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

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Abstract

We study the role of mortgage servicers in implementing the CARES Act mortgage forbearance program during the COVID-19 pandemic. Despite universal eligibility, around one-third of the nonperforming federally-backed loans in our sample fail to enter into forbearance. The relative frequency of these "missing" forbearances varies significantly across servicers for observably similar loans, with small servicers and nonbanks, and especially nonbanks with small liquidity buffers, having a lower propensity to provide forbearance. The incidence of forbearance-related complaints by borrowers is also higher for these servicers. We also use servicer-level variation to estimate the causal effect of forbearance on borrower outcomes. Assignment to a "high-forbearance" servicer translates to a significant increase in the probability of nonpayment, which moves essentially 1:1 with the forbearance probability. Part of this additional household liquidity is used to pay down high-cost credit card debt.

Keywords: mortgage, forbearance, debt relief, CARES Act, COVID-19, liquidity

JEL classification: G21, G23, G28

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1 Introduction

Financial intermediaries often play an important role in the transmission of public policy, particularly in the case of debt relief and emergency lending programs. But misaligned incentives or other frictions may prevent policies from being implemented "on the ground" as intended.[1]

In this paper we study the role of a particular type of intermediary — mortgage *servicers* — in implementing a large new government debt relief program providing forbearance to mortgage borrowers during the COVID-19 pandemic. We find that servicers significantly affect forbearance outcomes and the amount of liquidity ultimately provided to borrowers, and that variation in servicer behavior is systematically related to servicer liquidity constraints, size and organizational form.

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

Despite this universal eligibility, we document that a significant number of federally backed mortgage borrowers became delinquent during the pandemic without successfully entering into forbearance, and that the relative frequency of these "missing" forbearances varies significantly across mortgage servicers for otherwise identical loans. Our analysis focuses on Federal Housing Administration (FHA) and Veterans Administration (VA) mortgages, 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. Using loan-level data from eMBS we estimate that the probability of not receiv-

[1] Examples include loans to businesses 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).

ing forbearance conditional on delinquency varies between 10% and 60% controlling for loan and borrower characteristics, with a weighted interquartile range of 15 percentage points. Several pieces of evidence indicate that this variation reflects servicer behavior rather than unobserved loan and borrower heterogeneity.

We then investigate sources of these cross-servicer differences, and what they tell us about the role of servicer incentives and other frictions. We find that smaller servicers, nonbanks, and in particular nonbanks with low cash buffers at the start of the pandemic, are less likely to provide forbearance to borrowers. These findings indicate that scale economies and liquidity constraints, among other economic forces, were important in shaping servicer behavior. For example, mortgage nonpayment presents a source of significant liquidity risk because the servicer of an FHA or VA loan is required to finance payments to investors while borrowers are nonperforming — this liquidity risk is most significant for nonbanks without access to government backstops and insured deposits.

Given that past-due FHA and VA borrowers would have universally benefited from forbearance, servicer practices that limit forbearance uptake also result in lower borrower welfare. We also find direct evidence that borrowers are less satisfied with "low-forbearance" servicers, based on the incidence of borrower complaints related to mortgage forbearance submitted to the Consumer Financial Protection Bureau (CFPB).

In the second half of paper, we use variation in servicers' forbearance practices to identify the causal effect of forbearance on borrower outcomes. We sort servicers into high (above median) and low (below median) forbearance-availability groups based on the likelihood a delinquent loan received forbearance conditional on loan and borrower characteristics. Then we compare borrower-level outcomes at high- and low-availability servicers before and after the CARES Act in a difference-in-differences framework using dynamic mortgage data linked to borrower credit reports.

Our first finding is that forbearance causes mortgage nonpayment. The probability that a borrower is past-due is significantly higher for borrowers at high-forbearance servicers, by as much as 5 percentage points at the peak of the forbearance wave in May 2020. This difference in the past-due probability between high- and low-availability servicers is almost identical to the difference in the forbearance rate between the two groups of servicers, implying that essentially all of the additional forbearance induced by high-forbearance servicers results in borrower nonpayment. As a result, assignment to a high-forbearance servicer significantly increases household cash flows during the pandemic.

We then examine how borrowers use the additional cash made available through forbearance by examining borrowers' non-mortgage debt accounts. We find that borrowers with below-median credit card balances at high-forbearance servicers reduced their credit card balances by around \$20 relative to borrowers at low-availability servicers, equivalent to a treatment effect of \$400 per additional forbearance. This credit card paydown is about one-quarter of the average forbearance-driven savings in mortgage payments for borrowers at high-forbearance servicers. In contrast, there is no paydown of credit card debt for borrowers with above-median credit card debt, who may be more liquidity constrained and therefore more likely to use the additional funds for consumption. Although borrowers at high-forbearance servicers are more likely to miss mortgage payments, their credit scores did not decrease as a result, because nonpayment during forbearance is not reported to the credit bureaus. The causal effect of forbearance on credit scores is close to zero.

Our findings suggest that policies that reduce frictions from servicers could benefit borrowers by increasing access to forbearance and reducing variation in borrower outcomes that is unrelated to borrower fundamentals. For example, one possibility would be auto-enrolment in forbearance for borrowers drawing unemployment insurance or those that become seriously delinquent after being current prior to the pandemic.[2]

[2] By way of contrast to the mortgage forbearance program, CARES act student loan forbearance auto-enrolled all federal student loan borrowers.

1.1 Related literature

Our paper contributes to a growing body of research on forbearance during the COVID pandemic. Related work includes Cherry et al. (2021), An et al. (2021) and Zhao et al. (2020). This literature establishes that forbearance is significantly related to borrower characteristics and the depth of the economic shock posed by the onset of COVID-19, that borrowers experiencing income declines were more likely to enter into forbearance (Zhao et al., 2020) and that forbearance reduced inequality (An et al., 2021). Like us, these papers also document that a significant number of delinquent borrowers did not successfully enter into forbearance. Cherry et al. (2021) also find that non-banks offer forbearance at lower rates, studying variation in outcomes across large servicers for prime mortgages securitized through Fannie Mae.

We also contribute to a broader body of research studying financial frictions and incentives facing mortgage intermediaries, much of which studies the Great Recession and its aftermath. For example Agarwal et al. (2011) and Kruger (2018) find evidence that servicers were more likely to modify mortgages retained in their own portfolios compared to loans serviced for other investors and that servicers offered HAMP modifications at different rates due to variation in organizational structure and incentives (Agarwal et al., 2017a). Aiello (2021) finds evidence that financial constraints facing mortgage servicers significantly reduced their propensity to work out delinquent mortgages during the Great Recession.

Our research is also related to research showing that intermediary effects were important for the implementation of other types of relief provided during the COVID pandemic, for example Granja et al. (2020) which studies the Paycheck Protection Program.

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.[3,4] While in forbearance, borrowers can skip their mortgage payments without accruing unscheduled interest, late fees or penalties, or risking foreclosure. Missed payments are also not reported to credit bureaus and therefore do not affect the borrower's credit score.[5]

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 needs to *attest* to a hardship — no documentation or other proof of income loss is required. Forbearance is not automatic however, the borrower must request it from their servicer.

The CARES Act is silent about what should occur at the end of the forbearance period. In the weeks after the passage of the Act, however, regulators and the mortgage agencies stated that a range of options would be available, and borrowers would not be required to repay missed payments in a lump sum (e.g., Freddie Mac, 2020). In April 2020, the FHA announced a National Emergency Partial Claim program, under which most borrowers that re-perform after exiting forbearance can transfer accumulated missed payments into a subordinate interest-free note which is not due until the termination of the mortgage

[3]The CARES Act applies directly to "agency" mortgages backed by Fannie Mae, Freddie Mac, the FHA, VA, and other federal agencies, which together make up about 70% of US mortgage debt. Many nonagency borrowers have still been able to obtain forbearance from their servicers, although Cherry et al. (2021) find that forbearance rates are about 25% lower outside of the federally-backed market, by examining loans on either side of the conforming loan limit.

[4]The CARES 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).

[5]The CARES Act permits an initial forbearance of up to six months but servicers have more typically granted forbearance in three month increments, requiring the borrower to renew more frequently. An industry practitioner told us this reflects prior historical practice, when forbearance has primarily been used as a short-term disaster-relief tool.

through a property sale, refinancing or payoff (Department of Housing and Urban Development, 2020a,b).[6] Fannie Mae and Freddie Mac announced a similar payment deferral option in May (Federal Housing Finance Agency, 2020). Since missed payments do not accrue interest, deferral effectively provides a zero-interest loan to the borrower.

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

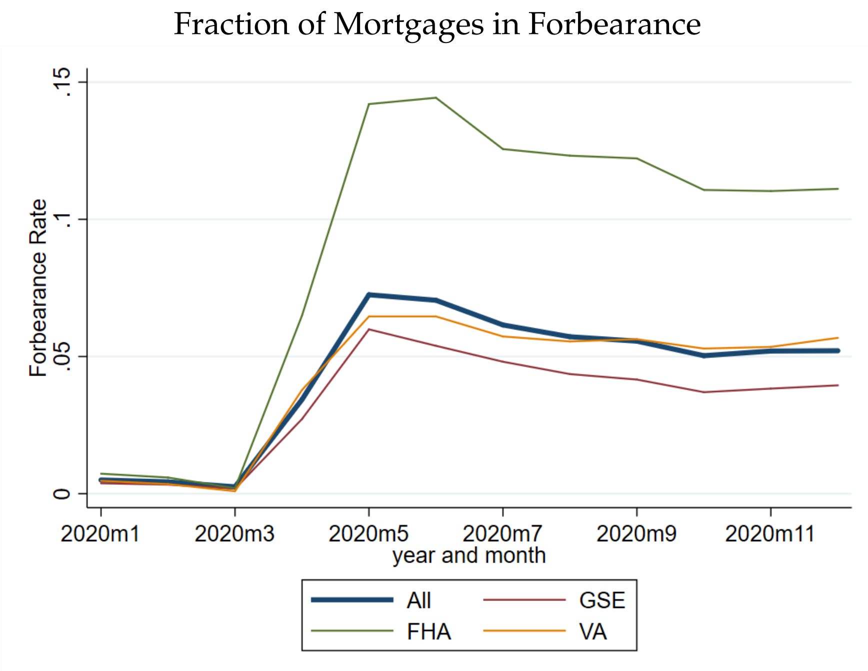
The analysis in this paper focuses on the $2 trillion of "government" mortgages insured by the FHA and VA. This segment of the mortgage market is of particular interest because it disproportionately serves low-income and high-risk borrowers, and because FHA loans in particular have a much higher forbearance and delinquency rate than the market as a whole. It is also the segment where intermediation frictions are likely to be most severe, because FHA loans present significant additional risks to mortgage servicers compared to other types of loans (see section 2.3).

