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

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

September 19, 2023

Abstract

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

Keywords: mortgage, forbearance, liquidity, nonbank, CARES Act, COVID-19

JEL classification: G21, G23, G28

*We thank Toni Whited (Editor); an anonymous referee; seminar participants at the Central Bank of Ireland, Korea Development Institute, Yonsei University, 2022 SFS Cavalcade, 2022 Fed System Micro Conference, Federal Housing Finance Agency, Federal Reserve Board, AREUEA Virtual Seminar, FDIC Consumer Research Conference, 2022 ASSA meetings, 2021 Philadelphia Fed Conference on Consumer Behavior in Credit and Payments Markets and 2021 AREUEA National Meetings; our discussants Gene Amromin, Neil Bhutta, Meta Brown, Jan Brueckner, Greg Buchak, Susan Cherry, Lara Loewenstein and Kyle Mangum; as well as Larry Cordell, Arpit Gupta, Ben Iverson, Joe Nichols, and numerous other Federal Reserve colleagues and industry practitioners for comments and insights about institutional details. Opinions expressed in this paper are those of the authors and do not represent the opinions of the Federal Reserve Board, the Federal Reserve Banks of New York or Philadelphia, or the Federal Reserve System.

†Kim: Federal Reserve Board (email: you.kim@frb.gov); Lee: Federal Reserve Bank of New York (email: donghoon.lee@ny.frb.org); Scharlemann: Federal Reserve Board (email: tess.scharlemann@frb.gov); Vickery: Federal Reserve Bank of Philadelphia (email: james.vickery@phil.frb.org).

1 Introduction

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

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

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

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

[1] Examples include emergency business loans under the Paycheck Protection Program (Granja et al., 2020), mortgage modifications under the Home Affordable Modification Program (HAMP) (Agarwal et al., 2017a), and streamlined refinancing under the Home Affordable Refinance Program (Agarwal et al., 2022).

Ginnie Mae, the part of the mortgage market which serves the highest-risk borrowers and which, because of institutional factors, poses the greatest liquidity risk to servicers.

Specifically, using loan-level data we estimate that the conditional probability that a past-due borrower failed to enter forbearance varies between 10% and 60% across servicers, with a weighted interquartile range of 15 percentage points. These estimated "servicer effects" are robust to a variety of estimation approaches, including conditioning on *lender* fixed effects so that servicer effects are identified via post-origination servicing transfers. Several pieces of evidence indicate that this variation in forbearance outcomes reflects servicer behavior rather than unobserved borrower characteristics; for example borrowers at high- and low-forbearance servicers have similar ex ante characteristics and delinquency rates. The effects of servicers are also heterogeneous across borrowers, with older and low-credit score borrowers appearing "hard to reach" in the sense that they are both less likely to enter into forbearance and also not especially responsive to being matched with a "high-forbearance" servicer.

These findings are consistent with qualitative evidence that servicers had significant leeway to influence forbearance takeup. As we discuss in section 2.2, reports from media and financial regulators indicate that servicers varied significantly in terms of responsiveness and frequency of communication with borrowers, the information provided, and their systems for evaluating and processing forbearance applications (e.g., Consumer Financial Protection Bureau, 2021a). In short, despite the forbearance program's streamlined design, intermediaries still played an important role in how it was implemented.

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

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

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

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

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

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

We conclude by considering policy implications of our results. Our findings, and those of other researchers, suggest that the CARES Act forbearance program successfully reached most borrowers in need without inducing widespread strategic behavior or other serious unintended consequences. However, our results also indicate that there is scope to improve access and reduce variation in forbearance outcomes unrelated to borrower fundamentals. Our results also speak to the policy debate about the systemic risk posed by nonbank mortgage intermediaries, and the debate about the costs and benefits of large banks. Specifically, we find that exposure to liquidity risk reduced nonbank servicers' willingness to provide liquidity to borrowers. Conversely, large banks had the highest propensity to facilitate forbearance, likely reflecting tight post-crisis regulation, scale economies, and ample liquidity due to deposit inflows and access to the lender of last resort. These findings imply that forbearance policy design should take into account the liquidity position of servicers and the availability of nonbank liquidity backstops.

1.1 Related literature

We contribute to several strands of literature. First, a number of papers study the behavior and incentives of mortgage servicers, in particular analyzing the 2008 crisis and its aftermath. Among these, Aiello (2022) finds that financial constraints distorted servicers' loan modification decisions, while Agarwal et al. (2017a) document that servicers offered modifications at divergent rates.[2] We bring new data to bear and study a streamlined debt relief program designed to overcome the frictions that plagued mortgage modification following the Great Recession. Nevertheless, our central finding is that servicers still played a key role in the implementation of debt relief and that financial frictions and organizational factors shaped servicer behavior and borrower outcomes.

Second, we add to research on forbearance and other financial assistance programs implemented in response to COVID-19. Cherry et al. (2021), An et al. (2022) and Zhao et al. (2020) present a wealth of information on patterns of forbearance takeup (e.g., forbearance rates were higher for vulnerable borrowers and those facing negative income shocks). Like us, Cherry et al. (2021) find that nonbanks provided mortgage forbearance at lower rates, while Cherry et al. (2022) find higher forbearance provision among better-capitalized nonbanks. Research on other pandemic relief programs also finds variation in outcomes across financial intermediaries (e.g., Granja et al. 2020). New work by Lee and Maghzian (2023) studies the macroeconomic effects of forbearance, finding a positive impact on local employment growth. Relative to this other work, we provide a much more detailed analysis of the role of mortgage servicers and also use cross-servicer variation and credit bureau data to study the effects of forbearance on borrowers.

Third, we contribute to work on the effects of mortgage debt relief and payment size changes. Our finding that forbearance induces nonpayment is related to Mayer et al. (2014), who find borrowers strategically defaulted to qualify for debt relief during the

[2] Also studying the 2008 crisis period, Agarwal et al. (2011) and Kruger (2018) find that servicers were more likely to modify mortgages retained in portfolio than serviced for investors. Bandyopadhyay et al. (2022) find that mortgage servicing generates private information which influences Ginnie Mae early buyouts.

2008 crisis (see section 6.6 for discussion). Several papers find that permanent or persistent reductions in mortgage payments due to modifications or interest rate resets reduce default and boost consumption, among other effects (Scharlemann and Shore, 2022; Abel and Fuster, 2021; Ganong and Noel, 2020; Agarwal et al., 2017a; Di Maggio et al., 2017; Fuster and Willen, 2017).[3] We instead study a setting where payments were temporarily deferred but with no permanent cut in payment size, finding that part of the liquidity from forbearance was used to pay down credit cards but most was saved or consumed.

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

2 Forbearance and the CARES Act

The CARES Act was signed into law on March 27, 2020, and included significant relief for mortgage borrowers.[4] Homeowners with federally-backed mortgages became eligible for up to 180 days of forbearance, renewable for an additional 180 days upon request. (The program was extended in 2021; see Federal Housing Finance Agency 2021 and The White

[3] Several of these papers study HAMP, the mortgage modification program launched in 2009. HAMP's design differed quite significantly from forbearance; e.g., HAMP modifications provided a permanent or long-lived reduction in payment size, thereby significantly reducing the present value of mortgage payments, and HAMP required borrowers to document income and financial hardship. Payment deferral was part of the HAMP modification toolkit, but it took a more permanent form: payment was deferred until mortgage termination. Deferral was also just one of several tools available to servicers, along with rate reductions, term extensions, and in some cases, principal forgiveness (Scharlemann and Shore 2016, 2022). CARES Act forbearance instead mirrored mortgage debt relief previously used for natural disasters: a temporary payment holiday. This in part reflected that COVID-19 was a significant temporary liquidity shock for many households but did not induce a home price crash or widespread negative equity.

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

House 2021.) Borrowers in forbearance could skip mortgage payments without accruing unscheduled interest, late fees or penalties, or risking foreclosure. Missed payments were also not reported as delinquencies to credit bureaus, protecting borrowers' credit scores.

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

The CARES Act is silent about what should occur at the end of forbearance, but in the weeks after its passage, regulators and the mortgage agencies stated that a range of options would be available and that a lump-sum repayment of skipped payments would not be required (e.g., Freddie Mac, 2020). In April 2020, the FHA announced a "partial claim" program for borrowers exiting forbearance in which accumulated missed payments could be transferred into a subordinate interest-free note due at mortgage payoff (Department of Housing and Urban Development, 2020a,b). Borrowers not able to resume payments would be eligible instead for a modification. Fannie Mae and Freddie Mac announced a similar payment deferral option in May (Federal Housing Finance Agency, 2020). Payments skipped in forbearance were not forgiven but did not accrue interest; therefore the program effectively provided an interest-free loan.

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

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

2.1 Forbearance trends

Figure 1 plots the evolution of mortgage forbearance and nonpayment over 2020. The top panel based on credit bureau data shows that forbearance was rare prior to the pandemic but rose sharply starting in April, just after the CARES Act was passed. The aggregate forbearance rate peaked in May at 7.3 percent, falling to 5.2 percent by December.[5] The share of past-due loans also rose and fell along similar lines (bottom panel, and figure A.1 of the Internet Appendix). Note: "past-due" in this context includes both borrowers who paused their payments in a forbearance plan and delinquent mortgages not in forbearance. In practice not all past-due borrowers obtained forbearance, and conversely some borrowers entered forbearance as a precaution but kept making scheduled payments.

