Mortgage Market Inequality: Effects of COVID-19 Loss Mitigation Programs*

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Abstract

Using novel administrative data matched to HMDA data, we show that CARES Act mortgage forbearance programs significantly reduced the mortgage delinquency rate gap between Black and White borrowers, despite more minority and lower-income borrowers suffering financial distress during the COVID-19 pandemic. We also find minority and lower-income borrowers took up longer-term loss mitigation options at higher rates upon forbearance exit. Our results demonstrate the importance of broad-based debt relief programs that combine short-term payment suspension with longer-term loss mitigation programs to reduce inequality in mortgage performance.

Keywords: mortgage forbearance, mortgage delinquency, inequality, COVID-19, loan modification, government intervention

JEL Classifications: D12, D63, G21, G50

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1 Introduction

Government interventions through the Coronavirus Aid, Relief, and Recovery (CARES) Act mortgage forbearance programs have proven to be crucial during the COVID-19 pandemic—forbearance provided some 8.4 million U.S. mortgage borrowers much needed short term debt relief[1] and prevented a default tsunami like the one that caused the dysfunction of the mortgage market following the Global Financial Crisis (see, e.g., Cherry et al. (2021); Pence (2022)). In this paper, we take a different angle from the existing literature to study the distributional effects of mortgage forbearance and subsequent longer-term loss mitigation programs.

The pandemic as a health crisis is well-known to have had a disparate impact on minority and lower-income families (see, e.g., van Dorn et al. (2020); Chakrabarti and Nober (2020); Polyakova et al. (2020)).[2] Therefore, this paper attempts to answer two important questions: First, did mortgage forbearance provide short-term help to these groups most in need? Second, did longer-term loss mitigation programs help these same borrowers stay in their homes? A priori, it is difficult to tell if minority or lower-income borrowers were able to leverage these forbearance and loss-mitigation programs more *conditional on needing help* because these programs were broad-based and did not target any specific group like other pandemic fiscal policies did.

To answer these two questions we leverage a novel administrative dataset collected specifically for tracking mortgage forbearances and match the data with the confidential Home Mortgage Disclosure Act (CHMDA) data that provide borrower race and income information. The matched data allow us to put each individual mortgage under the microscope and investigate racial and income patterns of these forbearance and loss-mitigation programs.

Our first important finding is that, due to the CARES Act mortgage forbearance program and private-sector participation, more minority and lower-income mortgage borrowers were able to avoid delinquency on their mortgages than their White and higher-income counterparts. Unconditionally, we find that, after accounting for forbearance, delinquency rates for Black borrowers fell from 6.9% in 2019 to 1.9% in 2020, while that of White borrowers fell from 1.3% to 0.5%. As a result, Black borrowers were able to shrink the delinquency rate gap between Black and White by

[1] See, RADAR "Examining Resolution of Mortgage Forbearances and Delinquencies – Third Quarter 2022," Federal Reserve Bank of Philadelphia CFI Report, October 2022.

[2] See, also, Federal Reserve Bank of Philadelphia's *COVID-19 Survey of Consumers* https://www.philadelphiafed.org/consumer-finance/consumer-credit/cfi-covid-19-survey-of-consumers-wave-5-updates.

4.3 percentage points by taking up forbearances. Furthermore, we show that minority and lower-income borrowers took up forbearance at significantly higher rates *conditional on having entered nonpayment*. Without forbearance, delinquency rates of minority and lower-income borrowers would have been twice as high as those of White and higher-income borrowers.

Although forbearance greatly helped reduce the unequal economic toll borne by minority and lower-income borrowers, forbearance only provides short-term relief. To that end, we turn to our second question on the effectiveness of longer-term debt relief provided by the GSEs, FHA and private lenders/investors when forbearance expires, which the CARES Act did not directly address. Did longer-term loss mitigation programs help minority and lower-income borrowers stay in their homes? With 95% of borrowers having exited forbearance, we can now answer this question in the second part of the paper.

We find that about 80% of the estimated 8.4 million borrowers that entered forbearance were able to resolve their forbearance to date,[3] around 72% of which were worked out in some way by mortgage servicers to help keep borrowers in their homes. Moreover, we find that Black, Hispanic, and lower-income borrowers were more likely to utilize the various loss-mitigation options after exiting forbearance. Based on these figures, the CARES Act and private-sector forbearance programs were broadly successful in helping minority and lower-income borrowers most in need in*both* the short-the longer-term.[4]

Our paper contributes to several strands of the literature. First, we show how government interventions in the mortgage market alleviates unequal impacts of the pandemic on different demographic groups. There is a widespread concern that the burden of the pandemic is disproportionately borne by disadvantaged groups.[5] Mongey et al. (2020) show that renters and less-educated, lower-income individuals with fewer liquid assets bear heavier burdens from social distancing practices. Agarwal et al. (2020) and Gerardi et al. (2021) also document that lower-income and minority borrowers were significantly less likely to refinance to take advantage of the large decline in interest rates during the pandemic. We show the large disparity in distress in the mortgage market that is broadly reflective of the overall economic well-being

[3]See Appendix Table A1 for how we calculate the number of borrowers in forbearance.

[4]While CARES Act forbearance programs only applied to federally insured mortgages, private lenders participated voluntarily.

[5]See, e.g., Zia Qureshi, "Tackling the inequality pandemic: Is there a cure?" Brookings Institution Report, November 17, 2020.

of minority and low-income individuals. However, we also show that mortgage forbearance and loss-mitigation programs implemented during the COVID-19 pandemic helped alleviate inequalities in mortgage performance.

Second, with our novel administrative data, we provide fresh evidence on how consumers exited forbearance and used repayment plans, payment deferrals and various payment-reduction options to reach longer-term debt relief. Our study complements several recent studies that focus on forbearance take up (See, e.g., Cherry et al. (2021); Bandyopadhyay (2020); McManus and Yannopoulos (2021); Kim et al. (2021).[6] Our study underscores the importance of combining short-term debt relief measures and longer-term payment reduction options to help troubled borrowers, especially more vulnerable minority and lower-income borrowers, achieve sustainable debt relief.

Finally, we add to the large literature on the design of effective consumer debt relief policies. Post-GFC, an oft-studied area is mortgage loan modifications (see, e.g., Cordell et al. (2009); Agarwal et al. (2011); Ghent (2011); Adelino et al. (2013); Mayer et al. (2014); Haughwout et al. (2016); Kruger (2018); Ganong and Noel (2020); Kalikman and Scally (2021)). A number of studies have found the high-profile Home Affordable Modification Program (HAMP) fell short of its potential in helping troubled mortgage borrowers during the GFC (see, e.g., Immergluck (2013); Agarwal et al. (2017)). In contrast, we find the CARES Act and private-sector responses to be effective in providing debt relief to distressed borrowers and in preventing severe disruptions to mortgage markets. The short-term forbearance relief bought policy makers time to design effective longer-term debt relief plans (see, e.g., An et al. (2021) for deliberations over longer-term loan modification policies). In that regard, our study provides insights for optimal policy design of mortgage loss-mitigation programs.

The remainder of this paper is organized as follows. In the next section, we provide a brief background of the CARES Act and private-sector forbearance programs as well as subsequent actions by federal regulators to extend protections to mortgage borrowers. We describe our data in Section 3. In Section 4, we explore how patterns of nonpayment with and without forbearance differed by borrower demographic and credit characteristics. In Section 5, we examine how the 95% of borrowers who entered forbearance during the pandemic have exited so far. We conclude in Section 6.

[6] Zhao et al. (2020) also study income and asset trends of borrowers who received COVID-19 forbearance using JPMorgan Chase data.

2 CARES Act Forbearances and Foreclosure Relief

A mortgage loan is in forbearance when a servicer allows a borrower to temporarily pause paying or pay a lower amount, with the stipulation that borrowers will pay back all arrears at a later date.[7] Forbearance has long been used for hurricane relief and short-term credit card debt relief (see Agarwal et al. (2005); Billings et al. (2019)).[8] Mortgage forbearance during the pandemic has taken the form of paused payments instead of reduced payments.

Section 4022 of the CARES Act mandated that borrowers of federally backed mortgages may be granted forbearances for up to 12 months, which was later extended to up to 18 months. The CARES Act targeted mortgages mainly insured by the Federal Housing Administration (FHA), Veterans Affairs (VA), and the two Government-Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac, collectively termed the Agencies. No fees, penalties, or additional interest accrue on the loan beyond what is scheduled. Servicers of private-sector mortgages, mainly portfolio loans and loans in private-label mortgage-backed securities (PLMBS), largely adopted these same forbearance practices.