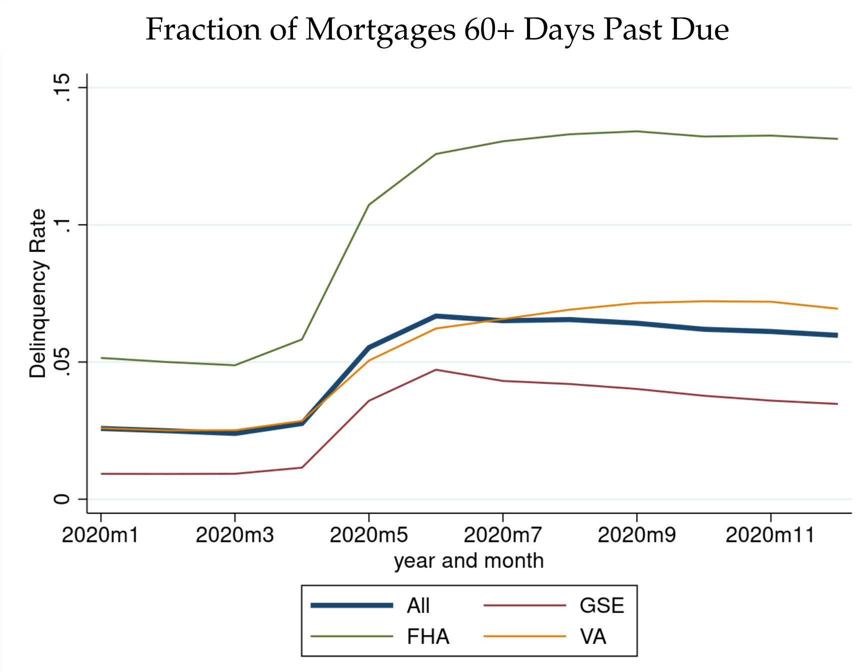
2.1 Forbearance trends

Figure 1 traces out the evolution of forbearance and delinquency over 2020. The top panel, which is based on credit bureau data, shows that forbearance was rare prior to the pandemic but increased sharply starting in April, just after the CARES Act is enacted. The aggregate forbearance rate peaked in May at 7.3 percent, and then declined slowly

[6] Moreover, the FHA requires servicers to evaluate all borrowers for this option, known as a "partial claim", prior to the end of the forbearance period. Loans are eligible for the partial claim if i) the mortgage was current or <30 days delinquent as of March 1 2020, ii) the property is owner occupied, and iii) the borrower indicates they have the ability to resume making on-time payments. For loans not eligible for a partial claim, the FHA instructs servicers to evaluate the borrower for loan mitigation options involving loan modification. See Department of Housing and Urban Development (2020a) for more details.

Figure 1: Forbearance Rate and Delinquency Rate Over 2020





Data sources: Author calculations from Federal Reserve Bank of New York (FRBNY) Consumer Credit Panel / Equifax data (top panel) and Black Knight McDash (bottom panel).

over the remainder of 2020 (to 5.2 percent as of December).[7] Delinquency, as measured by 60+ days past due (bottom panel) follows a similar shape.[8] At an individual level however, not all delinquent borrowers entered forbearance, and conversely some borrowers in forbearance continued making some or all of their scheduled mortgage payments.[9]

Forbearance and delinquency is much higher in the FHA segment than the overall market. This reflects the relatively low- and middle-income FHA borrower population and the high share of first-time homebuyers. VA mortgages have a forbearance and delinquency rate path similar to the market as a whole, while forbearance and nonpayment is relatively low for the typically prime mortgages securitized by the government sponsored enterprises (GSEs) Fannie Mae and Freddie Mac.[10]

2.2 Forbearance implementation and the role of servicers

The mortgage servicers that implemented the CARES Act forbearance programs on the ground vary widely in terms of size, regulation, funding, profitability and other characteristics. One might assume that servicers play a limited and passive role, given the essentially universal eligiblity for forbearance among agency borrowers and lack of documentation requirements. In practice however, borrowers and regulators report a wide range of servicer-related issues, including misinformation, processing errors, and communication difficulties, suggesting that servicer practices may indeed vary substantially. Because borrowers cannot choose their servicer, variations in servicer practice may sig-

[7] Other data sources paint a similar picture. Survey data from the Mortgage Banker's Association indicates a peak forbearance rate of 8.55% in June 2020 (Mortgage Bankers Association, 2020), while Black Knight estimates a peak forbearance rate of 8.8%, also in June (Black Knight, 2020).

[8] We use the term delinquency as shorthand for mortgages that are past due. Formally though, a borrower who misses payments while in forbearance is not delinquent on their payment obligations.

[9] We also include a plot of delinquency measured instead by 30+ days past due in the Internet Appendix.

[10] Statistics for the market as a whole include the three segments shown separately (which together comprise the agency mortgage market), as well as mortgages held in portfolio by banks and other investors and loans securitized through the private-label market. Fannie Mae and Freddie Mac are combined in the figure because their mortgage portfolios have similar characteristics and loan performance.

nificantly affect borrower outcomes.

Consumer Financial Protection Bureau (2021a) presents systematic qualitative evidence regarding issues with servicers based on the observations of Consumer Financial Protection Bureau (CFPB) supervisors. The report highlights the logistical challenges faced by servicers, stating that *"Many servicers reported operational constraints, resource burdens, and service interruptions. Many servicers also moved employees from other duties to respond to forbearance requests."* It also documents a range of deficient practices by servicers including:

i.) Providing incomplete or inaccurate information, such as telling consumers that only delinquent borrowers qualify for forbearance, that a fee must be paid to obtain forbearance, or that a lump-sum repayment is required at the end of forbearance;

ii.) Incorrectly sending collection or default notices, assessing fees, or initiating foreclosures for borrowers in forbearance;

iii.) Changing borrowers' preauthorized funds transfers without their consent, or failing to implement the borrowers' instructions to freeze payments;

iv.) Failure to process forbearance requests in a timely manner;

v.) Enrolling borrowers in automatic or unwanted forbearance;

vi.) Failure to enroll borrowers in an appropriate post-forbearance plan.

Consumer Financial Protection Bureau (2021b) tabulates data from the CFPB's complaints database, finding that forbearance complaints rose from fewer than 100 per month in January and February of 2020 to a peak of over 500 in April, and a level between 300-500 per month over the rest of 2020 and early 2021. Complaints most commonly relate to problems contacting or communicating with servicers, confusing or incomplete information about post-forbearance options, misleading or incorrect information about loan balance or performance reported on the borrower's monthly statements, and delays and denials in putting the borrower in a post-forbearance repayment plan.[11]

Media reports highlight many of the same issues. For instance Wall Street Journal (2020) describes how the wave of forbearance requests early in the pandemic overwhelmed many servicers' capacity, leading to extremely long telephone hold times, non-operational servicer websites, and misinformation to borrowers.

Not all borrowers experienced problems, however, and 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. We have also heard numerous anecdotes from practitioners about servicers that have engaged proactively with borrowers to explain forbearance and make them aware of their options (e.g., one large servicer contacts delinquent borrowers not in forbearance at a daily frequency). Taken together, the qualitative evidence suggests there has been a wide range of servicer practices, which in turn could lead to significant variation in borrower outcomes.

2.3 The role of servicer characteristics

We now discuss factors relating to financial constraints, regulation and organizational form that may lead to systematic variation in forbearance practices and outcomes across servicers. We study the importance of these different factors empirically in section 5.

1. Liquidity constraints. Mortgage servicers are required to temporarily advance scheduled payments on delinquent mortgages to investors and other parties, including

[11] To give a sense of the issues, the following are three complaints available in 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 "."*

principal, interest, taxes and insurance. Servicers facing more binding liquidity constraints may therefore wish to discourage borrowers from entering forbearance, if forbearance then induces borrowers to pause their payments.[12]

Servicer liquidity risk also varies across mortgages, in part because rules about servicing advances depend on the loan program and the servicing agreement with the investor. FHA mortgages typically present higher risk, because borrowers are much more likely to become delinquent, because the servicer is generally required to forward payments until loan termination or modification, and because FHA servicers face significant delays before being reimbursed for payment shortfalls (Kim et al., 2018).[13] Servicing advances for GSE mortgages are typically limited to four months of missed payments.

2. Regulation and legal risk. Mortgage servicers face stricter regulation and supervisory oversight as well as higher legal risk in the wake of the Great Recession.[14] This legal and regulatory risk is likely to be particularly salient for large banks, who face the toughest regulatory scrutiny and who were subject to the largest post-crisis legal settlements (Buchak et al., 2018). It therefore seems plausible that legal and regulatory risk could induce these servicers to adopt more "borrower-friendly" practices, by making forbearance easier to obtain.[15]

3. Capitalization and risk-shifting. Decisions about servicing practices involve a trade-off between risk and reward. Actions such as enabling easy access to forbearance,

[12]To emphasize this point, it is *nonpayment* rather than forbearance per se that creates a liquidity drain on the servicer's resources. Although the two do not necessarily go hand-in-hand (e.g., a significant number of borrowers in forbearance continued to make their mortgage payments), we later present evidence that making forbearance easier to obtain does in fact causally lead to higher nonpayment, almost one-to-one.

[13]Mitigating these risks, the FHA determined that CARES loans that re-perform after exiting forbearance can be made current by issuing a partial claim, as we have discussed, reimbursing the servicer for principal and interest advances during forbearance. Ginnie Mae also created a temporary liquidity facility for servicers, albeit with a high funding rate.

[14]Additional post-crisis regulation includes national mortgage servicing standards, higher bank capital requirements on servicing rights, and supervisory oversight from a new regulatory agency, the Consumer Financial Protection Bureau (CFPB). Legal risk is also much more salient, since banks were forced to pay out very large post-crisis legal settlements due to deficient servicing practices.

[15]Fuster et al. (2021) find that tighter regulatory oversight leads to more consumer-friendly servicing practices, using a cutoff rule in which banks are subject to CFPB supervision and enforcement.

or investing heavily in servicing technology or staff training, are likely to be costly in the short run but may reduce the likelihood of future regulatory or legal action and also perhaps improve customer satisfaction and retention. Undercapitalized servicers may thus have weaker incentives to provide high-quality servicing, in line with the classic risk-shifting hypothesis of Jensen and Meckling (1976).

4. Size and scale. Organizational form may also be a key driver of servicer practices. For example, large servicers may enjoy scale economies (e.g., due to fixed costs) that allow them to set up more sophisticated forbearance management systems. Or conversely, small, nimble servicers may be able to adjust their practices more quickly than large organizations with several layers of management.[16]

5. Technology and operational effectiveness. Servicers vary in terms of their prior investments in technology and human capital, such as the quality of information systems and the servicer's web portal, the extent to which servicing tasks are automated, the quality of risk measurement systems to identify defects and fraud, and the qualifications and training of servicing staff.[17] These prior investments may have improved servicers' ability to quickly and effectively implement large-scale forbearance.

3 Data and summary statistics

Our analysis combines loan-level data on mortgage characteristics and performance, FHA forbearance records, and regulatory data on the characteristics and financial condition of mortgage servicers. For the each of the two main stages of our analysis, we compile a different dataset, which we describe briefly here. Additional details on each of the data

[16] In a related context, papers such as Berger et al. (2005) find systematic differences in lending behavior between small and large banks, which they interpret as being due to differences in organizational form.

[17] Fuster et al. (2019) find that FHA mortgages originated by technology-based lenders have lower default rates, even controlling for detailed loan characteristics. This may be due to differences in underwriting practices, but could also in part reflect servicing behavior.

sources can be found in Appendix Section A.

For the first stage of the analysis (Section 5), we merge loan-level performance data with servicer characteristics. We draw the identity of each loan's servicer as well as origination characteristics and ongoing payment performance for loan securitized into Ginnie Mae MBS from eMBS. We append information on each loan's forbearance status and forbearance terms from Ginnie Mae's forbearance register. For independent mortgage banks ("nonbanks") we draw servicer characteristics from the mortgage call report (MCR) collected by the Conference of State Bank Supervisors. For banks, we draw servicer characteristics from Y-9C and call reports. Additionally, because eMBS data are comprehensive, we calculate some servicer characteristics for both banks and nonbanks (such as growth through servicing transfers and measures of servicing volume) using the eMBS data. To evaluate the relationship between borrowers' experience and servicing policy (Section 5.1), we merge in data from the CFPB complaints database at the servicer level. For each complaint, these data allow us to identify the categorical reason for the complaint (e.g., forbearance), the type of the loan the borrower has (FHA, VA, GSE, etc.), and the servicer's name. We summarize these complaints at the servicer level.

For the second stage of the analysis (Section 6), we match loan-level eMBS data with loan-level data from Black Knight McDash and the Equifax Credit Risk Insight Servicing and McDash (CRISM) dataset. From eMBS, we draw the loan's forbearance status and a de-identified servicer id. Due to data use restrictions, we cannot merge servicer characteristics, including nonbank status, into the CRISM data. From the CRISM data, we draw payment behavior, updated credit scores, geographic data, and additional information about the borrower's balance sheet. For more detail on the mechanics of this match, see Appendix Section A.1.