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

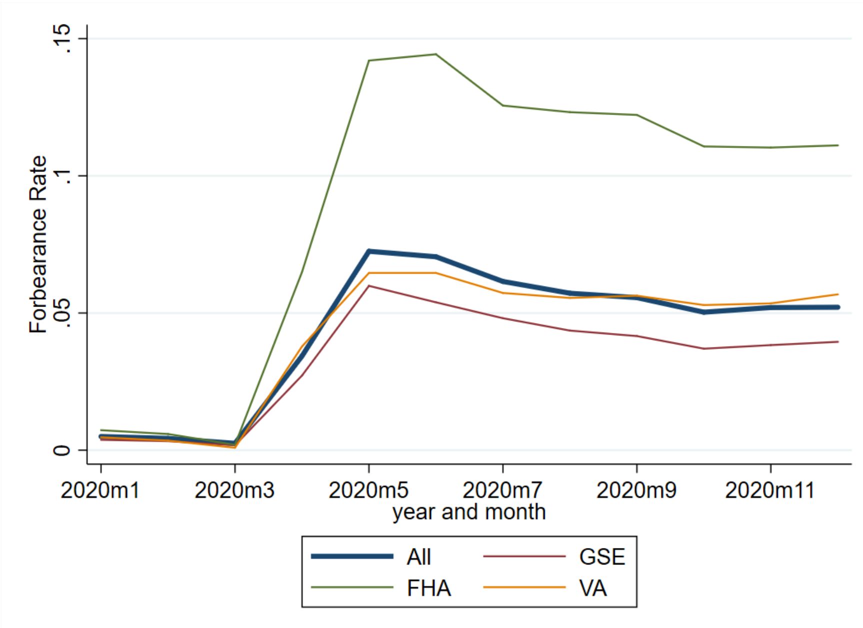
2.2 Forbearance implementation and the role of servicers

One might assume that servicers played a limited and passive role in implementing the CARES Act forbearance program, given its streamlined design and the fact that borrowers

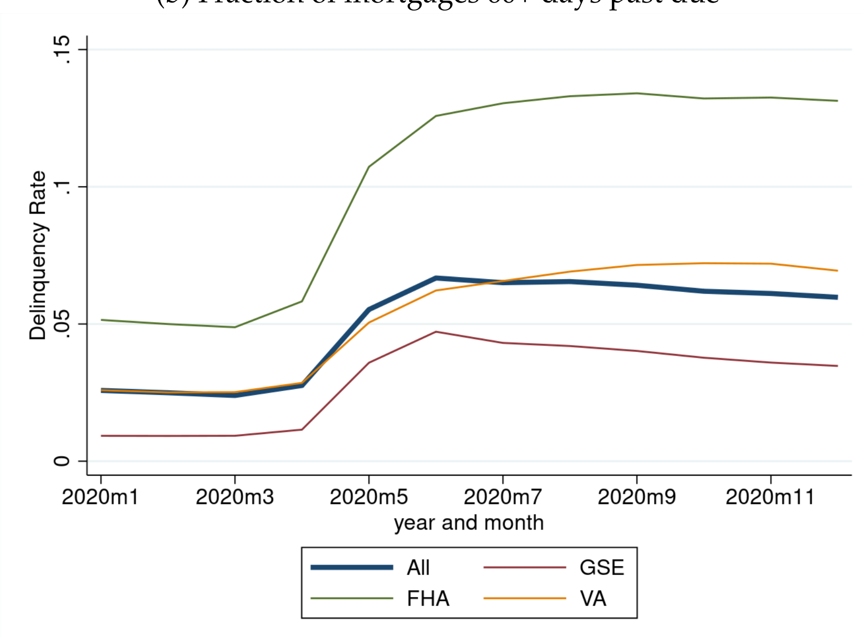
[5] Other data sources paint a similar picture but show a somewhat higher incidence of forbearance. Survey data from Mortgage Bankers Association (2020) indicate a peak forbearance rate of 8.55% in June 2020, while Black Knight (2020) reports a peak forbearance rate of 8.8%, also in June.

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

(a) Fraction of mortgages in forbearance



(b) Fraction of mortgages 60+ days past due



were not required to document hardship. But in practice, qualitative evidence suggests that servicers varied widely in their communication with borrowers and the information provided, as well as their systems for receiving and processing forbearance applications.

For example, Consumer Financial Protection Bureau (2021a) details forbearance-related servicing deficiencies observed by CFPB supervisors, including: (1) Providing incomplete or false information, e.g., that only delinquent borrowers qualified for forbearance, that a fee must be paid, or that lump-sum repayment was required; (2) Incorrectly sending collection or default notices, assessing fees, or initiating foreclosures for loans in forbearance; (3) Changing preauthorized funds transfers without consent, or failing to implement requests to freeze payments; (4) Failure to process forbearance requests in a timely way; (5) Enrolling borrowers in forbearance without consent; (6) Failure to set up an appropriate post-forbearance plan. We heard similar anecdotes in meetings with credit counselling agencies arranged as background for this project. Media reports highlighted similar issues and described how the wave of forbearance requests early in the pandemic overwhelmed many servicers' capacity, leading to long telephone hold times, non-operational servicer websites, and misinformation given to borrowers (e.g. Wall Street Journal, 2020).

These servicing issues are also evident in a sharp rise in forbearance complaints. Consumer Financial Protection Bureau (2021b) calculates that complaints to the CFPB related to forbearance spiked from 3-4% of all mortgage complaints in January and February 2020 to a peak of 21% in April, remaining persistently high at 12-15% over the rest of 2020 and early 2021. Complaints most commonly highlighted communication failures, confusing or incorrect information about post-forbearance options, problems in payment and forbearance reporting on borrowers' monthly statements, and delays and denials in putting the borrower in a post-forbearance repayment plan.[6]

[6]To give a sense of the issues, the following are three complaints taken from the public CFPB database: (1) *"I tried to reach out to <XXX> to request a forbearance ... Unfortunately, I was hung up on two times. I spent almost 3 hours on hold."*; (2) *"My initial 6 month forbearance has been approved, but I've been unable to make contact with the servicer to extend the forbearance. I've sent emails, left voice messages and tried online to extend the forbearance. They do not respond. I'm scared and I need help."*; (3) *"I have been trying for over a month to apply for*

At the other end of the scale, many servicers took significant steps to streamline the forbearance process, such as providing a prominent button or link on their website to a simple online application, and following up with delinquent borrowers frequently to make them aware of forbearance (e.g., one practitioner told us of a large bank servicer making such calls at a daily frequency). We quantify the cross-servicer variation in forbearance policies and outcomes more systematically in the following section.

3 Data and summary statistics

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

Loan-level mortgage data are drawn from eMBS. The data include the universe of securitized FHA and VA mortgages and report the servicer for each loan as well as loan characteristics and performance. We append data on each loan's forbearance status and forbearance terms from Ginnie Mae's forbearance register. We also match each servicer by name to servicer-level characteristics (e.g., size, liquidity ratio). For independent mortgage banks ("nonbanks") these characteristics are drawn from the mortgage call report (MCR) collected by the Conference of State Bank Supervisors, while for banks, they are drawn from FR Y-9C and call reports. eMBS itself is also used to calculate some servicer characteristics (e.g., aggregate servicing volume). We also match servicer data to borrower complaints from the CFPB complaints database (see section 5.2 for details).

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 "."

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

3.1 Summary statistics

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

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

Panel C of table 1 reports forbearance and nonpayment statistics for mortgages that

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

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

were current as of January 2020. Notably, 26% of loans that became past-due during the pandemic failed to enter into a forbearance plan. This is quite striking given that any FHA or VA borrower experiencing financial stress related to the pandemic was eligible for forbearance, and given that forbearance effectively provided a modest subsidy because no interest was charged on deferred balances. This fraction of "missing" forbearances is significantly lower — 9% — for loans entering serious delinquency (60+ days past due), but still well above zero. Conversely, 16% of borrowers remained current on their payments despite entering into forbearance. Most borrowers in forbearance skipped multiple payments, however, with 71% becoming at least 60 days past due.

4 Servicer-level variation in forbearance outcomes

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

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

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

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

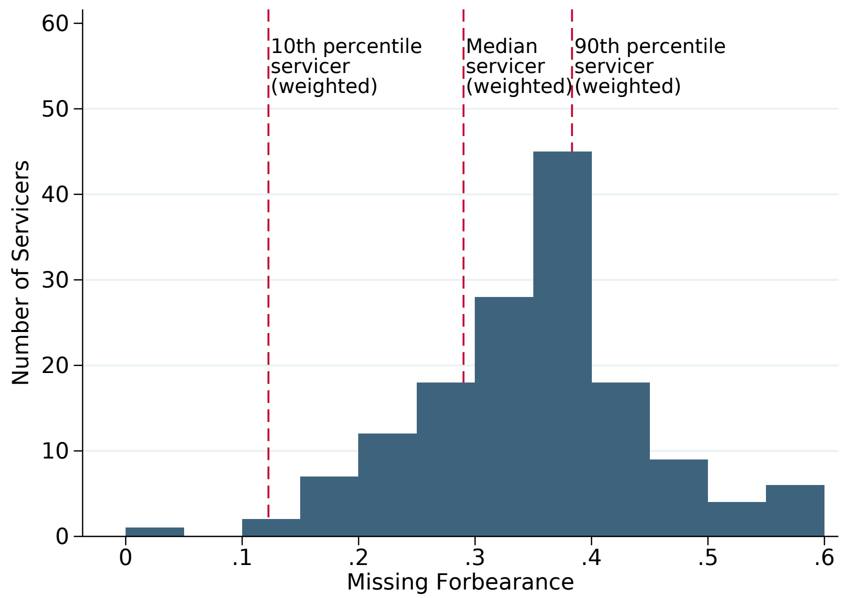
Figure 2 plots the distribution of servicer effects ($\widehat{\xi_s}$), showing very wide cross-servicer variation in forbearance outcomes for observably similar loans.[7] The figure normalizes the fixed effects to show the probability that a past-due loan with sample average characteristics fails to enter forbearance. The likelihood that the borrower "falls through the cracks" ranges from under 10% to almost 60%. This variation is not just 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% at the 10th percentile, with an interquartile range of 15 percentage points (pp).

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

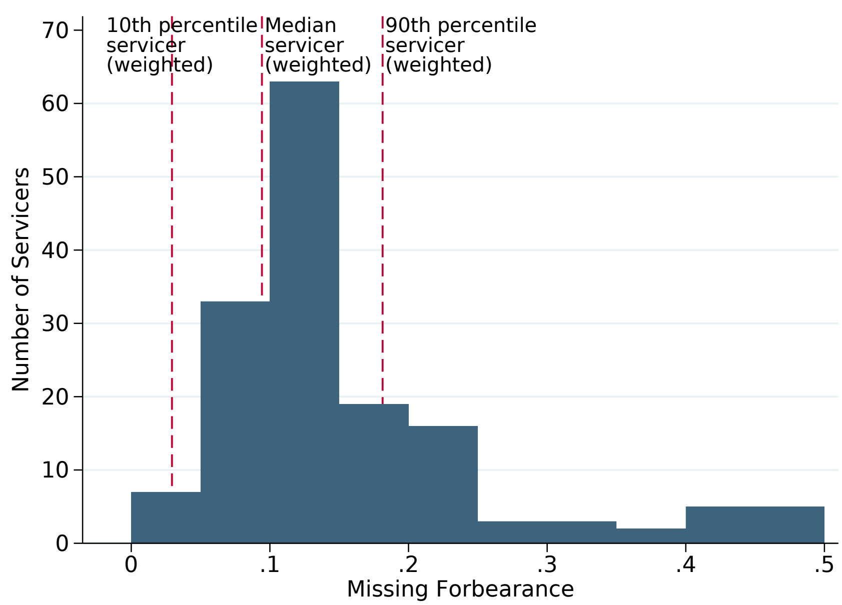
[7] These estimated servicer fixed effects are highly jointly statistically significant (f-statistic = 435). Moreover, including the servicer fixed effects doubles the R^2 of our model (comparing columns 1 and 2 in table A.2).