One crucial feature of the CARES Act Forbearance Program is that requirements to obtain forbearance are negligible. Borrowers needed only to request them, with no specific financial hardship or proof of inability to pay required. This contrasts with the federal Home Affordable Modification Program (HAMP) implemented during the Great Recession of 2008-09, which required proof of hardship and income documentation.[9]

Due in part to the minimal requirements to obtain forbearance, an estimated 9 million mortgages have entered forbearance since the onset of the pandemic. As shown in Figure 1, we classify borrowers into three groups: those who are delinquent but not in forbearance (the red area in Figure 1), those in forbearance and not making payments (the blue area), and those reported in forbearance but making timely payments (the purple area).[10] The share of all loans delinquent or reported in forbearance peaked at 12.3% in May 2020, declining to 5.4% by November 2021.

[7] https://www.consumerfinance.gov/ask-cfpb/what-is-forbearance-en-289/.

[8] See also Daniel Hartley, Eleni Packis, and Ben Weintraut, "Flooding and finances: Hurricane Harvey's impact on consumer credit," *Chicago Fed Letter*, 2019, No. 415 and Xudong An, Larry Cordell, Erik Dolson, Mallick Hossain and Nilim Roy, "Is Credit Card Forbearance Worth It?" *Philadelphia Fed SRC Research Breif*, July 2021.

[9] As described by Agarwal et al. (2017) and Ganong and Noel (2020), reporting and program requirements were so extensive that many servicers adopted their own private programs.

[10] These borrowers took up forbearance mainly for precautionary purposes.

We are most interested in borrowers in distress. Therefore, we focus on the group of borrowers who are delinquent or in forbearance and not paying on their mortgages (the combined blue and red areas in Figure 1). These two groups combined represent about 9% of all mortgage balances. Given the ease and low costs of obtaining forbearances, it is striking to see that over 2.5 million mortgages did not enter forbearance right away and remained or fell into delinquency.[11]

The CARES Act does not prescribe a resolution for forbearance. The two federal agencies overseeing all federally insured mortgages, the Federal Housing Finance Agency (FHFA) and Department of Housing and Urban Development (HUD), devised home-retention programs to avoid foreclosure. The central goal of these programs is to give borrowers flexibility to repay forborne arrears[12] and, if needed, to modify loan terms to lower monthly payments.[13] More details will be discussed in Section 5.

3 Data

Our primary data source is McDash Flash, a proprietary database from Black Knight Data & Analytics, LLC. McDash Flash data are assembled from Black Knight's Mortgage Servicing Platform (MSP),[14] which processes payments for around two-thirds of all mortgages in the U.S., including many of the large bank and non-bank servicers and subservicers. The data cover the full spectrum of mortgage products, including portfolio loans, PLMBS, FHA/VA,[15] and GSE loans. The McDash Flash database was specially designed to track forbearance and loss mitigation activities during the pandemic. In addition to standard performance variables, McDash Flash includes variables like the monthly dollar amounts of actual payments and scheduled pay-

[11] Some of those 2.5 million applied for forbearance later, but they could have avoided any delinquency by doing so sooner.

[12] For borrowers who can resume their regular payments, repayment options include repaying past due arrears as a lump sum, with a repayment plan, or deferring past due arrears with a non-interest bearing subordinated lien due at loan payoff.

[13] Industry experience found payment reduction to be effective in loan modification. Fuster and Willen (2017) shows that payment size has an economically large effect on repayment behavior, e.g., cutting required monthly payment in half reduces the delinquency hazard by about 55 percent. Ganong and Noel (2020) also argue that payment-reduction targets are more effective than debt-to-income targets used by federal programs during the Great Recession and more cost effective than principal forgiveness.

[14] For more information, see `https://www.blackknightinc.com/what-we-do/data-services/`.

[15] We classify all government-insured loans as FHA/VA, as they encompass loans in Government National Mortgage Association (GNMA) securities and "GNMA buybacks," which are loans pulled out of GNMA securities and brought on balance sheet at servicers as early as 90 days of delinquency.

ments,[16] and forbearance and loss mitigation start and end dates.

We merge McDash Flash data with three other databases to get a comprehensive view of borrowers' demographic information and financial condition. These are the Black Knight McDash data, the Credit Risk Insights Servicing McDash (CRISM) data, and the Confidential Home Mortgage Disclosure Act (CHMDA) data. The Black Knight McDash data contain performance histories and a full array of loan, product, borrower, and property information. CRISM contains anonymized borrower-level credit bureau data from Equifax. CHMDA data provide mortgage application information and include borrowers' race, sex, and household income at loan application.[17] The Internet Appendix A explains the matching algorithm and related match statistics, and Appendix Table A6 details the representativeness of our sample throughout the matching process.

Our final sample is a 20% random sample of our matched data, resulting in a sample of 1.96 million borrowers, around 1 million of which report whether the loan is in forbearance. We use the former, larger sample, to examine nonpayment rates and the latter, around 1 million borrowers, to examine forbearance opportunities. Table A2 shows summary statistics on the rich array of data from our sample of borrowers and mortgage loans in different states of forbearance and nonpayment status from April to December 2020.[18]

4 Nonpayment and Forbearance

To explore the differential rate of nonpayment during the pandemic with and without forbearance, we define two outcome variables. First, we define $EverNonpayment$ to examine nonpayment behavior without forbearance and equals one if a borrower ever

[16]Credit bureau and other databases typically only include scheduled payments, if they include any at all. As we will show, having actual payments is critical for determining how forbearances are resolved.

[17]For joint loans, we pull only primary borrower information from both CRISM and CHMDA for first mortgage loans and incorporate Black Knight McDash's mortgage performance data and McDash Flash forbearance data, creating a borrower-level dataset.

[18]Overall, borrowers in more financially vulnerable groups, e.g., minority, lower-income, lower credit score, and FHA/VA borrowers have higher rates of missed payments and forbearance.

falls into nonpayment during the pandemic:[19]

$$EverNonpayment = \begin{cases} 1 & \text{if ever missed payment during the pandemic} \\ 0 & \text{if never missed payment during the pandemic.} \end{cases} \tag{1}$$

As long as borrowers missed a payment, whether in forbearance or not, they will be identified as having been in nonpayment during the pandemic.

Second, we define $EverDelinquent$ to examine nonpayment behavior *with forbearance*: it equals 1 if borrowers ever fall into nonpayment *and* do not utilize forbearance.

$$EverDelinquent = \begin{cases} 1 & \text{if ever missed payment AND} \\ & \quad \text{never in forbearance during the pandemic} \\ 0 & \text{if never missed payment OR} \\ & \quad \text{ever in forbearance during the pandemic.} \end{cases} \tag{2}$$

This outcome explores the effect of the pandemic on borrower's financial distress *inclusive of* government forbearance programs, and is akin to credit-bureau reported delinquency.

Our empirical framework is a difference-in-differences (DID) specification using data spanning 2016 to 2020:[20]

$$\begin{aligned} Y_{izt} = \alpha_0 + \alpha_1 P_{izt} &+ \sum_{j,t} \gamma_{j,t} T_{j,izt} \\ &+ \sum_{j,t} \beta_{j,t} \left(T_{j,izt} * P_{izt}\right) + X'_{izt}\mathbf{\Gamma} + \tau_z + \varepsilon_{izt}, \end{aligned} \tag{3}$$

where Y_{izt} is either $EverNonpayment$ or $EverDelinquent$. The variable P_{izt} is equal to 1 for borrower i in zip code z at time t from the 2020 sample, $T_{j,izt}$ are demographic or income characteristic j, $\mathbf{X}$ is a vector of other characteristics of the borrower, and τ_z is a zip code fixed effect. Therefore, the coefficient β_j is the DID estimate for characteristic j. This is the additional likelihood of falling into nonpayment during the pandemic vis-à-vis 2019 for borrowers with characteristic j compared to the reference

[19] We define the pandemic time period for our sample as April-December 2020, as the lockdown of the economy began in March and the brunt of the pandemic's effect on the economy occurred through December. Around 95% of forbearance entry happened before December 2020 with around 60% occuring on April and May.

[20] To ensure comparability, we measure nonpayment and delinquency status from April to December of the sample year when examining our samples prior to 2020.

group.

Our main demographic variables are age, race, Hispanic status, and household income at application.[21] To make household income at application comparable across metropolitan statistical areas (MSAs) and origination years, we calculate the income relative to MSA median family income at application by dividing CHMDA-reported household income by MSA median family income at loan application using Census Bureau data. Then we divide income data into 4 quartiles, with the 1st quartile being the lowest income one. In addition, we include gender and age split into bins (age less than 35, 35-44, 45-54, 55-64, and 65 and older).

For loan and borrower attributes, we include various characteristics as of loan origination and as of January 2020 (the observation just before the onset of the pandemic). Characteristics include loan origination year fixed effects, log origination amount, origination credit score (in bins of below 620, 620-719, and 720 and above), original loan-to-value (LTV) ratio, investor type, the log of monthly payments in January 2020, whether delinquent before March (with categories of 30-90 days past due, 120+ days past due, and foreclosure initiated), credit score in January 2020, updated LTV[22] in January 2020 in bins of less than or equal to 40, (40,60], (60,80], (80,100], and greater than 100, and mortgage interest rates in January 2020.

