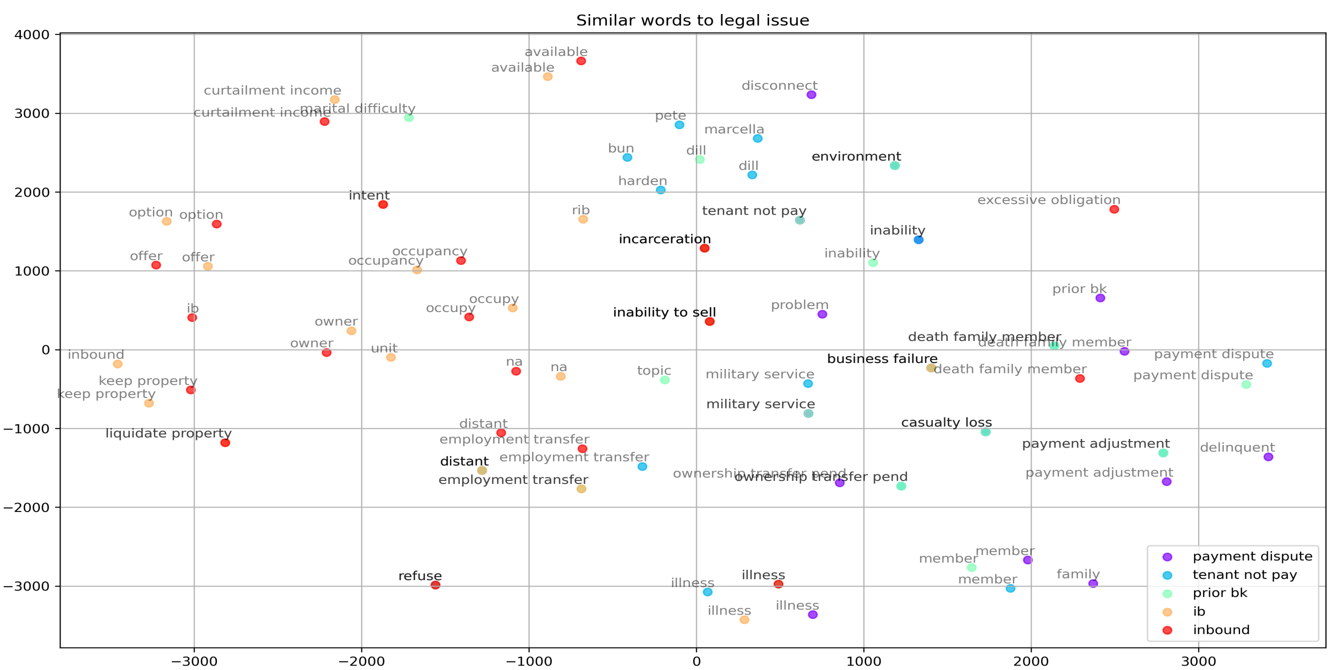

Figure 10: Inbound Communications and Legal Issues
Figure 10 is more comprehensive and nuanced to the legal aspects of Inbound communications, e.g., prior bankruptcy, ownership transfer, business failure, leniency from military service, non-payment by the tenant, payment disputes, etc.

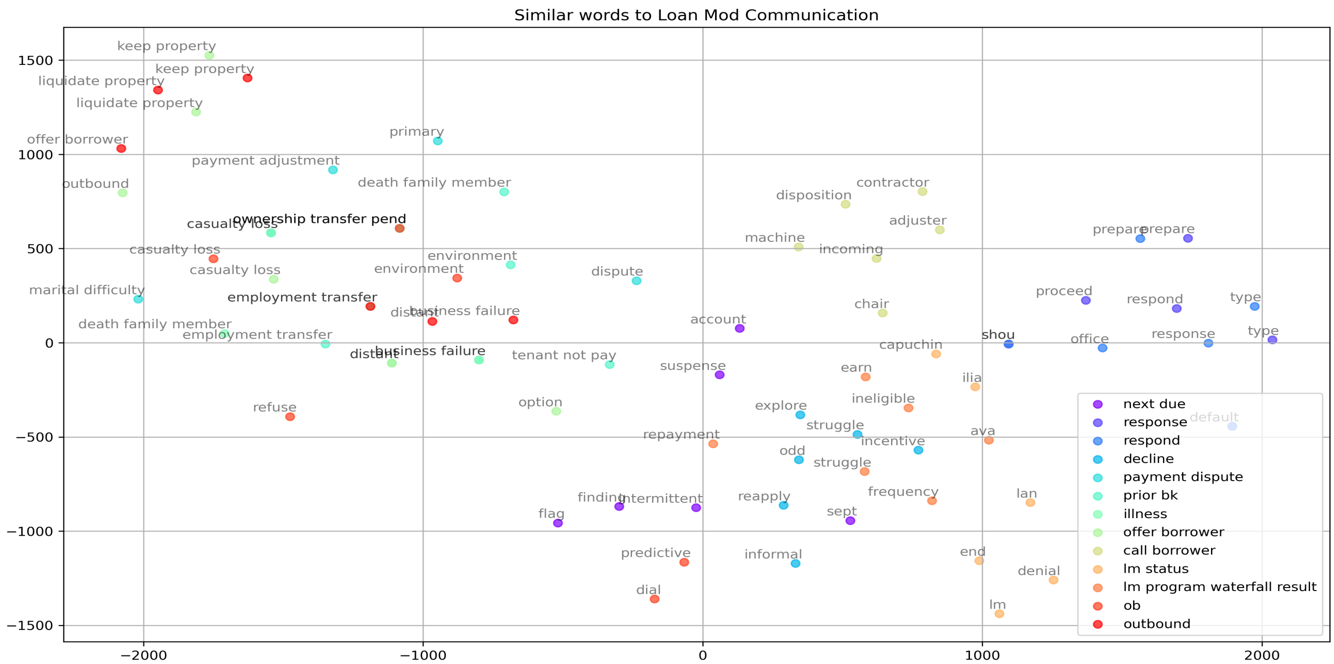

Figure 11: Outbound Communications and Loan Modification

Figure 11 captures the keywords related to selective verification by the servicer, e.g., decline, payment dispute, disposition, suspense, reapply, ineligible, denial, flag, intermittent, etc.

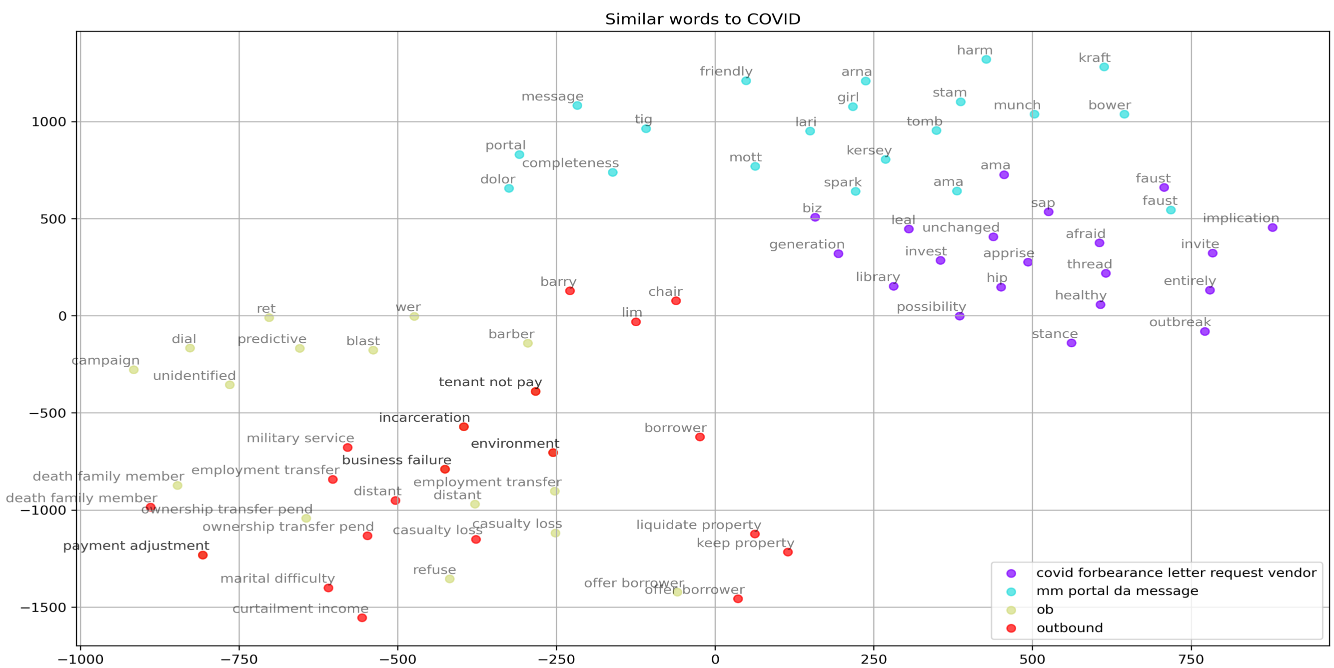

Figure 12: Outbound Communications and COVID

Figure 12 directly captures Outbound communications related to COVID-19 and as one can see there are not many words related to forbearance, since the servicers approve forbearance applications from the borrowers who fall under the purview of the CARES Act and try to dissuade other borrowers when the borrowers initiate conversations related to forbearance and/or foreclosure moratorium.

