STAFF REPORTS

NO. 1035
OCTOBER 2022

Intermediation Frictions in Debt Relief: Evidence from CARES Act Forbearance

You Suk Kim | Donghoon Lee | Tess Scharlemann | James Vickery

FEDERAL RESERVE BANK *of* NEW YORK

Intermediation Frictions in Debt Relief: Evidence from CARES Act Forbearance
You Suk Kim, Donghoon Lee, Tess Scharlemann, and James Vickery
Federal Reserve Bank of New York Staff Reports, no. 1035
October 2022
JEL classification: G21, G23, G28

Abstract

We study how intermediaries—mortgage servicers—shaped the implementation of mortgage forbearance during the COVID-19 pandemic and use servicer-level variation to trace out the causal effect of forbearance on borrowers. Forbearance provision varied widely across servicers. Small servicers and nonbanks, especially nonbanks with small liquidity buffers, facilitated fewer forbearances and saw a higher incidence of forbearance-related complaints. Easier access to forbearance substantially increased mortgage nonpayment but also reduced delinquencies outside of forbearance. Part of the liquidity from forbearance was used to reduce credit card debt, but most was saved or used for nondurable consumption.

Key words: mortgage, forbearance, liquidity, nonbank, CARES Act, COVID-19

Lee: Federal Reserve Bank of New York (email: donghoon.lee@ny.frb.org). Kim, Scharlemann: Federal Reserve Board (emails: you.kim@frb.gov, tess.scharlemann@frb.gov). Vickery: Federal Reserve Bank of Philadelphia (email: james.vickery@phil.frb.org). This paper was previously released by the Federal Reserve Board as a FEDS Note in March 2022. The authors thank seminar participants at the Korea Development Institute, Yonsei University, 2022 SFS Cavalcade, 2022 Fed System Micro Conference, Federal Reserve Board, AREUEA Virtual Seminar, FDIC Consumer Research Conference, 2022 ASSA meetings, 2021 Philadelphia Fed Conference on Consumer Behavior in Credit and Payments Markets, and 2021 AREUEA National Meetings. They also thank discussants Gene Amromin, Neil Bhutta, Meta Brown, Greg Buchak, Susan Cherry, Lara Lowenstein, and Kyle Mangum, as well as Larry Cordell, Arpit Gupta, Joe Nichols, and other Federal Reserve colleagues and industry practitioners for comments and insights about institutional details.

1 Introduction

Financial intermediaries are often crucial for implementing public policy, particularly in the case of debt relief and emergency lending programs.[1] Intermediaries have valuable data, technology, systems, and relationships that can help ensure successful policy outcomes. On the other hand, misaligned incentives or other frictions may prevent policies from being implemented as intended "on the ground".

In this paper we study the role of a particular type of intermediary — mortgage *servicers* — in implementing a large debt relief program providing forbearance to mortgage borrowers during the COVID-19 pandemic. We find that servicers significantly influenced forbearance outcomes, and that variation in servicer behavior is systematically related to servicer liquidity constraints, size and organizational form. We also use servicer variation to trace out the causal effects of forbearance for households. Easier access to forbearance increased household liquidity by inducing borrowers to pause their payments. Part of this liquidity infusion was used to pay down high-cost credit card debt, but funds were primarily used for precautionary saving and/or nondurable consumption.

The forbearance program, authorized by the CARES Act in March 2020, allowed borrowers with federally-backed mortgages to temporarily pause their mortgage payments without incurring fees, penalties or additional interest and without negative consequences for their credit history. The borrower simply needed to attest to a pandemic-related hardship to qualify for forbearance; no documentation of income loss was required.

Despite this universal eligibility, a quarter of the mortgages in our sample that became past-due during the pandemic did not successfully enter into forbearance. Furthermore the frequency of these "missing" forbearances varied significantly across mortgage servicers for otherwise equivalent loans. Our analysis focuses on "government" mortgages

[1] Examples include emergency business loans under the Paycheck Protection Program (Granja et al., 2020), mortgage modifications under the Home Affordable Modification Program (Agarwal et al., 2017a), and streamlined mortgage refinancing under the Home Affordable Refinancing Program (Agarwal et al., 2015).

securitized through Ginnie Mae; this is the segment of the mortgage market which serves the highest-risk borrowers and which, because of institutional factors, poses the greatest liquidity risk to servicers.

Specifically, using loan-level data we estimate that the conditional probability that a past-due borrower did not enter forbearance varies between 10% and 60% across servicers, with a weighted interquartile range of 15 percentage points. Several pieces of evidence indicate that this variation reflects servicer behavior rather than unobserved borrower characteristics. The magnitude of these servicer effects is also heterogeneous across borrowers, and older and low-credit score borrowers appear "hard to reach" in that they are less likely to enter into forbearance and are not especially responsive to being matched with a "high-forbearance" servicer.

Investigating these cross-servicer differences, we find that small servicers, nonbanks, and in particular nonbanks with low cash buffers, were significantly less likely to facilitate forbearance. These facts suggest that liquidity constraints, as well as some combination of scale economies and regulatory risk, were important in shaping servicer behavior. Liquidity constraints are important in our setting because Ginnie Mae servicers must finance payments to investors and other parties when the borrower stops paying. This risk is most relevant for nonbank servicers, which rely on short-term wholesale debt and cannot access government liquidity backstops.

The clear benefits of forbearance for borrowers suggest that servicer practices limiting forbearance uptake also reduced borrower welfare. Consistent with this interpretation, we show that borrowers were significantly less satisfied with servicers that facilitated fewer forbearances, based on complaints filed with the Consumer Financial Protection Bureau (CFPB).

We then use servicer-level variation in forbearance availability to study the causal effect of forbearance on borrowers. We sort servicers into high (above median) and low (below median) forbearance-availability groups based on the likelihood a past-due loan received forbearance conditional on loan and borrower characteristics. Then we compare borrower outcomes between these groups before and after the CARES Act in a difference-in-differences framework using dynamic mortgage data linked to borrower credit reports.

Studying payment outcomes, we find that assignment to a high-forbearance servicer reduced the likelihood of the borrower being past-due but not in forbearance by up to one-quarter (or 0.4 percentage points), with the largest effects early in the pandemic. However it also caused a much larger number of borrowers to stop making their payments. Quantitatively, the fraction of past-due borrowers was as much as 5 percentage points higher at high-forbearance servicers in 2020. (There was no difference prior to COVID-19.) This finding, that easier access to debt relief *induced* nonpayment, is reminiscent of research on strategic mortgage default, especially Mayer et al. (2014). In our setting however, several pieces of evidence suggest that these marginal nonpayers were primarily motivated by precautionary liquidity concerns rather than a purely strategic calculation to exploit forbearance as an interest-free loan.

Our results therefore indicate that forbearance provided significant liquidity to households by enabling borrowers to pause their payments. Furthermore the cross-servicer variation in effective program generosity is quantitatively important. We estimate that borrowers at high-forbearance servicers deferred an additional \$300 in mortgage payments from April-November 2020, equivalent to \$6,000 per marginal forbearance. In aggregate, switching all Ginnie Mae borrowers from low-to-high forbearance servicers would increase deferred payments over this short period by \$3.1 billion, equivalent to an effect of $\approx$ \$10 billion if generalizing our estimates to the entire mortgage market.

Part of this liquidity infusion from mortgage payment deferral was used by borrowers to reduce credit card debt, although the effect is limited to less liquidity-constrained households, defined as a below-median credit card utilization rate. For this group, credit card paydown accounts for about one-fifth of deferred mortgage payments. There is no evidence that funds were used to establish new auto tradelines, a proxy for auto purchases. We therefore conclude that, at least for borrowers on the margin, funds from payment deferral were mainly used for precautionary saving or nondurable consumption. We also confirm that the CARES forbearance program worked as intended to shield borrowers' credit from adverse consequences of nonpayment, finding a precisely-estimated effect of forbearance on credit scores close to zero.

We conclude by considering policy implications of our results. Our findings, as well as those of other researchers, suggest that the CARES Act forbearance program successfully reached most borrowers in need without inducing widespread strategic behavior or other serious unintended consequences. However, our results also highlight scope to improve access and reduce variation in forbearance outcomes unrelated to borrower fundamentals. For example, one possibility would be auto-enrollment in forbearance for borrowers in observable financial distress (e.g., those drawing unemployment insurance).

Our results also speak to the policy debate about the systemic risk posed by nonbank mortgage companies, and the debate about the costs and benefits of large banks. Our results suggest that exposure to liquidity risk reduced nonbank servicers' willingness to provide liquidity to borrowers. Conversely, large bank servicers had the highest propensity to facilitate forbearance, likely due to tight post-crisis regulatory scrutiny, scale economies, and ample liquidity due to access to deposits and the lender of last resort.

1.1 Related literature

We contribute to several strands of literature. First, a number of papers study the behavior and incentives of mortgage servicers, in particular studying the 2008 crisis and its aftermath. Aiello (2021) finds that financial constraints reduced servicers' propensity to modify delinquent mortgages, while Agarwal et al. (2017a) show that servicers offered

HAMP modifications at divergent rates due to variation in organizational structure and incentives. Agarwal et al. (2011) and Kruger (2018) find servicers were more likely to modify mortgages retained in portfolio than loans serviced for other investors. We bring new data to bear and study a streamlined debt relief program designed to overcome the frictions that plagued mortgage modification in the wake of the Great Recession. Nevertheless, we still observe large cross-servicer differences in outcomes and find that financial frictions shaped servicer behavior and borrower outcomes.

Second, a growing literature studies forbearance and other forms of government financial assistance during the COVID-19 pandemic. Cherry et al. (2021), An et al. (2022) and Zhao et al. (2020) present a wealth of information on forbearance takeup, finding that mortgage forbearance is higher for vulnerable borrowers and those experiencing negative income shocks. Like us, Cherry et al. (2021) find that nonbanks provided forbearance at lower rates. Cherry et al. (2022) find that better-capitalized nonbanks were more likely to provide forbearance, and trace out how nonbanks adjust their balance sheets in response to the shock of the pandemic. Research on other pandemic relief programs also finds variation in outcomes across financial intermediaries (e.g., Granja et al. 2020).

Third, we contribute to research on the effects of consumer debt relief (e.g., Agarwal et al., 2017a). Our finding that forbearance access induces nonpayment is related to Mayer et al. (2014), who find that mortgage borrowers strategically default to qualify for debt relief. Related to our analysis of the effects of payment deferral, several papers find that mortgage payment reductions reduce delinquency and increase consumption, among other effects (Abel and Fuster, 2021; Ganong and Noel, 2020; Di Maggio et al., 2017; Scharlemann and Shore, 2016; Fuster and Willen, 2017). One important distinction between our setting and these studies, however, is that forbearance represents a payment *deferral*, not a permanent reduction in the payments owed.

Finally, our results shed light on the behaviour of nonbank mortgage companies (for other contributions see Buchak et al., 2020; Gete and Reher, 2020; Jiang et al., 2020; Buchak et al., 2018) and large banks (see e.g., Huber, 2021). We also contribute to a broader literature studying how financial constraints, size, and organizational frictions affect product quality and firm outcomes (e.g., Matsa, 2011; Kugler and Verhoogen, 2011; Rose, 1990).

2 Forbearance and the CARES Act

The CARES Act was signed into law on March 27, 2020, and included significant relief for mortgage borrowers. Homeowners with federally-backed mortgages became eligible for up to 180 days of forbearance, renewable for an additional 180 days upon request.[2,3] Borrowers in forbearance were able to skip their mortgage payments without accruing unscheduled interest, late fees or penalties, or risking foreclosure. Missed payments were also not reported as delinquencies to credit bureaus, protecting borrowers' credit scores.

Eligibility under the CARES Act is very broad, extending to any agency mortgage borrower experiencing a direct or indirect financial hardship related to the pandemic. Importantly, the borrower simply needed to *attest* to a hardship — no documentation or other proof of income loss was required. Forbearance was not automatic, however; the borrower had to request and obtain it from their servicer.

The CARES Act is silent about what should occur at the end of the forbearance period, but in the weeks after its passage, regulators and the mortgage agencies stated that a range of options would be available and that a lump-sum repayment of skipped payments would not be required (e.g., Freddie Mac, 2020). In April 2020, the FHA announced

[2]The CARES Act applies directly to "agency" mortgages backed by Fannie Mae, Freddie Mac, the FHA, VA, and other federal agencies, which make up about 70% of US mortgage debt. Many nonagency borrowers were still able to obtain forbearance from their servicers, but Cherry et al. (2021) find that the nonagency forbearance rate was about 25% lower, by studying loans on either side of the conforming loan limit.

[3]The forbearance programs were subsequently extended in February 2021. Homeowners already in forbearance became eligible for a further six months of forbearance, and the enrollment window to request forbearance was extended to 6/30/2021 (The White House, 2021; Federal Housing Finance Agency, 2021).

a "partial claim" program for borrowers resuming payments after exiting forbearance in which accumulated missed payments could be transferred into a subordinate interest-free note due at the time the mortgage is paid off (Department of Housing and Urban Development, 2020a,b). Borrowers not able to resume payments would be eligible instead for a loan modification. Fannie Mae and Freddie Mac announced a similar payment deferral option in May (Federal Housing Finance Agency, 2020). Since deferred payments do not accrue interest, these programs effectively provide an interest-free loan to the borrower.

Despite these public assurances, there was significant uncertainty and confusion among borrowers and servicers about post-forbearance options, particularly in the early months of the pandemic (e.g., Wall Street Journal, 2020; Consumer Financial Protection Bureau, 2021a,b). For example, some servicers incorrectly told borrowers that a lump-sum repayment would be expected upon forbearance exit.

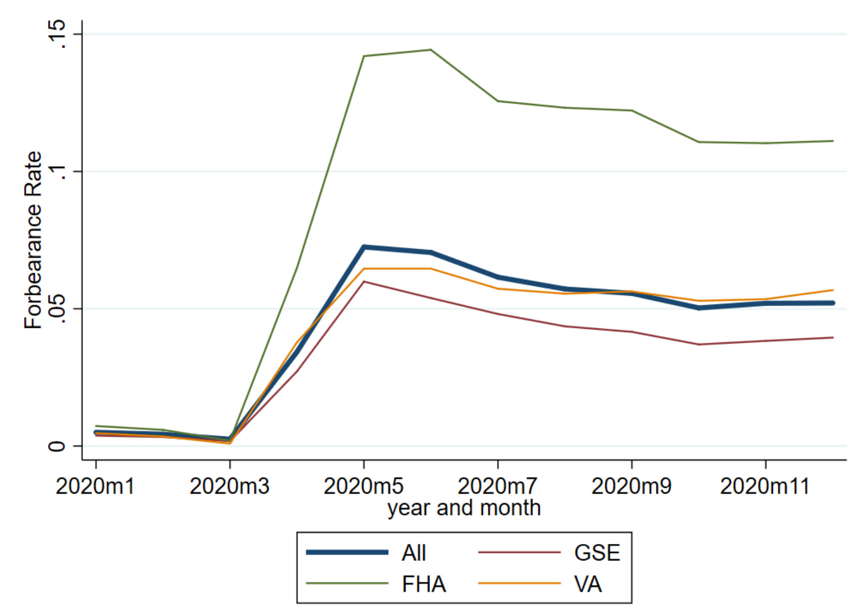
Our analysis focuses on the $2 trillion of "government" mortgages insured by the FHA and VA, all of which were covered by the CARES Act. This segment of the mortgage market is of particular interest because it disproportionately serves low-income and high-risk borrowers, and because FHA loans in particular experienced a much higher forbearance and nonpayment rate than the market as a whole. It is also the segment where intermediation frictions are likely to be most severe, because FHA loans are much riskier for mortgage servicers due to institutional factors (see section 5 for detailed discussion).