Moreover, we include information pertinent to the borrower's other credit accounts, including total number of accounts, number of accounts past due, whether more than one account is past due, and log of past due amount of non-first-mortgage accounts. Finally, we include an indicator variable for whether the loan is serviced by a bank.[23] For all our specifications, our reference group is White, non-Hispanic, male borrowers less than 35 years old, with relative household income in the 4th quartile, credit score in January 2020 between 620 and 719, credit score at origination between 620 and 719, and updated LTV bin of 60-80.

Finally, we include neighborhood characteristics or zip code fixed effects to control for any local determinants of housing and mortgage market outcomes. We include 2020 peak-to-trough county unemployment rates from the Bureau of Labor Statistics

[21]Note that we do not observe borrower's relative household income over time, only at the time of application.

[22]We calculate updated LTV in January by taking the principal remaining in January 2020 and dividing it by the house value at origination multiplied by the CoreLogic House Price Index (HPI) growth rate in the property's zip code from origination to January 2020. For zip codes missing CoreLogic HPI, we use county HPI instead.

[23]For regressions pertaining to our sample in 2020, we use the most recently observed servicer type by November 2020. For other regressions including samples before 2020, we include the servicer type first observed.

and other zip code level characteristics from the American Community Survey 2015-2019 Summary Files, which include log of population, share of adults with a college degree or higher, share of Black residents, log of median income, vacant housing shares, log of median house values, and mortgage shares of owner-occupied housing.

4.1 Results on Nonpayment

We first present results on the outcome $EverNonpayment$ defined in (1), which classifies all borrowers who missed a payment as borrowers in nonpayment, regardless of their forbearance take-up. We employ our multi-period DID specification described in equation (3) that includes race, income, loan and borrower characteristics, as well as zip code fixed effects. We present the results on our key demographic variables in Figure 2 with 2019 as the baseline. Our results show that racial and income disparities in mortgage distress were very small in the 2016-2019 pre-pandemic years after controlling for conventional risk factors, but they increased significantly in 2020, contributing to economic inequality during the pandemic.[24]

The results in Panel (a) show that Black borrowers are 5.2 percentage points more likely to fall into nonpayment during the pandemic compared to White borrowers. Due to our DID specification, this is *after* taking into account the baseline nonpayment rate differences during 2019. This is also true for Asian and Hispanic borrowers, with 2.4 percentage points and 5.0 percentage points higher rates, respectively, shown in Panels (b) and (c). Compared to the 5.4 percentage point increase in the average nonpayment rate from 2.2% in 2019 to 7.8% in 2020, this amounts to almost double the rate for Black and Hispanic borrowers. The results in Panels (d)-(f) show that lower-income borrowers are also more likely to fall into nonpayment during the pandemic, at 1.7, 1.4, and 0.9 percentage points, respectively. This is around a 31%, 26%, and 17% increase relative to the increase in nonpayment rates from 2019 to 2020.

These results are robust to excluding or including various controls. This is shown in Appendix Table A3, which presents the DID results using just the 2019 and 2020 sample of borrowers with various specifications, where Column (1) shows results from a specification that includes only the racial composition of borrowers, Column (2)

[24]In order to examine whether the differences in our multiperiod DID is coming from constant proportionality increases in nonpayment rates by race and income characteristics, Appendix Figure A1 presents results with the coefficients normalized by the overall mean of each year. We see that results on race hold, displaying elevated rates of nonpayment even compared to the overall rates. For income, the results are mixed, with the lowest income group displaying decreased rates but 2nd and 3rd income groups displaying higher rates.

a specification with only income-related variables. The specification in Column (3) includes both race and income variables and adds credit characteristics of borrowers. The specification in Column (4) includes local characteristics and Column (5) includes zip code fixed effects in lieu of local characteristics. We see that the coefficients are stable across specifications.

4.2 Results on Nonpayment Net of Forbearance

We examine further how effective COVID-19 forbearance programs have been in helping borrowers avoid delinquency. Toward that end, we examine the characteristics of borrowers who fell into delinquency and *did not* receive forbearance, by using $EverDelinqent$ defined in 2 as the outcome of our DID specification.

We present results for the multi-period DID specification on delinquencies in Figure 3. Unlike Figure 2, which showed a large negative impact on minority and lower-income borrowers from the pandemic relative to 2016-2020, Figure 3 shows the opposite effect, as minority and lower-income borrowers experienced a large decline in delinquency rates after removing borrowers that took up forbearance. Panel (a) and (b) show that Black and Hispanic borrowers experienced 3.4 and 0.9 percentage point lower changes in their rates of delinquency compared to what White borrowers experienced from 2019-2020.[25] This shows that forbearances significantly reduced the delinquency burden for minority and lower-income borrowers. Compared to the overall decline of 1.8 percentage points in the delinquency rate, this amounts to a significantly higher rate of decline for Black borrowers in particular. The overall pattern for income also holds in Panels (d)-(f), where borrowers in the 1st, 2nd, and 3rd quartiles experienced about 1.5, 1.0, and 0.4 percentage point lower changes in delinquency rates, respectively, from 2019 to 2020.

Similar to our DID specification on nonpayment rates, these results are robust as shown in Appendix Table A4, where the specifications across columns are the same as in Table A3. For example, delinquency rate of Black borrowers fell from 6.9% in 2019 to 1.9% in 2020, while that of white borrowers fell from 1.3% to 0.5%. In other words, Black borrowers were able to shrink the delinquency rate gap between Black and White by 4.3 percentage points by taking forbearance. This is the result shown

[25] Note that the delinquency rate overall decreased from around 2.2% to 0.6% from 2019 to 2020, so the coefficients represent an additional decrease in delinquency rate changes. This is due to how the CARES Act dealt with prior delinquencies, as borrowers of federally insured mortgages were granted forbearance if they requested it, without having to verify hardship. In practice, this meant that borrowers with delinquencies unrelated to the pandemic could also receive forbearances.

in column 1. After including all the controls we discussed previously, the Black-White delinquency rate gap is shown to reduce by 3.4 percentage points from 2019 to 2020, which is what we show in Figure 3 and discussed above.

The reversed pattern of inequality is attributable to the higher take-up rates of forbearance for minority and lower-income borrowers conditional on being in nonpayment. We also analyzed the take-up of forbearance by taking a sample of borrowers who ever fall into nonpayment during the pandemic and regressing whether they ever take up forbearance on various demographic and credit characteristics. Table A5 shows the results, where conditional on having experienced nonpayment during the pandemic, Black and Hispanic borrowers were more likely to take up forbearance by about 2 percentage points.[26]

On the whole, these results show that CARES Act forbearances—a blanket government policy with no specific target to reduce inequality—were effective in mitigating the adverse, skewed impact of the pandemic on minority and lower-income borrowers. This has provided short-term relief. As we discuss in the next section, how borrowers exited forbearance will determine whether these reductions in inequality will be sustained for the long term.

5 Forbearance Resolution

While forbearance relief has been provided to an estimated 9 million mortgages, that relief is temporary. Borrowers risk foreclosure if they cannot resolve their past-due arrears by resuming timely payments or paying off the loan. Since 95% of mortgages that entered forbearance have exited, we now have the sample mass to assess the success of the various longer-term loss-mitigation programs in reducing inequality.

Using our unique data, we can track actual payment amounts made on each mortgage and how servicers classify loss-mitigation outcomes. We then exploit this information to categorize forbearance outcomes of loans into three categories: 1) loans that were able to self-cure by making a lump-sum payment of their arrears; 2) loans resolved with some help, which include loans on repayment plans, loans that became current with past due arrears deferred, loans where terms were modified, or

[26] Gerardi et al. (2022) focuses on the unconditional, raw averages by race and find that Black and White borrowers had similar rates of take-up while Asian and Hispanic borrowers had slightly higher rates. As can be seen in Column (1) of Table A5, we find similar results when only including race variables. However, Black, Asian, and Hispanic borrowers take-up at higher rates when conditioning on various credit and local characteristics.

loans presently in trial modifications[27]; or 3) loans paid off directly from delinquency or forbearance[28] or loans that have yet to resolve their forbearances (currently in forbearance, delinquency, or have defaulted). Broadly speaking, loans in the third category are those who suffered a negative outcome after having been in forbearance.

Using the above categorization, we define an outcome variable $CurrentStatus$, using loan performance information through August 2022,

$$CurrentStatus = \begin{cases} 1 & \text{if self-cured,} \\ 2 & \text{if resolved with help or is in trial modification} \\ 3 & \text{if still in forbearance, defaulted, delinquent,} \\ & \quad \text{or paid off from delinquency or forbearance} \end{cases} \tag{4}$$

We now examine how $CurrentStatus$ differs by demographic, income, and credit profiles for our sample of borrowers who have ever entered forbearance via a cross-sectional multinomial logit regression with (4) as the dependent variable. We include all the demographic, loan, borrower attributes, and neighborhood characteristics described in Section 4.