3.1 Summary statistics

Table 1 presents summary statistics for the eMBS loan-level sample, which reflects the population of FHA and VA loans in Ginnie Mae securities as of February 2020. The dataset includes 10.3 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 disproportionately low-income, high-risk FHA borrower population.

Table 1: Summary Statistics

	(1) FHA	(2) VA	(3) Total
A. Loan characteristics:			
Current UPB ($000)	151,499.61	209,059.04	168,647.51
Orig LTV (%)	92.93	94.63	93.40
Orig DTI (%)	41.11	38.48	40.26
Orig credit score	682.00	714.81	692.65
Loan age (year)	5.39	3.95	4.93
30+ days delinquent in Feb 2020	0.06	0.03	0.05
60+ days delinquent in Feb 2020	0.02	0.01	0.02
B. Forbearance & delinquency: March-November 2020:			
Ever 30+ days delinquent	0.22	0.11	0.19
Ever 60+ days delinquent	0.15	0.08	0.13
Ever paid off	0.17	0.30	0.21
Ever in forbearance	0.17	0.08	0.14
C. Conditional forbearance & delinquency rates:			
Forbearance | delinquency (for loans current in Feb 2020):			
Ever in forbearance among loans ever 30+ days DQ	0.75	0.70	0.74
Ever in forbearance among loans ever 60+ days DQ	0.92	0.88	0.91
Delinquency | forbearance (for loans current in Feb 2020):			
Ever in 30+ days in DQ among borrowers ever in forbearance	0.85	0.84	0.85
Ever in 60+ days in DQ among borrowers ever in forbearance	0.71	0.72	0.72
N. Obs.	7,044,172	3,270,949	10,315,121

About 5% of loans were at least 30 days delinquent just before the onset of the pandemic. Nonpayment then increased sharply, with 19% of loans being 30 days or more delinquent at some point between March and November 2020 (22% of FHA loans and 11% of VA loans). 17% of FHA loans entered forbearance at some point between March and November, compared to 8% of VA loans. 21% of loans were paid off between March and November, primarily reflecting refinancing due to low mortgage interest rates.

Panel C of table 1 reports conditional forbearance and delinquency statistics for loans that were current as of February 2020. The table shows that 26% of FHA and VA loans that became delinquent during the pandemic did not enter into a forbearance plan. This fraction is significantly smaller – 9% – for loans that experienced serious delinquency (60+ days past due), but still well above zero. These facts are in some sense surprising given that any FHA or VA borrower that became distressed due to the effects of the pandemic was eligible for forbearance, and given that forbearance effectively provides a subsidy to the borrower. Conversely, 15% of borrowers remained current on their payments despite entering into forbearance. Most borrowers in forbearance skipped multiple payments however, with 72% 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, X_i is a set of loan controls (e.g., LTV and credit score bins) to account for forbearance demand, and ξ_s is a vector of servicer fixed effects.[18]

Our baseline model estimates equation 1 using the population of Ginnie Mae borrow-

[18]Coefficient estimates on loan and borrower controls are reported in table A.1 of the Internet Appendix.

ers 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 one-third of them became delinquent 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. [19] 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 serious 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

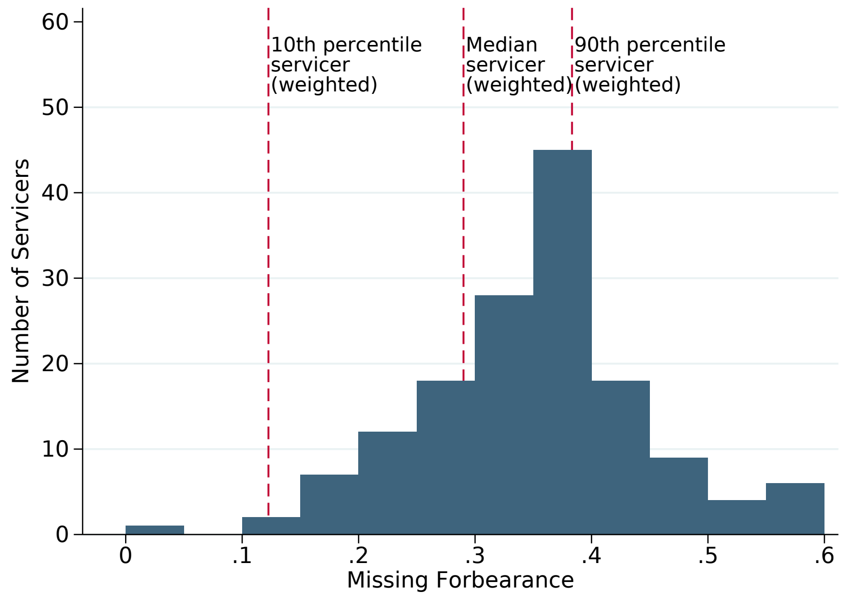
We also estimate an alternative set of servicer fixed effects by estimating equation 1 using the eMBS-CRISM matched sample. This allows us to control for a finer set of borrower and loan controls using information from borrower credit reports, including bins of borrower age, an updated credit score and information on nonmortgage debt balances.[20].

[19] Indeed, these estimated servicer fixed effects are highly statistically significant jointly with F-statistics of 435.17.

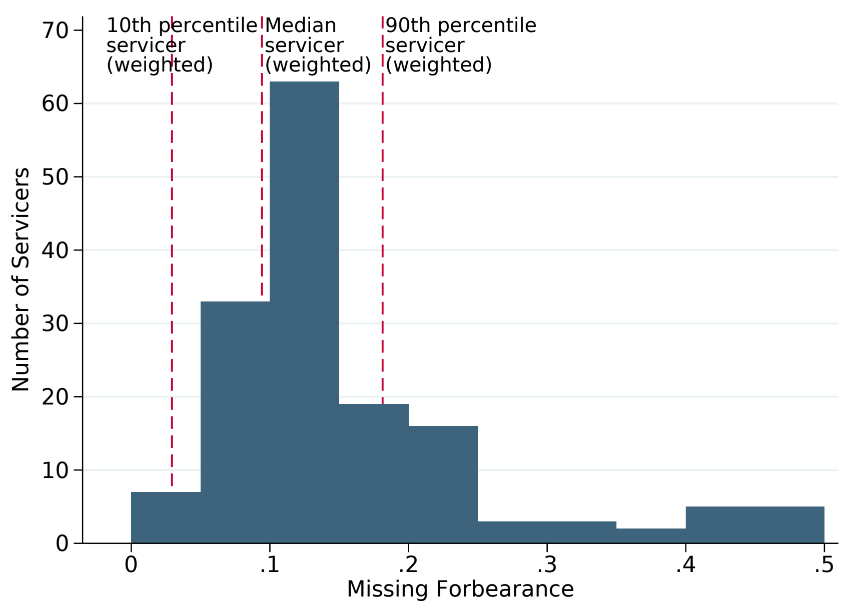
[20] Coefficient estimates are reported in section C of the Internet Appendix

Figure 2: **P(no forbearance | COVID delinquency).** Cross-servicer variation in probability that a past-due loan does not enter a forbearance plan. Based on servicer fixed effects estimated using eMBS data. Bars are unweighted counts of servicers. Dashed vertical lines show weighted percentiles (weighted by the number of loans that became past due between March and November of 2020.)

(a) Borrowers 30+ days past due



(b) Borrowers 60+ days past due



This approach also produces a similarly wide dispersion of servicer effects estimates (see figure A.2 of the Internet Appendix).

We also use the eMBS-CRISM model to examine how sensitive the fixed effects are to the set of controls used, comparing specifications based on the same sample but with i) no controls, ii) the controls available in eMBS 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). In particular the credit report controls available in CRISM make very little difference to the servicer fixed effects.

Within the eMBS sample, we also 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 delinquent 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 effects are identified only from mortgages where there was a transfer of servicing rights. These alternative fixed effects are strongly positively correlated with our main estimates in the top panel of figure 2, as shown in the Internet Appendix (figure A.4).

4.2 Servicer behavior or omitted borrower characteristics?

Our interpretation is that these striking differences in forbearance outcomes are driven by variation in servicer behavior. 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.[21]

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

1. Mortgages managed by high- vs low- forbearance servicers have similar ex-ante characteristics, measured in either the eMBS and eMBS-CRISM samples (see Internet Appendix tables A.3-A.5). Non-mortgage loan balances are also similar (e.g., auto, credit card and student loan balances are all within 10% comparing the two groups), and the two groups of loans also experienced similar macroeconomic conditions during the pandemic (e.g., the 12-month change in the county unemployment rate differs by only 0.2%).

   Perhaps the main difference is that loans managed by low-forbearance servicers are somewhat younger (4.5 vs 6.0 years in the eMBS-CRISM sample). Within age groups however the appendix shows that mortgages look very similar on observables, and our regressions always include a full set of loan age dummies.

2. There is almost no difference in mortgage loan performance between high and low-forbearance servicers in the months leading up to the pandemic. We measure this by estimating a loan-level delinquency model where the dependent variable is equal to 1 if a loan current at *t-1* becomes delinquent in month *t*.[22] Differences in conditional delinquency transition probabilities for mortgages managed by high-vs-low forbearance servicers are economically small, not consistently signed, and of-

[21] We emphasize that servicer forbearance policies *per se* were not likely an important dimension of borrower mortgage choice prior to the pandemic, given the stable economy, rising home prices, the infrequency of forbearance, and the fact that borrowers cannot directly choose their servicer. Even so, there could still be nonrandom assignment of borrowers to servicers in a way that is correlated with borrowers' desire to take advantage of forbearance during the pandemic.

[22] 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 loan 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.

ten not statistically significant – see figure A.6 and table A.10 of the Internet Appendix.[23] The same is true for credit card and auto delinquencies in the eMBS-CRISM matched sample. In contrast, during the pandemic itself, borrowers assigned to high-forbearance servicers become *much* more likely to stop paying their mortgages, as shown in figure A.6 and as discussed in detail in section 6.

This argues against an "omitted risk" explanation of the results, which would predict high-forbearance servicers experience higher non-payment rates not just during the pandemic, but also prior to it. Conversely it also speaks against the hypothesis that high-forbearance-servicer borrowers are more financially literate, which would be expected to result in 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 already discussed in section 4.1. It seems unlikely that servicer fixed effects are driven by unobservable loan and borrower characteristics but essentially uncorrelated with observable characteristics.

5 Servicer characteristics and forbearance outcomes

Now we study how a servicer's "forbearance propensity," as measured by its fixed effect, varies with servicer characteristics such as size, liquidity and organizational form. The goal of this analysis is to understand which economic factors (as discussed in section 2.3) are most important in shaping servicer behavior.

We estimate a simple cross-sectional regression of servicer effects on characteristics

[23] Servicer forbearance policies are unlikely to have been an important dimension of borrower mortgage choice prior to the pandemic, given the stable economy and low mortgage default rate, the infrequent as well as the the low pre-pandemic rate of forbearance, and the fact that ultimately borrowers have little choice in their mortgage servicer.

drawn from mortgage call reports (for nonbank mortgage companies), Y-9C and bank call reports (for banking organizations or nonbanks controlled by a bank), and data on total originations and servicing volumes aggregated from eMBS account-level data.[24] 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.

Estimates are reported in table 2 and reveal several patterns. First, large servicers are significantly more likely to enroll their borrowers in a forbearance plan, whether size is measured by the log of servicing assets (measured using eMBS) or balance sheet size (measured using regulatory reports). As we have discussed, large servicers may enjoy scale economies because of fixed costs in setting up efficient forbearance processes (e.g., a well-designed online application form). Alternatively, large servicers may have more resources to better train servicing staff, or may also behave in a more "borrower-friendly" way because they are more likely to be targeted by financial regulators.