2.1 Forbearance trends

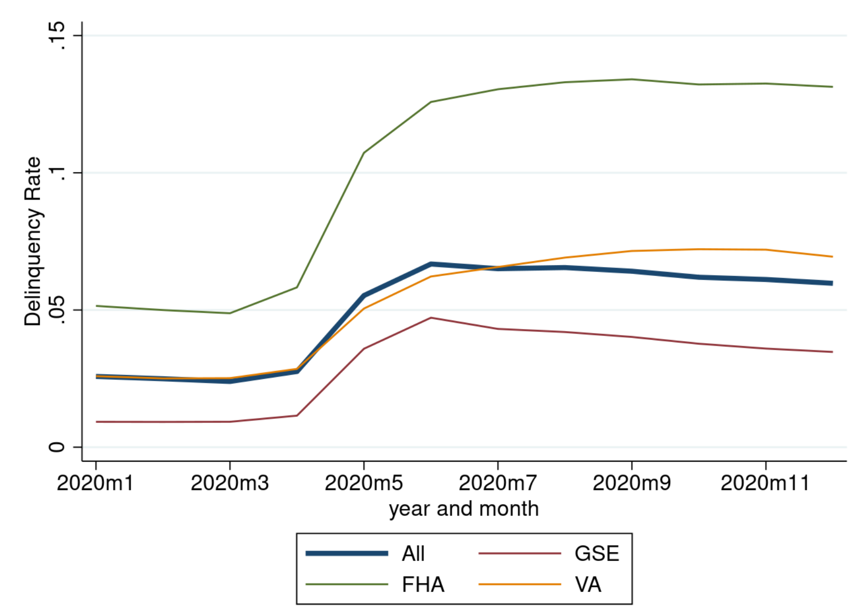
Figure 1 traces out the evolution of mortgage forbearance and nonpayment over 2020. The top panel based on credit bureau data shows that forbearance was rare prior to the pandemic but rose sharply starting in April, just after the CARES Act was passed. The aggregate forbearance rate peaked in May at 7.3 percent, falling to 5.2 percent by De-

Figure 1: **Share of mortgages in forbearance and past-due.** "Past-due" is defined as any loan behind schedule, including mortgages in forbearance where the borrower has paused their payments with the lender's consent. Dollar-weighted aggregate statistics constructed using data from the Federal Reserve Bank of New York (FRBNY) Consumer Credit Panel / Equifax (panel a) and Black Knight McDash (panel b). Aggregate statistics reflect agency mortgages covered by the CARES Act as well as mortgages held in portfolio by banks and other investors and loans securitized through the nonagency market.

(a) Fraction of mortgages in forbearance



(b) Fraction of mortgages 60+ days past due



cember.[4] The fraction of loans 60+ days past-due also rises and falls along similar lines (bottom panel), as does the 30+ days-past-due rate (figure A.1 of the Internet Appendix). Note: "past-due" in this context includes both borrowers who paused their payments in forbearance and delinquent mortgages not in a forbearance plan. In practice not all past-due borrowers entered forbearance, and conversely some borrowers entered into forbearance as a precaution but then kept making their scheduled payments.

As Figure 1 shows, the FHA forbearance and nonpayment rate was much higher than for the market as a whole, reflecting the lower-income FHA borrower population and high share of first-time homebuyers. VA mortgages behaved similarly to the overall market, while forbearance and nonpayment was relatively low for the typically prime loans securitized by government sponsored enterprises (GSEs) Fannie Mae and Freddie Mac.

2.2 Forbearance implementation and the role of servicers

One might assume that servicers played a limited and passive role in implementing the CARES Act forbearance program, given its streamlined design and the lack of required documentation of hardship. But in practice, qualitative and anecdotal evidence suggests that servicers varied widely in terms of their level of communication with borrowers and the information they provided, as well as their systems for receiving and processing forbearance applications.

For example, Consumer Financial Protection Bureau (2021a) provides a detailed account of forbearance-related servicing deficiencies observed by CFPB supervisors, including: (1) Providing incomplete or false information, such as telling consumers that only delinquent borrowers qualified for forbearance, that a fee must be paid for forbearance, or that a lump-sum repayment was required; (2) Incorrectly sending collection or default

[4]Other data sources paint a similar picture but indicate a somewhat higher forbearance rate. Survey data from Mortgage Bankers Association (2020) indicates a peak forbearance rate of 8.55% in June 2020, while Black Knight (2020) reports a peak forbearance rate of 8.8%, also in June.

notices, assessing fees, or initiating foreclosures for borrowers in forbearance; (3) Changing borrowers' preauthorized funds transfers without consent, or failing to implement borrowers' instructions to freeze payments; (4) Failure to process forbearance requests in a timely way; (5) Enrolling borrowers in automatic or unwanted forbearance; (6) Failure to set up an appropriate post-forbearance plan. We heard similar anecdotes in numerous meetings with credit counselling agencies we arranged as background for this project. Media reports also highlighted similar issues and described how the wave of forbearance requests early in the pandemic overwhelmed many servicers' capacity, leading to long telephone hold times, non-operational servicer websites, and misleading information provided to borrowers (e.g. Wall Street Journal, 2020).

These servicing issues are also evident in a sharp rise in forbearance complaints. Consumer Financial Protection Bureau (2021b) calculates based on the CFPB's repository that complaints related to forbearance spiked from 3-4% of all mortgage complaints in January and February 2020 to a peak of 21% in April, remaining persistently at 12-15% over the rest of 2020 and early 2021. Complaints most commonly cited communication failures, confusing or incorrect information about post-forbearance options, problems in payment and forbearance reporting on borrowers' monthly statements, and delays and denials in putting the borrower in a post-forbearance repayment plan.[5]

At the other end of the scale, many servicers took significant steps to streamline the forbearance process, such as providing a prominent button or link on their website to a simple online application, and following up with delinquent borrowers frequently to make them aware of forbearance (e.g., one practitioner told us of a large bank servicer

[5]To give a sense of the issues, the following are three complaints taken from the public CFPB database: (1) *"I tried to reach out to <XXX> to request a forbearance ... Unfortunately, I was hung up on two times. I spent almost 3 hours on hold."*; (2) *"My initial 6 month forbearance has been approved, but I've been unable to make contact with the servicer to extend the forbearance. I've sent emails, left voice messages and tried online to extend the forbearance. They do not respond. I'm scared and I need help."*; (3) *"I have been trying for over a month to apply for a 6-month mortgage forbearance plan (as allowed under the Federal Cares Act) with <XXX>. If you go to their website to apply, it doesn't matter if you are on a mobile device OR hard wired laptop OR desktop computer, it will not actually let you apply for a forbearance. When you submit, it says " CRITICAL ERROR "."*

making such calls on a daily basis). We quantify the cross-servicer variation in forbearance policies and outcomes more systematically in the following section.

3 Data and summary statistics

To measure the effects of servicers on forbearance outcomes, we assemble a novel dataset combining loan-level data on mortgage characteristics and performance, Ginnie Mae forbearance records, regulatory data on bank and nonbank servicers, complaints data, and credit bureau data on borrower liabilities and credit performance. We in fact utilize two different matches between these underlying datasets, as described below. Further details on each data source can be found in section A of the Internet Appendix.

Loan-level mortgage data are drawn from eMBS. The data include the universe of securitized FHA and VA mortgages and report the servicer for each loan as well as loan characteristics and performance. We append data on each loan's forbearance status and forbearance terms from Ginnie Mae's forbearance register. We also match each servicer by name to servicer-level characteristics (e.g., size, liquidity ratio). For independent mortgage banks ("nonbanks") these characteristics are drawn from the mortgage call report (MCR) collected by the Conference of State Bank Supervisors, while for banks, they are drawn from FR Y-9C and Call reports. eMBS itself is also used to calculate some servicer characteristics (e.g., aggregate servicing volume). We also match the data to forbearance-related complaints by borrowers aggregated to the servicer level from the CFPB complaints database (see section 5.3 for more details).

For the analysis in section 6 which uses servicer-level variation to study the effects of forbearance on borrowers, we instead use a merge between eMBS, loan-level data from Black Knight McDash, and the Equifax Credit Risk Insight Servicing and McDash (CRISM) dataset. This allows us to trace out effects on nonmortgage outcomes such as credit card debt and a proxy for auto purchases. We match eMBS and McDash/CRISM based on loan characteristics (for details, see Internet Appendix Section A.1.) From eMBS, we retain the loan's forbearance status and an anonymized servicer identifier. (Due to data use restrictions, we cannot merge servicer characteristics into the CRISM data.) From CRISM, we draw payment behavior, updated credit scores, geographic data, and additional details about the borrower's balance sheet. From McDash we draw mortgage-level information including some loan and borrower controls not available in eMBS (e.g., property location is available at the zip code rather than state level).

3.1 Summary statistics

Table 1 presents loan-level summary statistics from eMBS, reflecting the population of FHA and VA loans securitized into Ginnie Mae MBS pools as of January 2020. The dataset includes 10.1 million mortgages, of which about 70% are FHA loans. FHA loans have higher loan-to-value (LTV) ratios, higher debt-to-income (DTI) and lower average credit scores, reflecting the lower-income, higher-risk FHA borrower population.

About 5% of loans were at least 30 days past due just before the onset of the pandemic. Nonpayment then increased sharply, with 18% of loans being 30 days or more past-due at some point between March and November 2020 (21% of FHA loans and 11% of VA loans). 16% of FHA loans entered forbearance at some point between March and November, compared to 8% of VA loans. 24% of loans were paid off between March and November, primarily due to refinancing in response to falling mortgage rates. (Note: we use the term "past-due" to refer to any loan in arrears relative to its contractual repayment schedule. This includes loans in forbearance where payments have been paused with the servicer's consent, as well as delinquent mortgages not in forbearance.)

Panel C of table 1 reports forbearance and nonpayment statistics for mortgages that were current as of January 2020. Notably, 26% of loans that became past-due during the

Table 1: **Summary statistics.** Loan-level summary statistics for the eMBS sample. Reflects the population of active FHA and VA mortgages securitized into Ginnie Mae MBS pools as of January 2020.

	(1) FHA	(2) VA	(3) Total
A. Ex-ante loan characteristics:			
Unpaid balance ($000, as of Jan 2020)	150,580	207,148	167,304
Original loan-to-value (LTV) (%)	92.93	94.71	93.42
Original debt-to-income (DTI) (%)	41.08	38.45	40.23
Original credit score	682.18	714.80	692.69
Loan age (years, as of Jan 2020)	5.46	4.05	5.02
30+ days past-due in Jan 2020	0.06	0.03	0.05
60+ days past-due in Jan 2020	0.02	0.01	0.02
B. Forbearance & past-due rates during pandemic (Mar-Nov 2020):			
Ever 30+ days past due	0.21	0.11	0.18
Ever 60+ days past-due	0.15	0.08	0.13
Ever paid off	0.19	0.34	0.24
Ever in forbearance	0.16	0.08	0.14
C. Conditional forbearance & past-due rates during pandemic (Mar-Nov 2020):			
Forbearance | nonpayment (for loans current in Jan 2020):			
Ever in forbearance among loans ever 30+ days past-due	0.74	0.70	0.74
Ever in forbearance among loans ever 60+ days past due	0.91	0.88	0.91
Nonpayment | forbearance (for loans current in Jan 2020):			
Ever 30+ days past-due among loans ever in forbearance	0.84	0.84	0.84
Ever 60+ days past due among loans ever in forbearance	0.71	0.72	0.71
N. Obs.	6,943,846	3,185,050	10,128,896

pandemic failed to enter into a forbearance plan. This is quite striking given that any FHA or VA borrower experiencing financial stress related to the pandemic was eligible for forbearance, and given that forbearance effectively provided a subsidy to the borrower because no interest was charged on deferred balances. This fraction of "missing" forbearances is significantly lower — 9% — for loans entering serious delinquency (60+ days past due), but still well above zero. Conversely, 16% of borrowers remained current on their payments despite entering into forbearance. Most borrowers in forbearance skipped multiple payments however, with 71% becoming at least 60 days past due.

4 Servicer-level variation in forbearance outcomes

We measure cross-servicer variation in forbearance outcomes by estimating the following cross-sectional linear probability model using eMBS loan-level data:

$$\text{forbearance}_i = X_i\beta + \xi_s + \epsilon_i. \tag{1}$$

The dependent variable is an indicator for whether mortgage i entered forbearance from March-November 2020, ξ_s is a vector of servicer fixed effects, and X_i is a set of loan controls (e.g., LTV and credit score bins) to account for forbearance demand. (Coefficient estimates on these controls are reported in table A.2 of the Internet Appendix.)

Our baseline model estimates equation 1 on the sample of borrowers that were current prior to the onset of the pandemic (January 2020) but missed at least one payment from March to November. This set of borrowers would unambiguously benefit from forbearance, but as we have discussed, around a quarter of them became past-due without successfully entering into a forbearance plan.

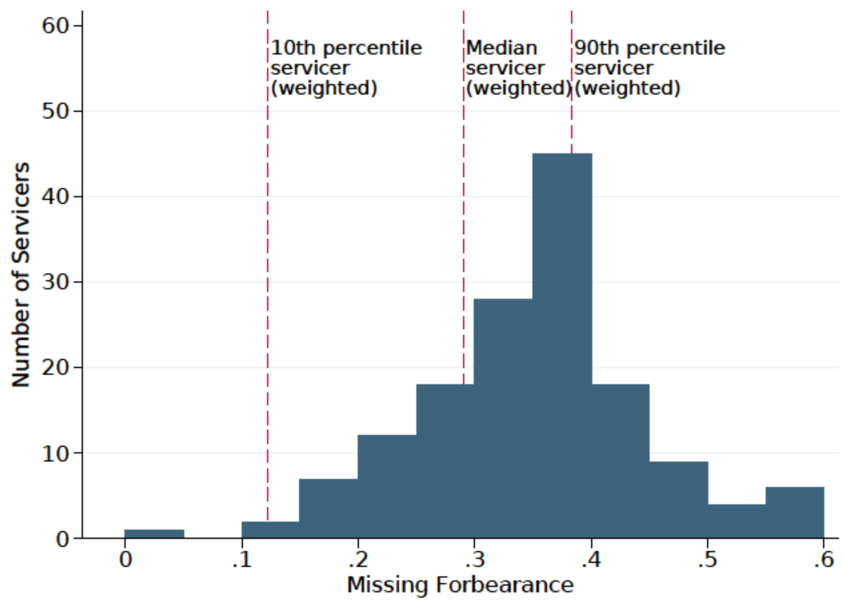
Figure 2 plots the distribution of the servicer fixed effects ($\widehat{\xi}_s$), showing very wide variation in forbearance outcomes across servicers for observably similar mortgages.[6] For the figure we normalize the fixed effects to show the probability that a past-due loan with sample average characteristics fails to enter into forbearance. The likelihood that the borrower "falls through the cracks" ranges from under 10% to almost 60%. This variation is not simply due to disparate outcomes among very small servicers. Weighting by loan count, the "no forbearance" probability is 38% for a servicer at the 90th percentile of the distribution compared to only 12% for a servicer at the 10th percentile.

The bottom panel of figure 2 presents the same histogram conditioning on more se-

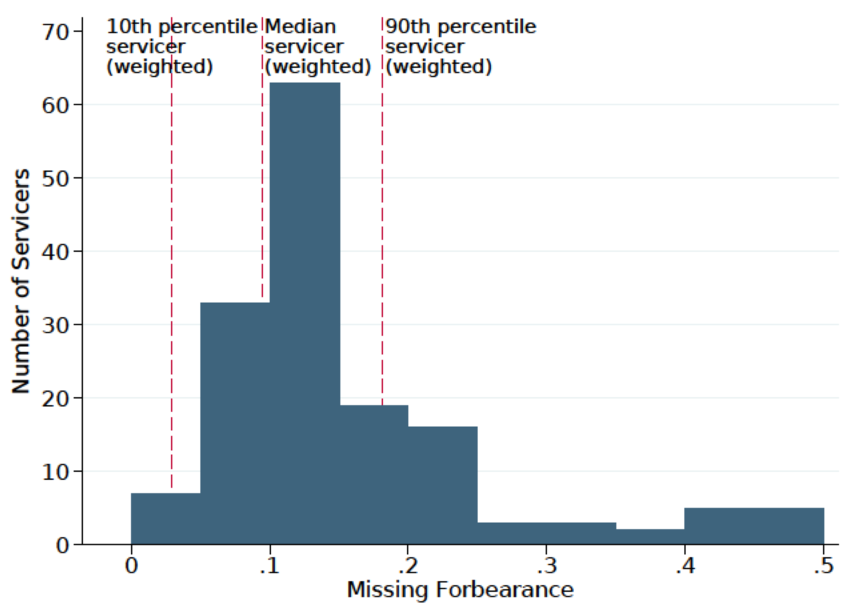
[6]Indeed, these estimated servicer fixed effects are highly jointly statistically significant (f-statistic = 435). Moreover, including the servicer fixed effects doubles the R^2 of our model (comparing columns 1 and 2 in table A.2).