Table 1 shows the distribution of borrowers by $CurrentStatus$. We first note that around 22.5% of borrowers ever in forbearance were able to self-cure through a lump sum payment, 58% needed some kind of help to cure, and 19.5% have yet to exit forbearance, paid off out of delinquency or forbearance, or are delinquent or defaulted. While around 80% of borrowers were able to exit forbearance one way or another, of those that have cured, 58%/80.5% = 72% received some sort of help.

Table 1 also breaks down the three large categories into the kinds of help they received to reperform or delinquency status they fell into. We can see that among those that received help, borrowers were most likely to have gone through a repayment plan (23%). Deferrals of past-due arrears where borrowers resume timely payment (18%) and formal modification (16%) are the next most likely options. That these rates of assistance occurred in the order preferred by servicers based on cost indicates the waterfall approach used to provide help was important.

[27]Trial modifications involve borrowers making at least three consecutive payments at their reduced amounts before finalizing new loan terms. They are reported as delinquent while they are making the three requisite payments, but we consider these loans as in progress to be resolved for our purpose.

[28]Loans are generally not allowed to refinance until three payments out of forbearance have been made, so we consider loans paying off directly from forbearance as those who could not retain their homes.

For the remaining 19.5% that did not self-cure or benefit from assistance, 11.5%, or over half, paid off directly from forbearance and delinquency. Since borrowers generally cannot refinance out of delinquency, this is an indication of borrowers being able to avoid foreclosure only because they had sufficient equity in their homes. The remaining borrowers are still in forbearance or out of forbearance and delinquent or defaulted.

Moreover, the likelihood of needing help to exit forbearance was not uniform across demographic and credit characteristics. Figure 4 shows the marginal effects of each demographic and credit characteristic as well as pre-pandemic delinquency status using the coefficients estimated from the multinomial logit model. Figure 4 Panel (a) presents marginal effects on $CurrentStatus = 1$ on selected demographic characteristics (Black, Hispanic, and first to third quartile of relative income indicators), credit characteristics (indicator variable for Credit Score in January 2020 being less than 620 or greater or equal to 720), and delinquency status prior to March 2020 (30-90 days past due (DPD), 120+ DPD, in foreclosure process). Panel (b) presents the marginal effects on $CurrentStatus = 2$, and Panel (c) on $CurrentStatus = 3$.

Examining Panel (a), we see that Black, lower-income, and lower credit score borrowers were less likely to self-cure from forbearance, at around 1-2 percentage points, or around 5%-10% relative to their means. Interestingly, Hispanic borrowers were 2 percentage points more likely to self-cure. Panel (b) shows that minorities and lower-income borrowers have a higher likelihood of receiving help to exit forbearance. The estimated marginal effects are around 2-5 percentage points, or around 3%-9% relative to their means. Both Panels (a) and (b) show that those who were delinquent pre-pandemic were much less likely to cure with or without help.

Finally, in Panel (c) we show that minority and lower-income borrowers are less likely to be in continued delinquency or to have had to pay off out of forbearance. Panel (c) shows that Black borrowers are around 2.5 percentage points less likely than White borrowers to be in the third category of loans, with Hispanic borrowers 5 percentage points less likely. These magnitudes amount to about 12% and 25% less likely relative to the average rate of being in category 3. Lower income borrowers are slightly less likely to be category 3 compared to the highest income borrower. However, we can also see that those with credit scores below 620 (6 percentage points) and in delinquency pre-pandemic (13, 17, and 30 percentage points, respectively) are significantly more likely to be in the last category.

Taken together, the results of the three outcomes show that minority and lower income borrowers were more likely to exit forbearance by receiving help in larger shares compared to White and higher income borrowers, who tended to self-cure from forbearance at higher rates. These results are in line with our overall findings of nonpayment and forbearance we document in Section 4. Minority and lower-income borrowers were relatively more economically disadvantaged by the pandemic but were more likely to have been helped by *both* short-term forbearance programs and these longer-term loss mitigation programs. Meanwhile, borrowers in pre-pandemic delinquencies, even for those that entered forbearance during the pandemic, their longer term prospects did not improve and they were much more likely to have paid off or still be in delinquency or forbearance.

6 Conclusion and Discussion

The COVID-19 pandemic produced unprecedented financial distress for households and businesses. However, through the CARES Act, the federal government response was also unprecedented, embarking on a massive program of mortgage forbearance that, along with private-sector participation, provided relief to some 15% of the $11 trillion mortgage market. We examine the impact of the pandemic on racial and income inequality among homeowners, both *inclusive* and *exclusive* of government fiscal assistance, and provide an assessment of the efficacy of longer-term home-retention programs to avoid foreclosure.

We document that the COVID-19 pandemic had a significantly larger negative impact on minorities and lower-income mortgage borrowers. We also show that federal and private forbearance programs provided a lifeline to many of those borrowers. As minority and lower-income borrowers took up forbearances at significantly higher rates, forbearance programs offset the racial and income disparities observed at the outset of the pandemic.

As the pandemic subsided and 95% of an estimated 8.4 million mortgages that entered forbearance exited, we then analyze the manner and ways these borrowers exited, again focusing on minority and lower income borrowers. Longer-term relief came in the form of repayment plans, deferrals of past-due arrears, and loan modification programs aimed at delaying or reducing borrowers mortgage payments. The last part of our analysis evaluates the effectiveness of these programs in achieving their goals. We show that most borrowers have been able to avoid foreclosure or long-term delinquency, and that further assistance in the form of repayment plans, loan deferrals, or loan modifications were especially helpful for minority and lower-income borrowers in resolving their forbearance spells.

Despite recent successes, challenges exist going forward. Ultra-low market rates were especially beneficial for loan modifications, but that has changed with recent high mortgage rates, making some loan modification options infeasible. For FHA loans, when servicers modify them, they are required to buy loans out of GNMA pools *at par*. FHA strikes the modification rate at the prevailing Primary Mortgage Market Survey (PMMS) rate to help servicers recoup the buyout outlay.[29] That worked well when market rates were below mortgage contract rates, but not today. To make modifications work in this time of high mortgage rates, FHA devised a Payment Supplement Assistance (PSA) plan allowing for in-pool modifications by using funds to top off the borrowers reduced payments, placing them into a 0% "partial claim" lien due at payoff.[30] Creative workout programs like these are needed to address needs of distressed borrowers under *all* market conditions.

[29] No other investor faces this constraint. GSEs bring loans on balance sheet so do not need to charge a market rate; GNMA has no balance sheet. PLMBS servicers can modify terms within the security pool. Portfolio lenders have loans on balance sheet.

[30] For a description of the PSA, see Bhagat (2022).

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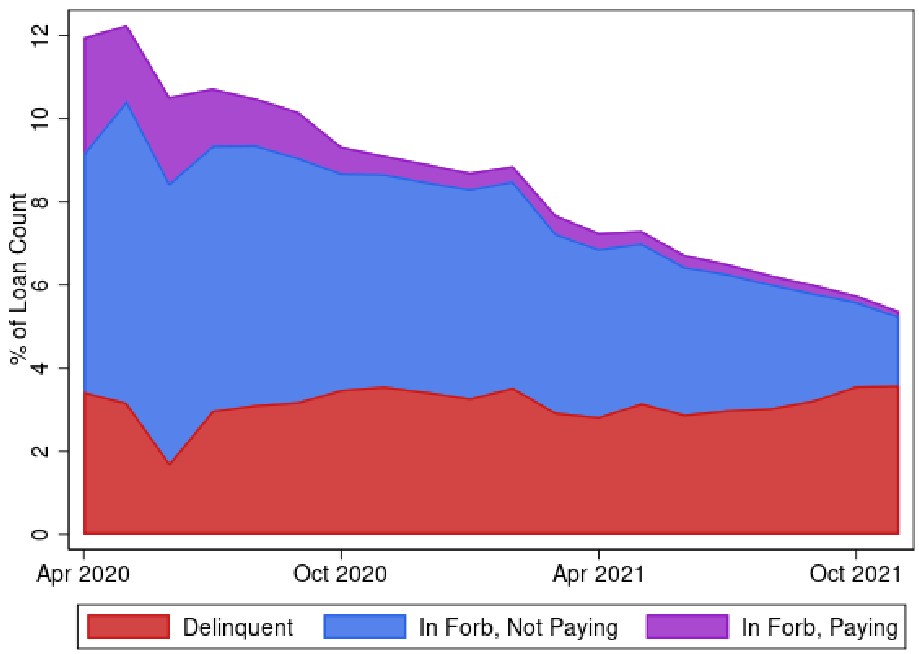
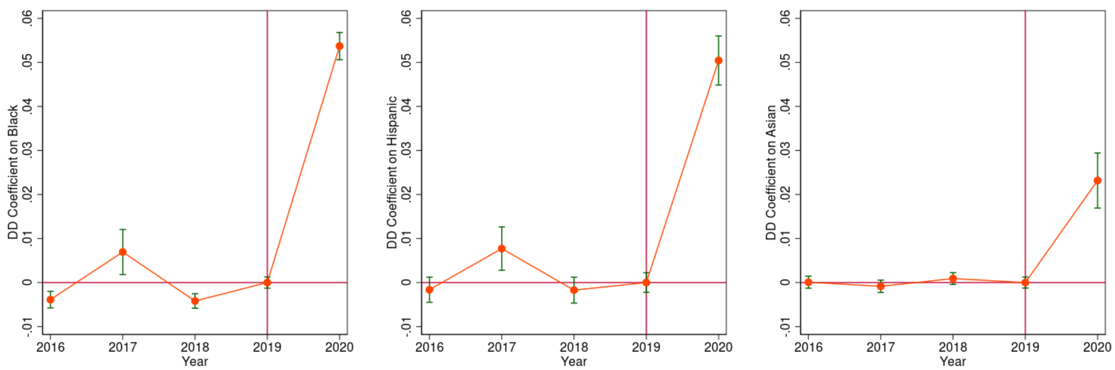
Figure 1. Delinquency and Forbearance Status of Loans