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

(a) Borrowers 30+ days past due



(b) Borrowers 60+ days past due



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%).

These estimated servicer effects are robust to alternative modelling choices, including:

1. Using the eMBS-CRISM matched sample, which allows us to control more finely for geography and include controls from borrower credit reports such as bins of borrower age, updated credit score and nonmortgage debt.[8]

2. Varying the set of eMBS-CRISM controls, comparing models with i) no controls, ii) only controls available in eMBS, and iii) all eMBS-CRISM controls. Servicer effects from these three models are highly correlated (figure A.3 of the Internet Appendix).

3. Three other specifications: i) retaining all mortgages in the sample, rather than just loans that became past due during COVID; ii) restricting to loans that became past-due in February or March, prior to the CARES Act; iii) including *lender* fixed effects, so that servicer effects are identified only from loans where servicing was transferred. This third approach is motivated by the fact that borrowers do select their lender, in ways that may be correlated with unobservables, but do not control whether servicing is later sold to a third party. These alternative sets of fixed effects are highly correlated with our main estimates (Internet Appendix figure A.4).[9]

[8] For histogram, see A.2 of the Internet Appendix. Coefficients on loan and borrower controls for this model are reported in table A.3. Terms-of-use restrictions on the CRISM dataset prevent us from retaining servicer information in the merged eMBS-CRISM dataset; we are however permitted to retain anonymous servicer identifiers, which is what we use to estimate the servicer fixed effects.

[9] The approach controlling for lender fixed effects is conceptually quite appealing, but there are two reasons why we don't use it as our primary method for estimating servicer effects. First, some lenders are not active in trading FHA and VA servicing rights; in these cases the method cannot estimate a servicer effect because the servicer and lender are collinear. E.g., we lose 60 out of 152 servicers from the cross-sectional sample used in section 5.1, including several very large servicers. Second, this method is not a panacea from an identification point of view, because servicers may still choose which servicing rights to trade in a way that is correlated with unobservables (see Bandyopadhyay et al. 2022 and Mayock and Shi 2022 for evidence that Ginnie Mae servicers have private information about borrowers). However, we do show that our main results look similar if using the "lender fixed effects" approach; see table A.11 and figures A.10 and A.11 in the Internet Appendix.

4.1 Servicer behavior or omitted borrower characteristics?

We interpret these striking differences in forbearance outcomes as being due to variation in servicer policies and practices. But an alternative explanation is that they reflect unobserved differences in forbearance *demand*. For instance, borrowers at "high-forbearance" servicers may happen to be more liquidity constrained and therefore benefit more from a payment holiday, or may be more financially literate. Although we include a rich set of controls, we of course cannot account for all factors that may affect forbearance demand.

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

1. Loans managed by high- vs low-forbearance servicers have similar average ex ante characteristics (Internet Appendix tables A.5-A.7); e.g., LTV is within 0.5%, and auto, credit card and student loan balances are each within 10%. Loans managed by low-forbearance servicers are somewhat younger (4.5 vs 6.0 years in eMBS-CRISM; marginally significant), but within age bins mortgages look similar on observables, and our regressions also always include loan age controls. The two sets of loans also experienced similar macroeconomic conditions during the pandemic: the 12-month change in the county unemployment rate differs by only 0.2pp. The historical path of unemployment back to 2006 is also similar in areas serviced by high- vs low-forbearance servicers as of 2020 (Internet Appendix figure A.5) suggesting the two sets of loans are geographically similarly exposed to the business cycle.

2. There is little difference in mortgage nonpayment rates, or credit card and auto delinquencies, between high- and low-forbearance servicers in the months prior to the pandemic (Internet Appendix figure A.6 and table A.8).[10] We also show us-

[10] We estimate account-level delinquency models where the dependent variable equals 1 if a borrower current at *t-1* is delinquent in month *t*. Studying transitions into delinquency is preferable to analyzing the *stock* of delinquencies because servicer quality can affect how long a mortgage remains delinquent, e.g., better servicers may help the borrower cure or modify. Also, servicers can purchase seriously delinquent loans out of Ginnie Mae pools and we do not observe loan performance in eMBS after repurchase; this could create a selection effect e.g., since banks are more likely than nonbanks to buy back loans.

ing McDash that the historical paths of mortgage delinquency in areas serviced by high- and low-forbearance servicers are similar, implying similar sensitivity of delinquency to the business cycle (Internet Appendix table A.7). In contrast, following the passage of the CARES Act, borrowers matched to high-forbearance servicers became *much* more likely to stop paying (see section 6 and figure A.6).

These findings speak against the hypothesis that borrowers at high-forbearance servicers were riskier on unobservables, because such an explanation would also predict higher nonpayment *prior* to the pandemic. They also speak against the story that high-forbearance-servicer borrowers were more financially literate, because this would be expected to *reduce* pre-COVID delinquency as shown by Gerardi et al. (2013) and Agarwal et al. (2017b). Finally, they show that variation in forbearance outcomes isn't due to differences in macro shocks or business-cycle risk.

3. Estimated servicer fixed effects are insensitive to the set of borrower and loan controls used, as discussed above, including the inclusion of *lender* fixed effects. In other words, there is little evidence of selection on observables.

4.2 Heterogeneity

Do servicers affect the behavior of all borrowers equally? Table 2 uses the eMBS-CRISM sample to study outcomes across borrowers with different characteristics, finding evidence of significant heterogeneity.

Column 1 shows that, overall, a past-due borrower is 13.6pp more likely to enter into forbearance when matched to a "high-forbearance" servicer, defined as a servicer fixed effect that exceeds the median. Columns 2-6 then interact this "high-forbearance" dummy with various borrower characteristics. Our prior is that servicer assignment would matter more for borrowers with a low propensity to seek forbearance, where there is more scope for behavior to change. This is what we see in columns 2 and 3; borrowers with low mortgage balances and in locations economically less-hard hit by COVID as measured by the local change in unemployment are both less likely to obtain forbearance overall *and* more sensitive to being matched with a high-forbearance servicer.

Table 2: **Heterogeneity in servicer effects.** Matched eMBS-CRISM sample, restricted to borrowers who were current in January 2020 but missed at least one payment between March and November. High-forbearance servicer is defined as a servicer with an above-median estimated fixed effect; similarly other explanatory variables are dummies equal to 1 if the variable exceeds its sample median. Standard errors are clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

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

	(1)	(2)	(3)	(4)	(5)	(6)
High-forbearance servicer	0.136***	0.182***	0.147***	0.120***	0.137***	0.189***
	(0.021)	(0.024)	(0.024)	(0.022)	(0.023)	(0.029)
High-forbearance servicer:						
$\times$ High unpaid mortgage balance		-0.054***				-0.044***
		(0.010)				(0.009)
$\times$ High Δ unemp rate (yoy)			-0.021**			-0.015**
			(0.009)			(0.006)
$\times$ High updated credit score (FICO V5)				0.020		0.003
				(0.013)		(0.011)
$\times$ High borrower age					-0.003	0.002
					(0.009)	(0.008)
High unpaid mortgage balance		0.123***				0.069***
		(0.009)				(0.010)
High Δ unemp rate (yoy)			0.061***			
			(0.006)			
High updated credit score (FICO V5)				0.057***		0.068***
				(0.012)		(0.009)
High borrower age					-0.020***	-0.013*
					(0.007)	(0.007)
Zipcode fixed effects	N	N	N	N	N	Y
Other controls	N	N	N	N	N	Y
N. Obs.	431,478	411,939	431,083	431,478	431,008	405,464
Adj. R^2	0.02	0.04	0.03	0.03	0.03	0.09

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

These results speak to the idea that some groups of borrowers are "hard to reach" — they are less likely to seek forbearance and also relatively unresponsive to servicer efforts to make forbearance easier to obtain. This is apparent in our later results too: easier access to forbearance only moderately reduces the number of past-due borrowers outside the forbearance safety net. Finally, although we do find significant heterogeneity, the overall effect of servicers on forbearance outcomes is broadly based, as seen by the fact that the uninteracted "high-forbearance" dummy is positive and large in each column of table 2.

5 Servicer characteristics and forbearance outcomes

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

1. Liquidity constraints. When a borrower stops making payments, the mortgage servicer is required to temporarily finance and advance payments on the borrower's behalf, including principal, interest, taxes and insurance. Servicers facing binding liquidity constraints therefore may wish to discourage borrowers from entering forbearance, to limit these cash outflows (given that forbearance and nonpayment are closely linked, as we show empirically below). This liquidity risk is particularly significant for FHA loans, because FHA servicers must forward payments for a much longer period and face significant delays and costs before being reimbursed, and also because FHA borrowers have higher default risk (Pence, 2022; Kim et al., 2018).[11] Nonbank mortgage companies are

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

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

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

3. Capitalization and risk-shifting. Servicers face a tradeoff in the sense that improving servicing quality and customer satisfaction is costly in the short run but may reduce legal risk and improve retention in the long run. Undercapitalized servicers may thus have weaker incentives to streamline access to forbearance, in line with the classic risk-shifting hypothesis of Jensen and Meckling (1976).

4. Size, scale and technology. Prior research shows that size and organizational form play key roles in shaping financial intermediary behavior (e.g., Berger et al., 2005). In our setting, e.g., scale economies may have enabled large servicers to develop sophisticated servicing platforms, facilitating communication and faster processing of forbearance requests. Or conversely, small, nimble servicers may have been able to adjust practices more quickly than large bureaucratic organizations with several layers of management.

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

5.1 Empirical analysis

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

Estimates are reported in table 3 and reveal several patterns. First, borrowers at large servicers are significantly more likely to enter into a forbearance plan, whether size is measured by the log of servicing assets or balance sheet assets. Second, organizational form matters. Nonbank mortgage companies are about 8pp less likely than banks to provide forbearance to a past-due borrower, while credit unions are about 19pp *more* likely. Third, internal liquidity at the start of the pandemic, measured by the ratio of cash to total assets, is strongly positively correlated with forbearance provision, but *only* for nonbanks. Together these servicer characteristics account for a significant share of the variation in servicer practices; the adjusted R^2 is between 0.4-0.5 in most of the specifications.