Figure 2: **P(no forbearance | COVID nonpayment).** Cross-servicer variation in probability that a loan did not enter forbearance conditional on becoming past due. Based on servicer fixed effects estimated using eMBS data conditional on loan and borrower characteristics (e.g. bins of LTV, credit score, DTI, log of loan balance, transformations of loan age etc.). Bars are unweighted counts of servicers in each bin. Dashed vertical lines show weighted percentiles, weighted by the number of loans that became past due between March and November 2020.

(a) Borrowers 30+ days past due



(b) Borrowers 60+ days past due



rious nonpayment (60+ days past due). The share of “missing” forbearances is significantly smaller for this group, but in proportionate terms the cross-servicer variation is even more stark — the likelihood of not receiving forbearance is six times higher for a “low-forbearance” servicer at the 90th percentile of the distribution compared to a “high-forbearance” servicer at the 10th percentile (18% compared to 3%).

4.1 Alternative estimates of servicer effects

The servicer effects presented above are quite robust to alternative modelling choices. First, we estimate an alternative set of servicer fixed effects using the eMBS-CRISM matched sample. This allows us to control for a finer set of controls incorporating information from borrower credit reports, including bins of borrower age, an updated credit score and non-mortgage debt balances.[7] This approach also produces a similarly wide dispersion of servicer effects estimates (see figure A.2 of the Internet Appendix).

Second, we then use the eMBS-CRISM model to measure how sensitive the fixed effects are to the set of controls used, comparing specifications with i) no controls, ii) the controls available in eMBS only, and iii) the full set of eMBS-CRISM controls. We find that the three resulting sets of servicer fixed effects are highly positively correlated (see figure A.3 of the Internet Appendix).

Third, within the eMBS sample, we estimate the servicer effects three other ways aside from the two presented in figure 2: i) including all mortgages in the sample, rather than just the loans that became past due during the pandemic; ii) restricting the sample to borrowers that became past-due early in the pandemic (February or March), prior to the passage of the CARES Act; and iii) including *lender* fixed effects, so that servicer fixed

[7] Coefficients on loan and borrower controls for this specification are reported in table A.3 of the Internet Appendix. Note that terms-of-use restrictions on the CRISM dataset prevent us from retaining servicer information in the merged eMBS-CRISM dataset; we are however permitted to retain anonymous servicer identifiers, which is what we use to estimate the servicer fixed effects.

effects are identified only from mortgages where there was a transfer of servicing. This third approach is motivated by the fact that borrowers do select their lender (in ways that may be correlated with unobservables) but do not control whether the servicing on their loan is subsequently sold to a third party. These alternative fixed effects are strongly positively correlated with our main estimates in figure 2 (figure A.4 of the Internet Appendix).

4.2 Servicer behavior or omitted borrower characteristics?

We interpret these striking differences in forbearance outcomes as being due to variation in servicer policies and practices. But an alternative explanation is that they reflect unobserved differences in forbearance *demand*. For instance borrowers at "high-forbearance" servicers may be more liquidity constrained and therefore benefit more from an extended payment holiday, or may be more financially literate. Our estimated fixed effects condition on a rich set of borrower and loan controls, particularly for the eMBS-CRISM sample, but of course do not control for all factors that may affect forbearance demand.[8]

However, three additional pieces of evidence suggest the servicer fixed effects we measure are not driven by unobserved borrower heterogeneity:

1. Mortgages managed by high- vs low- forbearance servicers have similar ex-ante characteristics, measured in either the eMBS or eMBS-CRISM samples (see Internet Appendix tables A.5-A.7). Borrower non-mortgage loan balances are also similar (e.g., auto, credit card and student loan balances are all within 10%), and the two groups of loans experienced similar macroeconomic conditions during the pandemic (e.g., the 12-month change in the county unemployment rate differs by only 0.2%). Loans managed by low-forbearance servicers are somewhat younger (4.5 vs

[8]Servicer forbearance policies *per se* were not likely to have been important in borrowers' mortgage choice prior to the pandemic, because borrowers cannot typically directly choose their servicer, and because forbearance is an infrequent event particularly given the stable economy and rising home prices leading into the pandemic. Even so, it is still possible there could be nonrandom assignment of borrowers to servicers in a way that is correlated with borrowers' demand for forbearance during the pandemic.

6.0 years in the eMBS-CRISM sample); but within age bins mortgages look very similar on observables, and our regressions also always include loan age controls.

2. There is little or no difference in mortgage nonpayment between high and low-forbearance servicers in the months prior to the pandemic. The same is true for credit card and auto delinquencies in the eMBS-CRISM matched sample. We measure this by estimating account-level delinquency models where the dependent variable is equal to 1 if a borrower current at *t-1* becomes delinquent in month *t*.[9] Controlling for loan characteristics, differences in delinquency transitions for borrowers managed by high-vs-low forbearance servicers are economically small, not consistently signed, and generally not statistically significant (see figure A.5 and table A.9 of the Internet Appendix). In contrast, during the pandemic itself, borrowers assigned to high-forbearance servicers become *much* more likely to stop paying their mortgages, as seen in figure A.5 and as discussed in detail in section 6.

   These findings are evidence against the hypothesis that high-forbearance-servicer borrowers were riskier on unobservables, because such an explanation would predict a higher nonpayment rate not just during the pandemic, but also prior to it. They also speak against the story that high-forbearance-servicer borrowers were more financially literate, because this would be expected to produce a lower pre-COVID delinquency rate in line with Gerardi et al. (2013) and Agarwal et al. (2017b).

3. Estimated servicer fixed effects are generally insensitive to the set of borrower and loan controls used, as shown in section 4.1. In other words, there is little evidence of selection on observables. Among these results, servicer effects are robust to includ-

[9] Measuring transitions into delinquency is preferable to measuring the *stock* of delinquent loans, for two reasons: i) servicer quality can affect the length of time a mortgage remains delinquent, e.g., better-quality servicers may make it easier for their borrowers to cure or obtain a loan modification; ii) servicers have the option to purchase seriously delinquent loans out of Ginnie Mae pools — such loans would no longer appear in the eMBS data after they are repurchased. This could create a selection effect since e.g., since banks are more likely to repurchase loans than nonbanks.

ing *lender* fixed effects so that identification comes only from servicing transfers. This suggests that cross-servicer variation in forbearance outcomes is not due to non-random matching of borrowers to lenders, because although borrowers pick their lender, they do not control whether the servicing is sold after origination.

4.3 Heterogeneity

Do servicers affect the behavior of all borrowers equally? Table 2 uses the eMBS-CRISM matched sample to study variation in the effect of servicers on forbearance outcomes across borrowers with different characteristics, finding evidence of significant heterogeneity. Column 1 of the table shows that, overall, a past-due borrower is 13.6 percentage points more likely to enter into forbearance when matched to a "high-forbearance" servicer, defined by a servicer fixed effect that is above the median. Columns 2-6 then interact this "high-forbearance" dummy with various borrower characteristics.

Our prior is that assignment to a high-forbearance servicer would have a larger effect for borrowers with a low propensity to seek forbearance, where there is more scope for behavior to change. This is what we see in columns 2 and 3; borrowers with low current mortgage balances, and borrowers in locations less-hard hit by the COVID recession measured by the local change in unemployment, are both less likely to obtain forbearance overall and more sensitive to whether they are matched with a high-forbearance servicer.

We observe a different pattern, however, for two relatively vulnerable groups: older borrowers and borrowers in poor current financial health as indicated by a low credit score measured just prior to the pandemic (columns 4 and 5). These two groups have low overall forbearance takeup, but their behavior is either less responsive to mortgage servicer assignment, or at least no more responsive, than the sample as a whole. (Results look similar in the multivariate specification in column 6.)

These results speak to the idea that a subset of borrowers are "difficult to reach" —

Table 2: **Heterogeneity in servicer effects.** Regressions studying heterogeneity in the effects of servicers on forbearance outcomes by borrower characteristics. Data are the matched eMBS-CRISM sample, restricted to borrowers who were current in January 2020 but missed at least one payment between March and November. High-forbearance servicer is defined as a servicer with an above-median estimated fixed effect; similarly other explanatory variables are dummies equal to 1 if the variable is above its sample median value. Standard errors are clustered at the servicer level.

Dependent variable = 1 if mortgage received forbearance, = 0 otherwise

	(1)	(2)	(3)	(4)	(5)	(6)
High-forbearance servicer	0.136***	0.182***	0.147***	0.120***	0.137***	0.189***
	(0.021)	(0.024)	(0.024)	(0.022)	(0.023)	(0.029)
High-forbearance servicer:						
× High unpaid loan balance		-0.054***				-0.044***
		(0.010)				(0.009)
× High Δ unemp rate (yoy)			-0.021**			-0.015**
			(0.009)			(0.006)
× High updated credit score				0.020		0.003
				(0.013)		(0.011)
× High borrower age					-0.003	0.002
					(0.009)	(0.008)
High unpaid loan balance		0.123***				0.069***
		(0.009)				(0.010)
High Δ unemp rate (yoy)			0.061***			
			(0.006)			
High updated credit score				0.057***		0.068***
				(0.012)		(0.009)
High borrower age					-0.020***	-0.013*
					(0.007)	(0.007)
Zipcode FE	N	N	N	N	N	Y
Other controls	N	N	N	N	N	Y
N. Obs.	431,478	411,939	431,083	431,478	431,008	405,464
Adj. R^2	0.02	0.04	0.03	0.03	0.03	0.09

they are less likely to seek forbearance overall, and are also not particularly responsive to servicer efforts to make forbearance easier to obtain. This is apparent in our later results as well; although easier access to forbearance induces many borrowers to pause their payments, it only moderately reduces the number of past-due borrowers outside of the forbearance safety net. Finally we note that although we find significant heterogeneity, the overall effect of servicers on forbearance outcomes is broadly based rather than being driven by a particular group, seen by the fact that the uninteracted "high-forbearance" dummy remains positive and highly significant in all columns of table 2.

5 Servicer characteristics and forbearance outcomes

Next we examine the economic factors shaping servicer behavior by studying how a servicer's propensity to provide forbearance, as measured by its fixed effect, varies with servicer characteristics such as size, liquidity and organizational form.

5.1 Economic drivers of servicer behavior

Economic forces that may shape servicer forbearance practices include:

1. Liquidity constraints. When a borrower stops making payments, the mortgage servicer is required to temporarily finance and advance payments on the borrower's behalf, including principal, interest, taxes and insurance. Servicers facing binding liquidity constraints therefore may wish to discourage borrowers from entering forbearance, to limit these cash outflows.[10] The liquidity risk of nonpayment is particularly significant for FHA loans, because FHA servicers must forward payments for a much longer period

[10] Note that it is nonpayment rather than forbearance per se that creates a liquidity drain on the servicer. While the two do not mechanically go hand-in-hand, we show empirically below that easier access to forbearance does in fact causally lead to higher nonpayment, almost one-to-one.

and face significant delays and costs before being reimbursed, and also because FHA borrowers have higher default risk (Pence, 2022; Kim et al., 2018).[11]

Nonbank mortgage companies are much more exposed to liquidity risk than banks, because they rely on short-term wholesale funding rather than insured deposits and do not have access to government liquidity backstops such as Federal Home Loan Bank advances or the discount window (Jiang et al., 2020). Reflecting this fragility, there were widespread fears in the early months of the pandemic about nonbank liquidity and the possibility of runs and a wave of nonbank failures (Pence, 2022; Loewenstein, 2021).

2. Regulatory and legal risk. Mortgage intermediaries were forced to pay out large legal settlements after the Great Recession, and today face much stricter regulation.[12] It therefore seems plausible that legal, regulatory and reputational risk could induce servicers to adopt "borrower-friendly" practices that make forbearance easier to obtain. Large commercial bank servicers are likely to be most concerned about these risks, because these firms are highly visible, face the toughest regulatory scrutiny, and were subject to the largest post-crisis legal settlements (Buchak et al., 2018).

3. Capitalization and risk-shifting. Servicers face a risk-return tradeoff in the sense that improving servicing quality and customer satisfaction (e.g., generous servicing policies, better training or technology) is costly in the short run but may reduce future legal risk and improve retention in the long run. Undercapitalized servicers may thus have weaker incentives to act in the borrower's best interests by making forbearance simple to obtain, in line with the classic risk-shifting hypothesis of Jensen and Meckling (1976).

[11] FHA servicers must typically forward payments until loan termination or modification or until the loan is repurchased by the servicer using its own funds, unlike GSE loans where advances are capped at four months. FHA servicers also face significant delays before being reimbursed for payment shortfalls, and Tozer (2019) estimates they are also typically not compensated for about $10,000 in costs per FHA claim.

[12] Additional post-crisis regulation includes national servicing standards, higher bank capital requirements on servicing rights, and supervisory oversight from the new Consumer Financial Protection Bureau (CFPB). Legal risk is also much more salient given the scale of post-crisis settlements (Buchak et al., 2018). In related work, Fuster et al. (2021b) find that CFPB supervision and enforcement results in more consumer-friendly mortgage servicing practices.

4. Size, scale and technology. A large literature finds that size and organizational form play a key role in shaping financial intermediary behavior (e.g., Berger et al., 2005). In our context, e.g., scale economies in technology adoption may have meant that large servicers entered the pandemic with more sophisticated online servicing platforms, facilitating borrower communication and enabling mass processing of forbearance requests. Or conversely, small, nimble servicers may have been able to adjust their practices more quickly than large bureaucratic organizations with several layers of management.

5.2 Empirical analysis

To investigate which factors are most relevant empirically, we regress the servicer fixed effects estimated previously on servicer characteristics drawn from mortgage call reports (for nonbank mortgage companies), Y-9C and bank call reports (for banks or nonbanks controlled by a bank), and servicer-level aggregations of eMBS loan-level data.[13]

Estimates are reported in table 3 and reveal several patterns. First, borrowers at large servicers are significantly more likely to enter into a forbearance plan, whether size is measured by the log of servicing assets (measured using eMBS) or balance sheet size (taken from regulatory reports). Second, organizational form matters. Nonbank mortgage companies are about 9 percentage points less likely to offer forbearance to a past-due borrower, while credit unions are about 13 percentage points more likely. Third, the level of internal liquidity at the start of the pandemic, measured by the ratio of cash to total assets, is strongly positively correlated with forbearance provision, but *only* for nonbanks.

These results support the view that liquidity constraints shaped servicer behavior. As discussed above, nonbanks were highly exposed to liquidity risk early in the pandemic

[13] We match financial institutions by name across these data sources. Data on financial structure from the National Information Center and other sources is used to cross-validate the accuracy of the match. Our analysis focuses on banks, credit unions and nonbank mortgage companies, and excludes government and government-sponsored enterprises such as state housing authorities and Federal Home Loan Banks.

Table 3: **Determinants of servicer effects.** Servicer-level regression of servicer forbearance fixed effects on characteristics drawn from bank and nonbank Call reports and eMBS. Column 1 is based on all servicers including banks, credit unions and nonbanks. Columns 2-4 reflect nonbank mortgage company servicers only. Columns 5-7 reflect bank servicers only. Weighted least squares, weighted by number of borrowers that were current in January 2020 but past due between March and November. Robust standard errors.

Dependent variable: servicer fixed effect. (Higher value $\Leftrightarrow$ higher P(forbear | nonpay))

	All	Nonbank mtg companies			Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Servicer characteristics							
log(Servicing assets)	0.035***	0.030***	0.027***		0.038***	0.039***	
	(0.006)	(0.008)	(0.005)		(0.009)	(0.010)	
log(Assets)				0.019***			0.025*
				(0.005)			(0.013)
Cash / assets			0.919***	1.047***		-0.661	-0.890
			(0.185)	(0.191)		(0.511)	(0.651)
Securities / assets			0.100	0.186**		0.251	0.454
			(0.085)	(0.090)		(0.354)	(0.314)
Capital / assets			0.032	0.080		1.079	0.763
			(0.104)	(0.113)		(0.699)	(0.798)
Servicing growth	-0.045	-0.003	-0.002	-0.019	-0.118	-0.085	-0.104
	(0.049)	(0.058)	(0.048)	(0.048)	(0.076)	(0.082)	(0.080)
Servicer type							
Nonbank mortgage company	-0.084***						
	(0.025)						
Credit union	0.186***						
	(0.032)						
N. Obs.	152	98	98	98	45	45	45

when most forbearance applications were received. We find that nonbank servicers were significantly less likely to provide forbearance, particularly for small nonbanks with low cash balances that faced the greatest liquidity risk. Banks in contrast were not liquidity-constrained because they have access to ample backstop sources of funding for mortgages and also experienced large deposit inflows after the onset of COVID-19 (Li et al., 2020).