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 were about 13 percentage points more likely. The lower rate of forbearance for nonbanks is consistent with a liquidity-based mechanism. Nonbank servicers rely primarily on short-term wholesale funding and do not have access to government backstops such as the Federal Reserve discount window and Federal Home Loan Bank system advances, and at the start of the pandemic when most forbearance plans began, there were significant concerns about a nonbank liquidity crunch. By discouraging forbearance, nonbanks could induce borrowers to keep making their mortgage payments, thereby mitigating their own liquidity outflows due to contractual obligations to forward mortgage pay-

[24] Institutions were matched by name across these different data sources. Information on financial structure from the National Information Center and other sources were used to cross-validate the accuracy of the match.

ments on nonperforming loans.

Third, and also consistent with a liquidity-constraints channel, the level of cash balances is significantly positively correlated with servicer forbearance propensity, but *only* for nonbanks. Precautionary cash holdings are not important for depository institutions, which have access to backstop sources of liquidity for mortgages (e.g., through the Federal Home Loan Bank system and the discount window), and also experienced large inflows of liquidity at the start of the pandemic. But for nonbanks, not only is the overall rate of forbearance lower, but forbearance is particularly depressed for servicers with a low level of ex ante precautionary cash balances.

Table 2: **Regression of conditional forbearance rates on servicer characteristics**: Weighted least squares, weighted by number of borrowers current in January 2020 but missed at least one payment between March and November. Column (1) is based on all servicers. Columns (2) through (4) reflect nonbank servicers only. Columns (5) through (7) reflect bank servicers only.

	All	Nonbank mtg companies			Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Servicer characteristics							
log(Servicing assets)	0.037***	0.031***	0.025***		0.043***	0.043***	
	(0.007)	(0.008)	(0.006)		(0.010)	(0.010)	
log(Assets)				0.018***			0.025*
				(0.004)			(0.015)
Cash / assets			0.955***	1.083***		-0.664	-0.942
			(0.174)	(0.177)		(0.537)	(0.699)
Securities / assets			0.144	0.246***		0.320	0.553
			(0.100)	(0.085)		(0.364)	(0.345)
Capital / assets			0.011	0.053		1.292	1.068
			(0.103)	(0.109)		(0.794)	(0.907)
Servicing growth	-0.008	0.011	-0.011	-0.035	-0.030	0.000	-0.018
	(0.047)	(0.055)	(0.045)	(0.042)	(0.086)	(0.089)	(0.090)
Servicer type							
Nonbank mortgage company	-0.087***						
	(0.025)						
Credit union	0.131***						
	(0.029)						
N. Obs.	152	98	98	98	45	45	45

5.1 Servicing quality: evidence from CFPB complaints

Given that past-due Ginnie Mae borrowers would have universally benefited from entering into forbearance, at least to some degree, servicer practices that limit forbearance uptake also reduce borrower welfare. To investigate further, we study whether borrowers are less satisfied with "low-forbearance" servicers, based on the frequency of mortgage forbearance-related complaints submitted to the CFPB complaints repository.[25]

Results are presented in Table 3. Our estimates indicate that the frequency of complaints (scaled by the number of serviced mortgages) is significantly higher for low-forbearance servicers. This is direct evidence of poorer servicing quality for these firms. When we replace the servicer forbearance propensity with servicer characteristics, we find in particular that liquidity matters; servicers with lower levels of precautionary cash balances were the subject of a higher rate of complaints.

5.2 Summary

To sum up the results of this section, we find that many nonperforming FHA and VA mortgages entitled to forbearance under the CARES Act did not in fact enter a forbearance plan — furthermore, forbearance outcomes varied significantly across mortgage servicers for observably equivalent loans. Several pieces of evidence indicate that these servicer effects reflect servicer behavior rather than unobserved loan and borrower heterogeneity. Small servicers and nonbanks were less likely to provide forbearance, particularly for nonbank servicers with low liquidity buffers at the start of the pandemic. Our results highlight 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

[25] We measure forbearance-related complaints using a set of keywords similar to the CFPB, and restricting the sample to complaints related to mortgage financing where the mortgage is a government loan, to be consistent with our Ginnie Mae sample.

Table 3: **CFPB complaints**: Forbearance-related complaints are normalized by the number of Ginnie Mae or total agency mortgages serviced (complaints per thousand loans). Weighted least squares, weighted by number of loans serviced as of January 2020. Forbearance-related complaints are normalized by the number of Ginnie Mae or total agency mortgages serviced (complaints per thousand loans).

	All lenders				Nonbanks only	
	(1)	(2)	(3)	(4)	(5)	(6)
Servicer forbearance propensity	-0.237***	-0.258***			-0.706**	
	(0.083)	(0.084)			(0.288)	
Servicer characteristics						
log(Servicing assets)			-0.017**	-0.005		-0.042
			(0.007)	(0.008)		(0.043)
Cash / assets				-0.431*		-1.522***
				(0.236)		(0.538)
Securities / assets				-0.377*		-0.278
				(0.191)		(0.318)
Capital / assets				-0.021		0.182
				(0.140)		(0.380)
Servicing growth			0.046	0.081		0.408**
			(0.049)	(0.054)		(0.204)
Frac. govt. loans that are FHA		0.087***	0.074**	0.096		
		(0.033)	(0.036)	(0.077)		
Frac. all loans that are FHA					-0.596**	-0.533*
					(0.289)	(0.288)
Servicer type						
Nonbank mortgage company		0.001	0.010	-0.043		
		(0.020)	(0.020)	(0.039)		
Credit union		0.071**	-0.002			
		(0.028)	(0.023)			
N. Obs.	129	129	129	125	92	92

Recession (Aiello, 2021).

6 Does forbearance cause nonpayment?

In this section, we use cross-servicer variation in forbearance practices (measured using the fixed effects methodology from the prior section) to estimate the causal effect of forbearance availability on the borrower's propensity to pause making mortgage payments. In the following section we also apply the same methodology to examine nonmortgage outcomes such as total nonmortgage debt.

For this portion of the analysis, we rely primarily on the CRISM-eMBS merge described in Section 3.[26] Usage restrictions on the CRISM dataset prevent us from retaining servicer information in the merged eMBS-CRISM dataset, but the merge does allow us to retain anonymous servicer identifiers. We use these identifiers to estimate servicer-level fixed effects using the same methodology as in the prior section. We then use the fixed effects as a source of plausibly exogenous variation in forbearance availability to trace the effects of forbearance on other borrower outcomes.

The key identification assumption underlying this approach is that servicer forbearance fixed effects are orthogonal to unobserved borrower characteristics which would affect outcomes during the pandemic (conditional on mortgage characteristics measured in CRISM). This is the same identification assumption required for our analysis in Section 4.2, where we present evidence of its validity.

[26]The eMBS data we used for Section 4 present some drawbacks for this part of the analysis. Most importantly, we lose the ability to track some loans because some servicers began purchasing loans in forbearance out of Ginnie Mae pools several months after the program went into place, and therefore exit the eMBS dataset at the same time. Additionally, the eMBS data allow us to observe the borrower's location only at the state level, a potentially significant drawback given that servicers may have different geographic exposures, and given that the geography of the virus drives economic stress.

6.1 Regression specification

We use a difference-in-difference approach to compare outcomes and behavior of borrowers at servicers with more- and less-generous forbearance practices. 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). We use the 6 month period preceding the March 2020 passage of the CARES Act to establish the absence of different pre-existing trends between high- and low-forbearance servicers. We attribute differences in borrower outcomes and behavior after March 2020 to differences in the accessibility of forbearance.

We estimate the following regression:

$$\mathbf{Y}_{it} = \sum_{\tau=-6,\tau\neq 0}^{8} \beta_\tau S_i^H \times 1_{t=\tau} + Z_{it}\gamma + \alpha_s + \alpha_{zt\tau} + \varepsilon_{it} \tag{2}$$

where Y_{it} is a borrower outcome such as nonpayment; S_i^H is an indicator variable equal to 1 for high-forbearance servicers; Z_{it} is a vector of loan and borrower characteristics which may affect mortgage nonpayment, including mortgage 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, loan type (FHA vs. VA), and several household balance sheet characteristics, measured in January 2020, including the household's other mortgage and non-mortgage debt, and delinquency on other mortgage and non-mortgage debt; α_s is a vector of servicer fixed effects, which account for persistent differences in borrower outcomes across servicers; and α_{zt} is a vector of zipcode x month x origination month FE to account for the time-varying geographic effects of the pandemic separately for loans originated in different times. We cluster standard errors at the servicer level. Note that our zip x month x origination month FE absorb any general equilibrium effects of the program. First stage regression results can be found in Appendix

Section C.2

6.2 Results

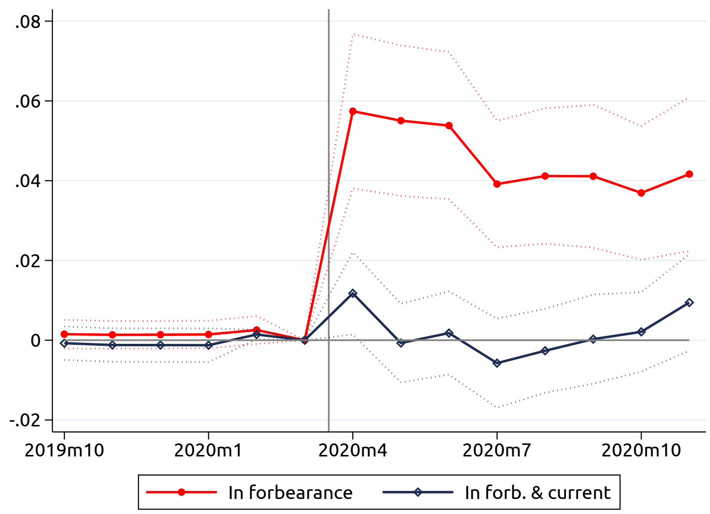
First, we confirm that the path of forbearance rates is actually higher among servicers we have categorized as high-forbearance-availability servicers. Figure 3(a) plots the estimates of β_τ from Equation 2 using a forbearance dummy as the outcome variable. The coefficients can be interpreted as the difference in the probability that a borrower is in a forbearance plan at a high-forbearance servicer vs. at low-forbearance servicer in a given month, all else equal.

Figure 3(a) confirms that forbearance rates are higher at high-forbearance servicers throughout the pandemic. At the peak in April, the share of borrowers in forbearance at high-forbearance servicers was about 5 percentage points (about 30%) higher than at low-availability servicers. The difference begins to diminish from May onwards, even as overall forbearance rates continue to rise, perhaps reflecting that low-forbearance-availability servicers partially "catch up" in their policies and practices. However the difference in forbearance rates remains high throughout the pandemic.

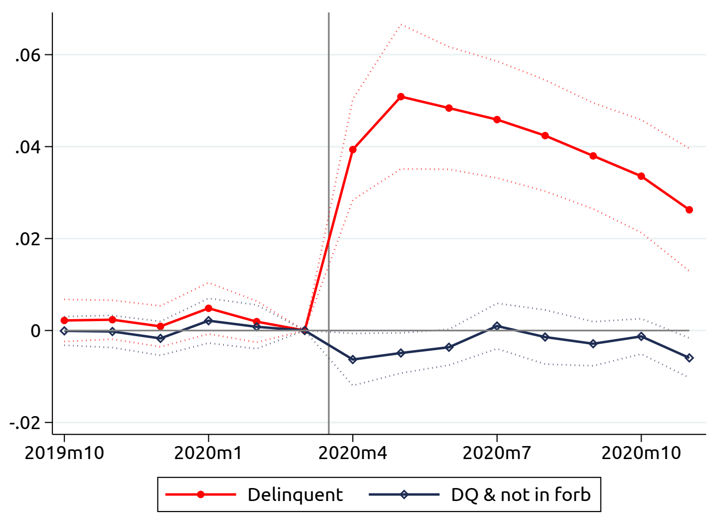
Next, we examine whether forbearance availability *causes* mortgage nonpayment. Given that forbearance significantly reduces the cost of missing mortgage payments, it seems reasonable to expect that the nonpayment rates will rise disproportionately at servicers that make it easier for borrowers to enter forbearance. On the other hand, it is possible that high-forbearance servicers mainly encourage higher entry into forbearance among borrowers who continue to make mortgage payments or among borrowers who would not otherwise have made their payments. If so, nonpayment rates would be unaffected by forbearance availability.