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

The high forbearance rate for large servicers, both banks and nonbanks, is also striking. Although it is difficult to pinpoint the mechanism underlying this result, large ser-

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

Table 3: **Determinants of servicer effects.** Servicer-level regression of servicer forbearance fixed effects on characteristics drawn from bank and nonbank call reports and eMBS. Column 1 is based on all servicers including banks, credit unions and nonbanks. Columns 2-4 reflect nonbank mortgage company servicers only. Columns 5-7 reflect bank servicers only. Weighted least squares, weighted by number of borrowers that were current in January 2020 but past due between March and November. Robust standard errors. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

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

	All	Nonbank mtg companies			Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Servicer characteristics							
log(Servicing assets)	0.035***	0.030***	0.027***		0.038***	0.039***	
	(0.006)	(0.008)	(0.005)		(0.009)	(0.010)	
log(Assets)				0.019***			0.025*
				(0.005)			(0.014)
Cash / assets			0.919***	1.047***		-0.657	-0.886
			(0.185)	(0.191)		(0.511)	(0.653)
Securities / assets			0.100	0.186**		0.244	0.448
			(0.085)	(0.090)		(0.360)	(0.319)
Capital / assets			0.032	0.080		1.068	0.753
			(0.104)	(0.113)		(0.703)	(0.802)
Servicing growth	-0.045	-0.003	-0.002	-0.019	-0.118	-0.084	-0.102
	(0.049)	(0.058)	(0.048)	(0.048)	(0.076)	(0.085)	(0.082)
Servicer type							
Nonbank mortgage company	-0.084***						
	(0.025)						
Credit union	0.186***						
	(0.032)						
N. Obs.	152	98	98	98	45	45	45
Adj. R^2	0.53	0.29	0.48	0.41	0.47	0.46	0.27

vicers may benefit from scale economies in technology investments (e.g., a well-designed online platform), may have better access to capital markets and more resources to train servicing staff, or may take a "borrower-friendly" approach because they are more likely to be targeted by financial regulators, particularly in the case of large banks.[14]

5.2 Servicing quality: evidence from CFPB complaints

Given the program's design, it seems clear that past-due FHA and VA borrowers would have benefited from forbearance; this implies that servicer practices limiting forbearance uptake reduced borrower welfare for our sample. To investigate further, we study whether borrowers were less satisfied with "low-forbearance" servicers based on the frequency of forbearance-related complaints for government loans submitted to the CFPB complaint platform. (For details of data construction see Internet Appendix section A.2.)

Results are presented in table 4. The dependent variable is the frequency of forbearance-related complaints per thousand Ginnie Mae mortgages serviced. We find that the complaint rate is significantly higher for low-forbearance servicers. This is direct evidence of poorer servicing quality for these firms. The inverse relationship between forbearance provision and complaints is more pronounced among nonbanks (column 5).

When we replace the servicer fixed effects with servicer characteristics (columns 3, 4 and 6), we find again that liquidity matters — servicers with lower cash and securities balances were subject to more complaints. Again, these relationships are concentrated among nonbank servicers. These results and those from table 3 show that liquidity constraints may reduce servicing quality, consistent with prior evidence on foreclosures and modifications from the Great Recession period (Aiello, 2022).

[14] Results in table 3 are related to contemporaneous analysis of the relationship between forbearance provision and servicer characteristics by Cherry et al. (2022) using a different but overlapping sample. Cherry et al. (2022) do not study the role of liquidity constraints, which is particularly important for our sample given the liquidity risk associated with Ginnie Mae mortgages (as discussed in section 5.1). In other respects our results and Cherry et al. (2022) are generally consistent; e.g., both studies find that large servicers and bank servicers are more likely to provide forbearance.

Table 4: **Servicer forbearance practices and CFPB complaints.** Servicer-level regression of relationship between volume of forbearance-related CFPB complaints and servicer forbearance practices (as measured by servicer fixed effects). Outcome variable is the number of forbearance-related mortgage complaints for government loans per thousand Ginnie Mae mortgages serviced. Weighted least squares, weighted by size of Ginnie Mae servicing portfolio as of January 2020. Robust standard errors. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Dependent variable: Forbearance complaints per thousand loans serviced

	All lenders				Nonbanks only	
	(1)	(2)	(3)	(4)	(5)	(6)
Servicer forbearance propensity	-0.222***	-0.235***			-0.622**	
	(0.073)	(0.077)			(0.303)	
Servicer characteristics						
log(Servicing assets)			-0.016**	-0.006		-0.031
			(0.007)	(0.008)		(0.041)
Cash / assets				-0.409*		-1.090**
				(0.229)		(0.485)
Securities / assets				-0.355**		-0.891***
				(0.174)		(0.301)
Capital / assets				-0.020		0.440
				(0.139)		(0.524)
Servicing growth			0.079	0.094		0.731*
			(0.060)	(0.060)		(0.409)
Frac. govt. loans that are FHA		0.069**	0.072**	0.089	-0.337	-0.486
		(0.032)	(0.036)	(0.077)	(0.503)	(0.562)
Servicer type						
Nonbank mortgage company		0.002	0.012	-0.033		
		(0.020)	(0.022)	(0.033)		
Credit union		0.070**	0.000			
		(0.028)	(0.025)			
N. Obs.	129	129	129	125	92	92
Adj. R^2	0.01	-0.01	-0.01	-0.00	-0.01	0.12

6 Effects of forbearance on borrowers

In this section we use cross-servicer variation to estimate the causal effect of forbearance access on borrower outcomes such as delinquency, nonmortgage debt, credit scores, and auto purchases. We then draw out broader implications and lessons from our findings.

6.1 Empirical strategy

We use a difference-in-differences approach to study the borrower effects of being matched with a "high-forbearance" servicer, again defined as a servicer with an above-median fixed effect. The sample period is October 2019 to December 2020. We use the six months up to March 2020 to establish the absence of differential pre-trends between high- and low-forbearance servicers, and attribute differential changes in borrower outcomes after March 2020 as being due to variation in access to forbearance. For this section we rely on the CRISM-eMBS matched sample, which allows us to i) observe outcomes from credit reports, ii) measure geography more finely, iii) include a richer set of controls, and iv) track payment status even for loans repurchased from MBS pools.[15]

We trace out the effects of servicers dynamically by regressing borrower outcomes (e.g., payment status) on a high-forbearance servicer dummy interacted with a set of time dummies, controlling for borrower and loan characteristics, static servicer dummies, and geography by time fixed effects. Specifically we estimate:

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

where Y_{it} is a borrower outcome for loan i in month t; β_t are coefficients on a vector of time dummies interacted with the high-forbearance-servicer dummy S_i^H; Z_{it} is a vector of

[15] Ginnie Mae issuers may repurchase a nonperforming loan from an MBS pool at par if the borrower misses 3+ payments. Buyouts were attractive in 2020 due to low yields. eMBS does not report loan performance after loans are repurchased, but we do observe performance on such loans in the CRISM-eMBS sample.

loan controls including characteristics at origination (e.g., loan amount, LTV, credit score), updated credit score as of January 2020 (measured by the Equifax Risk Score), updated principal balance, loan age, and borrower age; α_s is a vector of non-time varying servicer dummies; and $\alpha_{zt\tau}$ is a vector of zipcode $\times$ month $\times$ origination year (τ) fixed effects to account for the time-varying geographic effects of the pandemic for different loan cohorts. We omit the dummy for March 2020 from β_t, therefore normalizing outcomes to be equal between high- and low-forbearance servicers just prior to the CARES Act. As before, the sample consists of loans that were active and current in January 2020; we also exclude loans originated after October 2019. Standard errors are clustered by servicer.

6.2 Nonpayment

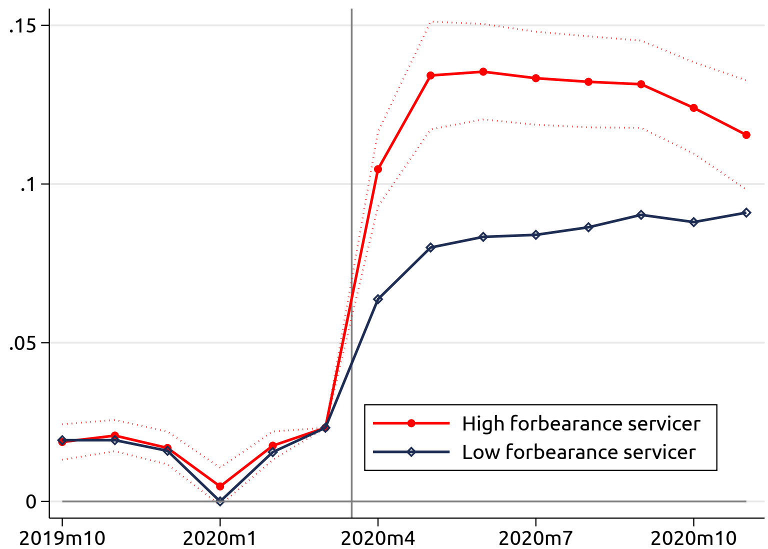
Figure 3 presents effects on mortgage payment behavior based on our estimates of $\hat{\beta}_t$. The top panel shows that easier access to forbearance significantly increased the overall mortgage nonpayment rate. The fraction of past-due borrowers at high- vs low-forbearance servicers track each other closely through March 2020, but then diverge sharply — the probability that a borrower becomes past-due increases about twice as quickly at high-forbearance servicers after the passage of the CARES Act. In levels, the difference in the nonpayment rate peaks as high as 5pp in May 2020. In contrast, the number of borrowers that are past-due but not in a forbearance plan is significantly *lower* at high-forbearance servicers (bottom panel of figure 3), particularly early in the pandemic.