The high forbearance rate for large servicers, both banks and nonbanks, is also striking. Although it is difficult to pinpoint the mechanism underlying this result, large servicers may benefit from scale economies in technology investments (e.g., a well-designed online platform), may have better access to capital markets and more resources to train servicing staff, or may take a "borrower-friendly" approach because they are more likely to be targeted by financial regulators, particularly in the case of large banks.[14]

5.3 Servicing quality: evidence from CFPB complaints

It seems clear given the program's design that past-due FHA and VA borrowers would unambiguously benefit from entering into forbearance; this in turn suggests that servicer practices limiting forbearance uptake also reduced borrower welfare for our sample. To investigate further, we study whether borrowers were less satisfied with "low-forbearance" servicers based on the frequency of mortgage forbearance-related complaints for government loans submitted by borrowers to the CFPB complaint platform.[15]

[14] Results in table 3 are related to contemporaneous analysis by Cherry et al. (2022) also studying the relationship between forbearance provision and servicer characteristics using a different but overlapping sample. Cherry et al. (2022) do not investigate the role of liquidity constraints, which is likely to be particularly important for our sample given the much greater liquidity risk associated with Ginnie Mae mortgages (as discussed in section 5.2). In other respects our results are consistent with Cherry et al. (2022); e.g., both studies find that large servicers and bank servicers are more likely to provide forbearance.

[15] We identify forbearance-related complaints using a similar approach to Consumer Financial Protection Bureau (2021b), searching for complaints with a narrative field containing the string "forbear" or "defer", restricting the sample to complaints related to a mortgage which is a government loan, to be consistent with our Ginnie Mae sample. As a cross-check, we confirm that we identify a comparable total sample to Consumer Financial Protection Bureau (2021b). We match CFPB complaints data to our main servicer dataset by name. We exclude from the sample any servicer for which we are unable to find a match; results are however similar if we retain these servicers and code them as having zero complaints.

Table 4: **Servicer forbearance practices and CFPB complaints.** Servicer-level regression of relationship between volume of forbearance-related CFPB complaints and servicer forbearance practices (as measured by servicer fixed effects). Outcome variable is the number of forbearance-related mortgage complaints for government loans per thousand Ginnie Mae mortgages serviced. Weighted least squares, weighted by size of Ginnie Mae servicing portfolio as of January 2020. Robust standard errors.

Dependent variable: Complaints per thousand loans serviced

	All lenders				Nonbanks only	
	(1)	(2)	(3)	(4)	(5)	(6)
Servicer forbearance propensity	-0.222***	-0.235***			-0.622**	
	(0.073)	(0.077)			(0.303)	
Servicer characteristics						
log(Servicing assets)			-0.016**	-0.006		-0.031
			(0.007)	(0.008)		(0.041)
Cash / assets				-0.410*		-1.090**
				(0.229)		(0.485)
Securities / assets				-0.356**		-0.891***
				(0.175)		(0.301)
Capital / assets				-0.020		0.440
				(0.140)		(0.524)
Servicing growth			0.079	0.095		0.731*
			(0.060)	(0.061)		(0.409)
Frac. govt. loans that are FHA		0.069**	0.072**	0.089	-0.337	-0.486
		(0.032)	(0.036)	(0.077)	(0.503)	(0.562)
Frac. all loans that are FHA						
Servicer type						
Nonbank mortgage company		0.002	0.012	-0.033		
		(0.020)	(0.022)	(0.034)		
Credit union		0.070**	0.000			
		(0.028)	(0.025)			
N. Obs.	129	129	129	125	92	92

Results are presented in Table 4. The dependent variable is the frequency of complaints per thousand Ginnie Mae mortgages serviced. The rate of complaints is significantly higher for low-forbearance servicers. This is direct evidence of poorer servicing quality for these firms. The inverse relationship between forbearance provision and complaints is particularly strong for nonbanks (column 5).

When we replace the servicer fixed effect in the regression with servicer characteristics (columns 3, 4 and 6), we find again that servicer liquidity matters. Servicers with lower cash balances and smaller securities portfolios were the object of a higher rate of forbearance-related complaints. Again, these relationships are concentrated among nonbank servicers. These results and those of the prior table show how liquidity constraints can lead to a deterioration of servicing quality, consistent with earlier evidence on foreclosures and modifications from the period of the Great Recession (Aiello, 2021).

6 Effects of forbearance on borrowers

In this section we use cross-servicer variation to estimate the causal effect of forbearance access on borrower outcomes, including payment behavior, nonmortgage debt, auto purchases and credit scores. We then draw out implications and lessons from our results for the overall design and effectiveness of the CARES Act forbearance program.

We use the CRISM-eMBS matched sample for this portion of the analysis. This sample allows us to observe nonmortgage debt and other outcomes from credit reports, measure geography more finely and control for a richer set of borrower and loan controls, and track payment status even for nonperforming loans repurchased from Ginnie Mae pools.[16]

[16] Ginnie Mae MBS issuers have the option to repurchase nonperforming mortgages out of securitized pools at par if the borrower has missed at least three payments. This was an attractive option during the pandemic because many pools were trading at a premium to par given record-low interest rates. Since eMBS is a dataset of loans in securitized pools, it does not include data on performance after loans are repurchased. We do continue to observe performance in the CRISM-eMBS matched sample, however.

6.1 Empirical strategy

We use a difference-in-difference approach to compare outcomes for borrowers matched to servicers with a high-versus-low propensity to provide forbearance. "High-forbearance" servicers are again defined as those with an above-median servicer fixed effect, estimated as described in Section 4.1 using the merged eMBS-CRISM data. We use the six months up to March 2020 to establish the absence of differential pre-trends between high- and low-forbearance servicers. We attribute differences in borrower outcomes and behavior observed after March 2020 to variation in forbearance access post-CARES Act.

We trace out the dynamic effects of servicer behavior by regressing various borrower outcomes (e.g., payment status) on a "high-forbearance servicer" dummy interacted with a set of time dummies as well as a set of borrower and loan controls and geography by time fixed effects. Specifically we estimate:

$$Y_{it} = \beta_t S_i^H + Z_{it}\gamma + \alpha_s + \alpha_{zt\tau} + \varepsilon_{it} \tag{2}$$

where Y_{it} is the borrower outcome in question for loan i in month t; β_t are coefficients on a vector of time dummies that are interacted with S_i^H, a high-forbearance servicer dummy; Z_{it} is a vector of loan and borrower controls including loan characteristics at origination, the borrower's updated credit score (measured by the Equifax Risk Score) as of January 2020, updated principal balance, loan age, borrower age, and loan type (FHA vs. VA); α_s is a vector of servicer dummies; and $\alpha_{zt\tau}$ is a vector of zipcode $\times$ month $\times$ origination year (τ) fixed effects to account for the time-varying geographic effects of the pandemic separately for different loan cohorts. Standard errors are clustered by servicer.

Like our earlier analysis, the estimation sample consists of loans that were active and current in January 2020, to exclude loans that were already past-due before the pandemic. We also exclude loans originated after October 2019, the start of our sample period.

6.2 Nonpayment

Figure 3 traces out the estimated effect of assignment to a high-forbearance servicer on mortgage payment outcomes based on the $\hat{\beta}_t$s from equation 2.

The top panel of figure 3 shows that easier access to forbearance induces a very significant increase in the mortgage nonpayment rate. The fraction of past-due borrowers at high vs low-forbearance servicers track each other closely through March 2020, but then diverge sharply after the passage of the CARES Act. Mortgage nonpayment rises sharply for both groups, but the probability that a borrower becomes past-due is much higher for borrowers at high-forbearance servicers, by more than half, or in level terms as much as 5 percentage points, at the forbearance peak around May 2020.

Notably however, high-forbearance servicers are associated with a significant *reduction* in the number of borrowers that are past-due but not in forbearance (bottom panel of figure 3). This is particularly evident in the early months of the pandemic.

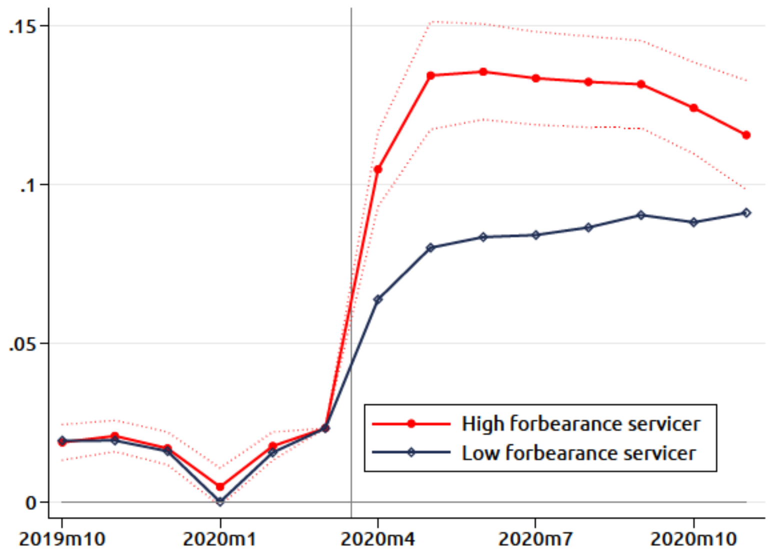
Table 5 summarizes and further unpacks these effects. The table reports average coefficients on the high-forbearance $\times$ time dummies during three phases of the pandemic for five different forbearance and payment outcomes.

The first row of table 5 reports the effect on the forbearance rate itself. In the early stages of the pandemic (April-July 2020), assignment to a high-forbearance servicer increases the forbearance rate by 5.6 percentage points (pp), a quantitatively important effect compared to the overall forbearance rate of 8.1 percent at low-forbearance servicers. The effect declines slightly to 4.5 percent later in 2020.

The second and third rows report estimates for nonpayment and nonpayment outside of forbearance, summarizing the visual evidence from figure 3. Comparing the first and second rows, a key takeaway point is that the effects on nonpayment are almost as large as the effects on forbearance itself (e.g., 4.9pp compared to 5.6pp for the April-July period).

Figure 3: **Forbearance access and mortgage payment behavior.** Estimated effect of assignment to a "high-forbearance" servicer on the overall probability of being past due (top panel) and probability of being past due and not in forbearance (bottom panel). Blue line shows the unconditional average monthly rate of nonpayment at low-forbearance servicers. Red line shows the additional effect of assignment to a high-forbearance servicer, by adjusting the unconditional average by the estimated βs from equation 2. 95% confidence intervals shown. Standard errors clustered at the servicer level. Sample includes loans that were current and active as of January 2020.

(a) Past due



(b) Past due, no forbearance

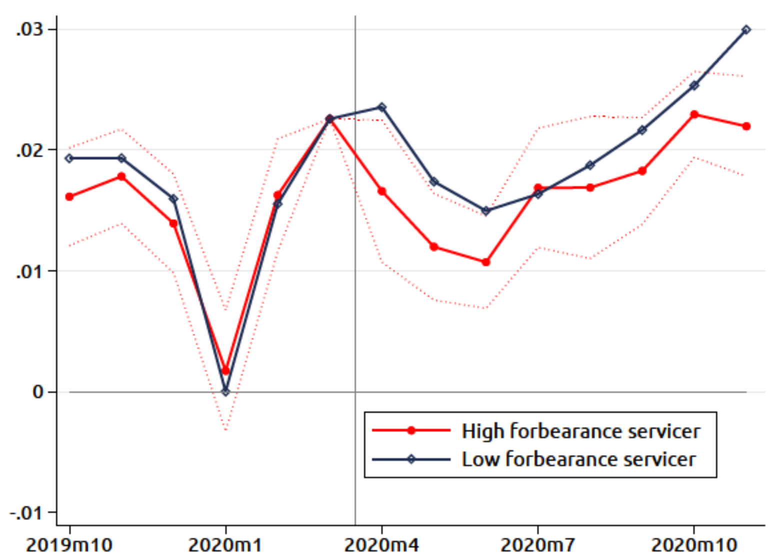


Table 5: **Forbearance and nonpayment outcomes.** Estimates of the average effect of assignment to a high-forbearance servicer on five different payment and forbearance outcomes. Estimates reported in columns (1), (3) and (5) are the average coefficient on the high-forbearance-servicer × time dummies (estimates of β_t from equation 2), over three phases of the pandemic: a pre-pandemic period (October 2019-February 2020); early pandemic (April-July 2020) and later pandemic (August-November 2020), along with the associated standard error of each mean. For context, Columns (2), (4) and (6) report the unconditional mean of the dependent variable at low-forbearance servicers during the period referenced. Standard errors are clustered at the servicer level.

Outcome variable:	Pre-pandemic		Pandemic			
	2019:m10-2020:m2		2020:m4 to 2020:m7		2020:m8 to 2020:m11	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coeff.	Mean	Coeff.	Mean	Coeff.	Mean
Forbearance	0.002	0.001	0.056^{***}	0.081	0.045^{***}	0.091
	(0.002)		(0.009)		(0.010)	
Missed payment	0.002	0.016	0.049^{***}	0.069	0.037^{***}	0.083
	(0.002)		(0.007)		(0.007)	
Missed payment, no forbearance	-0.001	0.016	-0.004^{**}	0.017	-0.004^{**}	0.022
	(0.002)		(0.002)		(0.002)	
Forbearance, no missed payment	-0.001	0.000	0.003	0.029	0.005	0.029
	(0.002)		(0.005)		(0.006)	
Forbearance, missed payment	0.003	0.000	0.053^{***}	0.052	0.041^{***}	0.061
	(0.002)		(0.007)		(0.008)	

In other words, a first-order effect of easier forbearance access is to induce nonpayment among borrowers who otherwise would have continued performing on their mortgage. We discuss the interpretation of this finding in section 6.5.

Easier forbearance access also reduces the number of past-due borrowers not in forbearance by about 0.4pp. This is a much smaller absolute effect, although in proportionate terms it represents a significant 20-25 percent reduction in the number of "missing" forbearances relative to the sample average for low-forbearance servicers.

As we have discussed, some borrowers entered forbearance as a precaution but continued making their scheduled payments; the fourth row of table 5 shows however that the share of such borrowers does not differ systematically between low- and high-forbearance servicers. The final row of table 5 confirms that the primary effect of easier forbearance access is to increase the share of borrowers who both skipped payments and entered forbearance (these estimates are essentially the difference between rows 2 and 3).

These results show that servicer policies significantly affected liquidity provision to households during the pandemic. Based on our estimates and some auxiliary assumptions, we calculate that borrowers matched to high-forbearance servicers deferred an additional $\approx$ \$300 in cumulative mortgage payments by November 2020 compared to otherwise equivalent borrowers at low-forbearance servicers (see Figure A.7 in the Internet Appendix). Since the treatment effect on the forbearance rate itself is about 5pp, this implies, on the margin, deferred payments of \$6,000 per additional forbearance, a significant sum. In aggregate, switching all Ginnie Mae borrowers from low-to-high forbearance servicers would increase deferred payments over the short period from April-November 2020 by \$3.1 billion, equivalent to an effect of $\approx$ \$10 billion if generalizing our estimates to the entire mortgage market.[17] Next we study how this liquidity was used by borrowers.

[17] The estimate of \$3.1 billion is computed by multiplying the estimate of the cumulative deferred payment from Figure A.7 in the Internet Appendix by the number of FHA and VA mortgages outstanding as reported in our table of summary statistics. Our estimate of the aggregate effect of $\approx$ \$10 billion is

6.3 Nonmortgage debt

First we study credit card debt, an alternative high-interest-rate form of borrowing often used by households during periods of financial stress. Liquidity constraints are likely to play a key role in determining whether funds from forbearance are used to reduce debt rather than for more immediate needs such as nondurable consumption (e.g., Telyukova, 2013; Gross and Souleles, 2002; Zeldes, 1989). Correspondingly in the spirit of Gross and Souleles (2002) we split the sample into high- and low- credit-card utilization groups based on the ratio of drawn balances to total credit limits summed across cards (measured ex ante over the six months to March 2020) and estimate results separately by group.