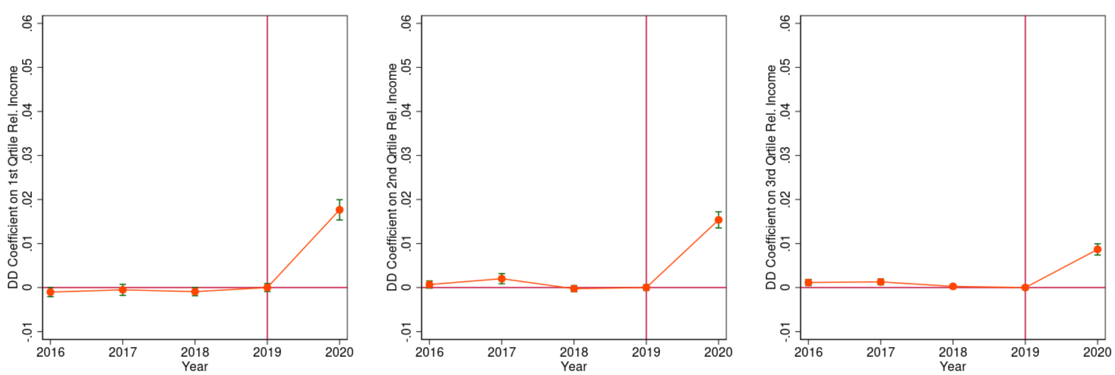
Notes: This figure plots percentages of loans that are delinquent or in forbearance based on data from Black Knight Data & Analytics, LLC. The red area depicts loans delinquent and not in forbearance, the blue area loans in forbearance and in nonpayment, and the purple area loans that are in forbearance and current on their mortgages.

Data sources: Black Knight Data & Analytics, LLC

Figure 2. Nonpayment Diff-in-Diff Coefficients, 2016-2020



(a) Black **(b)** Hispanic **(c)** Asian

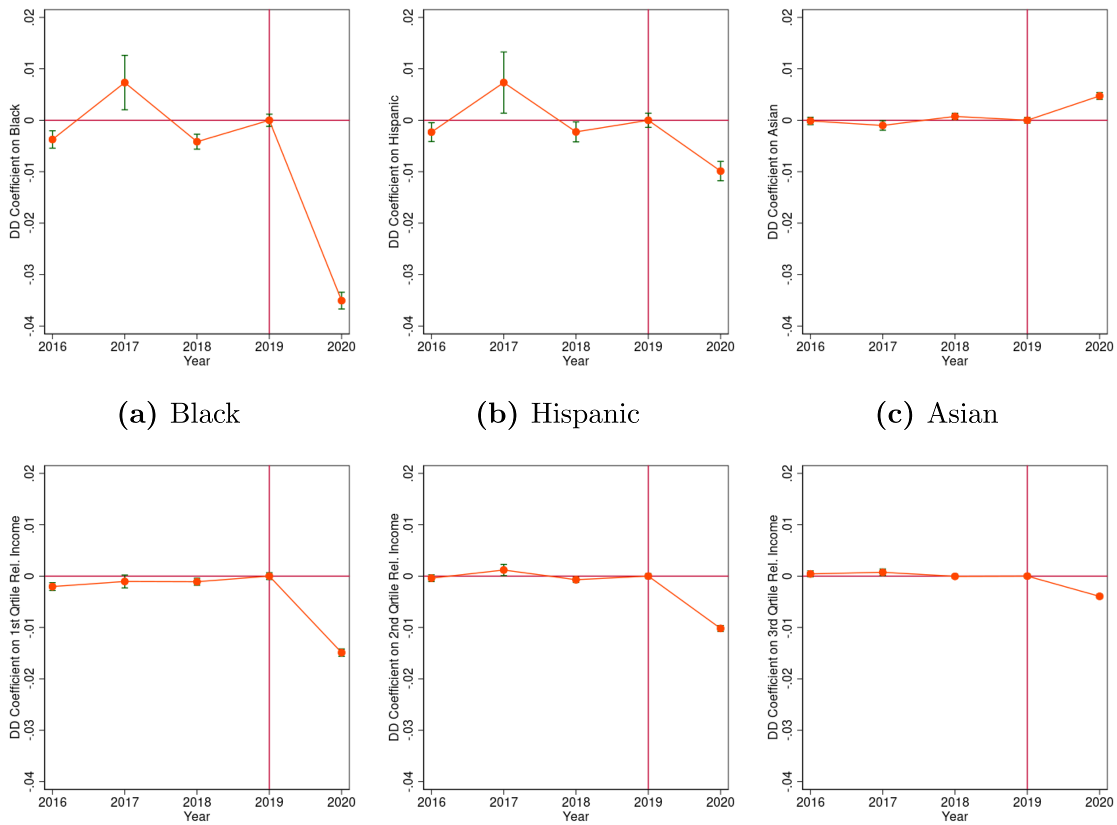


(d) 1st Qrtile Rel. Income **(e)** 2nd Qrtile Rel. Income **(f)** 3rd Qrtile Rel. Income

Notes: This figure plots the coefficients and 95% confidence intervals from the multiperiod Difference-in-Differences (DID) regressions on the outcome of whether the borrower is in nonpayment with our most complete specification (all controls and zip FE as described in Section 4) using 2019 as the baseline. Each panel plots coefficients on (a) Black indicator, (b) Hispanic indicator, (c) Asian indicator, (d) 1st Quartile of Income Relative to MSA Median, (e) 2nd Quartile of Relative Income, and (f) 3rd Quartile of Relative Income. Race, Hispanic, and Asian statuses, and borrower income quartiles are at application from CHMDA. Nonpayment rates in 2019 were 1.9%, 6.9%, 3.2%, 0.8% for White, Black, Hispanic, and Asian borrowers and 3.6%, 2.7%, 1.7%, 0.9% for borrowers in 1st, 2nd, 3rd, and 4th quartile of relative Income, respectively. In 2020, they were 6.3%, 16.3%, 12.9%, 7.5% for White, Black, Hispanic, and Asian borrowers and 10.0%, 8.8%, 6.9%, 5.1% for borrowers in 1st, 2nd, 3rd, and 4th quartile of relative income, respectively.

Data sources: Black Knight Data & Analytics, LLC; Credit Risk Insights Servicing McDash (CRISM); and Confidential Home Mortgage Disclosure Act (CHMDA).

Figure 3. Delinquency Diff-in-Diff Coefficients, 2016-2020

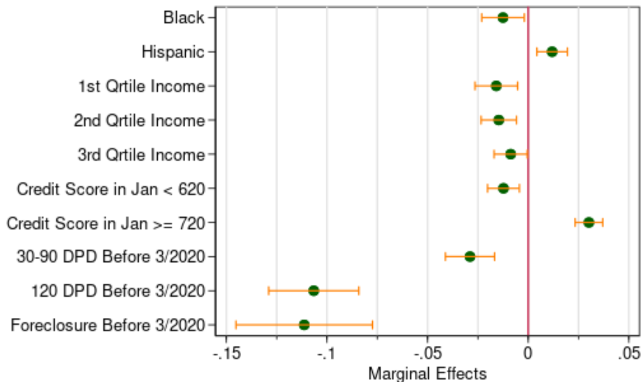


(a) Black **(b)** Hispanic **(c)** Asian

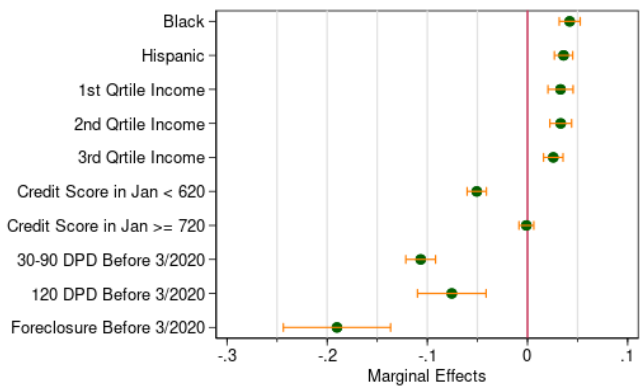
(d) 1st Qrtile Rel. Income **(e)** 2nd Qrtile Rel. Income **(f)** 3rd Qrtile Rel. Income