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

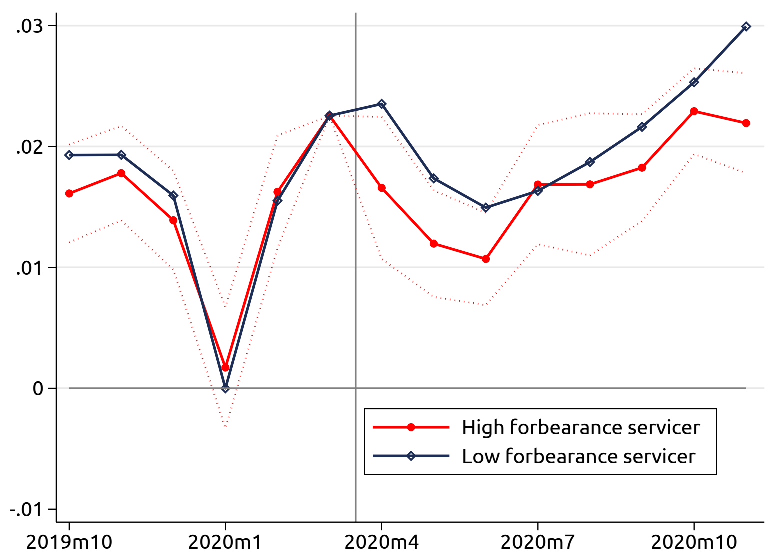
The first row of table 5 reports the effect on the forbearance rate itself. From April-July 2020, assignment to a high-forbearance servicer increases the forbearance rate by 5.6pp, a quantitatively important effect compared to the base forbearance rate of 8.1 percent at low-forbearance servicers. The effect declines slightly to 4.5 percent later in 2020.

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

(a) Past due



(b) Past due, no forbearance



The second and third rows report estimates for nonpayment and nonpayment outside of forbearance, summarizing the visual evidence from figure 3. Here, a key takeaway point is that the effects on nonpayment are almost as large as the effects on forbearance itself (e.g., 4.9pp compared to 5.6pp for the April-July period). In other words, easier forbearance access induced a large number of borrowers to stop making their mortgage payments. We discuss this finding further in section 6.6. Easier forbearance access also reduces the number of past-due borrowers *not* in a forbearance plan by 0.4pp. This is a much smaller absolute effect, but in proportionate terms it represents a significant 20-25 percent drop in the number of "missing" forbearances.

Table 5: **Forbearance and nonpayment outcomes.** Estimates of the average effect of assignment to a high-forbearance servicer on five different payment and forbearance outcomes. Estimates reported in columns (1), (3) and (5) are the average coefficient on the high-forbearance-servicer $\times$ time dummies (estimates of β_t from equation 3), over three phases of the pandemic: a pre-pandemic period (October 2019-February 2020); early pandemic (April-July 2020) and later pandemic (August-November 2020), along with the associated standard error of each mean. March 2020 dummy is omitted; thus effect is normalized to zero in that month. For context, columns (2), (4) and (6) report the unconditional mean of the dependent variable at low-forbearance servicers during the period referenced. Standard errors are clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

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

The fourth row of table 5 shows that the share of borrowers who entered forbearance purely as a precaution but continued making their scheduled payments does not differ systematically between low- and high-forbearance servicers. The final row of estimates confirms that the primary effect of easier forbearance access is to increase the number of borrowers who both skipped payments and entered forbearance.

These results show that servicer policies significantly affected liquidity provision to households. Based on our estimates and some auxiliary assumptions, we calculate that borrowers matched to high-forbearance servicers deferred an additional ≈ \$300 in cumulative mortgage payments by November 2020 compared to equivalent borrowers at low-forbearance servicers (see Internet Appendix figure A.9 for details). Since the treatment effect on the forbearance rate itself is about 5pp, this implies, on the margin, deferred payments of \$6,000 per additional forbearance, a significant sum. In aggregate, switching all Ginnie Mae borrowers from low-to-high forbearance servicers would increase deferred payments just over the April-November 2020 period by \$3.1 billion, equivalent to an effect of ≈ \$10 billion if generalizing our estimates to the entire mortgage market.[16] Next we study how this liquidity was used by borrowers.

6.3 Nonmortgage debt

We start by studying the effect of forbearance on credit card debt, an alternative form of borrowing often used during periods of financial stress. Liquidity constraints likely play a key role in determining whether funds from forbearance are used to reduce debt rather than more immediate needs like nondurable consumption (e.g., Telyukova, 2013; Gross and Souleles, 2002; Zeldes, 1989). Correspondingly in the spirit of Gross and Souleles (2002) we split the borrower sample into high- and low- credit card utilization groups

[16] The estimate of \$3.1 billion is computed by multiplying the estimate of the cumulative deferred payment from Figure A.9 in the Internet Appendix by the number of FHA and VA mortgages outstanding as reported in our table of summary statistics. Our estimate of the aggregate effect of ≈ \$10 billion is computed by then grossing up this estimate by the fraction of all forbearances that were in the FHA/VA segment as of the peak in June 2020, taken from Black Knight (2020).

based on the ratio of total drawn balance to total credit limit summed across cards (measured ex ante over the six months to March 2020) and estimate separate results by group.[17]

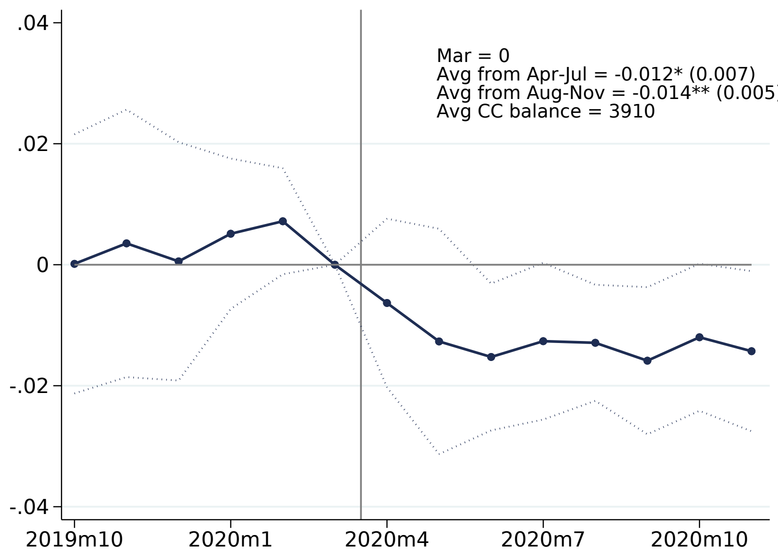
To begin, we document several pieces of evidence indicating that utilization is in fact a reasonable proxy for liquidity constraints, rather than simply being a measure of card transaction volume. First, in aggregate, about three-quarters of credit card balances are in fact revolving balances that accrue interest, rather than transaction balances paid off each month (Adams et al., 2022). Second, high utilization is strongly associated with low household income at the zip-code level (Internet Appendix table A.12). Third, individuals with high utilization have much lower credit scores; and fourth, such individuals are significantly more likely to be in default not only on their credit cards but also on mortgage and auto debt, both before and during the pandemic (Internet Appendix table A.13). Taken together this evidence supports the interpretation that high-utilization individuals are indeed more likely to be liquidity constrained.

Turning to our results, Figure 4 shows that liquidity from forbearance did indeed allow some borrowers to reduce credit card balances, with the effect concentrated among less liquidity-constrained (i.e., low utilization) households. The figure presents estimated $\hat{\beta}_t$s from our difference-in-difference equation using log(credit card debt) as the outcome variable. (Results are comparable if we instead use the level of credit card debt; see figure A.8 in the Internet Appendix.) For the low-utilization group, assignment to a high-forbearance servicer reduces credit card debt by 1.2 percent between April and July and 1.4 percent between August and November (top panel of figure 4). This is an average effect across all borrowers; scaled by the treatment effect on the forbearance rate of around 5pp, it represents a 20-30 percent reduction in credit card debt for marginal borrowers induced to enter into forbearance, accounting for about one-fifth of the forbearance liq-

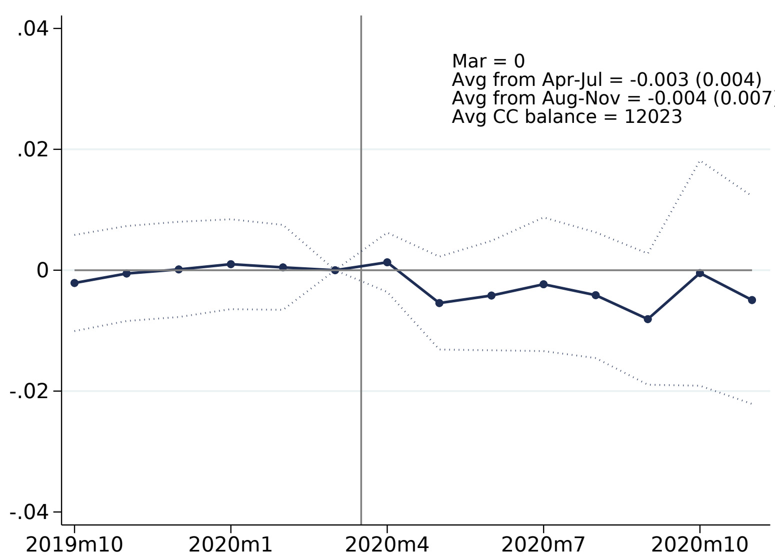
[17] Note: the card balance is the total outstanding balance at calendar-month end, reflecting unpaid balances from prior billing cycles as well as transactions incurred during the month. Equifax does not report the size of the borrower's payment or whether they just make their minimum payment, variables that would arguably be cleaner measures of financial constraints than the utilization rate. Even so, several pieces of evidence do suggest that utilization is a reasonable proxy for liquidity constraints, as we now discuss.

Figure 4: **Forbearance access and log of credit card balances.** Estimates and 95% confidence intervals of the effects of assignment to a high-forbearance servicer on log(total credit card debt). The top (bottom) panel shows estimates for borrowers with below (above) median credit card utilization (measured ex ante between October 2019 and March 2020). The median average utilization is calculated separately for each cohort of borrowers based on mortgage origination year. Standard errors are clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

(a) Low utilization borrowers



(b) High utilization borrowers



uidity infusion for the low-utilization group.[18] In contrast, we find little or no effect on credit card debt for high-utilization borrowers (bottom panel of figure 4).

We find no evidence that borrowers used forbearance to pay down other forms of debt like auto loans, student debt, or home equity liens (table A.9 in the Internet Appendix), perhaps because these debts have lower interest rates than credit cards, making them a lower priority for payoff. We also do not find discernable effects on nonmortgage delinquency. This may in part reflect the availability of forbearance for these other debt types.