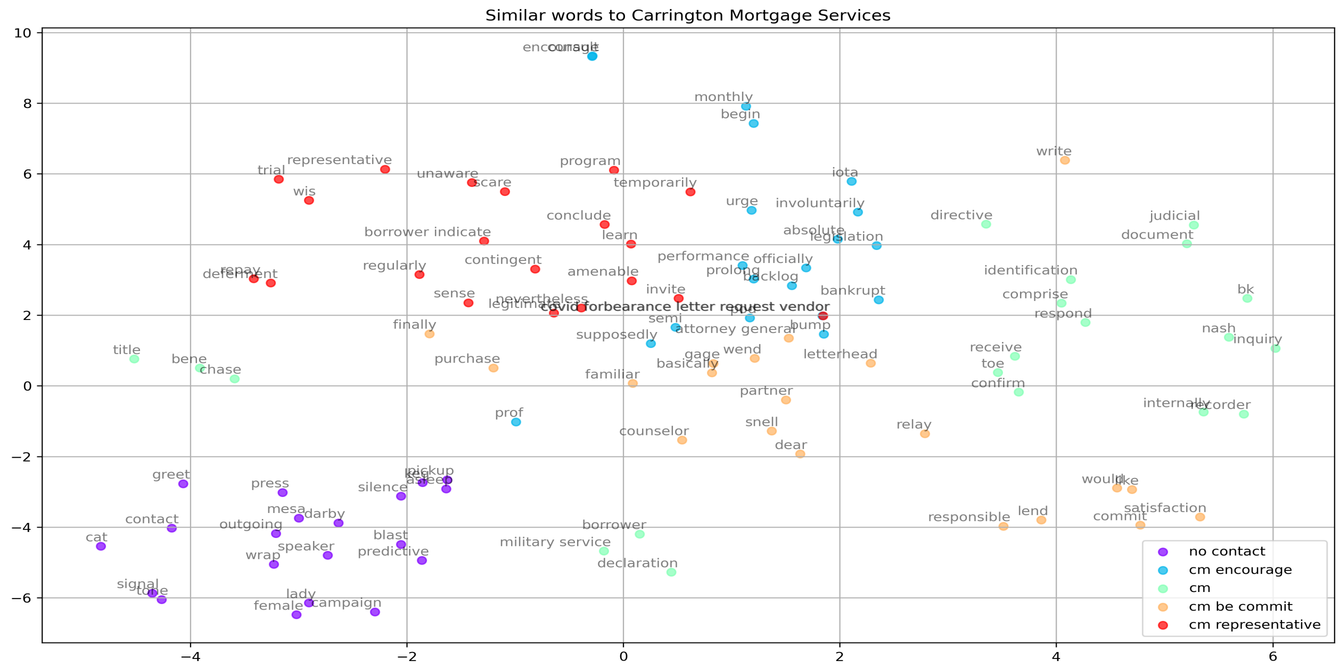

Figure 13: Outbound Communications related to Servicer

Figure 13 details the Outbound communications related to the specific servicer attributes such as performance, borrower indication, involuntary, representation, temporary, title, signal, silence, commitment, satisfaction, judicial, document, identification, etc.

11.4 US Map Spatial distribution for key variables

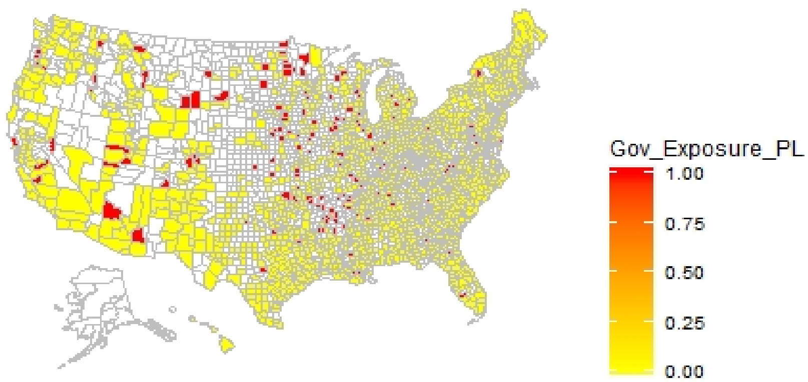

Figure 14: Percentage of Govt. loan Exposure by County in April 2020 among Performing Loans

The spatial distribution of key variables in this paper provide stronger evidence of the strategic behavior of borrowers in PL_Gov group. There are plenty of Non-Gov loans in Las Vegas in Figure 14 depicted by yellow color and Las Vegas was one of the major fatalities of the COVID-19 pandemic as the entire state runs on gambling and tourism revenue which were shut down abruptly.

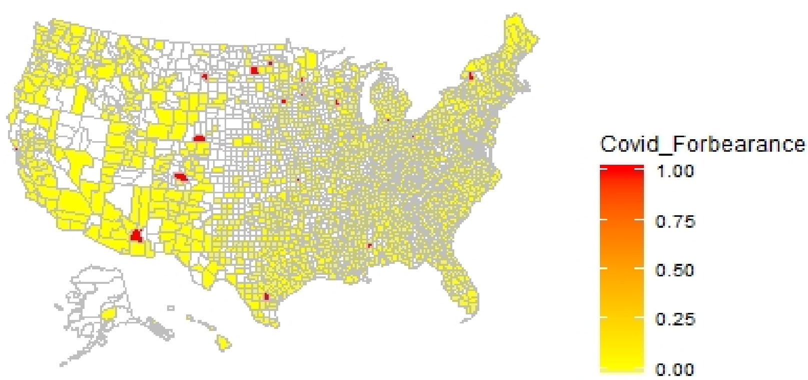

Figure 15: Percentage of COVID Forbearance Applications by County in April 2020
The forbearance applications of residents of Las Vegas were overcrowded (in Figure 15) by residents from the northern mountain states who arguably were affected much less severely by the first major hit of the COVID-19 during March - April.

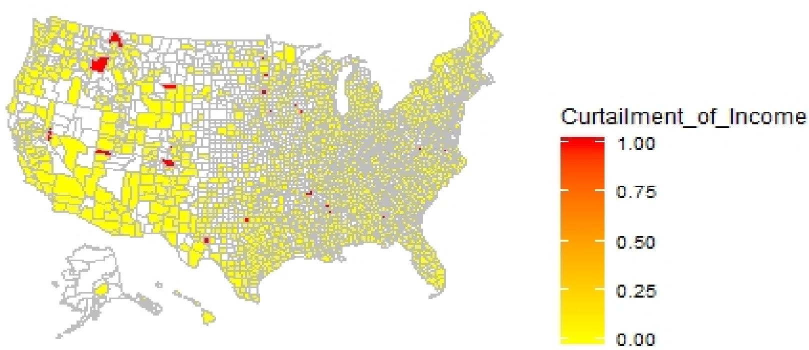

Figure 16: Percentage of Curtailment of Income by County in April 2020
The geographical distribution of the curtailment of income in Figure 16 also paints a similar picture in April 2020 data, where the residents of only a few pockets were facing severe financial hardship, but forbearance applications were rampant from all over the United States by the opportunistic/strategic PL_Gov borrowers.