Notes: This figure plots the coefficients and 95% confidence intervals from the multiperiod Difference-in-Differences (DID) regressions on the outcome of whether the borrower is delinquent, with our most complete specification (all controls and zip FE as described in Section 4) using 2019 as the baseline. Each panel plots coefficients on (a) Black indicator, (b) Hispanic indicator, (c) Asian indicator, (d) 1st Quartile of Income Relative to MSA Median, (e) 2nd Quartile of Relative Income, and (f) 3rd Quartile of Relative Income. Race, Hispanic, and Asian statuses, and borrower income quartiles are at application from CHMDA. Delinquency rates in 2019 were 1.9%, 6.9%, 3.2%, 0.8% for White, Black, Hispanic, and Asian borrowers and 3.6%, 2.7%, 1.7%, 0.9% for borrowers in 1st, 2nd, 3rd, and 4th quartile of relative Income, respectively. In 2020, they were 0.5%, 1.2%, 0.7%, 0.2% for White, Black, Hispanic, and Asian borrowers and 1.0%, 0.6%, 0.4%, 0.2% for borrowers in 1st, 2nd, 3rd, and 4th quartile of relative income, respectively. See Figure 2 for data sources.

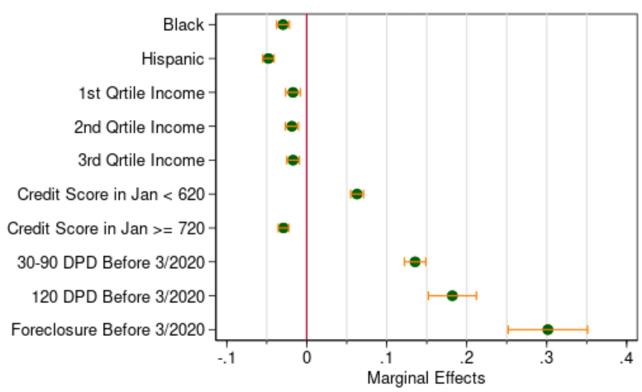
Figure 4. Transition from Forbearance to Longer-Term Debt Relief Logistic Regression Results



(a) Performing or Paid Off without Help



(b) Performing or Paid Off with Help



(c) Paid Off From or Is Currently Delinquent, in Forbearance, or Defaulted

Notes: This figure plots the marginal effects using coefficients estimated from a multinomial logit model with three outcomes summarized as follows: (a) exited forbearance into current status or payoff without help, (b) exited forbearance into current status or payoff with help, and (c) paid off from or currently in delinquency, defaulted or in forbearance. Further description of the categorizations can be found in the text. Reference group is White, 4th Quartile of Relative Income, GSE, Credit Score 620-720, not delinquent before March 2020. See Figure 2 for data sources.

Table 1. COVID-19 Forbearance Exits by Category

Category 1: Self-Cure	22.5%
Category 2: Current with Help	58.0%
Repayment Plan	22.7%
Deferral	18.1%
Modification	16.4%
Trial Modificaiton	0.9%
Category 3 Forbearance/Delinquent/Default	19.5%
Still in Forbearance	2.0%
In Loss Mitigation But Not Paying	1.6%
Delinquent, Not in Loss Mitigation	4.2%
Paid Off from Forbearance or Delinquency	11.7%
Default	0.1%
Total	100.0%

Notes: This table summarizes from our regression sample the disposition of all loans that entered forbearance into the three categories defined in Section 5. Dispositions were determined by gathering servicers' classifications and examining monthly payment patterns compared against scheduled payments. Repayment plans occur when borrowers make partial payments until the loan is brought current. Deferrals/Partial Claims occur when a non-interest bearing subordinated lien is established on all past-due arrears and the borrower resumes timely payment. Modifications reduce mortgage payments by altering loan terms through some combination of extending terms, lowering interest rates or deferring past due arrears or additional principal. See RADAR (2022) for details. Not shown here are servicing transfers, which are loans sold or transferred to another servicer while in forbearance where a status could not be determined.

Data sources: Black Knight Data & Analytics, LLC

Appendix A Data Matching Procedure

In this section, we describe the matching procedure across our datasets. The datasets we use are described in detail in Section 3 and are McDash Flash, Black Knight McDash Data, CRISM, and CHMDA data.

Matching loans in Black Knight's McDash Flash data to loans in Black Knight McDash data is straightforward as they are provided from the same source with unique loan identifiers. However, not all loans in the Black Knight McDash data are found in McDash Flash. Matching CRISM data with Black Knight McDash data is also straightforward, as Equifax uses loan performance data from McDash primary to match to mortgage loans held by borrowers in their credit history data and provide the unique loan identifier used in McDash. Equifax employs its own proprietary algorithm for matching loans in its credit histories with loans in the Black Knight McDash dataset, which uses loan information such as loan amount, zip code, origination date, and other criteria. Following Equifax guidance, we only take loans with a sufficiently high confidence on the match.

The bulk of our work is done to match loans in McDash to loans in CHMDA, which is information provided by the lenders at loan application. The matching algorithm is based on the work of Rosen (2011) and uses the following criteria:

1. Geography: CHMDA provides the Census Tract of the property, while McDash provides the zip code of the property. Therefore, we use a concordance between Census Tracts and zip codes provided by MABLE/Geocorr from the Missouri Census Data Center.[31] However, some Census Tracts may be matched to multiple zip codes, and vice versa. For these loans, we let them match to all possible combinations of zip code to Census Tract.

2. Loan origination characteristics: We match loans by their loan amount, lien status, occupancy, loan purpose, and loan type. For loan amounts prior to 2018, CHMDA required lenders to report loans in 1,000s of dollar amount, with rounding. As such, we only require loans to be within a \$500 band between CHMDA and McDash. However, for loan amounts in 2018 and later, CHMDA provides the full amounts down to the dollar. Because there were some cases in which loans were reported to the nearest \$10 amount, we allowed for differences of up to \$10.

[31] https://mcdc.missouri.edu/applications/geocorr.html.

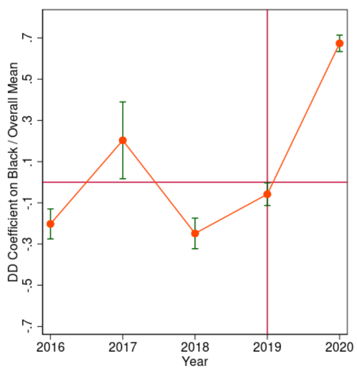
3. Closing date: Because there is some flexibility in how servicers and lenders report the closing date, we allow the most flexibility in this regard. First, the McDash data exhibits bunching on the 1st of the month, indicating the exact closing date is not recorded. Second, CHMDA allows some flexibility in reporting the closing date. Therefore, we first match loans using the exact dates as reported; then, for loans not matched using exact dates, we find loans that have closing dates within five days of each other; for loans still not matched, we allow any loan in the same month to be matched.

As can be seen from the procedure described above, it is possible that multiple matches for the same loan can occur. These cases include pure multiples, where two loans share the same characteristics. Or it could be an artifact of our inexact matching criteria. For example, multiple loans could be within the same loan amount band, or in Census Tracts that are large enough to have multiple zip codes. In order to avoid making judgments on these cases, we only use loans that were uniquely matched between McDash and CHMDA. Moreover, to preserve the anonymity of the data, we remove all identifying information for borrowers, servicers, and lenders.

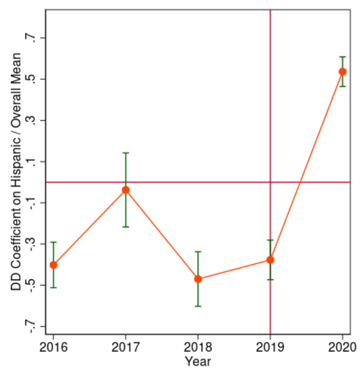
Appendix Table A6 shows the match rates and means of various characteristics of loans and borrowers across our matches. Column (1) shows our baseline data to examine the match, which are borrowers in CRISM that has a matched McDash loan in June 2020. Going across the columns, we see that about 65% of the CRISM borrowers are matched to CHMDA (Column 2), 69% are matched to McDash Flash (Column 3), and 47% are matched to both (Column 4).

We also see that loans matched to CHMDA, Flash, or both datasets do not differ significantly in their borrower or loan characteristics. There seems to be some indication that those matched to Flash data are slightly better selected than those in our baseline CRISM data. For example, borrowers with loans matched to both CHMDA and Flash belong to the highest credit score group at a slighly higher rate (62%) compared to the full sample of CRISM borrowers (58%). However, other differences are small or zero.