Figure 3(b) reports the monthly difference in the probability a borrower is past-due (i.e., has missed at least one payment) at high-forbearance servicers relative to low-forbearance

Figure 3: **Forbearance and Nonpayment.** Estimates and their 95% confidence intervalsof the effect of assignment to a "high-forbearance" servicer on the likelihood of forbearance and missed payments. Standard errors are clustered at the servicer level.



(a) In forbearance



(b) Past due

servicers. We find that the probability that a borrower is past-due is significantly higher for borrowers at high-forbearance servicers, by as much as 5 percentage points at the peak in May 2020. Moreover, the estimates for the probability that a borrower is past-due are similar to the estimates for the forbearance probability in Figure 3(a). This result indicates that effectively *all* of the additional forbearance at high-forbearance servicers drives borrower nonpayment. In other words, marginal forbearance recipients at high-forbearance servicers would not have missed payments had forbearance been more difficult to access.

Figure 3(a) confirms that this sharp increase in nonpayment is driven entirely by borrowers who are in forbearance plans. Conversely, there is also no difference in delinquency rates outside of forbearance among high-vs-low availability servicers (shown in the dark blue line in Figure 3(b)).

Additional results reported in Section I show that prepayment rates across high- and low-forbearance servicers were identical before and after the forbearance program went into place. This suggests that borrowers assigned to high-forbearance servicers were not diverted from refinancing into forbearance - an outcome that would complicate the welfare analysis of the program. Instead, on average, borrowers assigned to low-forbearance servicers who would have missed payments at high-forbearance servicers continued making payments and did not refinance.

These results indicate that forbearance availability directly affects borrower decisions about whether to defer mortgage payments during the pandemic, at least for the substantial set of marginal borrowers whose forbearance outcomes are affected by servicer practices. In other words, servicer policies significantly affect household cash flows during the pandemic.

7 Non-mortgage effects

Our results so far show that assignment to a "high-forbearance-availability" servicer induces borrowers to obtain forbearance and also to defer their mortgage payments. This deferral puts a significant amount of additional cash in the borrower's pocket. We now examine how borrowers use this additional liquidity, examining the rich set of information in CRISM about the borrower's non-mortgage debt accounts.

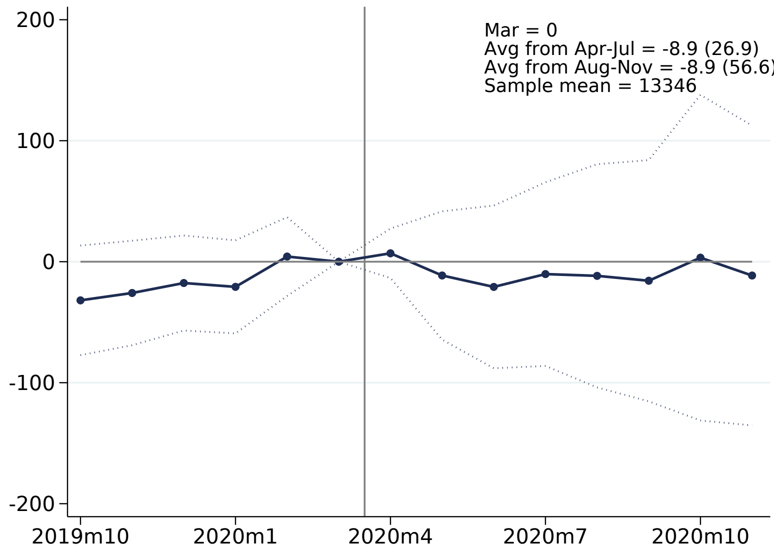
We estimate these effects using the same methodology, but replacing the dependent variable in Equation 2 with various nonmortgage outcomes. Results are presented in Figures 4 and 5.

Figure 4 shows that forbearance availability induced some borrowers to pay down credit card balances. Borrowers with below-median credit card utilization rate at high-forbearance servicers paid off around $40 relative to borrowers at low-availability servicers (Figure 4(b)). Because the forbearance rate is higher by 5 percentage points for borrowers at high-forbearance servicers[27], the result implies that marginal borrowers who received forbearance as a result of assignment to a high-forbearance servicer reduced their credit card balances by about $800. This difference is about a quarter of the average forbearance-driven savings in mortgage payments of those borrowers at high-forbearance servicers and is also about a quarter of the conditional mean credit card balance for borrowers with low credit card utilization. We do not find robust evidence that higher-utilization borrowers paid down credit cards, and the standard errors on these specifications are much larger (Figure 4(a)).

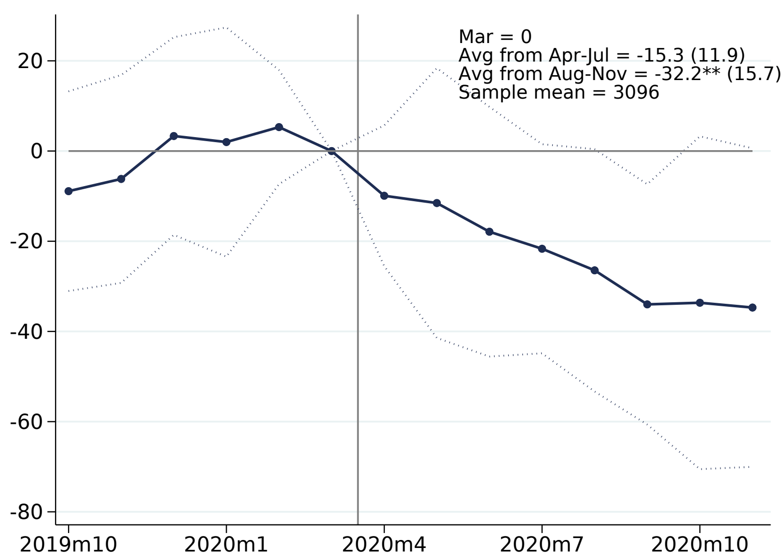
This finding shows that forbearance essentially provided a low-cost source of liquidity to households, partially replacing expensive credit card debts. Households with lower credit card utilization before the pandemic may be less liquidity-constrained than high-

[27] The difference in the forbearance rate across high- and low-forbearance servicers does not vary by credit utilization

Figure 4: **Effects of forbearance availability on credit card balances**. Figure plots estimates and their 95% confidence intervals of the effects of assignment to a high-forbearance servicer on credit card debt for borrowers with above- and below-median average credit card utilization for 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. Standard errors are clustered at the servicer level.

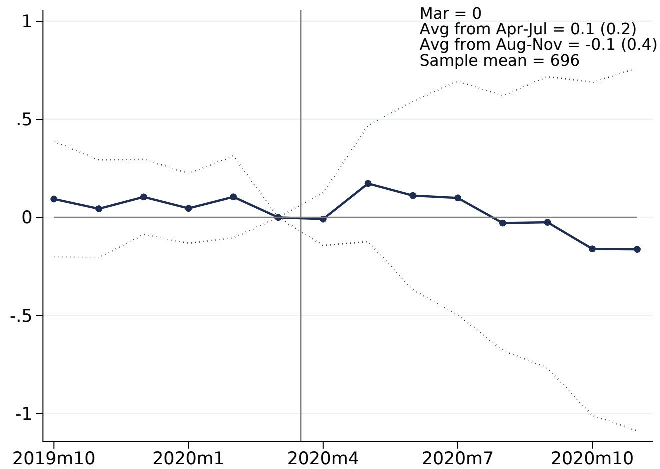


(a) Credit card balance among high-credit-card-utilization borrowers ($)



(b) Credit card balance among low-credit-card-utilization borrowers

Figure 5: **Effects of forbearance availability on updated credit score** . Figure plots estimates and their 95% confidence intervals of the effects of assignment to a high-forbearance servicer on the borrower's credit score (FICO Score version 5), as measured in CRISM. Standard errors are clustered at the servicer level.



utilization borrowers, which may explain why they were more willing to use the additional funds to pay down credit card debt rather than for consumption or to increase liquid assets.

We find no evidence that borrowers used forbearance to pay down other sources of debt like auto loans, student debt, or junior liens (Table A.11). This is perhaps unsurprising, as these forms of borrowing are much cheaper than credit card debt, making them a lower priority for payoff. (Additionally, our analysis in this section relies on a relatively small absolute difference in forbearance rates across servicer-types, so we are unlikely to have sufficient power to measure small changes in average balances.) We also do not find that households assigned to higher-forbearance servicers purchased more cars. We find no effect on the delinquency rates of non-housing debt, though the availability of other forbearance programs may have affected these outcomes as well.

Figure 5 shows that although borrowers at high-forbearance servicers are more likely to miss mortgage payments, their credit scores (FICO Score version 5)[28] did not decrease as a result, because nonpayment during forbearance is not reported to the credit bureaus.

[28]FICO is a registered trademark of Fair Isaac Corporation.

In fact, credit scores for the high-forbearance group of borrowers actually increase slightly (perhaps reflecting their paydown of credit card balances and/or avoiding delinquency on non-mortgage debt), although the effect is estimated with a large standard error once we include servicer fixed effects.

These results indicate that the CARES Act forbearance program provided a low-cost source of liquidity to mortgage borrowers, which in part allowed some borrowers to reduce other higher-cost sources of borrowing.

8 Moral Hazard

Forbearance may induce mortgage nonpayment through two channels. First, borrowers who experienced a negative income shock could miss mortgage payments and use the additional liquidity to smooth their consumption or avoid foreclosure. Second, borrowers who did not experience a reduction in income may miss payments simply because forbearance represented a low-cost form of borrowing. The second channel represents a form of moral hazard, in that it is an unintended consequence of the program.

The relative size of these two channels has important welfare implications for forbearance program design. If the liquidity channel dominates, then the CARES Act forbearance program reached the intended households, and the actions of "low-forbearance" servicers prevented more borrowers from benefiting from the program on the margin. If the moral hazard channel dominates, it would imply that the program design, including easy access to forbearance and the ability to defer payments until loan termination, led to poor targeting. These trade-offs are analogous to those faced by other social insurance programs such as unemployment insurance (e.g., Chetty, 2008) and personal bankruptcy (e.g., Indarte, 2020).

Our data are not particularly well-suited to estimate the extent of moral hazard, because we do not have access to high-frequency dynamic income and employment data for our sample. Even so, several pieces of evidence suggest that most borrowers who skipped payments in forbearance did so as a result of negative income shocks. First, Table A.12 shows that the characteristics of borrowers in forbearance are comparable between high- and low-availability servicers, suggesting that easier access did not draw observably less-risky borrowers on the margin. For example, the average non-mortgage balances and average credit scores are very similar between the two groups. Borrowers at high-forbearance servicers tend to be in forbearance longer and less likely exit forbearance, but the differences between the two groups are quantitatively small. If moral hazard were the main channel driving nonpayments, we might instead expect high-financial-literacy borrowers at high-forbearance servicers to use the program more intensively: to miss more payments and to remain in forbearance longer.

Zhao et al. (2020), who have access to borrower income data, provide more direct evidence that forbearance is mostly used by borrowers who experienced negative income shocks. They document that borrowers who made use of forbearance to miss payments experienced larger declines in income, were more likely to have lost their jobs, and more likely to have received unemployment benefits than those not in forbearance. Lambie-Hanson et al. (2021) present survey evidence indicating that at least three-quarters of borrowers entering forbearance had experienced a job disruption or income loss during the pandemic.

A final point is that in aggregate only a relatively small proportion of borrowers used forbearance to skip mortgage payments. In principle, many borrowers could have acted in an opportunistic manner to take advantage of the generous repayment terms offered through the forbearance program. But it is clear that the vast majority of borrowers who were able to make their mortgage payments did keep paying.