6.4 Other borrower outcomes

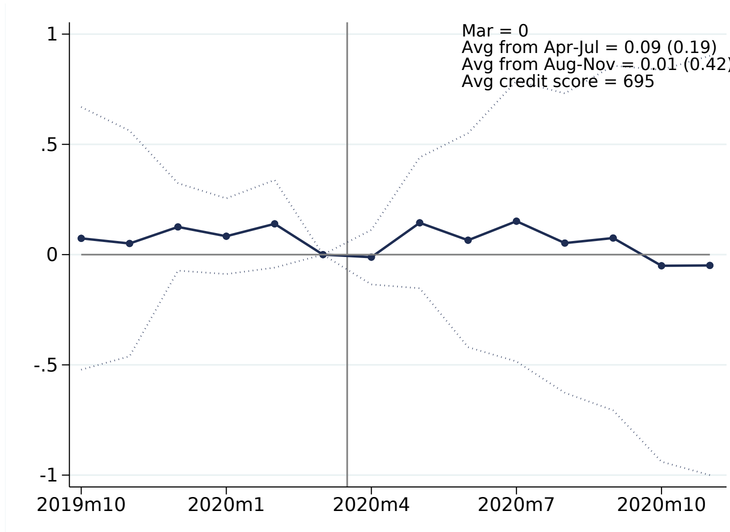
Credit scores. Using the same methodology, figure 5 shows that easier access to forbearance did not impair the credit scores of borrowers at high-forbearance servicers, despite the high nonpayment rate for this group.[19] This outcome is consistent with the intended design of the CARES Act forbearance program, which stipulated that nonpayment in forbearance should not be reported as a delinquency to credit bureaus. The point estimate is in fact slightly positive, which could be possible if, e.g., forbearance reduced nonmortgage delinquency, although it is not close to statistical significance.

Auto purchases. How much of the liquidity provided by forbearance was used for consumption? Credit bureau data do not typically measure consumption directly, but we do study a proxy for durable goods purchases often used in the literature, namely the establishment of new auto credit trade lines as a measure of automobile purchases (e.g., Abel and Fuster, 2021; Di Maggio et al., 2017). Borrowers at high-forbearance servicers are not more likely to buy an automobile — the point estimate is near zero and tightly enough estimated to rule out large effects (table A.9 of the Internet Appendix). This stands in con-

[18] Given the average credit card balance of $3,910 for low-utilization borrowers, a 1.4% paydown amounts to $55 per borrower. By comparison, we estimate that assignment to a high-forbearance servicer results in an additional ≈ $300 in total cumulative deferred mortgage-related payments up to November 2020 (figure A.9 of the Internet Appendix), 5-6 times larger than the estimated effect on credit card balances.

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

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



trast to Di Maggio et al. (2017), who study mortgage payment changes due to interest-rate resets, also using mortgage data linked to credit reports. Two plausible reasons for these differences are: i) forbearance is primarily a means to *defer* payments, whereas payment reductions due to interest rate resets do not have to be repaid; ii) borrowers induced on the margin to enter forbearance were likely experiencing financial uncertainty and stress, reducing their demand for expensive, illiquid, durable goods.

Prepayment. Internet Appendix table A.9 also reports estimates of the effect of forbearance on mortgage prepayment, an important outcome given that our study period featured a refinancing boom due to low interest rates (Fuster et al., 2023). It is possible that easier access to forbearance could have limited prepayment, because lenders required borrowers to exit forbearance first before refinancing. In practice however, we find little or no effect on prepayment. This implies that borrowers assigned to high-forbearance servicers were *not* diverted from refinancing into forbearance, an outcome that would have complicated an assessment of the program's welfare effects for participating borrowers.

Bankruptcy. Wang et al. (2020) document a striking decline in consumer bankruptcy during the COVID pandemic. We find no evidence however that servicing practices significantly affected bankruptcy outcomes; the difference in bankruptcy (including bankruptcy of any type) between high-and-low forbearance servicers is only about 1 percent of the sample mean, and quite tightly estimated (Internet Appendix table A.9). This may seem surprising in light of evidence that bankruptcy filings are very sensitive to cash-on-hand (Indarte, 2023). A plausible explanation however is that borrowers in sufficient distress to be near bankruptcy likely had strong incentives to file for forbearance regardless of their servicer, particularly considering the much greater complexity of the bankruptcy process.

6.5 Crowding-out effects?

Aside from borrowers, forbearance provision might also affect *lenders*. Specifically, by draining liquidity, forbearance might limit servicers' capacity to originate new loans, particularly for nonbanks without access to deposits or the lender of last resort. (This hypothesis is reminscent of Chakraborty et al. 2018, who find that higher mortgage lending during the 2000s housing boom crowded out commercial lending.)

We test for crowding-out effects using a difference-in-differences approach, tracing out how lending by high- versus low-forbearance servicers evolved after the CARES Act was passed using using eMBS data aggregated by servicer-month as well as quarterly data from bank and nonbank call reports. We use a poisson model, which has better econometric properties than the log-linear models often used in finance applications (Cohn et al., 2022; Correia et al., 2020). Specifically we assume that loan volume for servicer s in month or quarter t follows a poisson distribution with conditional mean λ_{st} given by:

$$\lambda_{st} = exp(\beta_t S_s^H + \delta_t X_s + \alpha_s + \gamma_t) \qquad (3)$$

where β_t are coefficients on time dummies interacted with the high-forbearance-servicer dummy S_s^H; δ_t are coefficients on time dummies interacted with servicer characteristics X_s (for the eMBS regressions X_s includes a nonbank dummy and log of servicing assets); and α_s and γ_t are servicer and time dummies. $\delta_t X_s$ controls dynamically for other factors that may affect lending; e.g., Fuster et al. (2023) show that the nonbank share of mortgage lending fell temporarily at the start of the pandemic, perhaps due to funding issues.

Results are reported in the Internet Appendix. Figure A.12 presents β_t estimates for total agency mortgage lending and for Ginnie Mae lending based on eMBS data aggregated by servicer-month. Agency lending by high-forbearance servicers does drop post-CARES in April and May 2020, statistically significantly in April. But thereafter, we find no general decline in lending by high-forbearance servicers. Figure A.13 repeats the exercise just for nonbanks using quarterly mortgage originations from nonbank call reports; this includes both agency and non-agency lending, unlike eMBS. Lending by high-forbearance servicers drops in relative terms from the first to second quarter of 2020 but the effects are not statistically significant. Figure A.14 reports results for banks using call and FR Y-9C data. Since these filings do not report originations we instead focus on outstanding loans on balance sheet (total loans or commercial and industrial loans). Unsurprisingly given banks' strong liquidity position during this period (Li et al., 2020), we find no evidence of crowding-out; estimates if anything have the opposite sign. Finally figure A.15 estimates an alternative Ginnie Mae specification at the loan level; results are similar to figure A.12.

To summarize, we find little robust evidence of crowding out effects. The lack of such effects may be surprising, particularly for nonbank mortgage companies given their limited access to external finance. We believe this reflects a combination of factors. First, confidence bounds on our estimates are quite wide; we lack power to identify moderate lending effects. Second, although nonbank liquidity stress was significant early in the pandemic when most forbearance applications were received, liquidity constraints later eased as nonbanks enjoyed a cash infusion from the flood of mortgage prepayments (Pence, 2022; Fuster et al., 2023). (Consistent with this narrative, we do find some evidence of a lending effect in April 2020, as discussed earlier.) Third, although nonbank lending does require some internal liquidity, originations are primarily funded by bank warehouse lines; these credit lines mostly remained intact during the pandemic (Pence, 2022). Finally we caution that estimates here are less-cleanly identified than elsewhere in our paper, since forbearance and lending policies may be co-determined (e.g., a nonbank with strong warehouse lender relationships may have more capacity to provide forbearance *and* to expand lending). Such omitted variable biases may attenuate our estimates.

We conclude that forbearance did not appear to significantly crowd out lending during the COVID episode, but that such effects may still be important during a future forbearance event, particularly if it involves a prolonged servicer liquidity crunch.

6.6 Broader implications

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

Our finding that access to forbearance induced nonpayment is reminiscent of the strategic default literature, in particular Mayer et al. (2014), who find that mortgage borrowers defaulted in order to qualify for generous modifications from subprime lender Countrywide during the 2008 financial crisis. There are some notable differences between their setting and ours, however, and several pieces of evidence described below suggest that the marginal nonpayers in our sample primarily entered forbearance due to genuine liquidity concerns rather than a strategic decision to obtain an interest-free loan.

First, unlike Mayer et al. (2014) we find that marginal nonpayers look similar on observables to "control group" borrowers who obtained forbearance from low-forbearance servicers (see table A.10 in the Internet Appendix). If moral hazard was the main driver of nonpayment, we might instead expect marginal nonpayers to be financially literate and higher-income, as Mayer et al. (2014) do find in their setting. Furthermore, although borrowers at high-forbearance servicers stay in forbearance slightly longer and are less likely to exit, the effects are small (e.g., the probability of forbearance exit is 0.31 at high-forbearance servicers compared to 0.35 at low-forbearance servicers). In other words there is little evidence that borrowers that obtained forbearance on the margin acted to "max out" the zero-interest financing provided by payment deferral.

Second, liquidity from forbearance was generally *not* used to pay down debt or to purchase automobiles, suggesting deferred payments were primarily used for precautionary savings or nondurable consumption. This interpretation is consistent with Lee and Maghzian (2023), and with a survey from April 2020 studied in Anderson et al. (2022). Households were asked how they would use funds from forbearance; the top response was "necessary" consumption, followed by saving, then debt consolidation. Although we do find evidence of credit card debt paydown, it is limited to less liquidity-constrained households and even for this group accounts for only one-fifth of deferred payments.

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

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

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

Against these positives, our results also highlight several program limitations. While takeup was high, not all past-due borrowers obtained forbearance and wide cross-servicer variation unrelated to borrower fundamentals indicates that forbearance was not implemented uniformly. Furthermore, our results show that debt relief was connected to servicers' financial health and organizational form. Nonbanks, less regulated and subject to significant liquidity risk (Pence, 2022; Cherry et al., 2022; Kim et al., 2018), facilitated fewer forbearances particularly when the nonbank was small or had low liquid asset buffers. In contrast, large banks and credit unions had the most "borrower-friendly" outcomes, likely reflecting tighter regulation and secure access to funding. Finally, although we find little evidence of significant strategic default, forbearance did provide a subsidy in that interest was not charged on deferred balances; it is not clear that such a feature is necessary in order to simply provide temporary liquidity to households.