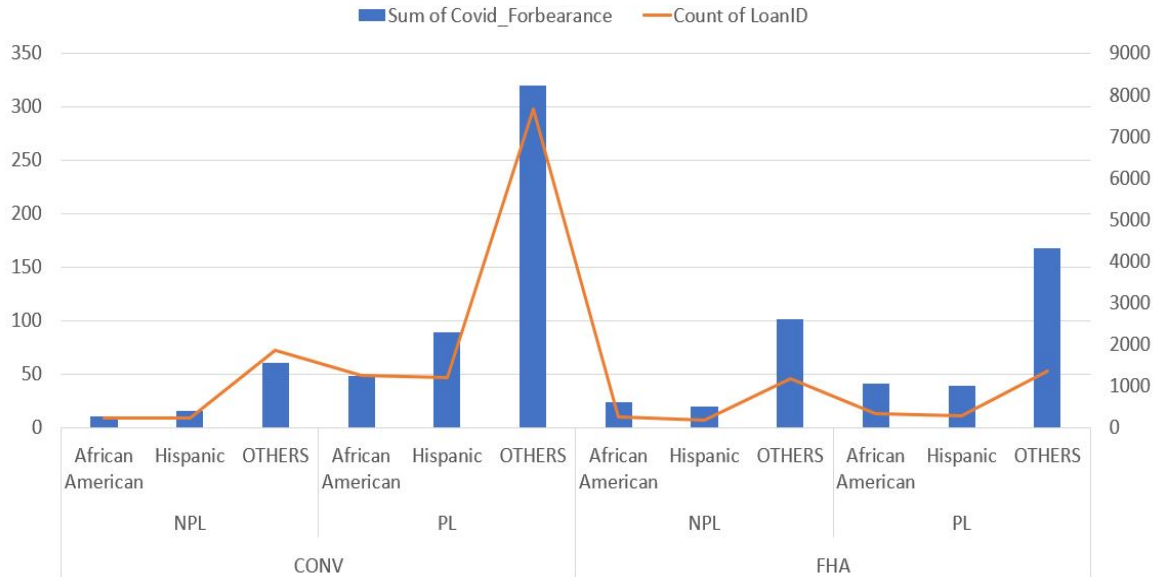

Figure 17: Forbearance by Delinquency Status and Race in April 2020
The number of forbearance applications are on the primary axis for each category on the left and the counts of LoanID's in each bucket are on the secondary axis on the right. This is done so that the relative number of forbearance applications can be compared across the buckets.

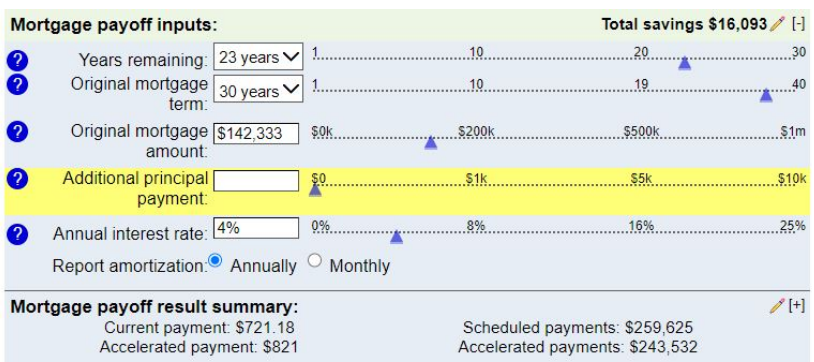

Figure 18: Average Mortgage Principal and Interest for Gov-backed loans
I use a mortgage calculator and use the terms of Gov-backed of mortgage from the Summary Statistics Table 1.

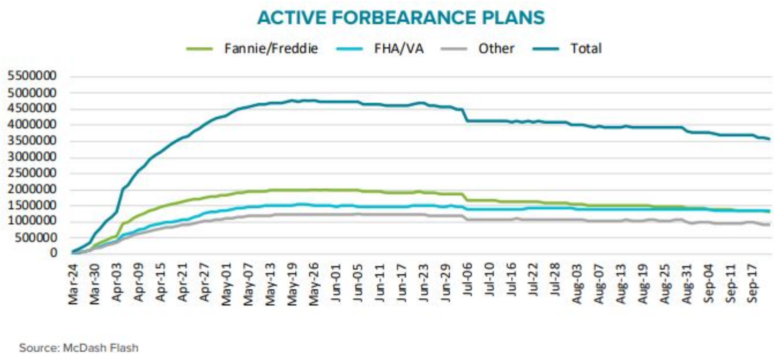

Figure 19: National Active Forbearance Plans
National Active Forbearance Plans for Gov and GSE loans have converged in August. The Non-Gov Forbearance Plans are lower.

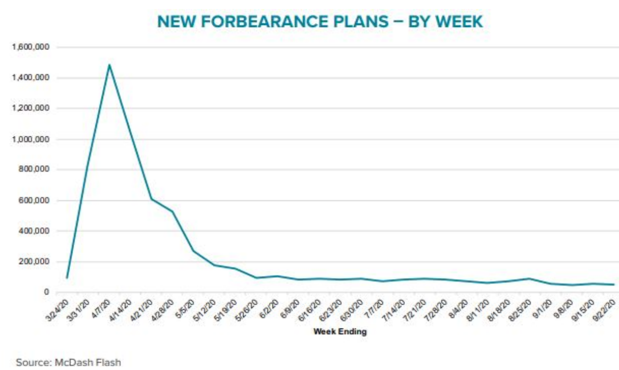

Figure 20: National New Forbearance Plans - by week
The weekly time series of National New Forbearance Plans has declined and flattened from May 2020.

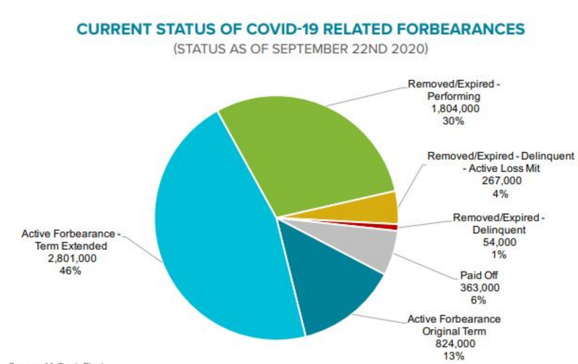

Figure 21: Status of COVID related Forbearance in August 2020
Pie-Chart to show the relative proportion of Status of COVID related Forbearance in August 2020.

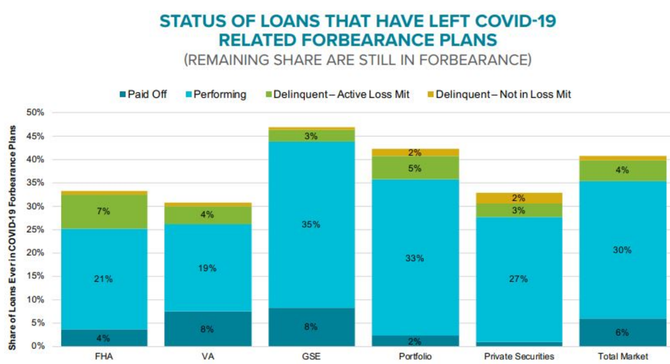

Figure 22: Status of Loans leaving COVID-19 related Forbearance Plans
Status of Loans leaving COVID-19 related Forbearance Plans across Gov and Non-Gov loans.

Table 1: Summary Statistics: Data for April 2020 performance report (all loans)
This table reports the descriptive statistics for the mortgages as of the April 2020 servicer reporting date. Panel A summarizes the statistics for all loans while Panels B and C summarize the data based on whether the mortgages are government-back loans (Panel B) or non-government program loans (Panel C).