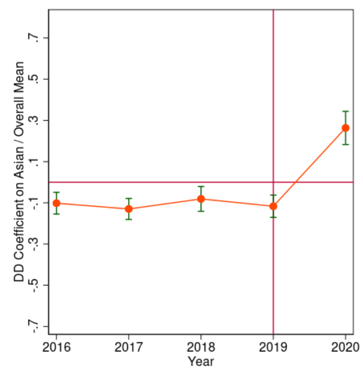
Appendix Figure A1. Nonpayment Diff-in-Diff Coefficients, Proportional Hazard Perspective, 2016-2020



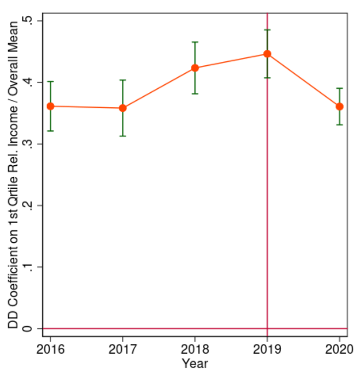
(a) Black



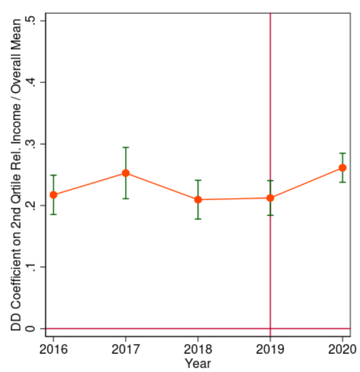
(b) Hispanic



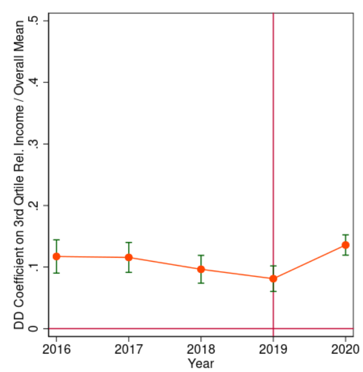
(c) Asian



(d) 1st Qrtile Rel. Income



(e) 2nd Qrtile Rel. Income



(f) 3rd Qrtile Rel. Income

Notes: This figure plots the coefficients divided by overall means in each year and 95% confidence intervals from the multiperiod Difference-in-Differences (DID) regressions with our most complete specification. Each panel plots coefficients on (a) Black indicator, (b) Hispanic indicator, (c) Asian indicator, (d) 1st Quartile of Income Relative to MSA Median, (e) 2nd Quartile of Relative Income, and (f) 3rd Quartile of Relative Income. Race and borrower income quartiles are at application from CHMDA. See Figure 2 for data sources.

Appendix Table A1. Estimates of Number of Loans Ever in COVID-19 Forbearance

	U.S. Mortgage Market Size		Loans Ever in Forbearance		Share of
	Loan Counts (Thousands)	Loan Balance ($Billions)	Loan Counts (Thousands)	Loan Balance ($Billions)	Forbearance Never Missed a Payment
FHA/VA	12,100	2,273	2,919	596	9%
GSE	27,900	6,597	3,294	871	15%
Portfolio	10,500	2,821	1,474	378	17%
PLMBS	2,500	418	758	144	31%
Total	**53,000**	**12,109**	**8,445**	**1,990**	**14%**

Notes: This table presents our estimates of the number of loans ever entered in COVID-19 forbearance in the U.S. single family mortgage market extrapolated from our McDash Flash sample by November 15, 2022. The first column lists the market size for different investors. FHA/VA includes GNMA securities and portfolio loans that are GNMA buybacks purchased out of securities pools. Portfolio loans exclude from IMF figures home equity loans and GNMA buybacks. GNMA = Government National Mortgage Assn., FHA/VA = Federal Housing Administration/Veterans Affairs, GSE = Government-Sponsored Enterprise, and PLMBS = Private Label Mortgage Backed Securities. The second column lists our extrapolated number of loans ever entered in forbearance: we track the numbers of new forbearances in our McDash Flash sample each week since the pandemic to November 15, and calculate their shares as percentage of the sample; we then apply the shares to the market size to get the estimates of new forbearances each week in the market; lastly we sum up all extrapolated new forbearances from each week to get the total forbearances of 8.445 million by November 15. An independent calculation from Black Knight produces a similar estimate (https://www.blackknightinc.com/wp-content/uploads/2022/12/BKI_MM_Oct2022_Report.pdf). The third column lists the shares of loans in forbearance that have never missed a payment calculated from our McDash Flash sample.

Data sources: Black Knight Data & Analytics, LLC

Appendix Table A2. Sample Means of Our Sample and Subsamples

Variable	(1) *Full Sample*	(2) *Never Miss Pay*	(3) *Ever Miss, Ever Forb*	(4) *Ever Miss, Never Forb*
Ever in Nonpayment	0.078	-	-	-
Ever in Forbearance	0.101	0.037	-	-
Primary Borrower Characteristics				
White	0.777	0.798	0.717	0.761
Black	0.064	0.053	0.128	0.132
Asian	0.057	0.052	0.058	0.022
Hispanic	0.094	0.082	0.160	0.111
Household Income	106,769	106,529	88,156	65,380
Age	51.0	51.5	47.2	47.8
Credit Score at Orig	737	743	701	674
Credit Score in Jan 2020	749	767	679	584
Mortgage Loan Characteristics and Performance				
GSE Loan	0.632	0.687	0.519	0.279
FHA/VA Loan	0.255	0.216	0.425	0.645
Private Label MBS Loan	0.014	0.005	0.010	0.018
Portfolio Loan	0.099	0.093	0.047	0.058
Origination LTV	79	78	86	89
Updated LTV Jan 2020	48	45	54	54
Delinquent Pre-Pandemic	0.013	0.003	0.088	0.481
Foreclosure Pre-Pandemic	0.002	0.000	0.005	0.066
Large Servicer	0.975	0.962	0.963	0.945
Loan Amount	240,988	233,179	231,089	168,683
Current Interest Rate	4.13	4.09	4.30	4.49
Equifax Credit Bureau Characteristics				
Total Non-Mortgage Debt	33882.21	32382.85	47887.68	30202.47
Total Monthly Payments	2960.79	2863.61	3285.66	2222.53
Has Auto Debt	0.551	0.538	0.638	0.571
Has Credit Card Debt	0.951	0.952	0.940	0.803
Has Student Loan Debt	0.170	0.161	0.250	0.201
Credit Card Utilization	0.271	0.245	0.485	0.675
More than 1 Acct DPD	0.016	0.008	0.077	0.220
Observations	1,957,724	980,870	87,303	5,930

Notes: This table shows sample means for our full sample as well as from a subsample of mortgages with forbearance reporting further broken down into mortgages that: never missed a payment (Column (2)), ever missed a payment but remains in forbearance (Column (3)), and Ever missed a payment and was never in forbearance (Column (4)).
Data sources: Black Knight Data & Analytics, LLC; Credit Risk Insights Servicing McDash (CRISM); and Confidential Home Mortgage Disclosure Act (CHMDA).

Appendix Table A3. Diff-in-Diff Estimates of Nonpayment Rates, 2019-2020

Dep Var: Ever in Nonpayment	(1) *Race*	(2) *Income*	(3) *Credit Chars*	(4) *Local Chars*	(5) *Zip FE*
Black	0.050***		0.052***	0.053***	0.052***
	(0.002)		(0.002)	(0.002)	(0.002)
Asian	0.023***		0.024***	0.023***	0.024***
	(0.004)		(0.003)	(0.003)	(0.003)
Hispanic	0.053***		0.005***	0.050***	0.050***
	(0.004)		(0.004)	(0.003)	(0.003)
Borrower Income: 1st Qrtile.		0.022***	0.017***	0.017***	0.017***
		(0.002)	(0.001)	(0.001)	(0.001)
Borrower Income: 2nd Qrtile.		0.019***	0.015***	0.015***	0.014***
		(0.001)	(0.001)	(0.001)	(0.001)
Borrower Income: 3rd Qrtile.		0.01***	0.009***	0.008***	0.009***
		(0.001)	(0.001)	(0.001)	(0.001)
Credit Score in Jan < 620			0.091***	0.091***	0.090***
			(0.001)	(0.001)	(0.001)
Credit Score in Jan ≥ 720			-0.037***	-0.037***	-0.037***
			(0.000)	(0.000)	(0.000)
FHA/VA Loan			0.012***	0.012***	0.012***
			(0.000)	(0.000)	(0.000)
PLMBS Loan			0.008***	0.007***	0.007***
			(0.001)	(0.001)	(0.001)
Portfolio Loan			-0.016***	-0.016***	-0.015***
			(0.001)	(0.001)	(0.001)
Log Orig Amt			0.009***	0.008***	0.009***
			(0.001)	(0.000)	(0.000)
Num of DPD All Accts			0.018***	0.018***	0.018***
			(0.001)	(0.001)	(0.001)
Observations	3,800,964	3,800,964	3,800,964	3,800,964	3,800,964
R-squared	0.026	0.020	0.210	0.211	0.219
Average Rate	0.054	0.054	0.054	0.054	0.054
Zip Code FE	N	N	N	N	Y

Notes: Clustered standard errors at the county-level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The reference group for the categorical variables is White, male, age below 35, GSE loan holders with credit scores 620-719, 4th quartile in relative borrower income, and updated LTV 60-80. Other control variables include missing or other race, sex and age bins, loan origination year FE, LTV ratio, log origination amount, credit score at origination, whether servicer is a bank, log monthly payment amount, updated LTV bins, number of DPD credit accounts, more than 1 account DPD, and delinquency status before march for Column 3. Column 4 includes peak-to-trough county unemployment rate in 2020 and zip code log of population, college share, Black share, log median income, vacant housing share, log median housing value, and mortgage share of owner-occupied housing. Column 5 replaces local characteristics with zip-code fixed effects. See Table A2 for data sources.