9 Conclusion

Our evidence indicates that servicer policies and practices played an important role in the implementation of the CARES Act mortgage forbearance program. Despite universal eligibility for forbearance among agency mortgage borrowers, a significant fraction of delinquent borrowers did not successfully enter into a forbearance program, and that the relative frequency of these "missing" forbearances varies significantly across mortgage servicers for otherwise identical loans. Forbearance outcomes are systematically related to servicer characteristics including size, liquidity and organizational form, consistent with the role of incentives in shaping servicer behavior.

Using estimated servicer-level variation in forbearance practices, we also find that forbearance has significant causal effects on borrower financial outcomes. In particular, we find that assignment to a "high-forbearance" servicer translates to a significantly higher non-payment rate, without any negative effect on borrowers' credit scores, and that part of this additional household liquidity is used to pay-down high-cost credit card debt. It does not appear that assignment to a high-forbearance servicer prevented negative housing outcomes like delinquency outside of forbearance, default, or forced sales.

We emphasize that our results represent the marginal effect of forbearance among different types of servicers, and therefore do not necessarily represent the average effect of the program on its recipients as a whole. Furthermore, our results do not speak to any general equilibrium effects of forbearance.

Our results have important implications for whether, ex post, servicers benefited from making the program widely available. To servicers, forbearance take-up that does not prevent delinquency or foreclosure is costly; the servicer does not internalize non-housing program benefits, and unless the servicer is very large, it does not internalize general equilibrium benefits. Our results suggest that servicers with fewer resources successfully preserved liquidity by restricting access to forbearance.

Overall, the CARES Act mortgage forbearance program has been successful in enrolling a large number of borrowers in a short period of time, significantly mitigating the negative shock of the COVID-19 pandemic on household liquidity. The low aggregate level of nonpayment suggests that despite a high rate of induced missed payments among forbearance users, the program was well-targeted to households that experienced hardship. Even so, our results show that idiosyncratic differences across servicers played a significant role in the rollout of the program and shaped household outcomes. Policymakers may wish to consider whether future debt relief programs can include features (e.g., auto-enrollment) that overcome servicer reluctance and mitigate variation in outcomes that is unrelated to borrower fundamentals, or whether centralizing some portions of the program's operations could overcome the specific challenges faced by smaller servicers.

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Internet Appendix for:

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

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March 8, 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. 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 res-

[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 forbearance among of borrowers who entered forbearance in March but had already exited prior to June.

idential 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.

FRBY Consumer Credit Panel / Equifax Data (CCP). The CCP is a representative panel of the credit history of an anonymous 5% sample 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 eMBS-CRISM merge

Unlike eMBS, CRISM does not include servicer identities. We are however able to merge CRISM with a vector of anonymous servicer identifiers by undertaking a fuzzy match between CRISM/McDash with eMBS loan-level data based 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 matched dataset allows us to trace out the effects of servicer variation in forbearance practices on other borrower outcomes (e.g., total household debt and the performance of non-mortgage debt). It also enriches the set of available borrower-level characteristics relative to the eMBS-only dataset (e.g., since CRISM/McDash includes finer ge-

[2]Note that 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 able to retain an anonymized servicer identifier, however.

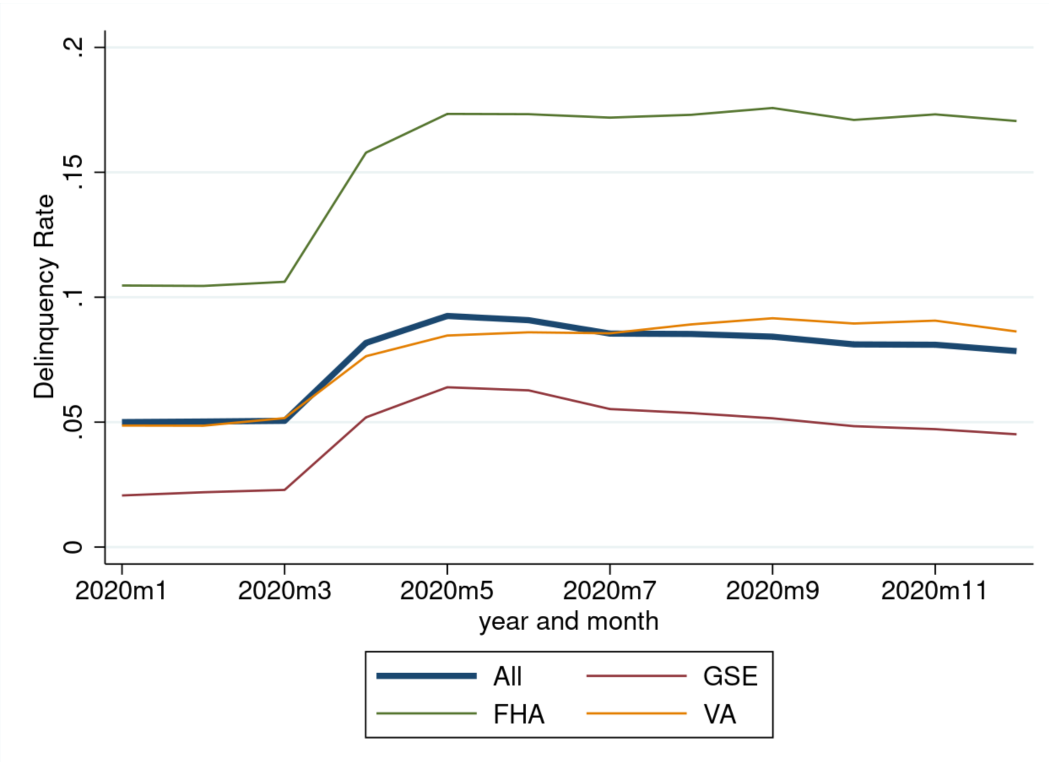
ographic information on the property location, and allows us to observe the borrower's refreshed credit score just prior to the pandemic). A limitation however is that only a subset of loans can be matched, whereas in eMBS we essentially are able to observe the entire universe of FHA and VA mortgages.

Table A.13 presents summary statistics of loan characteristics of the full eMBS data and the merged eMBS-CRISM data. As shown by the number of observations in the two columns, about 25% of loans in the eMBS data are matched to CRISM in part because of coverage of the CRISM data and our restrictive matching criteria. Although many eMBS loans are excluded in the merged data, loan characteristics are still similar between the two different data sets.

B Mortgages 30+ days past due, by segment

Fraction of active mortgages that are at least 30 days past due (including those that are in forbearance). Author calculations based on Black Knight McDash servicing data.

Figure A.1: **Delinquency Rate, 30+ Days**



C Loan-level estimates

C.1 eMBS sample

Notes: Linear probability regression of the probability that a loan enters forbearance from March 2021 onwards, based on eMBS loan-level data. Sample is loans that are active as of January 2021. Regressions include state and servicer fixed effects.

Table A.1: First-stage regression: dependent variable = 1 if in forbearance

	(1) Ever DQ sample	(2) Full sample
Ever servicer change	-0.031***	0.001**
	(0.002)	(0.000)
Months since last servicer change	0.001***	-0.000***
	(0.000)	(0.000)
First-time homebuyer	0.035***	0.029***
	(0.001)	(0.000)
DTI at orig:		
$25 < \text{dti} \leq 50$	0.044***	0.029***
	(0.002)	(0.000)
$\text{dti} > 50$	0.087***	0.072***
	(0.002)	(0.001)
Loan age (year)	-0.016***	-0.003***
	(0.000)	(0.000)
Loan age (year) $\times$ Loan age (year)	0.000***	0.000***
	(0.000)	(0.000)
Ln(Current UPB)	0.097***	0.021***
	(0.001)	(0.000)
CS at orig:		
$620 < \text{orig cs} \leq 680$	0.016***	-0.020***
	(0.001)	(0.000)
$680 < \text{orig cs} \leq 740$	0.023***	-0.067***
	(0.002)	(0.001)
$\text{orig cs} > 740$	0.003	-0.108***
	(0.002)	(0.001)
Loan purpose: refinace	0.043***	0.012***
	(0.002)	(0.000)
LTV at orig:		
$80 < \text{LTV} \leq 95$	0.028***	0.012***
	(0.002)	(0.000)
$95 < \text{LTV} \leq 100$	0.034***	0.021***
	(0.002)	(0.000)
$\text{LTV} > 100$	-0.027***	-0.021***
	(0.002)	(0.001)
30+ days delinquent in Feb 2020		-0.293***
		(0.010)
FHA		-0.121***
		(0.001)
Servicer FE	Y	Y
State FE	Y	Y
N. Obs.	1,197,226	9,764,941
Adj. R^2	0.10	0.09

C.2 eMBS-CRISM sample

Table A.2: **First-stage forbearance regression: eMBS-CRISM.** Dependent variable = 1 if mortgage enters forbearance. Loan-level linear probability model of probability that past-due loan enters into a forbearance plan based on eMBS-CRISM matched sample. Sample is loans that are current as of January 2020 and become past-due between March and November 2020. Regressions include geography and servicer fixed effects.

	(1) *Forbearance|delinquent*	(2) *Forbearance|delinquent*
First-time homebuyer	0.0255***	0.0312***
	(0.00174)	(0.00170)
DTI at orig:		
25 <dti ≤ 50	0.0458***	0.0569***
	(0.00379)	(0.00371)
dti >50	0.0693***	0.0894***
	(0.00410)	(0.00401)
Loan age (years) × Loan age	0.000***	0.000
	(0.000)	(0.000)
Ln(Current UPB)	0.0682***	0.102***
	(0.00186)	(0.00143)
620 <orig cs ≤ 680	-0.00672*	0.00590*
	(0.00267)	(0.00263)
680 <orig cs ≤ 740	-0.0105***	0.0108***
	(0.00285)	(0.00278)
Loan purpose:		
Refinance	0.0197***	0.0193***
	(0.00296)	(0.00290)
LTV at origination:		
80 <LTV ≤ 95	0.0150***	0.0188***
	(0.00357)	(0.00348)
95 <LTV ≤ 100	0.0243***	0.0284***
	(0.00358)	(0.00347)
FHA	0.0645***	0.0836***
	(0.00241)	(0.00231)
Borrower age:		
30 <age ≤ 45	0.0144***	
	(0.00251)	
45 <age ≤ 60	0.0148***	
	(0.00265)	
age >60	-0.0207***	
	(0.00308)	
Riskscore+	0.000136***	
	(0.00000764)	
Ln(Consumer debt)+	0.0247***	
	(0.000512)	
Delinq. consumer debt+	-0.0333***	
	(0.00182)	
Other housing debt+	0.00818***	
	(0.00201)	
Delinq. other housing debt+	-0.0227*	
	(0.00923)	
Credit utilization+	0.00982***	
	(0.00217)	
N	425142	429841
State FE	No	No
Servicer FE	Yes	Yes
Zipcode FE	Yes	Yes

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: **"Missing" forbearance rate: eMBS-CRISM sample.** Histogram based on servicer fixed effects for eMBS-CRISM matched sample.