PANEL A: All Loans

PANEL A	count	mean	sd	median	min	max	range	skew	kurtosis
Covid_Forbearance_Flag	19159	6.74%	0.251	0	0	1	1	3.451	9.911
Unemployed_Flag	19159	3.48%	0.183	0	0	1	1	5.079	23.8
Prior_Unemployment_Flag	19159	0.64%	0.08	0	0	1	1	12.359	150.755
FC_Moratorium_Flag	19159	6.74%	0.251	0	0	1	1	3.451	9.911
Curtailment_of_Income_Flag	19159	4.86%	0.215	0	0	1	1	4.198	15.628
Inbound_Borrower_Flag	19159	22.31%	0.416	0	0	1	1	1.33	-0.23
Outbound_Borrower_Flag	19159	29.38%	0.455	0	0	1	1	0.906	-1.18
Dlq	19159	1.429	2.049	0	0	5	5	0.987	-0.837
original_balance	19159	96791.008	84115.159	70947.24	1972.51	747750	745777.49	2.353	8.299
original_appraisal	19159	119747.758	97459.965	90000	3122.24	978200	975077.76	2.821	11.993
original_fico	19159	612.567	67.522	613	372	847	475	0.244	-0.13
current_rate	19159	0.066	0.029	0.058	0	0.197	0.197	0.427	-1.026
orig_ltv	19159	80.504	23.657	88.585	2.704	139.349	136.645	-1.082	0.527
current_balance	19159	10.801	1.08	10.898	0.01	13.584	13.574	-0.692	1.589
Gov	19159	0.348	0.476	0	0	1	1	0.64	-1.591
corporate_adv	19159	6.897	1.767	7.174	0.482	12.197	11.715	-1.34	3.213
rem_term	19159	190.817	112.797	202	6	526	520	0.061	-1.032
mod_flag	19159	0.354	0.478	0	0	1	1	0.611	-1.627
N	19159								

PANEL B: Government Loans

Covid_Forbearance_Flag	6660	11.13%	0.31	0	0	1	1	2.47	4.11
Unemployed_Flag	6660	5.23%	0.22	0	0	1	1	4.02	14.19
Prior_Unemployment_Flag	6660	1.07%	0.1	0	0	1	1	9.53	88.79
FC_Moratorium_Flag	6660	12.57%	0.33	0	0	1	1	2.26	3.1
Curtailment_of_Income_Flag	6660	7.76%	0.27	0	0	1	1	3.16	7.96
Inbound_Borrower_Flag	6660	32.43%	0.47	0	0	1	1	0.75	-1.44
Outbound_Borrower_Flag	6660	41.80%	0.49	0	0	1	1	0.33	-1.89
Dlq	6660	2.26	2.17	1	0	5	5	0.25	-1.73
original_balance	6660	142333.67	78248.12	126424	21825	730987	709162	1.78	5.35
original_appraisal	6660	149441.5	84418.46	131000	23000	890000	867000	1.96	6.66
original_fico	6660	617.38	65.13	628	376	813	437	-0.02	-0.21
current_rate	6660	0.04	0.01	0.04	0.01	0.1	0.09	1.76	4.47
orig_ltv	6660	95.92	7.55	98.11	9.97	130.77	120.79	-2.83	13.79
current_balance	6660	11.51	0.71	11.59	0.01	13.41	13.4	-1.8	15.37
corporate_adv	6660	5.95	2.41	6.21	0.48	11.47	10.99	-0.58	-0.07
rem_term	6660	274.79	61.87	283	7	446	439	-1.44	2.72
mod_flag	6660	0.69	0.46	1	0	1	1	-0.83	-1.31
N	6660								

PANEL C: Non-Government Loans

Covid_Forbearance_Flag	12499	4.40%	0.21	0	0	1	1	4.45	17.77
Unemployed_Flag	12499	2.54%	0.16	0	0	1	1	6.03	34.33
Prior_Unemployment_Flag	12499	0.42%	0.06	0	0	1	1	15.4	235.33
FC_Moratorium_Flag	12499	3.63%	0.19	0	0	1	1	4.96	22.56
Curtailment_of_Income_Flag	12499	3.31%	0.18	0	0	1	1	5.22	25.22
Inbound_Borrower_Flag	12499	16.91%	0.37	0	0	1	1	1.77	1.12
Outbound_Borrower_Flag	12499	22.75%	0.42	0	0	1	1	1.3	-0.31
Dlq1	12499	0.99	1.83	0	0	5	5	1.56	0.65
original_balance	12499	72523.93	76741.5	50993.05	1972.51	747750	745777.49	3.63	17.55
original_appraisal	12499	103925.67	100213.71	74000	3122.24	978200	975077.76	3.48	16.07
original_fico	12499	610	68.63	605	372	847	475	0.38	-0.05
current_rate	12499	0.08	0.03	0.08	0	0.2	0.2	-0.29	-0.69
orig_ltv1	12499	72.29	25.17	77.54	2.7	139.35	136.65	-0.53	-0.28
current_balance	12499	10.42	1.05	10.47	3	13.58	10.58	-0.38	1.48
corporate_adv	12499	7.4	0.98	7.37	5.02	12.2	7.18	0.74	0.9
rem_term	12499	146.07	108.18	125	6	526	520	0.91	0.31
mod_flag	12499	0.17	0.38	0	0	1	1	1.72	0.96
N	12499								

Table 2: Summary Statistics: Data for April 2020 performance report (granular)
This table goes one step further on Panels B and C in Table 1, by creating separate buckets form Performing (PL) and Non-Perfoming (NPL) loans among Govt-backed (Gov) and Non-Gov-backed (Non-Gov) loans.

PANEL A: Performing and Govt-backed loans

	count	mean	sd	median	min	max	range	skew	kurtosis
Covid_Forbearance_Flag	3657	13.18%	0.34	0	0	1	1	2.18	2.74
Unemployed_Flag	3657	1.48%	0.12	0	0	1	1	8.04	62.7
Prior_Unemployment_Flag	3657	0.57%	0.08	0	0	1	1	13.08	169.05
FC_Moratorium_Flag	3657	0.16%	0.04	0	0	1	1	24.62	604.17
Curtailment_of_Income_Flag	3657	4.73%	0.21	0	0	1	1	4.26	16.18
Inbound_Borrower_Flag	3657	24.99%	0.43	0	0	1	1	1.15	-0.67
Outbound_Borrower_Flag	3657	27.89%	0.45	0	0	1	1	0.99	-1.03
Dlq4	3657	0.53	1.03	0	0	5	5	3.26	11.37
original_balance	3657	134613.71	74617.33	118907	21825	653015	631190	1.73	4.72
original_appraisal	3657	141636.78	81805.48	125000	23000	890000	867000	2.06	7.35
original_fico	3657	615.57	66.86	625	376	813	437	0.04	-0.27
current_rate	3657	0.04	0.01	0.04	0.02	0.1	0.08	1.93	6.45
orig_ltv	3657	95.89	7.71	98.16	9.97	124.39	114.42	-3.07	16.2
current_balance	3657	110525.8	70592.05	96412.37	522.02	669748.08	669226.06	1.61	4.53
corporate_adv	3657	603.63	2370.6	187.44	0.62	95760.35	95759.73	25.17	853.19
rem_term	3657	271.36	66.4	281	9	446	437	-1.44	2.36
mod_flag	3657	0.73	0.44	1	0	1	1	-1.05	-0.89
N	3657								

PANEL B: Performing and Non-Govt-backed loans

Covid_Forbearance_Flag	10157	4.54%	0.21	0	0	1	1	4.37	17.08
Unemployed_Flag	10157	1.19%	0.11	0	0	1	1	9	78.94
Prior_Unemployment_Flag	10157	0.30%	0.05	0	0	1	1	18.32	333.5
FC_Moratorium_Flag	10157	0.01%	0.01	0	0	1	1	100.75	10150
Curtailment_of_Income_Flag	10157	2.64%	0.16	0	0	1	1	5.91	32.92
Inbound_Borrower_Flag	10157	13.22%	0.34	0	0	1	1	2.17	2.71
Outbound_Borrower_Flag	10157	14.43%	0.35	0	0	1	1	2.02	2.1
Dlq	10157	0.2	0.77	0	0	5	5	5.33	29.86
original_balance	10157	65724.2	61534.64	49605.26	2025.39	709600	707574.61	3.57	19.04
original_appraisal	10157	94719.04	83717.5	70000	3122.24	978200	975077.76	3.61	18.49
original_fico	10157	613.93	68.78	610	402	847	445	0.35	-0.04
current_rate	10157	0.08	0.03	0.09	0	0.2	0.2	-0.4	-0.52
orig_ltv	10157	72.22	24.81	77.05	2.7	139.35	136.65	-0.47	-0.34
current_balance	10157	48789.55	56157.64	32970.4	19.14	699407.76	699388.62	3.65	20.23
Gov	10157	0	0	0	0	0	0	NA	NA
corporate_adv	10157	1867.42	2898.92	1404.94	150	99951.25	99801.25	14.74	364.16
rem_term	10157	140.73	105.79	119	6	494	488	0.96	0.45
mod_flag	10157	0.16	0.36	0	0	1	1	1.88	1.52
N	10157								