Figure 4 shows that the liquidity provided by forbearance did indeed allow some borrowers to reduce credit card balances, with the effect concentrated among less liquidity-constrained (i.e., low utilization) households.[18] For the low-utilization group, assignment to a high-forbearance servicer reduced credit card debt by 1.2 percent between April and July and 1.4 percent between August and November (top panel of figure 4). This is an average effect across all borrowers regardless of forbearance status; scaled by the treatment effect on the forbearance rate of around 5pp, it represents a 20-30 percent reduction in credit-card debt for the marginal borrowers induced to enter into forbearance, accounting for about one-fifth of the total liquidity infusion provided by forbearance for the low-utilization group.[19] In contrast, we find little or no corresponding change in credit card debt for high-utilization borrowers (bottom panel of figure 4).

We find no evidence that borrowers used forbearance to pay down other types of

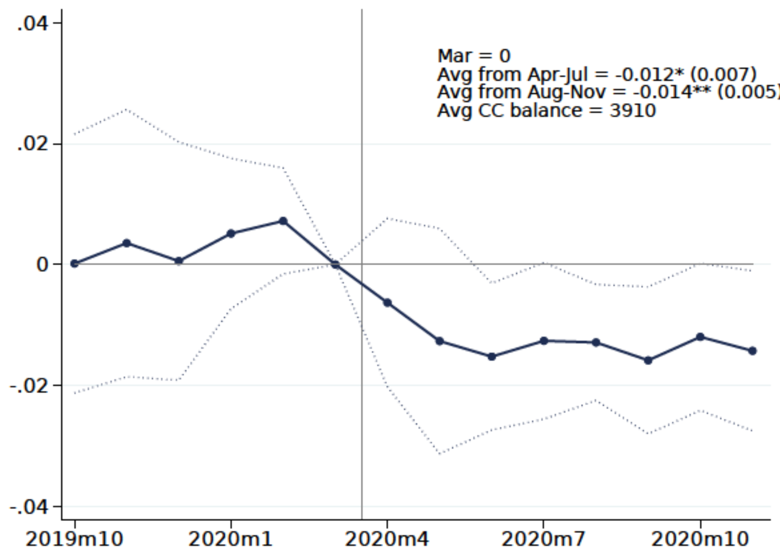
computed by then grossing up this estimate by the fraction of all forbearances that were in the FHA/VA segment as of the peak in June 2020, taken from Black Knight (2020).

[18] The figure is based on estimating our difference-in-difference equation using log(credit card debt) as the outcome variable. As an alternative specification, figure A.6 in the Internet Appendix presents estimates using the *level* of credit card debt; these alternative estimates show similar patterns to figure 4.

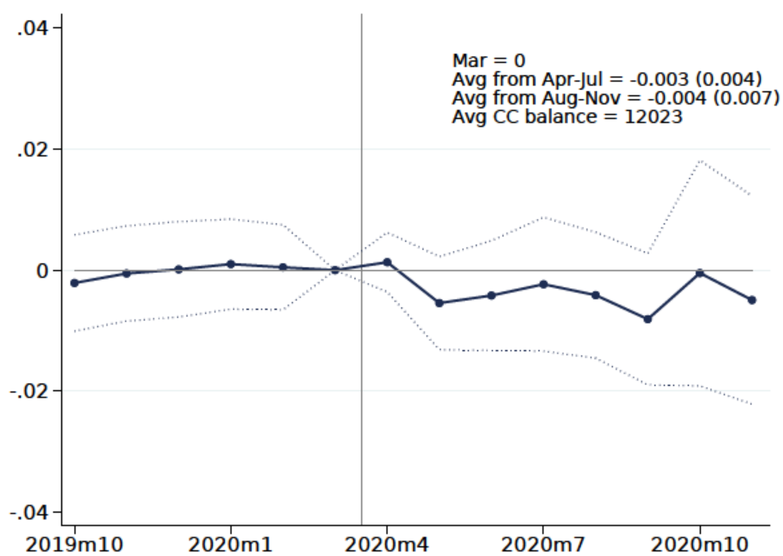
[19] Given the average credit-card balance of \$3,910 for low-utilization borrowers, a 1.4% paydown amounts to \$55 per borrower. By comparison, we estimate that assignment to a high-forbearance servicer results in an additional $\approx$ \$300 in total cumulative deferred mortgage-related payments up to November 2020 (see figure A.7 of the internet appendix), 5-6 times larger than the estimated effect on credit card balances.

Figure 4: **Forbearance access and log of credit card balances.** Estimates and 95% confidence intervals of the effects of assignment to a high-forbearance servicer on log(total credit card debt). The top (bottom) panel shows estimates for borrowers with below (above) median credit card utilization (measured ex ante between October 2019 and March 2020). The median average utilization is calculated separately for each cohort of borrowers based on mortgage origination year. Standard errors are clustered at the servicer level.

(a) Low utilization borrowers



(b) High utilization borrowers



debt like auto loans, student debt, or junior home equity liens (table A.10 in the Internet Appendix), perhaps because these forms of borrowing are cheaper than credit card debt, making them a lower priority for payoff. Reported in the same table, we find little or no effects on delinquency for non-mortgage debt. This may in part reflect the availability of forbearance for these other debt types.

6.4 Other outcomes

6.4.1 Credit scores

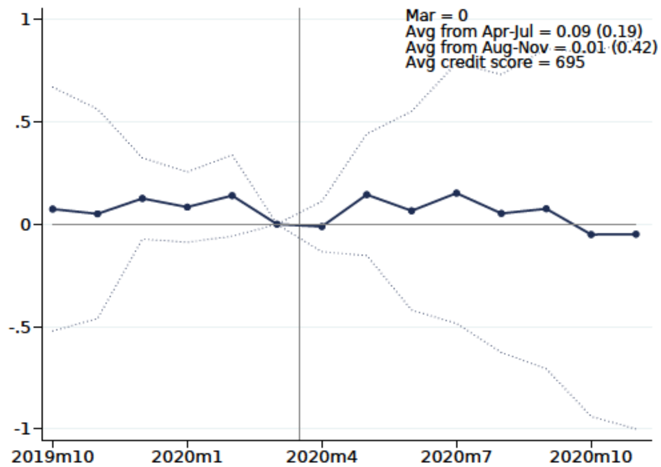
Employing the same methodology, Figure 5 shows that easier access to forbearance did not damage the credit scores of borrowers at high-forbearance servicers, despite the high nonpayment rate for this group.[20] This outcome is consistent with the intended design of the CARES Act forbearance program, which stipulated that nonpayment in forbearance should not be reported as a delinquency to credit bureaus. The point estimate is in fact slightly positive, which could be possible if, e.g,., forbearance reduced non-mortgage delinquency, although it is not close to statistical significance.

6.4.2 Auto purchases

How much of the liquidity made available through forbearance was used for consumption? Although credit bureau data unfortunately do not in general allow us to measure consumption directly, we do study a proxy for durable goods purchases often used in the literature; the establishment of new auto credit trade lines as a measure of automobile purchases (e.g., Abel and Fuster, 2021; Di Maggio et al., 2017). We find no evidence that borrowers at high-forbearance servicers were more likely to purchase an automobile —

[20] Credit score is measured by FICO score version 5. FICO is a registered trademark of Fair Isaac Corporation.

Figure 5: **Effects of forbearance availability on updated credit score.** Estimates and 95% confidence intervals of the effects of assignment to a high-forbearance servicer on the borrower's updated credit score (FICO score version 5), based on the eMBS-CRISM matched sample. Standard errors are clustered at the servicer level.



the point estimate is close to zero and tightly estimated enough to rule out large effects (table A.10 of the Internet Appendix). This stands in contrast to Di Maggio et al. (2017), who study the effects of mortgage payment changes due to interest-rate resets also using mortgage data linked to credit reports. Two plausible reasons for the differences in findings are: i) forbearance is primarily a means to *defer* mortgage payments, whereas payment reductions due to interest rate resets do not have to be repaid; ii) borrowers induced on the margin to enter forbearance were likely experiencing financial uncertainty and stress, and thus likely had low demand for expensive, lumpy, durable goods.

6.4.3 Prepayment

Table A.10 of the Internet Appendix also reports estimates of the effect of forbearance on mortgage prepayment, an important outcome given that our study period featured a refinancing boom due to lower interest rates (Fuster et al., 2021a). It is possible that easier access to forbearance could have limited prepayment, because lenders required borrowers to exit forbearance first before refinancing. In practice however, we find little or no effect on prepayment. This implies that borrowers assigned to high-forbearance servicers were *not* diverted from refinancing into forbearance, an outcome that would have complicated the welfare analysis of the program given the substantial benefits of refinancing for borrowers.

6.4.4 Bankruptcy

Wang et al. (2020) document a striking decline in consumer bankruptcy filings during the COVID pandemic. We find no evidence that servicers significantly affected the likelihood of bankruptcy; the difference in the bankruptcy rate (including bankruptcy of any type) between high-and-low forbearance servicers is only about 1 percent of the sample mean, and quite tightly estimated. This may seem surprising in light of evidence that bankruptcy filings are very sensitive to cash-on-hand (Indarte, 2020). A possible explanation is that we measure a local treatment effect: borrowers in sufficient distress to be close to bankruptcy likely had strong incentives to file for forbearance regardless of servicer, particularly given the complexity of the bankruptcy process compared to forbearance.

6.5 Summary and policy implications

Stepping back, what can we learn from our results about the overall design and effectiveness of the CARES Act forbearance program? For example, was the program too generous, resulting in widespread moral hazard and strategic default by borrowers not facing liquidity problems? Or alternatively was the program not streamlined enough, as indicated by the many borrowers who became delinquent without obtaining forbearance? Cross-servicer variation helps shed light on these questions because, as we have shown, it produced some quasi-random variation in program generosity on the margin.

Our finding that access to forbearance induced nonpayment by borrowers is closely related to the strategic default literature, and in particular to Mayer et al. (2014) who find that mortgage borrowers defaulted in order to qualify for generous modifications from subprime lender Countrywide during the 2008 financial crisis. There are some important differences between the two settings, however, and several pieces of evidence described below suggest that the marginal nonpayers in our sample primarily sought forbearance because of genuine liquidity concerns rather than because of a strategic desire to take advantage of a source of interest-free borrowing.

First, unlike Mayer et al. (2014) we find that marginal nonpayers look similar on observables (e.g., nonmortgage balances, credit scores) to "control group" borrowers who obtained forbearance from low-forbearance servicers; see Table A.8 in the Internet Appendix. If moral hazard was the main driver of nonpayment, we might instead expect marginal nonpayers to be financially literate, higher-income borrowers, as Mayer et al. (2014) do find in their setting. Furthermore, although borrowers at high-forbearance servicers stay in forbearance slightly longer and are less likely to exit, the effects are small (e.g., the probability of forbearance exit is 0.31 at high-forbearance servicers compared to 0.35 at low-forbearance servicers.) In other words there is little evidence that borrowers that obtained forbearance on the margin acted to "max out" the zero-interest financing provided by payment deferral.

Second, the liquidity made available through forbearance was generally *not* used to pay down debt or to purchase automobiles, suggesting deferred payments were primarily used for precautionary savings or nondurable consumption. This interpretation is also consistent with survey data from April 2020 presented in Anderson et al. (2021). Households were asked how they would use funds from forbearance; the most popular response was spending on "necessary" consumption, followed by saving, and then debt consolidation. Although we find evidence of credit-card debt paydown, this response is limited to less liquidity-constrained households and even for this group accounts for only about one-fifth of deferred payments.

Third, external evidence suggests that forbearance was mostly used by borrowers experiencing negative income or expenditure shocks. Lambie-Hanson et al. (2021) present survey data that at least three-quarters of borrowers entering forbearance had experienced a job disruption or income loss. Zhao et al. (2020) document using rich administrative data that borrowers in forbearance had experienced larger income declines, and were more likely to have lost their jobs or to have have received unemployment benefits. Further, in aggregate less than one in ten borrowers made use of forbearance, despite the easy qualification requirements. This suggests opportunistic behavior was relatively rare.

A final point: in our context the benefits of strategic default are fairly modest because forbearance is only an interest-free payment *deferral*; it is not debt forgiveness, unlike the setting in Mayer et al. (2014). Consistent with this point, An et al. (2022) find that less than one-in-ten borrowers exiting forbearance maximized the interest benefit of payment deferral by rolling skipped payments into a long-term "partial claim" due when the mortgage is paid off. Requiring even a simple attestation of economic hardship may have limited strategic behavior, in line with experimental evidence in Anderson et al. (2021).

Aside from the question of strategic default, our results show the CARES Act forbearance program worked as intended to allow borrowers to pause their payments without negative effects on their credit scores; furthermore it did not inadvertently prevent borrowers from refinancing. More broadly, the program successfully reached a high proportion of vulnerable borrowers — three-quarters of FHA and VA borrowers who became past-due successfully obtained forbearance, rising to nine-tenths for seriously past-due borrowers, a high takeup rate compared to many government programs.

That said, the failure to reach all past-due borrowers highlights the forbearance program's limits, as does the wide variation in outcomes across servicers unrelated to borrower fundamentals. These policy shortcomings could cause more serious and long-lasting problems in a future stress event involving a more prolonged economic and housing market downturn. In designing future debt relief policies, policymakers may therefore wish to consider ways to standardize servicer practices (e.g., more detailed guidelines about minimum borrower outreach) or implement forms of forbearance auto-enrolment for borrowers observably in distress (e.g., tied to unemployment insurance claims). Auto-enrolment may be particularly valuable for "hard-to-reach" borrowers identified in our analysis such as those with low credit scores.

Our results, and those of Cherry et al. (2022), also show how debt relief outcomes are connected to the financial health and regulation of mortgage intermediaries. Nonbanks are now responsible for a majority of mortgage lending and servicing, but these entities are less regulated than banks and face significant liquidity and run risk (Pence, 2022; Kim et al., 2018). We show that nonbanks were less likely to provide debt relief, particularly when the nonbank was small or had low liquid asset buffers. In contrast the more "borrower-friendly" outcomes for large bank servicers may reflect tighter regulation and oversight of these intermediaries as well as their lower liquidity risk. Our findings highlight the importance of appropriate nonbank regulation and the potential benefits of public nonbank liquidity backstops such as that provided in 2020 through the Ginnie Mae Pass-Through Assistance Program (Ginnie Mae, 2020).

7 Conclusion

We show that mortgage intermediaries played a key role in shaping the implementation of the CARES Act mortgage forbearance program. Forbearance outcomes varied widely across servicers for otherwise similar loans. Small servicers, nonbanks, and particularly nonbanks with low liquid asset buffers facilitated fewer forbearances and saw a higher volume of forbearance-related borrower complaints. Servicer effects are heterogeneous across borrowers with older and low credit-score borrowers seemingly “hard to reach”.

We also use cross-servicer variation to trace out the causal effects of forbearance for borrowers, showing that easier access to forbearance resulted in significant liquidity provision by inducing nonpayment among borrowers who otherwise would have kept making their mortgage payments. Several pieces of evidence suggest that these “marginal” nonpayers generally paused their payments due to liquidity concerns rather than purely strategic considerations, although part of the liquidity was used to consolidate debt through credit card debt paydown.

Overall, we interpret our results as evidence that the CARES Act forbearance program successfully reached most borrowers in need without inducing widespread strategic behavior or other unintended consequences, thereby balancing the tradeoffs inherent in any social insurance program (e.g., see Chetty 2008 on unemployment insurance or Indarte 2020 on personal bankruptcy). That said, significant idiosyncratic variation in outcomes across servicers as well as the failure to reach a significant share of past-due borrowers indicate program limitations which could be mitigated through changes in design. Further consideration of optimal program design seems prudent given that forbearance is likely to be an important debt-relief tool in the future.

References

ABEL, J. AND A. FUSTER (2021): "How Do Mortgage Refinances Affect Debt, Default, and Spending? Evidence from HARP," *American Economic Journal: Macroeconomics*, 13, 254–91.

AGARWAL, S., G. AMROMIN, I. BEN-DAVID, S. CHOMSISENGPHET, AND D. EVANOFF (2011): "The role of securitization in mortgage renegotiation," *Journal of Financial Economics*, 102, 559–578.