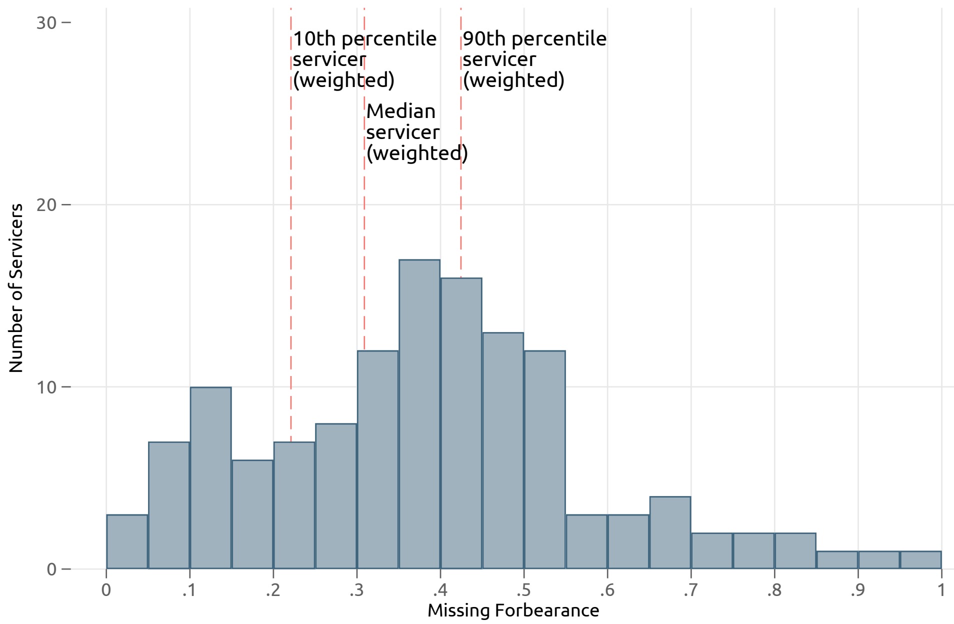
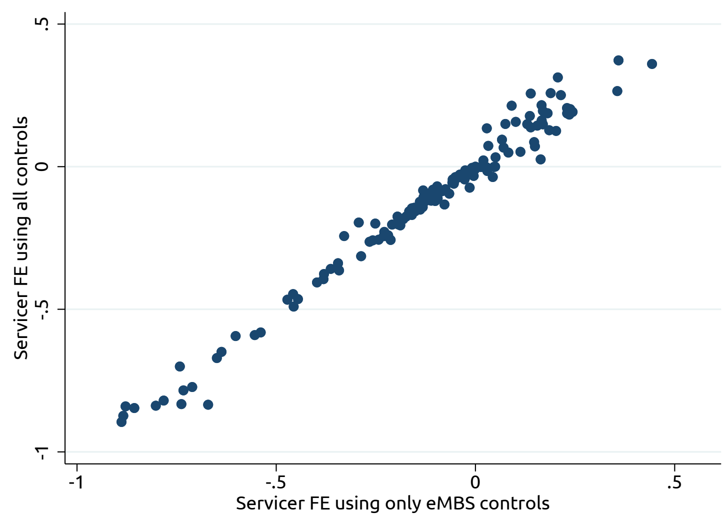
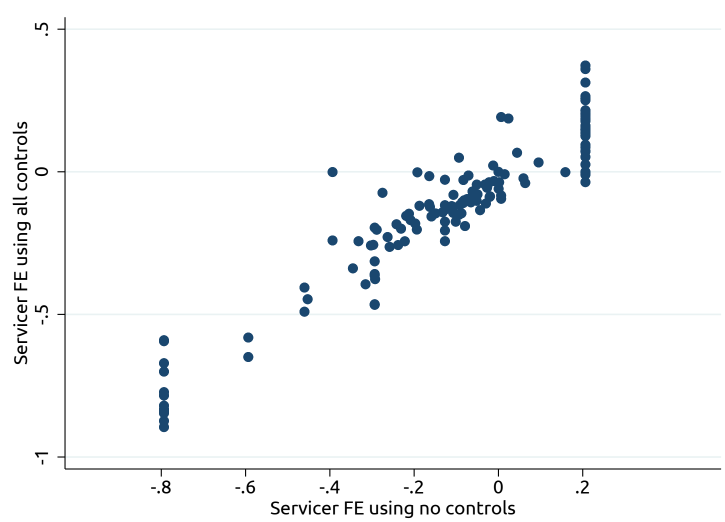


Figure A.3: **Robustness of servicer fixed effects to controls: eMBS-CRISM sample.** Panel (a) shows the correlation between servicer FE estimated using borrower and servicer characteristics available only in eMBS and servicer FE estimated using borrower and servicer characteristics available in CRISM.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

(a) Servicer FE Estimated using all controls and controls only available in eMBS

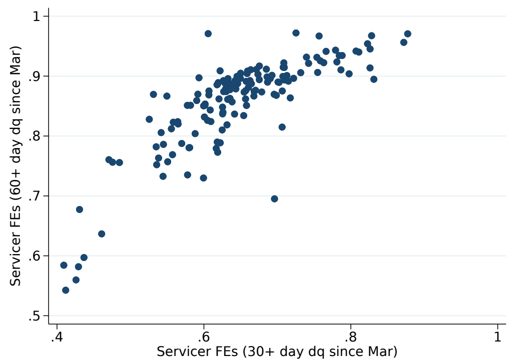


(b) Servicer FE estimated using full set of eMBS-CRISM controls vs no controls

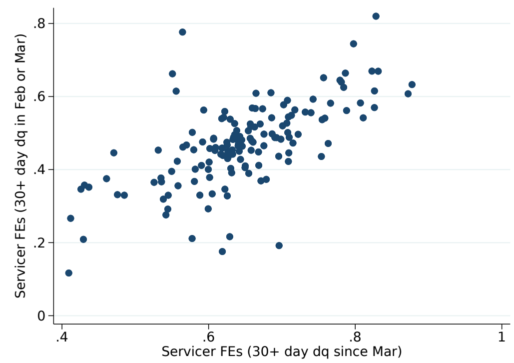


D.1 Comparison of fixed effects across approaches

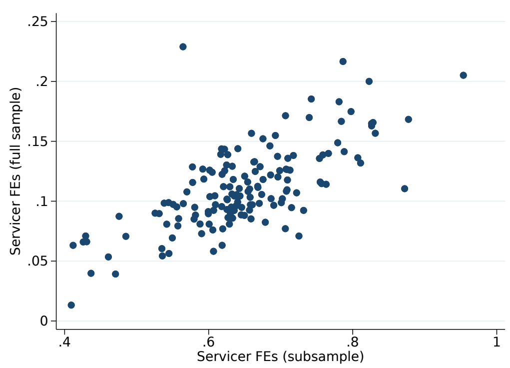
Figure A.4: **Correlation between servicer fixed effects from different specifications**: These figures show correlations between the baseline servicer fixed effect estimates and three alternative sets of estimates, based on: (i) using the subsample of loans which became at least 60 days delinquent (DQ) 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 delinquent (panel c); include lender fixed effects in the model, so that identification of servicer fixed effects is based on servicing transfers (panel d).



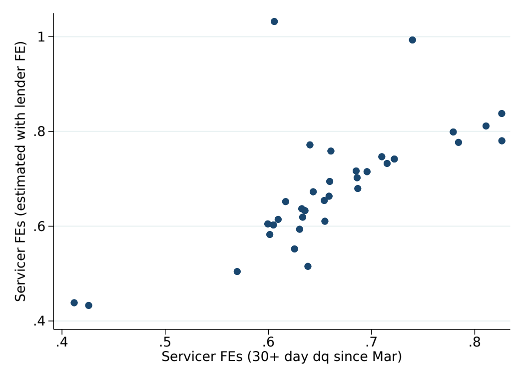
(a) 60+ day past due post-March 2020



(b) Missed payment in Feb/Mar 2020



(c) include all loans in sample



(d) include lender fixed effects

E Borrower Characteristics by Servicer Type

Table A.3: Borrower Characteristics across Servicers (CRISM-eMBS match) This table presents summary statistics measured as of February 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	184,313.66	163,431.85
Auto Loan Balance	16,102.42	15,254.90
Credit Card Balance	8,969.34	8,709.84
12-mo change CNTY UR (8/20)	6.02	5.80
FHA	0.67	0.70
FICO V5 (updated)	693.90	703.46
LTV at origination	93.92	94.22
Loan age (year)	4.49	6.04
N. Obs.	1,244,059	1,521,734

Table A.4: **Borrower characteristics across servicers by origination year (CRISM-eMBS match)** This table presents summary statistics measured as of February 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	135,368.15	136,303.53
Current Mortgage Balance	135,368.15	136,303.53
12-mo change CNTY UR (8/20)	6.15	5.82
FHA	0.83	0.77
FICO V5 (updated)	712.85	707.77
LTV at origination	93.59	93.64
Loan age (year)	8.52	8.63
Auto Loan Balance	13,323.52	13,931.91
Credit Card Balance	9,135.99	8,821.26
N. Obs.	330,927	709,437

(b) Origination year from 2014 to 2017

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	184,124.12	178,095.05
Current Mortgage Balance	184,124.12	178,095.05
12-mo change CNTY UR (8/20)	6.06	5.81
FHA	0.68	0.68
FICO V5 (updated)	695.99	701.66
LTV at origination	94.05	94.82
Loan age (year)	4.59	4.82
Auto Loan Balance	16,511.15	16,469.54
Credit Card Balance	9,324.28	8,966.78
N. Obs.	383,878	499,469

(c) Origination year since 2018

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	220,666.63	206,795.61
Current Mortgage Balance	220,666.63	206,795.61
12-mo change CNTY UR (8/20)	5.92	5.75
FHA	0.57	0.59
FICO V5 (updated)	680.54	696.57
LTV at origination	94.02	94.60
Loan age (year)	1.91	2.11
Auto Loan Balance	17,543.53	16,315.86
Credit Card Balance	8,607.69	8,046.91
N. Obs.	529,254	312,828

Table A.5: **Borrower characteristics across servicers by origination year (eMBS)** This table presents summary statistics measured as of February 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 data).

(a) Origination year up to 2013

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	114,464.79	118,121.23
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	1,894,045

(b) Origination year from 2014 to 2017

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	178,017.12	175,246.78
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	1,200,859

(c) Origination year since 2018

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Current Mortgage Balance	216,955.67	203,728.56
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	1,326,763

F Alternative specifications: Role of servicer characteristics in forbearance policy

Table A.6: Servicer FEs (conditional on 60+ dq)

	All	Nonbank mtg companies			Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Servicer characteristics							
log(Servicing assets)	0.025^{***}	0.024^{***}	0.017^{**}		0.023^{***}	0.024^{***}	
	(0.005)	(0.007)	(0.007)		(0.007)	(0.006)	
log(Assets)				0.011^{***}			0.015^{*}
				(0.004)			(0.009)
Cash / assets			0.622^{***}	0.701^{***}		-0.317	-0.483
			(0.142)	(0.134)		(0.395)	(0.448)
Securities / assets			0.188	0.266^{***}		0.127	0.258
			(0.115)	(0.080)		(0.189)	(0.211)
Capital / assets			0.007	0.033		0.793	0.671
			(0.125)	(0.126)		(0.635)	(0.653)
Servicing growth	-0.033	-0.031	-0.059	-0.076	-0.050	-0.037	-0.047
	(0.046)	(0.057)	(0.060)	(0.056)	(0.080)	(0.083)	(0.083)
Servicer type							
Nonbank mortgage company	-0.021						
	(0.017)						
Credit union	0.078^{***}						
	(0.020)						
N. Obs.	151	97	97	97	45	45	45

Table A.7: Servicer FEs (controlling for lender FEs)

	All	Nonbank mtg companies			Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Servicer characteristics							
log(Servicing assets)	0.037***	0.035***	0.030***		0.038***	0.036***	
	(0.006)	(0.008)	(0.006)		(0.009)	(0.009)	
log(Assets)				0.022***			0.022*
				(0.004)			(0.012)
Cash / assets			0.937***	1.094***		-0.288	-0.529
			(0.207)	(0.210)		(0.450)	(0.586)
Securities / assets			0.120	0.238**		0.397	0.590*
			(0.108)	(0.091)		(0.332)	(0.310)
Capital / assets			0.037	0.088		0.916	0.737
			(0.106)	(0.114)		(0.688)	(0.774)
Servicing growth	0.015	0.038	0.019	-0.009	-0.025	0.012	-0.003
	(0.047)	(0.057)	(0.045)	(0.044)	(0.076)	(0.082)	(0.082)
Servicer type							
Nonbank mortgage company	-0.065***						
	(0.023)						
Credit union	0.140***						
	(0.027)						
N. Obs.	152	98	98	98	45	45	45

Table A.8: Servicer FEs (conditional on delinquency transition in Feb-Mar 2020)