PANEL C: Non-Performing and Govt-backed loans

Covid_Forbearance_Flag	3003	8.62%	0.28	0	0	1	1	2.95	6.68
Unemployed_Flag	3003	9.79%	0.3	0	0	1	1	2.7	5.32
Prior_Unemployment_Flag	3003	1.67%	0.13	0	0	1	1	7.55	55.04
FC_Moratorium_Flag	3003	27.67%	0.45	0	0	1	1	1	-1.01
Curtailment_of_Income_Flag	3003	11.46%	0.32	0	0	1	1	2.42	3.85
Inbound_Borrower_Flag	3003	41.49%	0.49	0	0	1	1	0.35	-1.88
Outbound_Borrower_Flag	3003	58.74%	0.49	1	0	1	1	-0.35	-1.87
Dlq	3003	4.37	1.02	5	2	5	3	-1.46	0.71
original_balance	3003	151734.91	81484.54	135695	24600	730987	706387	1.81	5.79
original_appraisal	3003	158945.96	86563.52	140500	25000	800000	775000	1.88	6.13
original_fico	3003	619.58	62.89	631	392	810	418	-0.11	-0.12
current_rate	3003	0.04	0.01	0.04	0.01	0.09	0.08	1.57	2.71
orig_ltv	3003	95.95	7.35	98.05	38.16	130.77	92.61	-2.5	10.12
current_balance	3003	136656.28	81399.43	121333.65	0.01	665499.18	665499.17	1.68	4.87
corporate_adv	3003	4969.19	8068.78	2128.66	7.03	89295.04	89288.01	4.02	23.74
rem_term	3003	278.97	55.59	284	7	418	411	-1.33	2.76
mod_flag	3003	0.64	0.48	1	0	1	1	-0.59	-1.65
N	3003								

PANEL D: Non-Performing and Non-Govt-backed loans

Covid_Forbearance_Flag	2342	3.80%	0.19	0	0	1	1	4.83	21.33
Unemployed_Flag	2342	8.41%	0.28	0	0	1	1	2.99	6.97
Prior_Unemployment_Flag	2342	0.94%	0.1	0	0	1	1	10.17	101.37
FC_Moratorium_Flag	2342	19.34%	0.4	0	0	1	1	1.55	0.41
Curtailment_of_Income_Flag	2342	6.23%	0.24	0	0	1	1	3.62	11.1
Inbound_Borrower_Flag	2342	32.92%	0.47	0	0	1	1	0.73	-1.47
Outbound_Borrower_Flag	2342	58.84%	0.49	1	0	1	1	-0.36	-1.87
Dlq	2342	4.39	1.05	5	2	5	3	-1.48	0.64
original_balance	2342	102013.65	118082.73	59776.37	1972.51	747750	745777.49	2.57	7.06
original_appraisal	2342	143853.8	145765.45	89950	13070	975000	961930	2.5	7.11
original_fico	2342	592.96	65.29	585	372	845	473	0.51	0.03
current_rate	2342	0.07	0.03	0.07	0	0.15	0.15	0.13	-1.04
orig_ltv	2342	72.62	26.66	79.42	4.3	138.5	134.2	-0.74	-0.13
current_balance	2342	90729.69	115243.56	49559.65	45.29	793649.71	793604.42	2.56	7.04
corporate_adv	2342	8367.93	14368.58	4529.73	170	198219.24	198049.24	7.02	70.28
rem_term	2342	169.24	115.18	158	6	526	520	0.68	-0.16
mod_flag	2342	0.24	0.43	0	0	1	1	1.2	-0.57
N	2342								

Table 3: Multivariate Analysis of Borrower Forbearance for all loans

This table reports the regression results for early forbearance. Columns (1) and (2) report the results for all loans with and without county fixed effects, respectively. Not surprising, the positive and statistically coefficients (at the 1% level) for inbound and outbound confirm that the probability of forbearance increases with any communication with the servicer, whether initiated by the borrower or servicer. This is to be expected since forbearance requires an active request on the part of the borrower and thus necessitates communication with the servicer. The estimated coefficients for inbound and outbound in my preferred specification that includes county fixed effects (column 2) reveal that the probability of forbearance is essentially the same regardless of whether the servicer or borrower initiated the contact.

	(1)	(2)	(3)	(4)
	All Loans		FHA/VA Loans	Non-FHA/VA Loans
Inbound Call	2.772***	2.939***	3.279***	2.627***
	(0.181)	(0.199)	(0.219)	(0.232)
Outbound Call	2.209***	3.094***	3.020***	3.145***
	(0.32)	(0.483)	(0.413)	(0.722)
AssetType_n	-1.088**	-0.169	-0.181	-0.654
	(0.414)	(0.501)	(0.617)	(0.83)
Government (FHA/VA) Loan	-0.714	0.107		
	(0.475)	(0.471)		
corporate_adv	-0.173	0.263	0.502	-6.723*
	(0.345)	(0.31)	(0.341)	(3.307)
Inbound Call X Government	0.453**	0.27		
	(0.146)	(0.166)		
Inbound Call X Performing Loan	0.827***	0.506**	0.197	1.065***
	(0.151)	(0.169)	(0.208)	(0.262)
Outbound Call X Government	0.691	-0.103		
	(0.438)	(0.429)		
Outbound Call X Performing Loan	2.134***	1.381**	1.379*	1.255
	(0.385)	(0.461)	(0.567)	(0.793)
AssetType_Gov	-0.164	-0.207		
	(0.155)	(0.147)		
current_balance	-9.172***	16.991***	19.264*	13.474*
	(0.787)	(4.604)	(9.022)	(5.814)
orig_ltv	0.001	0	-0.006	0.004
	(0.002)	(0.002)	(0.006)	(0.003)
original_fico	0.000059	0.000404	0.0003	0.0002
	(0.000467)	(0.000476)	(0.001)	(0.001)
current_rate	-9.754***	-3.181*	-23.120***	-1.362
	(1.782)	(1.62)	(6.442)	(1.775)
currentratetype_new	0.048	0.178	0.003	0.089
	(0.162)	(0.152)	(0.297)	(0.191)
Borrower Noted Unemployment	0.623***	0.690***	0.396	1.037***
	(0.174)	(0.174)	(0.232)	(0.258)
Borrower Noted Income Curtailment	2.144***	2.031***	2.007***	2.005***
	(0.152)	(0.161)	(0.218)	(0.233)
AIC	7992.973	7273.096	3408.143	2665.806
Log Likelihood	-3979.486			
Fixed Effect	None	County	County	County
Num. obs.	96,244	96,244	33,343	62,901

Table 4: Multivariate Analysis of Borrower Forbearance for Purchase and Cashout loans