These shortcomings could have more serious consequences in a future event involving a more prolonged economic and housing downturn. In designing debt relief policies, policymakers may therefore wish to consider ways to standardize servicer practices (e.g., more detailed guidelines about borrower outreach) or implement forbearance auto-enrollment for borrowers observably in distress (e.g., tied to unemployment insurance claims). Auto-enrollment may be most useful for "hard-to-reach" borrowers identified in our analysis such as those with low credit scores. Fannie Mae and Freddie Mac have indeed taken some recent steps to streamline forbearance enrollment (e.g., Fannie Mae, 2020). That said, such policies could also have unintended consequences by undermining the liquidity position of servicers; this in turn could reduce credit supply, amplifying the downturn. Therefore, forbearance policy design should take into account the financial condition of servicers and the availability of nonbank liquidity backstops like the Ginnie Mae Pass-Through Assistance Program (Ginnie Mae, 2020) set up during the pandemic.

7 Conclusion

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

We also use cross-servicer variation to trace out the causal effects of forbearance for borrowers. We show that easier access to forbearance increased household liquidity by inducing borrowers to pause their mortgage payments. Several pieces of evidence suggest that these "marginal" nonpayers generally paused their payments due to liquidity concerns, although some used the funds to consolidate debt by paying down credit cards.

Overall, we interpret our results as evidence that the CARES Act forbearance program successfully reached most borrowers in need without inducing widespread strategic behavior or other unintended consequences, thereby balancing the tradeoffs inherent in any social insurance program (e.g., see Chetty 2008 on unemployment insurance or Indarte 2023 on bankruptcy). That said, our results also highlight program limitations which may be mitigated through design changes. Further research on forbearance design is warranted since forbearance is likely to be an important debt-relief tool in the future.

References

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

ADAMS, R., V. M. BORD, AND B. KATCHER (2022): "Credit Card Profitability," *FEDS Notes. Washington: Board of Governors of the Federal Reserve System*.

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

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

AGARWAL, S., G. AMROMIN, S. CHOMSISENGPHET, T. LANDVOIGT, T. PISKORSKI, A. SERU, AND V. YAO (2022): "Mortgage Refinancing, Consumer Spending, and Competition: Evidence from the Home Affordable Refinance Program," *The Review of Economic Studies*, 90, 499–537.

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

AIELLO, D. J. (2022): "Financially constrained mortgage servicers," *Journal of Financial Economics*, 144, 590–610.

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

Anderson, J., D. Harrison, and M. Seiler (2022): "Reducing Strategic Forbearance under the CARES Act: an Experimental Approach Utilizing Recourse Attestation," *Journal of Real Estate Finance and Economics*, 65, 230–262.

Bandyopadhyay, A., D. Kim, and P. S. Smith (2022): "Adverse selection in mortgage markets: Evidence from Ginnie Mae early buyouts," *Working Paper*.

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

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

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

——— (2020): "Beyond the Balance Sheet Model of Banking: Implications for Bank Regulation and Monetary Policy," NBER Working Paper 25149, National Bureau of Economic Research.

Chakraborty, I., I. Goldstein, and A. MacKinlay (2018): "Housing Price Booms and Crowding-Out Effects in Bank Lending," *The Review of Financial Studies*, 31, 2806–2853.

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

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

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

COHN, J. B., Z. LIU, AND M. I. WARDLAW (2022): "Count (and count-like) data in finance," *Journal of Financial Economics*, 146, 529–551.

CONSUMER FINANCIAL PROTECTION BUREAU (2021a): "COVID-19 Prioritized Assessments, Special Edition," Supervisory Highlights 23.

——— (2021b): "Mortgage Forbearance Issues Described in Consumer Complaints," Complaint Bulletin, April.

CORREIA, S., P. GUIMARÃES, AND T. ZYLKIN (2020): "Fast Poisson estimation with high-dimensional fixed effects," *The Stata Journal*, 20, 95–115.

DEPARTMENT OF HOUSING AND URBAN DEVELOPMENT (2020a): "FHA's COVID-19 Loss Mitigation Options," Mortgagee Letter 2020-22, July 8.

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

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

FANNIE MAE (2020): "Servicing Guide: Section D2-3.2-01: Forbearance Plan (09/09/2020)," Tech. Rep. September 9.

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

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

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

FUSTER, A., A. HIZMO, L. LAMBIE-HANSON, J. VICKERY, AND P. WILLEN (2023): "How Resilient is Mortgage Credit Supply? Evidence from the COVID-19 Pandemic," *Working Paper*.

FUSTER, A., M. PLOSSER, AND J. VICKERY (2021): "Does CFPB Oversight Crimp Credit?" CEPR Discussion Paper 15681.

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

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

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

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

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

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

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

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

INDARTE, S. (2023): "Moral Hazard versus Liquidity in Household Bankruptcy," *The Journal of Finance*, 78, 2421–2464.

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

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

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

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

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

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

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

LEE, S. C. AND O. MAGHZIAN (2023): "Household Liquidity and Macroeconomic Stabilization: Evidence from Mortgage Forbearance," *Working Paper, Harvard University*.

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

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

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

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

MAYOCK, T. AND L. SHI (2022): "Adverse selection in the market for mortgage servicing rights," *Journal of Housing Economics*, 58, 101858.

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

PENCE, K. (2022): "Liquidity in the mortgage market: How does the COVID-19 crisis compare with the global financial crisis?" *Real Estate Economics*, 50, 1405–1424.

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

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

——— (2022): "The effect of changing mortgage payments on default and prepayment: Evidence from HAMP resets," *Real Estate Economics*, 50, 1231–1256.

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

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

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

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

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

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

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

Internet Appendix for:

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

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

September 19, 2023

A Datasets

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

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

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

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

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

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

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

A.1 Details of eMBS-CRISM merge

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

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

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

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

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

	(1) eMBS	(2) eMBS-CRISM match
Ever 30+ days past-due	0.17	0.18
Ever in forbearance	0.13	0.14
Unpaid mortgage balance ($)	171,731.42	173,088.57
Original LTV (%)	93.43	94.60
Original DTI (%)	40.36	40.25
Original credit score (FICO V5)	692.56	696.80
Loan age (year)	4.97	5.33
FHA	0.68	0.70
VA	0.32	0.30
N. Obs.	11,015,574	3,068,450

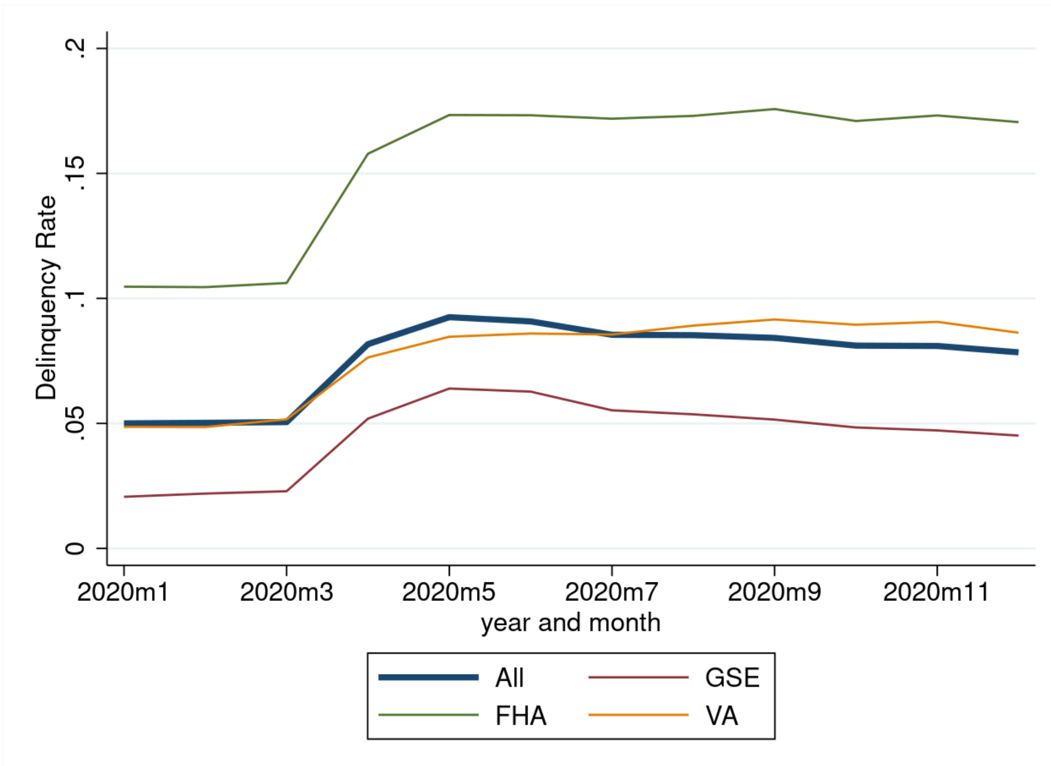
A.2 Construction of CFPB complaints dataset

We identify forbearance-related complaints using a similar approach to Consumer Financial Protection Bureau (2021b). We search the full CFPB complaints dataset for complaints with a narrative field containing the string "forbear" or "defer", restricting the sample to complaints related to a mortgage which is a government loan, to be consistent with our Ginnie Mae sample. As a form of cross-validation, we confirm that we identify a comparable total sample to Consumer Financial Protection Bureau (2021b).

We then match CFPB complaints data to our main servicer dataset by name. We exclude from the sample any servicer for which we are unable to find a match with the CFPB dataset. Results are however similar if we retain these servicers in the sample and code them as having zero complaints.