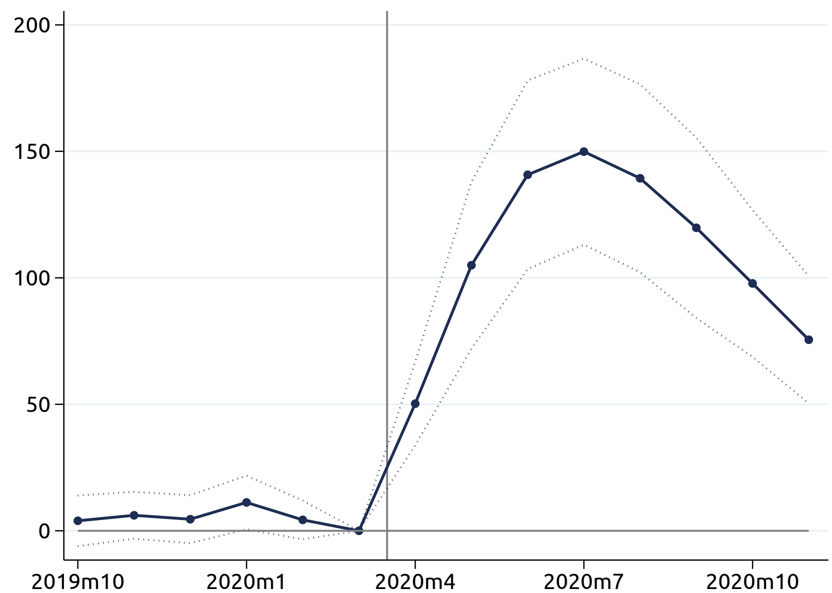
	All	Nonbank mtg companies			Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Servicer characteristics							
log(Servicing assets)	0.032***	0.029***	0.017***		0.031**	0.035***	
	(0.008)	(0.010)	(0.006)		(0.012)	(0.010)	
log(Assets)				0.012**			0.018
				(0.006)			(0.014)
Cash / assets			0.997***	1.078***		-0.970	-1.101
			(0.277)	(0.283)		(0.680)	(0.761)
Securities / assets			0.327**	0.399***		0.055	0.273
			(0.126)	(0.107)		(0.373)	(0.367)
Capital / assets			0.073	0.100		1.798*	1.521
			(0.143)	(0.146)		(0.967)	(1.003)
Servicing growth	0.011	0.066	0.016	-0.001	-0.079	-0.064	-0.082
	(0.062)	(0.067)	(0.043)	(0.043)	(0.108)	(0.111)	(0.110)
Servicer type							
Nonbank mortgage company	-0.019						
	(0.032)						
Credit union	0.087**						
	(0.035)						
N. Obs.	148	96	96	96	44	44	44

Table A.9: Servicer FEs (full sample including current loans)

	All	Nonbank mtg companies			Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Servicer characteristics							
log(Servicing assets)	0.037***	0.031***	0.025***		0.043***	0.043***	
	(0.007)	(0.008)	(0.006)		(0.010)	(0.010)	
log(Assets)				0.018***			0.025*
				(0.004)			(0.015)
Cash / assets			0.955***	1.083***		-0.664	-0.942
			(0.174)	(0.177)		(0.537)	(0.699)
Securities / assets			0.144	0.246***		0.320	0.553
			(0.100)	(0.085)		(0.364)	(0.345)
Capital / assets			0.011	0.053		1.292	1.068
			(0.103)	(0.109)		(0.794)	(0.907)
Servicing growth	-0.008	0.011	-0.011	-0.035	-0.030	0.000	-0.018
	(0.047)	(0.055)	(0.045)	(0.042)	(0.086)	(0.089)	(0.090)
Servicer type							
Nonbank mortgage company	-0.087***						
	(0.025)						
Credit union	0.131***						
	(0.029)						
N. Obs.	152	98	98	98	45	45	45

G Deferred payments

Figure A.5: **Deferred payments** This shows the results of the coefficients from Equation 2, where the dependent variable is a measure of the total borrowing through forbearance: the number of missed payments times the monthly mortgage payment (including taxes and insurance). This is an estimate, 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.



(a) Carried mortgage balance ($)

H Pre-CARES Act delinquencies

Figure A.6: **New 30-day delinquencies.** Difference in the transition probability into delinquency for high-forbearance vs low-forbearance servicers (estimates of coefficients from Equation 2). The y-axis indicates the fraction of newly delinquent mortgages, defined as loans that are past due in month t but current in month t-1. Includes same borrower and loan controls as our main eMBS specification (reported in table A.1). Standard errors are clustered by servicer.

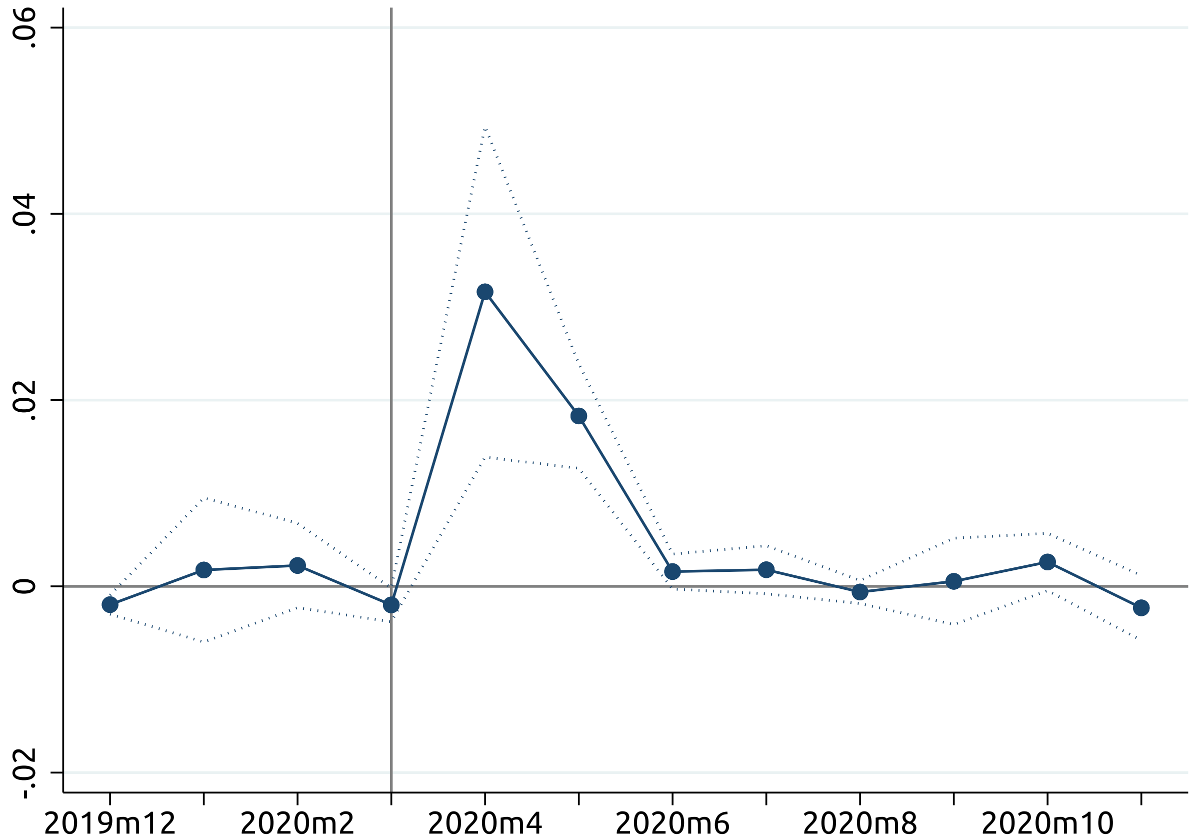


Table A.10: **Pre-CARES-Act delinquencies** This table presents estimates of regressions of various measures of delinquencies before the CARES Act on the dummy variable for high-forbearance servicers as well as other controls. The eMBS data from December 2019 and January 2020 are used for the estimates 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). The dependent variable for Tables (a) and (b) is the dummy variable for turning 30-day delinquent for the mortgage. The dependent variables for Tables (c) and (d) are whether a borrower is delinquent in the credit card and auto loan accounts, respectively. EMBS controls include the dummy for FHA loans, loan size, the dummy for first-time homebuyers, LTV, credit score, DTI, and the dummy for purchase loans. CRISM controls include updated credit scores and a borrower's age. Standard errors are clustered at the servicer level.

	(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

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

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.0032	-0.0013	-0.0009	-0.0009
	(0.0031)	(0.0020)	(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	0.015	0.015	0.015	0.015
N. Obs.	5,756,749	5,400,684	5,393,643	5,385,113

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

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.0089	-0.0018	0.0022*	0.0025**
	(0.0085)	(0.0030)	(0.0013)	(0.0011)
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	0.099	0.099	0.099	0.099
N. Obs.	5,769,271	5,400,702	5,393,661	5,385,130

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

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.0059*	-0.0025**	-0.0013**	-0.0010*
	(0.0035)	(0.0012)	(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	0.031	0.031	0.031	0.031
N. Obs.	5,769,271	5,400,702	5,393,661	5,385,130

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

I Additional non-mortgage results

Table A.11: **Non-mortgage results** This table presents a summary of estimates of equation (2) for various outcome variables. Column (1) report averages of the estimates of β_1 to β_4 and standard errors of the averages in the parenthesis. Columns (2) report averages of the estimates of β_5 to β_8 and standard errors of the averages in the parenthesis. For outcome variables related to auto loans, we report "NA" under column (1) because the Equifax data for the period contains an error. Standard errors are clustered at the servicer level.

	(1) 2020:m4 to 2020:m7	(2) 2020:m8 to 2020:m11	(3) Sample mean	(4) N. Obs.
Auto loan balance	NA	10.019	15,352	35,357,290
		(27.975)		
Other consumer loan balance	0.604	5.873	4,184	35,356,333
	(4.734)	(10.295)		
Transition to delinquency (credit card)	0.00017	0.00019	0.01017	33,284,225
	(0.00025)	(0.00030)		
Transition to delinquency (auto loan)	NA	0.00001	0.00523	33,284,225
		(0.00007)		
Transition to delinquency (other consumer loan)	-0.00002	0.00000	0.00353	33,284,225
	(0.00009)	(0.00008)		
Mortgage prepayment	0.0000	-0.0005	0.0143	33,550,744
	(0.0006)	(0.0009)		
Auto loan origination	NA	-0.000	0.023	35,723,355
		(0.000)		

J Characteristics of Borrowers in Forbearance

Table A.12: Comparing Characteristics of Borrowers in Forbearance across Servicers This table presents summary statistics measured as of February 2020 for borrowers that were ever in forbearance with high- and low-forbearance servicers using the merged eMBS-CRISM data.

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Months in forbearance (as of Nov 2020)	4.88	5.86
Ever exited from forebarance	0.34	0.31
Current Mortgage Balance	197,614.49	171,090.71
Auto Loan Balance	18,313.27	17,718.46
Credit Card Balance	10,912.77	11,514.34
12-mo change CNTY UR (8/20)	6.58	6.32
FHA	0.79	0.81
FICO V5 (updated)	647.57	662.15
LTV at origination	94.31	94.73
Loan age (year)	3.89	5.61
N. Obs.	153,010	234,236

K Comparison between Full and Matched Samples

Table A.13: **Comparison between Full and Matched Samples** This table presents summary statistics measured as of February 2020 for the eMBS data and the merged eMBS-CRISM data.

	(1) eMBS	(2) eMBS-CRISM match
Ever 30+ days delinquent	0.19	0.19
Ever in forbearance	0.14	0.15
Current UPB ($)	168,647.51	171,873.43
Orig LTV (%)	93.40	94.58
Orig DTI (%)	40.26	40.21
Orig credit score	692.65	696.85
Loan age (year)	4.93	5.33
FHA	0.68	0.71
VA	0.32	0.29
N. Obs.	10,315,121	2,883,200