I separate the sample to only cash-out and no-cash-out in this table. The Cash Out loans in this PE firm portfolio are distressed loans, which they bought at a significant discount in 2017. No promissory notes are attached to these Cash Out loans. These borrowers have lower FICO scores and are subprime. But from the time, they were acquired by the PE firm, they have mostly remained performing loans. Because the cash-out loans were bought at such discount and they comprise of subprime borrowers which mostly have been making payments, the focus has been less on re-couping corporate advances, since the servicer and the PE firm both share the profit in a liquidation/exit event. Because most Cash Out loans are non-Gov, the borrowers have to provide evidence to the servicer to get Forbearance approved. This is corroborated by positive significance of IB_PL. Both the OB_PL and OB_GOV are positive significant, indicating the servicer calls are significant for GOV PL borrower. On the other hand, the borrower calls significant when they have GOV loan. Both the IB_GOV and IB_PL are positive but insignificant in Columns 2-4 with County fixed effects. This means, the borrower makes less calls when they have GOV and PL, as they are provisioned for forbearance under the CARES Act. OB_PL is positive significant in Column 2-3, since servicer makes mandatory calls in GOV loan case if the Borrower is PL. OB_PL is negative highly significant for Non-Gov loans (which are not Cash-Out), i.e., the servicer makes more calls for non-GOV borrowers to let them know they have to verify their unemployment status and financial hardship, otherwise they are ineligible for forbearance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Purchase Mortgages				Cash-out Refinance Mortgages			
	All Loans		FHA/VA	Non-FHA/VA	All Loans		FHA/VA	Non-FHA/VA
Inbound Call	2.7711***	2.9722***	3.2793***	2.180***	2.6980***	2.7712***	3.139***	2.692***
	(0.287)	(0.3479)	(0.2187)	(0.571)	(0.2518)	(0.1268)	(0.443)	(0.264)
Outbound Call	1.6704***	2.1738***	3.0196***	19.228***	2.1714***	2.8869***	19.345***	2.918***
	(0.4038)	(0.5297)	(0.4126)	(0.347)	(0.3837)	(0.3593)	(0.209)	(0.726)
AssetType_n	-0.204	0.3569	-0.1808	16.335***	-1.8966**	-1.0973***	1.499**	-1.326
	(0.5658)	(0.589)	(0.617)	(1.171)	(0.6033)	(0.1293)	(0.499)	(0.884)
Government (FHA/VA) Loan	-1.7975***	-1.2754			-12.0984***	-11.4466***		
	(0.5349)	(0.6568)			(0.4401)	(0.2338)		
corporate_adv	0.1178	0.4746	0.502	-18.438	-2.3454	-1.1616	4.358*	-9.931**
	(0.3386)	(0.346)	(0.3413)	(10.488)	(1.4114)	(1.2119)	(1.947)	(3.559)
Inbound Call X Government	0.4134	0.1944			0.5063	0.0656		
	(0.2602)	(0.3016)			(0.4504)	(0.2692)		
Inbound Call X Performing Loan	0.5852**	0.3183	0.1966	0.797	1.2644***	0.9958***	0.079	1.173***
	(0.1908)	(0.2014)	(0.2081)	(0.7)	(0.2632)	(0.1064)	(0.378)	(0.292)
Outbound Call X Government	1.4391***	1.0081			12.0484***	11.5780***		
	(0.4326)	(0.5613)			(0.405)	(0.2338)		
Outbound Call X Performing Loan	1.4717**	1.0571*	1.3792*	-16.010***	2.6507***	1.8388***	0.062	1.846*
	(0.5004)	(0.5089)	(0.5674)	(0.82)	(0.5716)	(0.1263)	(0.499)	(0.845)
AssetType_Gov	-0.1993	-0.2795			-0.2702	-0.1664		
	(0.3389)	(0.301)			(0.4694)	(0.2856)		
current_balance	-7.2208***	14.1777*	19.2638*	-5.259	-7.8821***	16.6653**	75.064	16.701*
	(0.9811)	(7.2097)	(9.0217)	(15.407)	(1.5093)	(5.4343)	(63.105)	(6.884)
orig_ltv	-0.0041	-0.0032	-0.0059	0.013	0.0015	0.001	-0.041	0.002
	(0.0045)	(0.0051)	(0.0061)	(0.008)	(0.0022)	(0.0022)	(0.049)	(0.003)
original_fico	-0.0001	-0.0008	-0.0002	-0.005	0.0004	0.0009	-0.002	0
	(0.0006)	(0.0007)	(0.0007)	(0.003)	(0.0008)	(0.0007)	(0.004)	(0.001)
current_rate	-18.9145***	-14.0843***	-23.1202***	-17.760*	-6.3670***	-0.7243	-54.996	-0.968
	(4.9283)	(4.2271)	(6.4416)	(7.698)	(1.8336)	(1.7762)	(30.443)	(1.895)
currentratetype_new	0.1746	0.3908	0.003	0.64	0.1467	0.1225	0.0003	0.241
	(0.2483)	(0.2345)	(0.2966)	(0.489)	(0.2228)	(0.226)	(0.0005)	(0.229)
Borrower Noted Unemployment	0.3541	0.3803	0.3963	0.134	1.0615***	1.1448***	1.36	1.189***
	(0.2254)	(0.2234)	(0.2321)	(0.608)	(0.272)	(0.223)	(0.868)	(0.28)
Borrower Noted Income Curtailment	2.0287***	1.9053***	2.0072***	0.995	2.3170***	2.1810***	2.504***	2.193***
	(0.1959)	(0.2031)	(0.2182)	(0.637)	(0.2419)	(0.1611)	(0.521)	(0.256)
AIC	4687.395	3684.592	3125.64	223.096	3289.827	2411.503	91.332	2203.831
Log Likelihood	-2326.697				-1607.07			
Fixed Effects	None	County	County	County	None	County	County	County
Num. obs.	35750.000	35750.000	31273.000	4477.000	60494.000	60494.000	2070.000	58424.000

Table 5: Multivariate Analysis of Borrower Forbearance and Race
In Table 5, I add an indicator whether a borrower in Black and interact the dummy variable with IB, OB, IB_PL and OB_PL to make further inferences beyond Table 4. Firstly, for Non-Gov Black borrowers, there is a huge negative significance towards forbearance, with and without county fixed effect in Table 5. This clearly shows, all else equal, Black borrowers are discriminated against availing forbearance applications. Also, for Non-Gov Black borrowers, IB_PL_Black is positive and significant with no fixed effects. With county fixed effects, the result is also economically significant, however the statistical significance is not bourne out in the county fixed effect due to small sample size when grouped by county.
OB_PL is still negative for Non-Gov loans with race in the specification, providing robustness of the selective behavior by the servicer, as detailed in the previous section. OB_Black for Non-Gov loans is highly positive and significant, with and without county fixed effects. This implies the servicers verify the Unemployment status or financial hardship for Black borrowers and then and then only are those Black borrowers are approved on their forbearance applications. OB_PL_Black is negative and significant without county fixed effects, which means Black borrowers who have performing loans are dissuaded by the servicers with their forbearance applications. Typically a borrower who has a performing loan ex-ante should be in financial distress ex-ante. Essentially, the servicer is trying to reduce the ex-post risk for Black borrowers. If the Black borrowers are really in financial distress, they need to prove it in black and white and get their forbearance approved. On the flip side, these borrowers are not encouraged by the servicer to apply for forbearance and are mostly pre-empted by adding an income verification clause.

	(1)	(2)	(3)	(4)	(5)	(6)
	All Loans		FHA/VA Loans		Non-FHA/VA Loans	
Inbound Call	2.2319^{***}	2.6727^{***}	3.2027^{***}	3.3648^{***}	1.8695^{***}	1.8817^{***}
	(0.2754)	(0.3798)	(0.2062)	(0.2582)	(0.5097)	(0.3850)
Outbound Call	0.2602	1.9040^{**}	2.1668^{***}	3.1023^{***}	1.4771^{***}	19.9902^{***}
	(0.3084)	(0.5886)	(0.2336)	(0.4711)	(0.4436)	(0.5709)
AssetType_n	-1.0236^{*}	0.4955	-1.5982^{**}	-0.3012	-0.3179	17.9754^{***}
	(0.4330)	(0.6446)	(0.5309)	(0.6930)	(0.7133)	(0.4405)
Gov	-3.1633^{***}	-1.7033^{*}				
	(0.4501)	(0.6719)				
Black	-0.9346	-0.3006	-0.3018	0.4258	-29.3945^{***}	-52.9484^{***}
	(0.6573)	(0.7690)	(0.6449)	(0.7629)	(0.9410)	(0.9052)
corporate_adv	-0.0615^{**}	-0.0241	-0.0545^{**}	-0.0198	-0.1633	-0.3023
	(0.0203)	(0.0199)	(0.0211)	(0.0204)	(0.1930)	(0.2364)
Inbound Call X Government	0.9447^{***}	0.5606				
	(0.2534)	(0.3231)				
Inbound Call X Performing Loan	0.4287	0.1033	0.3874	0.0072	0.9865	0.3951
	(0.2198)	(0.2355)	(0.2274)	(0.2514)	(0.6394)	(0.3921)
Inbound Call X Black	0.0797	-0.1952	-0.0172	-0.2187	0.4552	-0.4292
	(0.3563)	(0.4033)	(0.3755)	(0.4311)	(1.0909)	(1.2637)
Inbound Call X Performing Loan X Black	1.0892	1.1840	1.0405	1.0202	14.5899^{***}	37.1040
	(0.6471)	(0.6103)	(0.6460)	(0.6256)	(1.3884)	(5308.7008)
Outbound Call X Government	2.4230^{***}	1.3121^{*}				
	(0.4095)	(0.5874)				
Outbound Call X Performing Loan	2.2692^{***}	1.0948	2.6058^{***}	1.4769^{*}	1.3874^{*}	-17.3784^{***}
	(0.4377)	(0.5630)	(0.4756)	(0.6358)	(0.6651)	(0.4108)
Outbound Call X Black	0.9429	0.3988	0.3865	-0.3640	29.4304^{***}	52.3158^{***}
	(0.6668)	(0.7904)	(0.6277)	(0.7456)	(1.2576)	(0.9052)
Outbound Call X Performing Loan X Black	-1.2053^{*}	-1.1254^{*}	-1.1010	-0.8566	-15.7338^{***}	-18.2862
	(0.6125)	(0.5723)	(0.6089)	(0.5837)	(1.0205)	(5412.8656)
AssetType_Gov	-0.2585	-0.4327				
	(0.3734)	(0.3454)				
current_balance	-0.0920	0.1292	-0.1624^{**}	0.1734	-0.0205	-0.0927
	(0.0473)	(0.0889)	(0.0540)	(0.1080)	(0.1691)	(0.2751)
orig_ltv	-0.0150^{***}	-0.0056	-0.0234^{***}	-0.0084	-0.0119	0.0036
	(0.0043)	(0.0056)	(0.0051)	(0.0072)	(0.0076)	(0.0174)
original_fico	-0.0017^{**}	-0.0014	-0.0015^{*}	-0.0010	-0.0050^{*}	-0.0085^{*}
	(0.0006)	(0.0008)	(0.0007)	(0.0008)	(0.0022)	(0.0036)
current_rate	-24.7370^{***}	-12.1368^{*}	-43.1878^{***}	-22.6451^{***}	-11.5115	-14.6377
	(5.0955)	(5.0962)	(5.5675)	(6.8337)	(6.6101)	(8.6513)
currentratetype_new	0.0363	0.4382	-0.4367	0.2032	0.1956	0.9364
	(0.2606)	(0.2745)	(0.3944)	(0.3956)	(0.3744)	(0.5797)
Borrower Noted Unemployment	0.3068	0.3236	0.2180	0.3024	0.8731	0.2683
	(0.2468)	(0.2531)	(0.2637)	(0.2760)	(0.6727)	(0.5892)
Borrower Noted Income Curtailment	1.9243^{***}	1.8378^{***}	2.0206^{***}	1.9731^{***}	0.8551	0.8601
	(0.2044)	(0.2237)	(0.2220)	(0.2495)	(0.5318)	(0.5551)
AIC	4021.2615	3022.3850	3653.3871	2658.0711	398.9610	173.7232
Log Likelihood	-1988.6307		-1808.6936		-181.4805	
Fixed Effects	*None*	*County*	*None*	*County*	*None*	*County*
Num. obs.	28843	28843	25845	25845	2998	2998