AGARWAL, S., G. AMROMIN, I. BEN-DAVID, S. CHOMSISENGPHET, T. PISKORSKI, AND A. SERU (2017a): "Policy Intervention in Debt Renegotiation: Evidence from the Home Affordable Modification Program," *Journal of Political Economy*, 125, 654–712.

AGARWAL, S., G. AMROMIN, S. CHOMSISENGPHET, T. LANDVOIGT, T. PISKORSKI, A. SERU, AND V. YAO (2015): "Mortgage Refinancing, Consumer Spending, and Competition: Evidence from the Home Affordable Refinancing Program," NBER Working Papers 21512, National Bureau of Economic Research, Inc.

AGARWAL, S., S. CHOMSISENGPHET, AND Y. ZHANG (2017b): "How does working in a finance profession affect mortgage delinquency?" *Journal of Banking Finance*, 78, 1–13.

AIELLO, D. J. (2021): "Financially constrained mortgage servicers," *Journal of Financial Economics*.

AN, X., L. CORDELL, L. GENG, AND K. LEE (2022): "Inequality in the Time of COVID-19: Evidence from Mortgage Delinquency and Forbearance," Tech. rep.

ANDERSON, J., D. HARRISON, AND M. SEILER (2021): "Reducing Strategic Forbearance under the CARES Act: an Experimental Approach Utilizing Recourse Attestation," *The Journal of Real Estate Finance and Economics*.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein (2005): "Does function follow organizational form? Evidence from the lending practices of large and small banks," *Journal of Financial Economics*, 76, 237–269.

Black Knight (2020): "Forbearances rise after three weeks of declines," McDash Flash Blog June 26.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018): "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of Financial Economics*, 130, 453 – 483.

——— (2020): "Beyond the Balance Sheet Model of Banking: Implications for Bank Regulation and Monetary Policy," .

Cherry, S., E. Jiang, G. Matvos, T. Piskorski, and A. Seru (2022): "Shadow Bank Distress and Household Debt Relief: Evidence from the CARES Act," *AEA Papers and Proceedings*, 112, 509–15.

Cherry, S. F., E. X. Jiang, G. Matvos, T. Piskorski, and A. Seru (2021): "Government and Private Household Debt Relief during COVID-19," NBER Working Papers 28357, National Bureau of Economic Research.

Chetty, R. (2008): "Moral Hazard versus Liquidity and Optimal Unemployment Insurance," *Journal of Political Economy*, 116, 173–234.

Consumer Financial Protection Bureau (2021a): "COVID-19 Prioritized Assessments, Special Edition," Supervisory Highlights 23.

——— (2021b): "Mortgage forbearance issues described in consumer complaint," Complaint Bulletin, April.

Department of Housing and Urban Development (2020a): "FHA's COVID-19 Loss Mitigation Options," Mortgagee Letter 2020-22, July 8.

——— (2020b): "HUD Issues New CARES Act Mortgage Payment Relief for FHA Single Family Homeowners," Press Release, April 1.

DI MAGGIO, M., A. KERMANI, B. KEYS, T. PISKORSKI, R. RAMCHARAN, A. SERU, AND V. YAO (2017): "Monetary Policy Pass-Through: Mortgage Rates, Household Consumption, and Voluntary Deleveraging," *American Economic Review*, 107, 3550–88.

FEDERAL HOUSING FINANCE AGENCY (2020): "FHFA Announces Payment Deferral as New Repayment Option for Homeowners in COVID-19 Forbearance Plans," News release, May 13.

——— (2021): "FHFA Extends COVID-19 Forbearance Period and Foreclosure and REO Eviction Moratoriums," Press release, February 25.

FREDDIE MAC (2020): "Freddie Mac: Lump Sum Repayment is Not Required in Forbearance," Homeownership blog, April 16.

FUSTER, A., A. HIZMO, L. LAMBIE-HANSON, J. VICKERY, AND P. WILLEN (2021a): "How Resilient is Mortgage Credit Supply? Evidence from the COVID-19 Pandemic," *Working Paper*.

FUSTER, A., M. PLOSSER, AND J. VICKERY (2021b): "Does CFPB Oversight Crimp Credit?" CEPR Discussion Papers 15681, C.E.P.R. Discussion Papers.

FUSTER, A. AND P. S. WILLEN (2017): "Payment Size, Negative Equity, and Mortgage Default," *American Economic Journal: Economic Policy*, 9, 167–91.

GANONG, P. AND P. NOEL (2020): "Liquidity versus Wealth in Household Debt Obligations: Evidence from Housing Policy in the Great Recession," *American Economic Review*, 110, 3100–3138.

GERARDI, K., L. GOETTE, AND S. MEIER (2013): "Numerical ability predicts mortgage default," *Proceedings of the National Academy of Sciences*, 110, 11267–11271.

GETE, P. AND M. REHER (2020): "Mortgage Securitization and Shadow Bank Lending," *The Review of Financial Studies*, 34, 2236–2274.

GINNIE MAE (2020): "Availability of Pass-Through Assistance Program for Participants in Ginnie Mae's Single-Family MBS Program," All Participants Memo APM 20-03.

GRANJA, J., C. MAKRIDIS, C. YANNELIS, AND E. ZWICK (2020): "Did the Paycheck Protection Program Hit the Target?" NBER Working Papers 27095, National Bureau of Economic Research, Inc.

GROSS, D. B. AND N. S. SOULELES (2002): "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data," *The Quarterly Journal of Economics*, 117, 149–185.

HUBER, K. (2021): "Are Bigger Banks Better? Firm-Level Evidence from Germany," *Journal of Political Economy*, 129, 2023–2066.

INDARTE, S. (2020): "Moral Hazard versus Liquidity in Household Bankruptcy," Working paper.

JENSEN, M. C. AND W. H. MECKLING (1976): "Theory of the firm: Managerial behavior, agency costs and ownership structure," *Journal of Financial Economics*, 3, 305–360.

JIANG, E., G. MATVOS, T. PISKORSKI, AND A. SERU (2020): "Banking without Deposits: Evidence from Shadow Bank Call Reports," Working Paper 26903, National Bureau of Economic Research.

KIM, Y. S., S. M. LAUFER, K. PENCE, R. STANTON, AND N. WALLACE (2018): "Liquidity Crises in the Mortgage Market," *Brookings Papers on Economic Activity*, 49, 347–428.

KRUGER, S. (2018): "The effect of mortgage securitization on foreclosure and modification," *Journal of Financial Economics*, 129, 586–607.

KUGLER, M. AND E. VERHOOGEN (2011): "Prices, Plant Size, and Product Quality," *The Review of Economic Studies*, 79, 307–339.

LAMBIE-HANSON, L., J. VICKERY, AND T. AKANA (2021): "Recent Data on Mortgage Forbearance: Borrower Uptake and Understanding of Lender Accommodations," *Research Brief, Federal Reserve Bank of Philadelphia*.

LEE, D. AND W. V. DER KLAAUW (2010): "An introduction to the FRBNY Consumer Credit Panel," Staff Reports 479, Federal Reserve Bank of New York.

LI, L., P. E. STRAHAN, AND S. ZHANG (2020): "Banks as Lenders of First Resort: Evidence from the COVID-19 Crisis," *The Review of Corporate Finance Studies*, 9, 472–500.

LOEWENSTEIN, L. (2021): "Why Wasn't there a Nonbank Mortgage Servicer Liquidity Crisis?" *Economic Commentary*.

MATSA, D. A. (2011): "Running on Empty? Financial Leverage and Product Quality in the Supermarket Industry," *American Economic Journal: Microeconomics*, 3, 137–73.

MAYER, C., E. MORRISON, T. PISKORSKI, AND A. GUPTA (2014): "Mortgage Modification and Strategic Behavior: Evidence from a Legal Settlement with Countrywide," *American Economic Review*, 104, 2830–57.

MORTGAGE BANKERS ASSOCIATION (2020): "Share of mortgage loans in forbearance increases to 8.55%," Press Release June 15.

PENCE, K. (2022): "Liquidity in the mortgage market: How does the COVID-19 crisis compare with the global financial crisis?" *Real Estate Economics*.

ROSE, N. L. (1990): "Profitability and Product Quality: Economic Determinants of Airline Safety Performance," *Journal of Political Economy*, 98, 944–964.

SCHARLEMANN, T. C. AND S. H. SHORE (2016): "The Effect of Negative Equity on Mortgage Default: Evidence From HAMP's Principal Reduction Alternative," *The Review of Financial Studies*, 29, 2850–2883.

TELYUKOVA, I. A. (2013): "Household Need for Liquidity and the Credit Card Debt Puzzle," *The Review of Economic Studies*, 80, 1148–1177.

THE WHITE HOUSE (2021): "Fact Sheet: Biden Administration Announces Extension of COVID-19 Forbearance and Foreclosure Protections for Homeowners," Release, February 16.

TOZER, T. (2019): "A Primer and Perspective on Ginnie Mae," *Milken Institute Discussion Paper*.

WALL STREET JOURNAL (2020): "Struggling Borrowers Want To Pause Their Mortgage Payments. It Hasn't Been Easy," Tech. Rep. April 16.

WANG, J., J. YANG, B. C. IVERSON, AND R. KLUENDER (2020): "Bankruptcy and the COVID-19 Crisis," *Available at SSRN 3690398*.

ZELDES, S. P. (1989): "Consumption and Liquidity Constraints: An Empirical Investigation," *Journal of Political Economy*, 97, 305–346.

ZHAO, C., D. FARRELL, AND F. GREIG (2020): "Did Mortgage Forbearance Reach the Right Homeowners? Income and Liquid Assets Trends for Homeowners during the COVID-19 Pandemic," Policy Brief, J.P. Morgan Chase Institute.

Internet Appendix for:

"Intermediation Frictions in Debt Relief: Evidence from CARES Act Forbearance"

You Suk Kim, Donghoon Lee, Tess Scharlemann, and James Vickery

September 6, 2022

A Datasets

eMBS loan-level data. eMBS provides information on the characteristics of the population of mortgages securitized into agency MBS. The data include standard underwriting fields such as credit score at origination, loan-to-value ratio, loan amount, mortgage rate, and property location (state). The data set also includes dynamic information about loan performance, such as updated principal balance, nonpayment status, and crucial for our analysis, the servicer identity. Our sample consists of FHA and VA loans, which account for 92% of all loans securitized into Ginnie Mae MBS.

Ginnie Mae forbearance register. We measure forbearance outcomes using Ginnie Mae data listing the monthly loan-level forbearance history of loans securitized into Ginnie Mae MBS. The file indicates the start date of the forbearance policy, the scheduled end date, and the number of months of forbearance granted. The data were first released publicly in June 2020, and were backfilled to the start of the pandemic for loans that were in forbearance as of June. They have subsequently been updated on a monthly basis.[1]

Financial Call Reports. Data on servicer characteristics are drawn from quarterly regulatory filings. For bank servicers we use the bank call reports and FR Y-9C. For independent mortgage banks we use mortgage call reports (MCRs) data. MCRs are filed by financial data companies holding a license through the Nationwide Mortgage Licensing System, including all bank and nonbank agency MBS servicers. The data include balance sheet and income data and other information on business activities. Together the bank and nonbank call report datasets allow us to link servicer characteristics to forbearance and delinquency outcomes.

Black Knight McDash and CRISM. Black Knight McDash (hereafter "McDash") includes loan characteristics and performance for the servicing portfolios of the largest residential mortgage servicers in the US, covering around two-thirds of the servicing market. The Equifax Credit Risk Insight Servicing and McDash (CRISM) dataset is a match between McDash and credit bureau data on nearly 79 million individual consumers, including information on other forms of debt (e.g., credit cards, junior liens, and student loans) for primary borrowers and all co-borrowers on the McDash mortgages.

Federal Reserve Bank of New York (FRBNY) Consumer Credit Panel / Equifax Data (CCP). The CCP is a representative panel of the credit history of an anonymous 5% sam-

[1]One relatively minor reporting issue is that the initial release of the forbearance data only includes loans that were in forbearance as of June 2020. Thus, the data do not allow us to observe a forbearance spell for borrowers who entered forbearance in March but had already exited prior to June.

ple of the U.S. adult population (see Lee and der Klaauw (2010) for details of the dataset). Narrative codes in the CCP together with scheduled payment variables allow us to measure the incidence of mortgage forbearance. The CCP does not include loan performance data for mortgages in forbearance plans, since that information is not reported to credit bureaus. We use the CCP to calculate forbearance rates for the overall mortgage market (Figure 1), and to cross-validate the forbearance information in the Ginnie Mae data.

A.1 Details of eMBS-CRISM merge

Unlike eMBS, CRISM does not report the identity of the servicer. We are however able to merge CRISM with anonymized servicer identifiers through a fuzzy match between CRISM/McDash with eMBS loan-level data, matching on mortgage balance at origination, origination year-month, mortgage rate, credit score, whether a loan is an FHA or VA loan, and state.[2]

This eMBS-CRISM matched dataset allows us to trace out the effects of servicer variation in forbearance practices on other borrower outcomes (e.g., credit card debt and credit scores). It also enriches the set of available borrower-level characteristics relative to the eMBS-only dataset. For example, CRISM/McDash includes finer geographic information on the property location, and allows us to observe the borrower's refreshed credit score just prior to the pandemic. A limitation however is that only a subset of loans can be matched with precision, whereas in eMBS we essentially are able to observe the entire universe of FHA and VA mortgages.

Table A.1 reports summary statistics of loan characteristics for the full eMBS data and for the merged eMBS-CRISM dataset. As shown by the number of observations in the two columns, about 30% of loans in the eMBS data are matched to CRISM; this reflects both the fact that CRISM does not cover the entire market, and our restrictive matching criteria (we require essentially an exact match on all fields). The characteristics of matched loans are however very similar to the full eMBS sample, however.

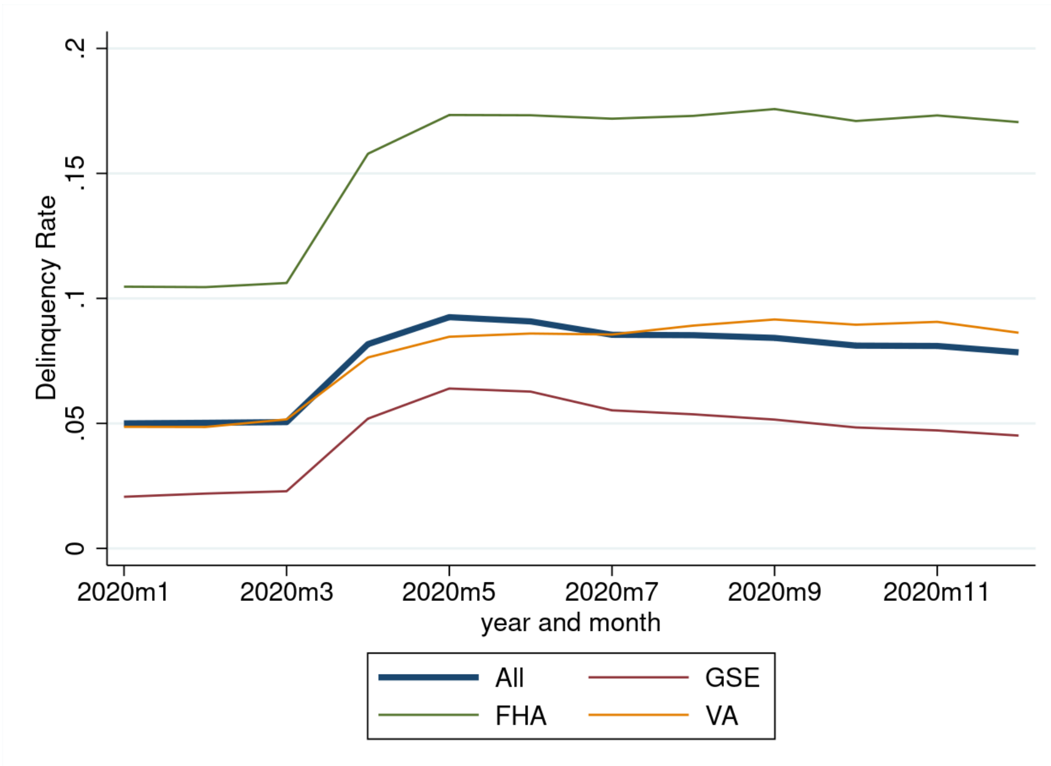
[2]The Federal Reserve's terms of use agreement with Black Knight does not permit us to retain servicer characteristics in this merged dataset. We are permitted to retain an anonymized servicer identifier, however. This allows us to measure servicer-level variation in forbearance outcomes, by estimating fixed effects for these identifiers.