Appendix Table A4. Diff-in-Diff Estimates of Delinquency Rates, 2019-2020

Dep Var: *=1 if Delinquent and Never in Forb.*	(1) *Race*	(2) *Income*	(3) *Credit Chars*	(4) *Local Chars*	(5) *Zip FE*
Black	-0.043***		-0.035***	-0.034***	-0.034***
	(0.001)		(0.001)	(0.001)	(0.001)
Asian	0.008***		0.005***	0.005***	0.005***
	(0.000)		(0.000)	(0.000)	(0.000)
Hispanic	-0.011***		-0.010***	-0.010***	-0.009***
	(0.000)		(0.001)	(0.001)	(0.001)
Borrower Income: 1st Qrtile.		-0.019***	-0.014***	-0.015***	-0.015***
		(0.000)	(0.000)	(0.000)	(0.000)
Borrower Income: 2nd Qrtile.		-0.014***	-0.010***	-0.010***	-0.010***
		(0.000)	(0.000)	(0.000)	(0.000)
Borrower Income: 3rd Qrtile.		-0.006***	-0.004***	-0.004***	-0.004***
		(0.000)	(0.000)	(0.000)	(0.000)
Credit Score in Jan < 620			0.041***	0.041***	0.040***
			(0.001)	(0.001)	(0.001)
Credit Score in Jan ≥ 720			-0.009***	-0.009***	-0.009***
			(0.000)	(0.000)	(0.000)
FHA/VA Loan			0.004***	0.004***	0.004***
			(0.000)	(0.000)	(0.000)
PLMBS Loan			0.013***	0.013***	0.013***
			(0.001)	(0.001)	(0.001)
Portfolio Loan			0.000	0.000	-0.000
			(0.000)	(0.000)	(0.000)
Log Orig Amt			-0.000*	0.000	0.000
			(0.000)	(0.000)	(0.000)
Num of DPD All Accts			0.010***	0.010***	0.010***
			(0.001)	(0.001)	(0.001)
Constant	0.019***	0.009***	0.026***	0.015***	0.019***
	(0.000)	(0.000)	(0.002)	(0.004)	(0.002)
Observations	2,917,343	2,917,343	2,917,343	2,917,343	2,917,343
R-squared	0.011	0.009	0.361	0.361	0.369
Average Rate	-0.018	-0.018	-0.018	-0.018	-0.018
Zip Code FE	N	N	N	N	Y

Notes: Standard errors in parentheses are clustered at the county level, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See Table A3 for other control variables and reference groups and Table A2 for data sources.

Appendix Table A5. Forbearance Take-Up Conditional on Nonpayment Regression Results

Dep Var: Ever Miss	(1) *Race*	(2) *Income*	(3) *Credit Chars*	(4) *Local Chars*	(5) *Zip FE*
Black	0.007**		0.032***	0.025***	0.019***
	(0.003)		(0.003)	(0.003)	(0.004)
Asian	0.057***		0.018***	0.014***	0.011***
	(0.003)		(0.003)	(0.003)	(0.004)
Hispanic	0.033***		0.036***	0.032***	0.021***
	(0.003)		(0.003)	(0.003)	(0.003)
Borrower income: 1st Qrtile.		-0.066***	0.004	0.003	0.004
		(0.003)	(0.003)	(0.003)	(0.004)
Borrower Income: 2nd Qrtile.		-0.035***	0.009***	0.009***	0.010***
		(0.003)	(0.003)	(0.003)	(0.003)
Borrower Income: 3rd Qrtile.		-0.019***	0.004*	0.004*	0.005
		(0.002)	(0.002)	(0.002)	(0.003)
Credit Score in Jan < 620			-0.036***	-0.035***	-0.033***
			(0.003)	(0.003)	(0.004)
Credit Score in Jan ≥ 720			0.023***	0.023***	0.024***
			(0.002)	(0.002)	(0.002)
30-90 DPD Before March			-0.127***	-0.127***	-0.125***
			(0.005)	(0.005)	(0.006)
120 DPD Before March			-0.178***	-0.178***	-0.176***
			(0.012)	(0.012)	(0.014)
Foreclosure Before March			-0.316***	-0.316***	-0.327***
			(0.019)	(0.019)	(0.022)
FHA/VA Loan			-0.014***	-0.014***	-0.016***
			(0.002)	(0.002)	(0.003)
PLMBS Loan			0.014	0.014	0.018
			(0.012)	(0.012)	(0.013)
Portfolio Loan			-0.035***	-0.035***	-0.032***
			(0.005)	(0.005)	(0.005)
Log Orig Amt			0.030***	0.026***	0.023***
			(0.003)	(0.003)	(0.004)
Log Monthly Payment			0.015***	0.016***	0.014***
			(0.002)	(0.002)	(0.003)
Num of All Accts			0.004***	0.004***	0.003***
			(0.000)	(0.000)	(0.000)
Num of DPD All Accts			-0.012***	-0.012***	-0.010***
			(0.002)	(0.002)	(0.002)
Constant	0.901***	0.948***	0.338***	0.345***	0.446***
	(0.002)	(0.002)	(0.033)	(0.059)	(0.043)
Observations	98,719	98,719	98,719	98,719	98,719
R-squared	0.003	0.007	0.097	0.098	0.277
Average Rate	0.912	0.912	0.912	0.912	0.912
Zip Code FE	N	N	N	N	Y

Notes: Clustered standard errors at the county-level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See Table A3 for other control variables and reference groups and Table A2 for data sources.

Appendix Table A6. Match Rates and Characteristics

	(1) *All CRISM*	(2) *CHMDA-Matched*	(3) *Flash-Matched*	(4) *Both-Matched*
Match Rate	100%	65%	69%	47%
		Means		
Current Credit Score	746.30	748.57	754.46	755.60
Current Credit Score < 620	0.06	0.05	0.06	0.05
Current Credit Score 620-719	0.19	0.20	0.16	0.16
Current Credit Score ≥ 720	0.58	0.61	0.58	0.62
Current Credit Score Missing	0.17	0.14	0.20	0.17
Credit Score at Orig	728.55	730.95	729.64	732.47
Credit Score at Orig < 620	0.04	0.03	0.04	0.03
Credit Score at Orig 620-719	0.30	0.31	0.29	0.30
Credit Score at Orig ≥ 720	0.52	0.55	0.55	0.58
Credit Score at Orig Missing	0.15	0.11	0.12	0.09
Age	52.43	51.51	52.54	51.85
Age < 35	0.10	0.12	0.10	0.11
Age 35-44	0.22	0.23	0.22	0.23
Age 45-54	0.24	0.24	0.24	0.24
Age 55-64	0.23	0.22	0.24	0.23
Age ≥ 65	0.20	0.19	0.21	0.20
GSE Loan	0.61	0.61	0.63	0.64
FHA/VA Loan	0.27	0.28	0.25	0.25
PLMBS Loan	0.04	0.03	0.04	0.03
Portfolio Loan	0.08	0.09	0.08	0.09
Orig Amount	227068.14	230939.35	227620.43	229701.10
LTV Ratio	78.74	79.30	78.21	86.18
Monthly Payment	2875.76	2883.66	2879.48	2893.09
Closing Year	2013.38	2014.08	2013.33	2013.85
Current Interest Rate	4.28	4.20	4.26	4.20
Count of Accounts	7.46	7.50	7.41	7.44
Count of DPD Accounts	0.06	0.06	0.06	0.05
Non-FM Balance Past Due	33.65	27.80	33.28	29.28

Notes: We start with a 20% sample of borrowers with first-mortgage loans in the CRISM data observed in June 2020. Column (2) are borrowers with loans matched to CHMDA data. Column (3) are borrowers with loans matched to McDash Flash data. Column (4) are loans matched to both. See Table A2 for data sources.