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 6: Differences in Differences

To address the endogeneity concerns from the strategic overcrowding of forbearance applications by Gov-backed performing loan borrowers and the endogeneity emanating from selective verification by the servicer, I use Difference-in-Differences approach. The treatment group comprises of the Govt.-backed loans and the control group contains the Conventional/Private Label Non-Govt. backed loans. The treatment time is end of March 2020, when the effect of CARES Act is internalized. In Table 6, the first variable is the interaction between treatment group and treatment time. In all columns (1)-(6), the interaction is statistically significant, implying significant causal impact of CARES Act on the treatment group. This clearly addresses the endogeneity concerns.

	(1)	(2)	(3)	(4)	(5)	(6)
	All Loans		Inbound Communications		Outbound Communications	
After_March_2020_X_Gov	6.6243^{***}	6.6480^{***}	6.5795^{***}	6.2790^{***}	6.2565^{***}	6.3283^{***}
	(0.5883)	(0.9369)	(0.5832)	(0.6014)	(0.5816)	(0.6832)
Inbound Call	2.4607^{***}	3.2348^{***}	3.0057^{***}	3.8570^{***}		
	(0.2536)	(0.3597)	(0.2728)	(0.4061)		
Outbound Call	0.7644^{**}	2.5906^{***}			1.1442^{***}	3.2238^{***}
	(0.2735)	(0.5492)			(0.2668)	(0.5963)
AssetType_n	-1.3161^{**}	0.7332	-0.1727	0.6966	-1.4215^{***}	0.4652
	(0.4404)	(0.5443)	(0.2966)	(0.3644)	(0.3693)	(0.5514)
Gov	-8.2762^{***}	-6.6097^{***}	-6.6315^{***}	-5.5770^{***}	-7.6262^{***}	-6.5326^{***}
	(0.7661)	(1.2329)	(0.6573)	(0.7222)	(0.7148)	(0.9812)
corporate_adv	-0.1832^{***}	-0.1012^{***}	-0.1616^{***}	-0.0884^{***}	-0.2109^{***}	-0.1633^{***}
	(0.0277)	(0.0187)	(0.0248)	(0.0198)	(0.0227)	(0.0208)
Inbound Call X Government	0.8808^{***}	-0.0461	1.0352^{***}	0.2352		
	(0.2460)	(0.3158)	(0.2407)	(0.3278)		
Inbound Call X Performing Loan	0.8933^{***}	0.1936	1.2170^{***}	0.6775^{**}		
	(0.1928)	(0.2096)	(0.2222)	(0.2409)		
Outbound Call X Government	2.0149^{***}	0.6839			2.2600^{***}	1.0501
	(0.3733)	(0.5634)			(0.3679)	(0.5808)
Outbound Call X Performing Loan	2.1639^{***}	0.5864			3.0530^{***}	1.3807^{**}
	(0.4017)	(0.4656)			(0.3941)	(0.5035)
AssetType_Gov	-0.3351	-0.5857^{*}	-0.1123	-0.5491	-0.4950	-0.7052^{*}
	(0.3331)	(0.2948)	(0.2950)	(0.3154)	(0.3050)	(0.3047)
current_balance	-0.0704	0.0975	-0.0530	0.2068^{**}	0.0390	0.2699^{***}
	(0.0530)	(0.0730)	(0.0460)	(0.0719)	(0.0453)	(0.0751)
orig_ltv	-0.0126^{**}	0.0021	-0.0142^{***}	-0.0016	-0.0127^{**}	-0.0068
	(0.0048)	(0.0048)	(0.0043)	(0.0050)	(0.0039)	(0.0050)
original_fico	-0.0021^{**}	-0.0009	-0.0024^{***}	-0.0015^{*}	-0.0018^{**}	-0.0012
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
current_rate	-18.6557^{***}	-10.7210^{**}	-21.8364^{***}	-9.2600^{*}	-20.9353^{***}	-9.3156^{*}
	(5.3494)	(4.0850)	(5.2717)	(4.3092)	(5.0597)	(4.3302)
currentratetype_new	-0.2190	0.2646	0.0120	0.2879	-0.0680	0.2741
	(0.2559)	(0.2304)	(0.2353)	(0.2315)	(0.2177)	(0.2257)
Borrower Noted Unemployment	0.5279^{*}	0.6688^{**}	0.8085^{**}	1.0197^{***}	-0.6248^{**}	-0.5150^{**}
	(0.2410)	(0.2323)	(0.2666)	(0.2733)	(0.1914)	(0.1845)
Borrower Noted Income Curtailment	2.0100^{***}	1.9669^{***}	2.9142^{***}	2.9683^{***}	-0.1915	-0.1544
	(0.1959)	(0.2055)	(0.2487)	(0.2634)	(0.1273)	(0.1301)
AIC	3245.3400	2528.2219	3954.6566	3029.6796	4354.0823	3269.9377
BIC	3398.0575		4081.9212		4481.3469	
Log Likelihood	-1604.6700		-1962.3283		-2162.0412	
Fixed Effects	*None*	*County*	*None*	*County*	*None*	*County*
Num. obs.	35750	35750	35750	35750	35750	35750

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 7: Differences in Differences, Gov for IB and NonGov for OB

For robustness checks, I also create Non-Gov dummy in Table 7 as the Outbound communications of the servicers for selective verification of unemployment status mostly targets the Non-Gov borrowers. I still find strong positive statistical significance for the interaction of term of the Treatment time and the treated (here treatment group in Non-Gov).