Table A.1: **Comparison between eMBS and eMBS-CRISM matched sample.** Summary statistics reflect eMBS data fields, and are measured as of January 2020.

	(1) eMBS	(2) eMBS-CRISM match
Ever 30+ days past-due	0.17	0.18
Ever in forbearance	0.13	0.14
Current UPB ($)	171,731.42	173,088.57
Orig LTV (%)	93.43	94.60
Orig DTI (%)	40.36	40.25
Orig credit score	692.56	696.80
Loan age (year)	4.97	5.33
FHA	0.68	0.70
VA	0.32	0.30
N. Obs.	11,015,574	3,068,450

B Mortgages 30+ days past due, by segment

Figure A.1: **Past-Due Rate, 30+ Days.** Fraction of active mortgages that are at least 30 days past due relative to scheduled payments, inclusive of mortgages that are in forbearance. Calculations based on Black Knight McDash servicing data.



C Loan-level estimates

C.1 eMBS sample

Table A.2: **First-stage forbearance regression.** Dependent variable = 1 if mortgage entered forbearance from March-November 2020. Cross-sectional linear probability model. eMBS loan-level data. Sample is loans active as of January 2020. Sample for columns 1 and 2 restricted to mortgages that became past due from March-November 2020.

	Past-due sample		Full sample	
	(1) Excluding Svcr FE	(2) Including Svcr FE	(3) Excluding Svcr FE	(4) Including Svcr FE
Ever servicer change	-0.061***	-0.021***	-0.002***	0.003***
	(0.001)	(0.002)	(0.000)	(0.000)
Months since last servicer change	0.000***	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
yes FTHB	0.035***	0.030***	0.023***	0.022***
	(0.001)	(0.001)	(0.000)	(0.000)
Debt-to-income (DTI) at origination:				
$25 < \text{dti} \leq 50$	0.019***	0.043***	0.021***	0.026***
	(0.002)	(0.002)	(0.000)	(0.000)
$\text{dti} > 50$	0.058***	0.081***	0.060***	0.064***
	(0.002)	(0.002)	(0.001)	(0.001)
Loan age (year)	0.001**	-0.016***	-0.000***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan age (year) × Loan age (year)	-0.000***	0.000***	-0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Current UPB)	0.108***	0.104***	0.028***	0.026***
	(0.001)	(0.001)	(0.000)	(0.000)
Credit score (CS) at origination:				
$620 < \text{orig cs} \leq 680$	0.052***	0.016***	-0.009***	-0.017***
	(0.001)	(0.001)	(0.000)	(0.000)
$680 < \text{orig cs} \leq 740$	0.072***	0.025***	-0.050***	-0.061***
	(0.002)	(0.002)	(0.000)	(0.001)
$\text{orig cs} > 740$	0.062***	0.010***	-0.081***	-0.093***
	(0.002)	(0.002)	(0.001)	(0.001)
Loan purpose:				
refinace	0.033***	0.035***	-0.001***	0.002***
	(0.002)	(0.002)	(0.000)	(0.000)
Loan-to-value (LTV) at origination:				
$80 < \text{LTV} \leq 95$	0.025***	0.026***	0.008***	0.006***
	(0.002)	(0.002)	(0.000)	(0.000)
$95 < \text{LTV} \leq 100$	0.032***	0.034***	0.017***	0.016***
	(0.002)	(0.002)	(0.000)	(0.000)
$\text{LTV} > 100$	0.036***	0.045***	0.022***	0.019***
	(0.003)	(0.003)	(0.001)	(0.001)
FHA	0.077***	0.099***	0.064***	0.065***
	(0.001)	(0.001)	(0.000)	(0.000)
30+ days past-due in Jan 2020			-0.305***	-0.300***
			(0.010)	(0.010)
Servicer fixed effects	N	Y	N	Y
State fixed effects	Y	Y	Y	Y
N. Obs.	1,189,326	1,189,326	9,774,503	9,774,503
Adj. R^2	0.05	0.10	0.07	0.08

C.2 eMBS-CRISM sample

Table A.3: **First-stage forbearance regression: eMBS-CRISM.** Dependent variable = 1 if mortgage entered forbearance from March-November 2020. Cross-sectional linear probability regression model. eMBS-CRISM matched loan-level sample. Sample is loans that were active as of January 2020 and became past due from March-November 2020.

	(1) Forbearance | past-due	(2) Forbearance | past-due
30 $<$age $\leq$ 45	0.0157*** (0.003)	
45 $<$age $\leq$ 60	0.0129*** (0.003)	
age $>$60	-0.0278*** (0.003)	
Riskscore (Feb 2020)$^{+}$	0.000225*** (0.000)	
Ln(Consumer debt)$^{+}$	0.00522*** (0.000)	
Delinq. consumer debt^{+}	-0.00217*** (0.000)	
Other housing debt^{+}	0.00356*** (0.000)	
Delinq. other housing debt^{+}	-0.00252** (0.001)	
Credit utilization^{+}	0.0185*** (0.002)	
First Time Homebuyer	0.0244*** (0.002)	0.0294*** (0.002)
25 $<$dti $\leq$ 50	0.0481*** (0.004)	0.0566*** (0.004)
dti $>$50	0.0776*** (0.004)	0.0883*** (0.004)
Age of loan (years)	-0.0146*** (0.001)	-0.0128*** (0.001)
Age of loan (years) $\times$ Age of loan (years)	0.000148*** (0.000)	0.0000562 (0.000)
Ln(Current UPB)	0.0759*** (0.002)	0.102*** (0.001)
620 $<$orig cs $\leq$ 680	-0.00406 (0.003)	0.00728** (0.003)
680 $<$orig cs $\leq$ 740	-0.00592* (0.003)	0.0142*** (0.003)
orig cs $>$740	-0.02187*** (0.003)	0.0000*** (0.003)
Refinance	0.0191*** (0.003)	0.0188*** (0.003)
80 $<$LTV $\leq$ 95	0.0172*** (0.004)	0.0180*** (0.003)
95 $<$LTV $\leq$ 100	0.0235*** (0.004)	0.0256*** (0.003)
LTV $>$100	0.0238*** (0.005)	0.0281*** (0.004)
FHA	0.0641*** (0.002)	0.0820*** (0.002)
N	416298	421941
Servicer fixed effects	Yes	Yes
State fixed effects	No	Yes
Zipcode fixed effects	Yes	No

Standard errors in parentheses
$^{+}$ Measured as of February 2020
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Alternative measures of servicer fixed effects

Figure A.2: **P(no forbearance | COVID nonpayment) in eMBS-CRISM sample.** Cross-servicer variation in probability that a loan that became past-due during the pandemic failed to receive forbearance. Based on servicer fixed effects estimated using eMBS-CRISM data conditional on loan and borrower characteristics (e.g. bins of LTV, credit score, DTI, log of loan balance, transformations of loan age etc.). Bars are unweighted counts of servicers in each bin. Dashed vertical lines show weighted percentiles, weighted by the number of loans that became past due between March and November 2020.

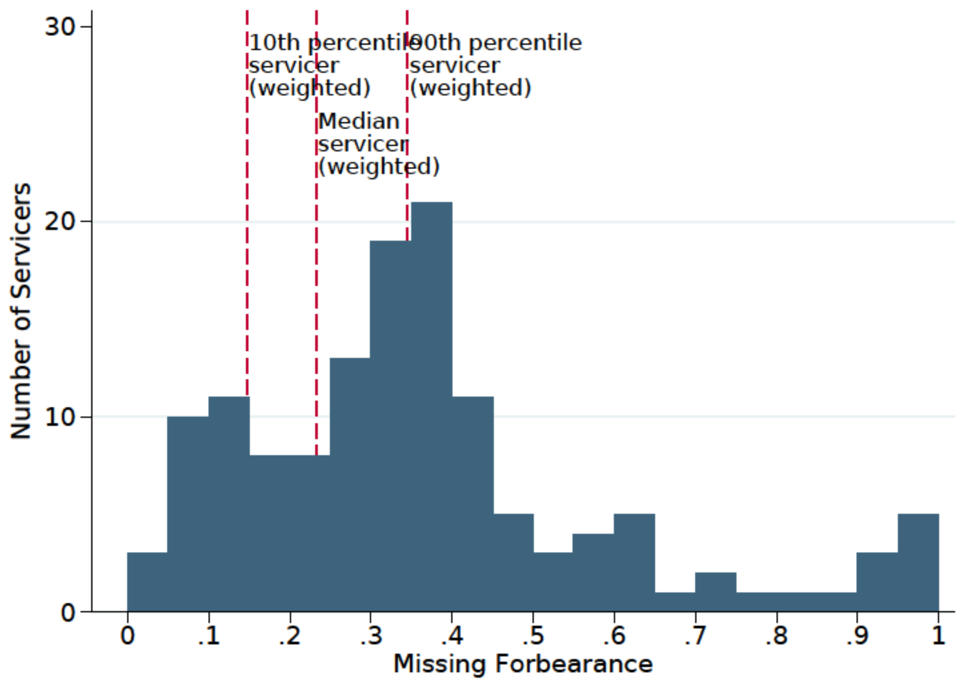
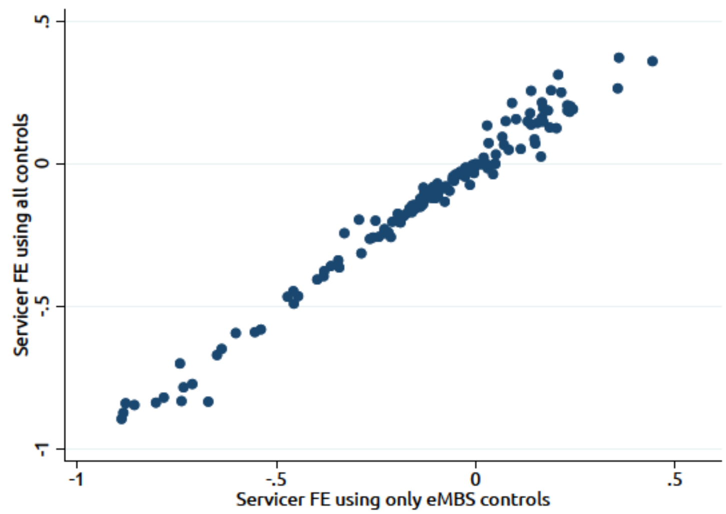
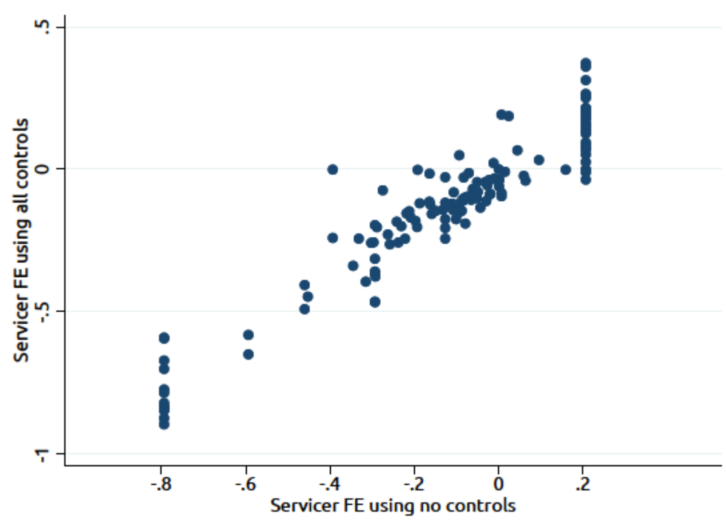


Figure A.3: **Robustness of servicer fixed effects to controls: eMBS-CRISM sample.** Panel (a) shows the correlation between servicer fixed effects estimated using borrower and servicer characteristics available only in eMBS and servicer fixed effects estimated using borrower and servicer characteristics available in CRISM. Panel (b) shows the correlation between servicer fixed effects estimated without controls and servicer fixed effects estimated using all controls available in the CRISM-eMBS merge.

(a) Servicer fixed effects estimated using all controls vs controls only available in eMBS

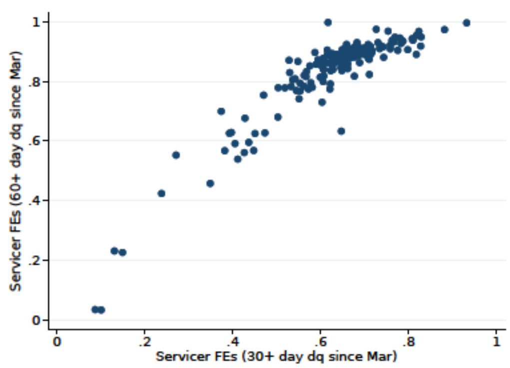


(b) Servicer fixed effects estimated using full set of eMBS-CRISM controls vs no controls

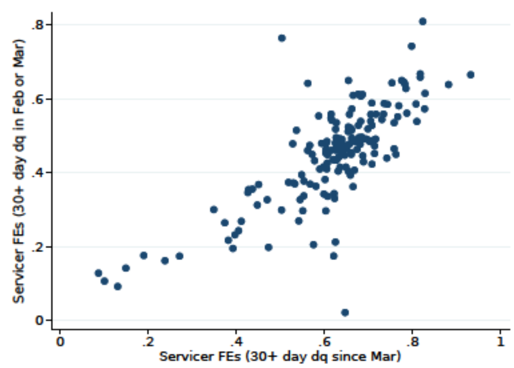


D.1 Comparison of fixed effects across approaches

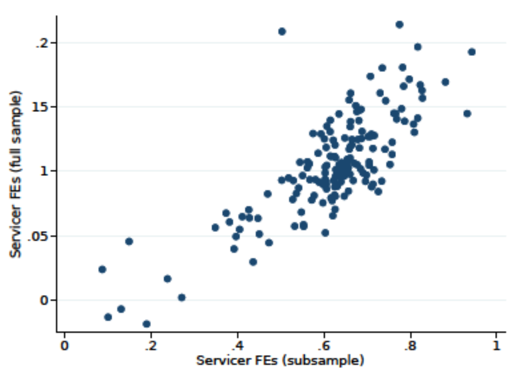
Figure A.4: **Correlation between servicer fixed effects from different specifications**: Correlations between the baseline servicer fixed effect estimates and three alternative sets of estimates, based on: (i) using the subsample of loans which became at least 60 days past due after March 2020 (panel a); (ii) using the subsample of borrowers who missed at least a payment in February or March 2020 (panel b); using the entire sample for estimation, rather than just borrowers that became past due (panel c); include lender fixed effects in the model, so that identification of servicer fixed effects is based on servicing transfers (panel d).



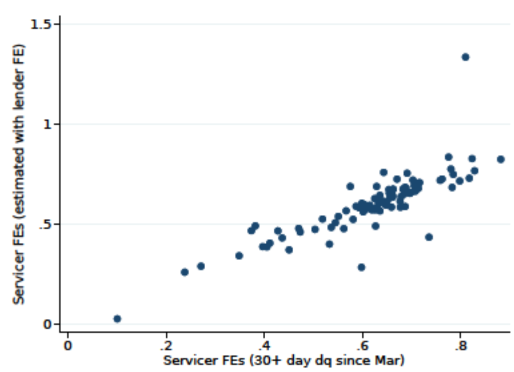
(a) 60+ day past due post-March 2020



(b) Missed payment in Feb/Mar 2020



(c) include all loans in sample



(d) include lender fixed effects

E Summary statistics: servicer-level sample

Table A.4: **Servicer level summary statistics.** Servicing assets and growth are measured using eMBS. Financial characteristics for banks and nonbank mortgage companies are measured using bank and nonbank Call reports.