	(1)	(2)	(3)	(4)	(5)	(6)
	All Loans		Inbound Communications		Outbound Communications	
After_March_2020_X_Gov	6.6243***	6.6480***	6.5795***	6.2790***		
	(0.5883)	(0.9369)	(0.5832)	(0.6014)		
After_March_2020_X_NonGov					4.7099***	4.5125***
					(0.9804)	(1.0035)
Inbound Call	2.4607***	3.2348***	3.0057***	3.8570***		
	(0.2536)	(0.3597)	(0.2728)	(0.4061)		
Outbound Call	0.7644**	2.5906***			2.6076***	3.8210***
	(0.2735)	(0.5492)			(0.1788)	(0.4421)
AssetType_n	−1.3161**	0.7332	−0.1727	0.6966	−1.1151*	0.0564
	(0.4404)	(0.5443)	(0.2966)	(0.3644)	(0.4413)	(0.5347)
Gov	−8.2762***	−6.6097***	−6.6315***	−5.5770***		
	(0.7661)	(1.2329)	(0.6573)	(0.7222)		
NonGov					−3.5564**	−2.4699*
					(1.1291)	(1.1568)
corporate_adv	−0.1832***	−0.1012***	−0.1616***	−0.0884***	−0.1009***	−0.0695***
	(0.0277)	(0.0187)	(0.0248)	(0.0198)	(0.0163)	(0.0182)
Inbound Call X Government	0.8808***	−0.0461	1.0352***	0.2352		
	(0.2460)	(0.3158)	(0.2407)	(0.3278)		
Inbound Call X Performing Loan	0.8933***	0.1936	1.2170***	0.6775**		
	(0.1928)	(0.2096)	(0.2222)	(0.2409)		
Outbound Call X Government	2.0149***	0.6839				
	(0.3733)	(0.5634)				
Outbound Call X Non-Government					−0.5191	−1.2545*
					(0.5188)	(0.5718)
Outbound Call X Performing Loan	2.1639***	0.5864			3.0772***	1.8117***
	(0.4017)	(0.4656)			(0.3239)	(0.4992)
AssetType_Gov	−0.3351	−0.5857*	−0.1123	−0.5491	−0.6606	−0.4843
	(0.3331)	(0.2948)	(0.2950)	(0.3154)	(0.3557)	(0.2914)
current_balance	−0.0704	0.0975	−0.0530	0.2068**	−0.0704	0.2702***
	(0.0530)	(0.0730)	(0.0460)	(0.0719)	(0.0399)	(0.0735)
orig_ltv	−0.0126**	0.0021	−0.0142***	−0.0016	−0.0183***	−0.0069
	(0.0048)	(0.0048)	(0.0043)	(0.0050)	(0.0035)	(0.0050)
original_fico	−0.0021**	−0.0009	−0.0024***	−0.0015*	−0.0022***	−0.0015*
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)
current_rate	−18.6557***	−10.7210**	−21.8364***	−9.2600*	−29.0106***	−14.5034**
	(5.3494)	(4.0850)	(5.2717)	(4.3092)	(5.2108)	(4.6068)
currentratetype_new	−0.2190	0.2646	0.0120	0.2879	−0.0420	0.3452
	(0.2559)	(0.2304)	(0.2353)	(0.2315)	(0.2006)	(0.2303)
Borrower Noted Unemployment	0.5279*	0.6688**	0.8085**	1.0197***	−0.7835***	−0.7555***
	(0.2410)	(0.2323)	(0.2666)	(0.2733)	(0.1741)	(0.1777)
Borrower Noted Income Curtailment	2.0100***	1.9669***	2.9142***	2.9683***	−0.2202	−0.2116
	(0.1959)	(0.2055)	(0.2487)	(0.2634)	(0.1163)	(0.1227)
AIC	3245.3400	2528.2219	3954.6566	3029.6796	5683.7921	4454.4821
BIC	3398.0575		4081.9212		5811.0567	
Log Likelihood	−1604.6700		−1962.3283		−2826.8960	
Fixed Effects	*None*	*County*	*None*	*County*	*None*	*County*
Num. obs.	35750	35750	35750	35750	35750	35750

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 8: Differences in Differences, removing 2 or less observations per county

Finally, because of multi-collinearity issues discusses in Section 6, I exclude those counties which have one or less loans for the whole time horizon of 5 months. Table 8 again shows strong statistical significance among counties with more than one loans for the interaction term.

	(1)	(2)	(3)	(4)	(5)	(6)
	All Loans		Inbound Communications		Outbound Communications	
Interaction	6.6137^{***}	6.0908^{***}	6.5615^{***}	6.1486^{***}	6.2421^{***}	6.0306^{***}
	(0.5889)	(0.6775)	(0.5836)	(0.5832)	(0.5819)	(0.5895)
Inbound Call	2.4870^{***}	3.2611^{***}	3.0545^{***}	3.8719^{***}		
	(0.2544)	(0.3632)	(0.2731)	(0.4094)		
Outbound Call	0.8978^{**}	2.7987^{***}			1.2758^{***}	3.3759^{***}
	(0.2761)	(0.6108)			(0.2694)	(0.6615)
AssetType_n	-1.1251^{**}	0.9906	−0.1293	0.7092	-1.2550^{***}	0.6351
	(0.4225)	(0.6250)	(0.2973)	(0.3661)	(0.3579)	(0.6374)
Gov	-8.4231^{***}	-6.1146^{***}	-6.6397^{***}	-5.4512^{***}	-7.7384^{***}	-6.2794^{***}
	(0.7716)	(1.0131)	(0.6591)	(0.7063)	(0.7239)	(0.9009)
corporate_adv	-0.1796^{***}	-0.0982^{***}	-0.1565^{***}	-0.0863^{***}	-0.2108^{***}	-0.1617^{***}
	(0.0282)	(0.0188)	(0.0252)	(0.0199)	(0.0230)	(0.0209)
Inbound Call X Government	0.8981^{***}	−0.0417	1.0470^{***}	0.2370		
	(0.2480)	(0.3166)	(0.2426)	(0.3284)		
Inbound Call X Performing Loan	0.8637^{***}	0.1867	1.1701^{***}	0.6665^{**}		
	(0.1941)	(0.2117)	(0.2212)	(0.2436)		
Outbound Call X Government	2.1255^{***}	0.7326			2.3564^{***}	1.0845
	(0.3725)	(0.5739)			(0.3712)	(0.5900)
Outbound Call X Performing Loan	1.9753^{***}	0.3248			2.8769^{***}	1.2012^{*}
	(0.3899)	(0.5570)			(0.3858)	(0.6010)
AssetType_Gov	−0.2769	−0.5593	−0.0672	−0.5356	−0.4618	-0.6863^{*}
	(0.3335)	(0.2954)	(0.2968)	(0.3159)	(0.3057)	(0.3059)
current_balance	−0.0755	0.0985	−0.0522	0.2081^{**}	0.0343	0.2693^{***}
	(0.0549)	(0.0733)	(0.0469)	(0.0721)	(0.0465)	(0.0753)
orig_ltv	-0.0129^{**}	0.0022	-0.0146^{***}	−0.0015	-0.0130^{***}	−0.0068
	(0.0048)	(0.0048)	(0.0043)	(0.0050)	(0.0039)	(0.0050)
original_fico	-0.0023^{***}	−0.0009	-0.0025^{***}	-0.0015^{*}	-0.0020^{**}	−0.0012
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
current_rate	-18.5651^{***}	-10.7232^{**}	-21.7854^{***}	-9.2273^{*}	-20.2961^{***}	-9.2813^{*}
	(5.4535)	(4.0943)	(5.3461)	(4.3101)	(5.1844)	(4.3247)
currentratetype_new	−0.1930	0.2655	0.0388	0.2873	−0.0412	0.2747
	(0.2594)	(0.2307)	(0.2378)	(0.2316)	(0.2216)	(0.2257)
Borrower Noted Unemployment	0.5562^{*}	0.6916^{**}	0.8448^{**}	1.0553^{***}	-0.6066^{**}	-0.5051^{**}
	(0.2434)	(0.2329)	(0.2697)	(0.2734)	(0.1926)	(0.1840)
Borrower Noted Income Curtailment	2.0476^{***}	1.9879^{***}	2.9676^{***}	2.9624^{***}	−0.1738	−0.1503
	(0.1988)	(0.2086)	(0.2510)	(0.2664)	(0.1283)	(0.1299)
AIC	3149.8709	2519.4062	3858.9352	3020.5540	4241.1855	3263.9657
BIC	3302.1351		3985.8221		4368.0724	
Log Likelihood	−1556.9354		−1914.4676		−2105.5928	
Fixed Effects	*None*	*County*	*None*	*County*	*None*	*County*
Num. obs.	34861	34861	34861	34861	34861	34861

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$