(a) All servicers

	Mean	Std. dev.	Median
Servicer forbearance propensity	0.00	0.11	-0.01
Nonbank mortgage company	0.62	0.49	1.00
Credit union	0.01	0.11	0.00
log(Servicing assets)	25.63	1.63	26.07
Servicing growth	0.08	0.23	0.04
Observations	152		

(b) Nonbank mortgage companies only

	Mean	Std. dev.	Median
Servicer forbearance propensity	-0.04	0.08	-0.04
log(Servicing assets)	25.43	1.49	26.01
log(Assets)	8.86	1.59	9.71
Servicing growth	0.12	0.23	0.16
Cash / assets	0.05	0.04	0.04
Securities / assets	0.08	0.10	0.00
Capital / assets	0.21	0.09	0.19
Observations	98		

(c) Banks only

	Mean	Std. dev.	Median
Servicer forbearance propensity	0.07	0.11	0.10
log(Servicing assets)	26.03	1.75	26.60
log(Assets)	13.26	1.77	14.50
Servicing growth	0.02	0.23	-0.06
Cash / assets	0.08	0.03	0.08
Securities / assets	0.20	0.07	0.22
Capital / assets	0.12	0.02	0.12
Observations	45		

F Borrower characteristics: high-vs-low forbearance servicers

Table A.5: **Ex ante borrower characteristics across servicers: eMBS-CRISM matched sample.** Summary statistics measured as of January 2020 for high- and low-forbearance servicers using the merged eMBS-CRISM data. We define "high-forbearance" servicers as those with above-median servicer fixed effects (estimated as described in Section 4, using the merged eMBS-CRISM data).

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	184,736.49	165,272.18
Auto Loan Balance	16,103.48	15,331.09
Credit Card Balance	8,951.05	8,740.05
12-mo change CNTY UR (8/20)	6.07	5.86
FHA	0.69	0.70
FICO V5 (updated)	694.22	703.49
LTV at origination	93.94	94.28
Loan age (year)	4.50	6.01
N. Obs.	1,270,977	1,626,621

Table A.6: **Ex ante borrower characteristics across servicers by origination year: eMBS-CRISM matched sample.** Summary statistics measured as of January 2020 for high- and low-forbearance servicers using the merged eMBS-CRISM data. We define "high-forbearance" servicers as those with above-median servicer fixed effects (estimated as described in Section 4, using the merged eMBS-CRISM data).

(a) Origination year up to 2013

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	136,335.32	137,011.41
Auto Loan Balance	13,399.83	13,955.28
Credit Card Balance	9,167.34	8,856.06
12-mo change CNTY UR (8/20)	6.16	5.87
FHA	0.83	0.77
FICO V5 (updated)	711.80	707.34
LTV at origination	93.66	93.67
Loan age (year)	8.52	8.66
N. Obs.	350,093	741,283

(b) Origination year from 2014 to 2017

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	185,845.28	180,704.64
Auto Loan Balance	16,547.14	16,564.76
Credit Card Balance	9,320.18	8,996.56
12-mo change CNTY UR (8/20)	6.11	5.88
FHA	0.71	0.68
FICO V5 (updated)	696.65	702.02
LTV at origination	93.92	94.92
Loan age (year)	4.62	4.79
N. Obs.	363,104	553,867

(c) Origination year since 2018

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	221,930.34	209,119.38
Auto Loan Balance	17,511.62	16,346.45
Credit Card Balance	8,574.99	8,052.02
12-mo change CNTY UR (8/20)	5.98	5.81
FHA	0.59	0.59
FICO V5 (updated)	681.59	697.33
LTV at origination	94.11	94.58
Loan age (year)	1.90	2.12
N. Obs.	557,780	331,471

Table A.7: **Ex ante borrower characteristics across servicers by origination year: eMBS sample** Summary statistics measured as of January 2020 for high- and low-forbearance servicers using the eMBS sample. We define "high-forbearance" servicers as those with above-median servicer fixed effects (estimated as described in Section 4, using the eMBS sample).

(a) Origination year up to 2013

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	114,464.79	118,119.20
12-mo change CNTY UR (8/20)	5.95	5.91
FHA	0.80	0.77
Orig credit score	699.49	705.85
Orig LTV (%)	92.62	92.67
Loan age (year)	10.26	10.11
N. Obs.	1,039,878	1,893,974

(b) Origination year from 2014 to 2017

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	178,017.12	175,241.83
12-mo change CNTY UR (8/20)	6.09	5.87
FHA	0.69	0.61
Orig credit score	690.85	702.36
Orig LTV (%)	93.38	93.06
Loan age (year)	4.62	4.71
N. Obs.	1,150,984	1,200,757

(c) Origination year since 2018

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	216,955.67	203,721.30
12-mo change CNTY UR (8/20)	6.15	5.77
FHA	0.69	0.58
Orig credit score	683.56	696.60
Orig LTV (%)	94.56	93.46
Loan age (year)	2.05	2.12
N. Obs.	1,843,638	1,326,624

Table A.8: **Characteristics of borrowers in forbearance: high vs low forbearance servicers.** Summary statistics measured as of January 2020 for borrowers that were ever in forbearance, for high- vs low-forbearance servicers based on the merged eMBS-CRISM data.

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Months in forbearance (as of Nov 2020)	5.73	6.60
Ever exited from forebarance	0.35	0.31
Current Mortgage Balance	196,713.93	172,327.63
Auto Loan Balance	18,242.10	17,765.52
Credit Card Balance	10,841.62	11,487.21
12-mo change CNTY UR (8/20)	6.61	6.36
FHA	0.83	0.82
FICO V5 (updated)	648.79	663.06
LTV at origination	94.22	94.77
Loan age (year)	3.89	5.60
N. Obs.	140,001	237,422

G Pre-CARES Act loan performance by servicer type

Figure A.5: **Transition probability to 30-day delinquency: high vs low forbearance servicers.** Difference in monthly transition probability from current to past due between borrowers matched to high-forbearance vs low-forbearance servicers (estimates of coefficients from Equation 2), estimated using the eMBS-CRISM sample. y-axis indicates the fraction of newly past due mortgages, defined as loans that are past due in month t but current in month t-1. Specification includes same borrower and loan controls as our main eMBS-CRISM specification (reported in table A.2). Standard errors are clustered by servicer.

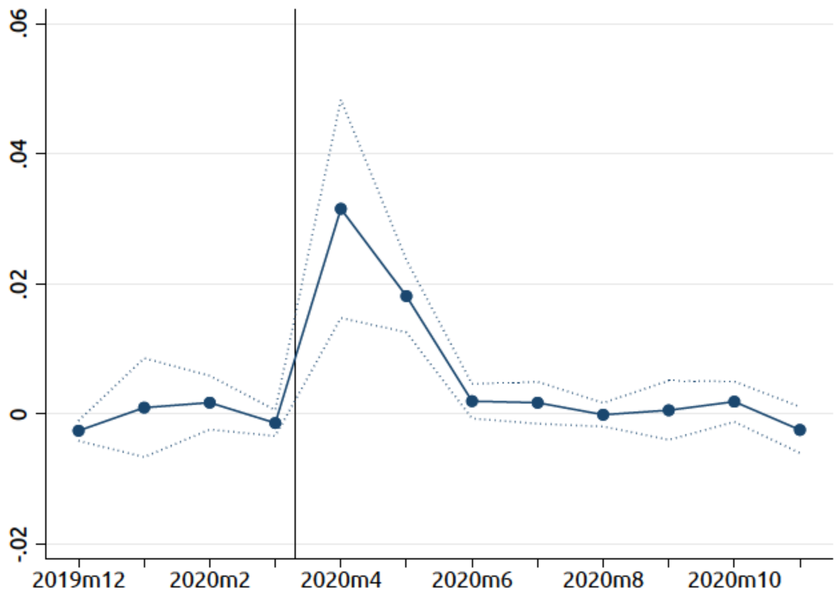


Table A.9: **Pre-CARES Act loan performance.** Relationship between high-forbearance servicer dummy and various measures of loan delinquency in the period prior to the passage of the CARES Act. eMBS data from December 2019 and January 2020 are used for the estimates in table (a), and the matched eMBS-CRISM data from December 2019 and January 2020 are used for the estimates in tables (b), (c), and (d). Dependent variable for tables (a) and (b) is the dummy variable for transitioning from current to 30+ days delinquent for the mortgage. Dependent variables for tables (c) and (d) are whether a borrower has a delinquent credit card and auto loan account, respectively. eMBS controls include the dummy for FHA loans, loan size, dummy for first-time homebuyer, LTV, credit score, DTI, and dummy for purchase loans. CRISM controls include updated credit scores and a borrower's age. Standard errors clustered at the servicer level.

(a) New 30-day mortgage delinquencies (eMBS only)

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.0027**	-0.0016***	-0.0015***	-0.0016***
	(0.0013)	(0.0005)	(0.0005)	(0.0005)
eMBS controls		Y	Y	Y
State FE		Y		
Orig Year-Month FE		Y		
FHA x State x Orig Year-Month FE			Y	
Nonbank x FHA x State x Orig Year-Month FE				Y
Sample mean	0.013	0.013	0.013	0.013
N. Obs.	22,010,182	20,180,908	20,180,907	20,180,906

(b) New 30-day mortgage delinquencies (eMBS-CRISM match)

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.0027	-0.0009	-0.0005	-0.0005
	(0.0029)	(0.0019)	(0.0017)	(0.0016)
eMBS controls		Y	Y	Y
CRISM controls			Y	Y
Zipcode FE		Y	Y	
Orig Year-Month FE		Y	Y	
FHA x Zipcode x Orig Year-Month FE				Y
Sample mean	0.014	0.014	0.014	0.014
N. Obs.	6,117,275	5,748,527	5,741,020	5,732,113

(c) Credit card delinquencies (eMBS-CRISM match)

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.0077	-0.0018	0.0023*	0.0025**
	(0.0082)	(0.0029)	(0.0013)	(0.0010)
eMBS controls		Y	Y	Y
CRISM controls			Y	Y
Zipcode FE		Y	Y	
Orig Year-Month FE		Y	Y	
FHA x Zipcode x Orig Year-Month FE				Y
Sample mean	0.100	0.100	0.100	0.100
N. Obs.	6,136,120	5,748,577	5,741,070	5,732,164

(d) Auto loan delinquencies (eMBS-CRISM match)

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.0056	-0.0024**	-0.0011**	-0.0009
	(0.0034)	(0.0011)	(0.0005)	(0.0005)
eMBS controls		Y	Y	Y
CRISM controls			Y	Y
Zipcode FE		Y	Y	
Orig Year-Month FE		Y	Y	
FHA x Zipcode x Orig Year-Month FE				Y
Sample mean	0.032	0.032	0.032	0.032
N. Obs.	6,136,120	5,748,577	5,741,070	5,732,164

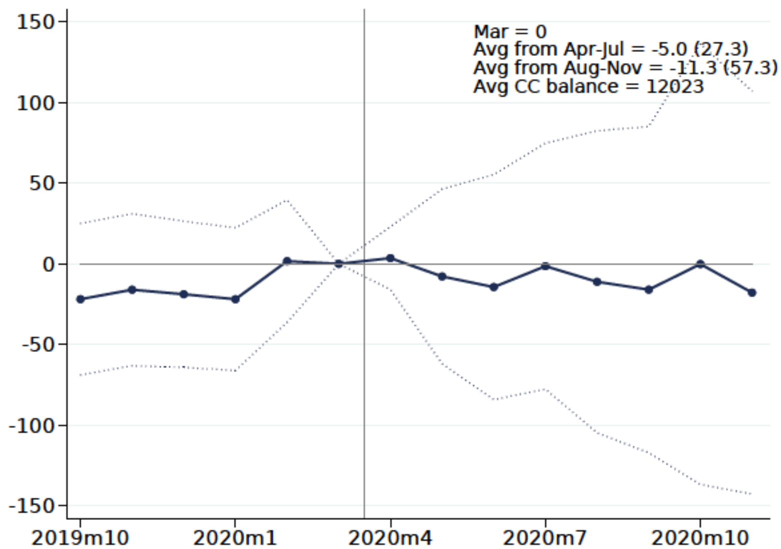
H Additional non-mortgage results

Table A.10: **Non-mortgage results.** Estimates of the average effect of assignment to a high-forbearance servicer on various nonmortgage outcomes measured in CRISM. Estimates reported in columns (1), (3) and (5) are the average coefficient on the high-forbearance-servicer $\times$ time dummies (estimates of β_t from equation 2) over three phases of the pandemic: a pre-pandemic period (October 2019-February 2020); early pandemic (April-July 2020) and later pandemic (August-November 2020), along with the associated standard error of each mean. For context, columns (2), (4) and (6) report the unconditional mean of the dependent variable at low-forbearance servicers during the period referenced. For outcome variables related to auto loans, we report "NA" during the early pandemic period because the CRISM data on auto loans for the period contains significant reporting error. Standard errors are clustered at the servicer level.

	Pre-pandemic		Pandemic			
	2019:m10-2020:m2		2020:m4 to 2020:m7		2020:m8 to 2020:m11	
	(1) Coeff.	(2) Mean	(3) Coeff.	(4) Mean	(5) Coeff.	(6) Mean
Log of auto loan balance	0.000061	6.304	NA	6.055	0.002225	6.165
	(0.003665)				(0.006727)	
Log of other consumer loan balance	0.001	3.476	0.000	3.389	0.004	3.360
	(0.003)		(0.002)		(0.005)	
Transition to delinquency (credit card)	-0.00001	0.012	0.00014	0.008	0.00014	0.007
	(0.00010)		(0.00022)		(0.00028)	
Transition to delinquency (auto loan)	-0.000144*	0.004	NA	0.004	0.000026	0.004
	(0.000077)				(0.000062)	
Transition to delinquency (other consumer loan)	-0.00003	0.004	-0.00001	0.003	0.00001	0.003
	(0.00006)		(0.00009)		(0.00008)	
Mortgage prepayment	0.0003	0.013	0.0004	0.019	-0.0001	0.023
	(0.0004)		(0.0005)		(0.0009)	
Auto loan origination	0.000391	0.018	NA	0.030	-0.000061	0.023
	(0.000344)				(0.000308)	
Bankruptcy	0.000047	0.004	0.000030	0.004	-0.000047	0.004
	(0.000075)		(0.000039)		(0.000105)	

Figure A.6: **Effects of forbearance availability on credit card balances.** Estimates and 95% confidence intervals of the effects of assignment to a high-forbearance servicer on credit card debt levels for borrowers with above- and below-median credit card utilization. Utilization is measured over the period from October 2019 to March 2020; the median average utilization is calculated for each cohort of borrowers with the same mortgage origination year. Estimated using the eMBS-CRISM matched sample. Standard errors are clustered at the servicer level.

(a) High-credit-card-utilization borrowers ($)



(b) Low-credit-card-utilization borrowers ($)

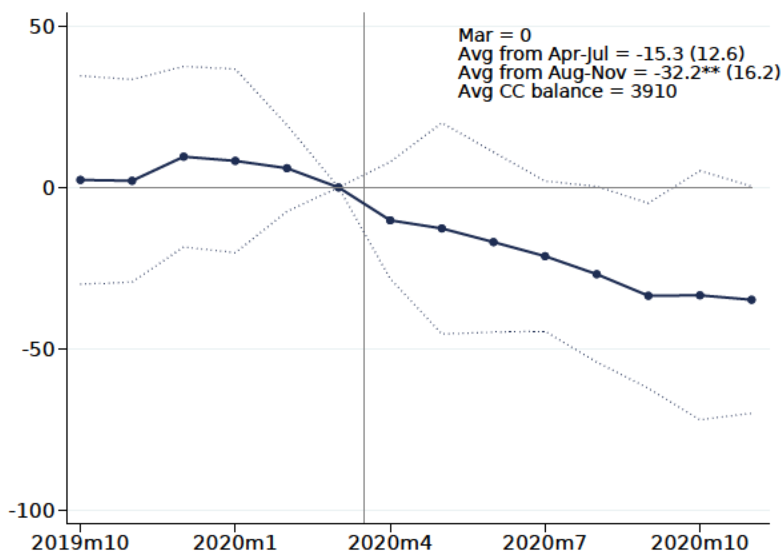


Figure A.7: **Deferred mortgage payments.** Estimates of effect of assignment to a high-forbearance servicer on cumulative deferred mortgage payments. Estimated as coefficients from Equation 2 in a model where the dependent variable measures total cumulative borrowing through forbearance: the number of missed payments times the monthly mortgage payment inclusive of taxes and insurance. We assume that taxes and insurance sum to equal 30% of the principal and interest payment, the average among FHA loans. This is an approximation, as we cannot directly observe whether borrowers make partial payments or continue to pay taxes and insurance. The coefficients can be interpreted as the average difference in cumulative deferred payments among borrowers at high- vs. low servicers. We assume that loans that exit forbearance do not immediately repay their deferred balances; we do not directly observe borrowers' repayment plans.