B Mortgages 30+ days past due, by segment

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



C Loan-level estimates

C.1 eMBS sample

Table A.2: **First-stage forbearance regression.** Dependent variable = 1 if mortgage entered forbearance from March-November 2020. Cross-sectional linear probability model. eMBS loan-level data. Sample is loans active as of January 2020. Sample for columns 1 and 2 restricted to mortgages that became past due from March-November 2020. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

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

C.2 eMBS-CRISM sample

Table A.3: **First-stage forbearance regression: eMBS-CRISM.** Dependent variable = 1 if mortgage entered forbearance from March-November 2020. Cross-sectional linear probability regression model. eMBS-CRISM matched loan-level sample. Sample is loans that were active as of January 2020 and became past due from March-November 2020. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1) Forbearance | past-due	(2) Forbearance | past-due
30 <Borrower age ≤ 45	0.0157***	
	(0.003)	
45 <Borrower age ≤ 60	0.0129***	
	(0.003)	
Borrower age >60	-0.0278***	
	(0.003)	
Riskscore (Feb 2020)+	0.000225***	
	(0.000)	
Ln(Consumer debt)+	0.00522***	
	(0.000)	
Delinq. consumer debt+	-0.00217***	
	(0.000)	
Other housing debt+	0.00356***	
	(0.000)	
Delinq. other housing debt+	-0.00252**	
	(0.001)	
Credit utilization+	0.0185***	
	(0.002)	
First Time Homebuyer	0.0244***	0.0294***
	(0.002)	(0.002)
25 <Orig DTI ≤ 50	0.0481***	0.0566***
	(0.004)	(0.004)
Orig DTI >50	0.0776***	0.0883***
	(0.004)	(0.004)
Loan age (year)	-0.0146***	-0.0128***
	(0.001)	(0.001)
Loan age (year) × Loan age (year)	0.000148***	0.0000562
	(0.000)	(0.000)
Ln(Unpaid mortgage balance)	0.0759***	0.102***
	(0.002)	(0.001)
620 <Orig CS ≤ 680	-0.00406	0.00728**
	(0.003)	(0.003)
680 <Orig CS ≤ 740	-0.00592*	0.0142***
	(0.003)	(0.003)
Orig CS >740	-0.02187***	0.0000***
	(0.003)	(0.003)
Refinance	0.0191***	0.0188***
	(0.003)	(0.003)
80 <Orig LTV ≤ 95	0.0172***	0.0180***
	(0.004)	(0.003)
95 <Orig LTV ≤ 100	0.0235***	0.0256***
	(0.004)	(0.003)
Orig LTV >100	0.0238***	0.0281***
	(0.005)	(0.004)
FHA	0.0641***	0.0820***
	(0.002)	(0.002)
Servicer fixed effects	Y	Y
State fixed effects	N	Y
Zipcode fixed effects	Y	N
N	416,298	421,941

D Alternative measures of servicer fixed effects

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

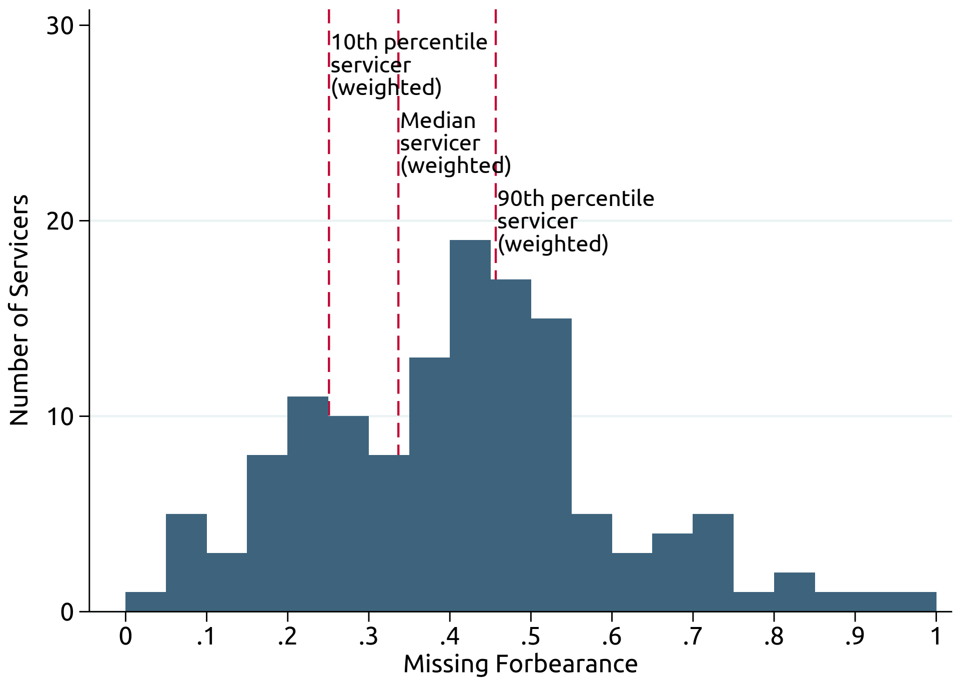
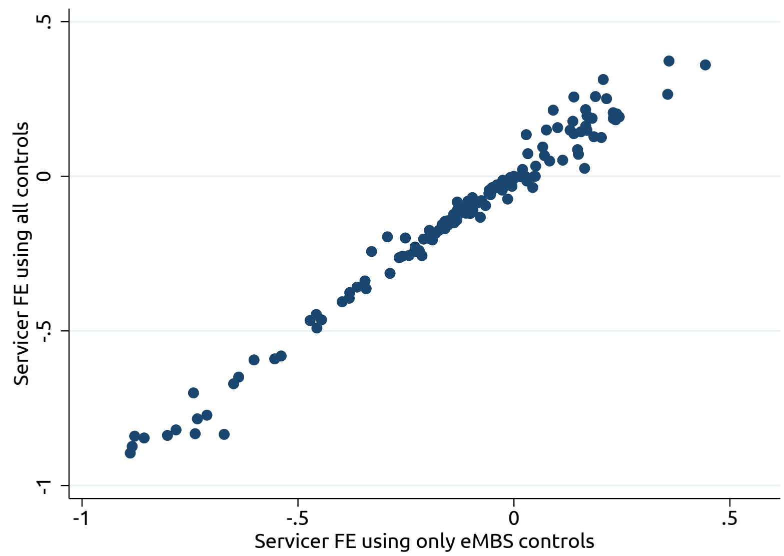
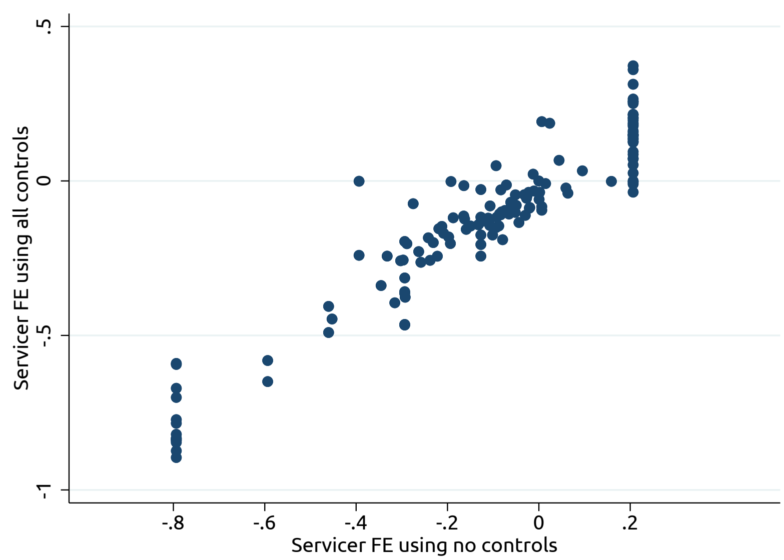


Figure A.3: **Robustness of servicer fixed effects to controls: eMBS-CRISM sample.** Panel (a) shows the correlation between servicer fixed effects estimated using borrower and servicer characteristics available only in eMBS and servicer fixed effects estimated using borrower and servicer characteristics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

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

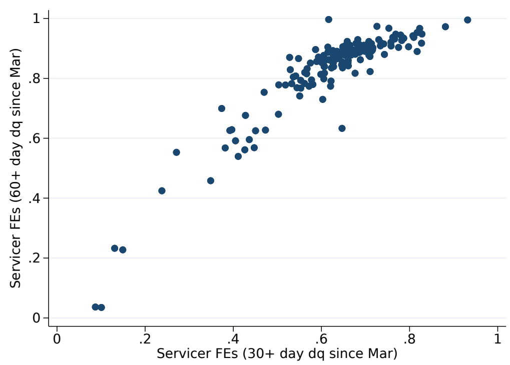


(b) Servicer fixed effects estimated using full set of eMBS-CRISM controls vs no controls

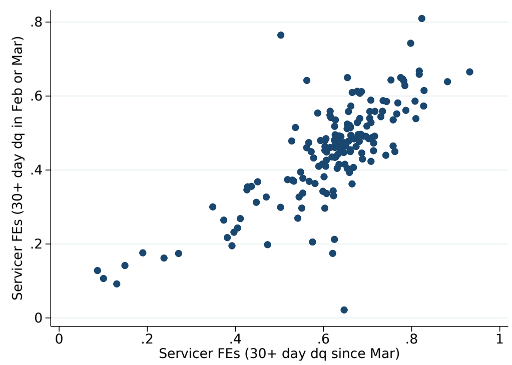


D.1 Comparison of fixed effects across approaches

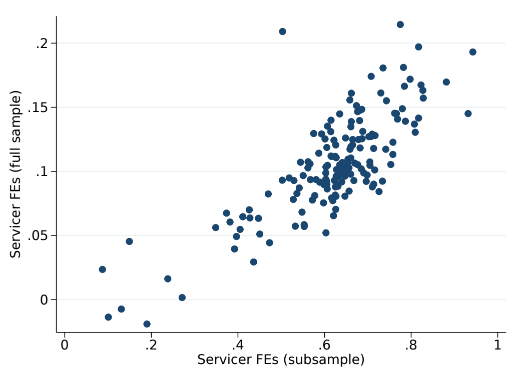
Figure A.4: **Correlation between servicer fixed effects from different specifications**: Correlations between the baseline servicer fixed effect estimates (shown on the x-axis) and four alternative sets of estimates, based on: (i) using the subsample of loans which became at least 60 days past due after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



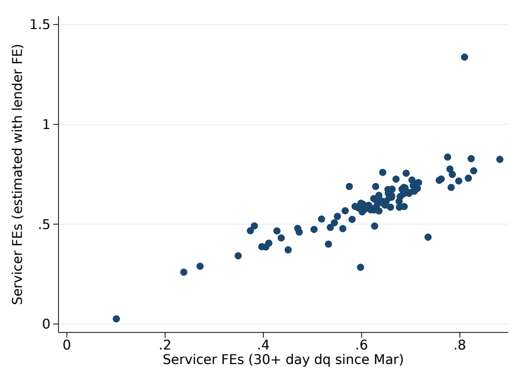
(a) 60+ day past due post-March 2020



(b) Missed payment in Feb/Mar 2020



(c) include all loans in sample



(d) include lender fixed effects

E Summary statistics: servicer-level sample

Table A.4: **Servicer-level summary statistics.** Servicing assets and growth are measured using eMBS. Financial characteristics for banks and nonbank mortgage companies are measured using bank call and Y-9C reports and nonbank mortgage call reports.

(a) All servicers

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

(b) Nonbank mortgage companies only

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

(c) Banks only

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

F Borrower characteristics by servicer type

Table A.5: **Ex ante borrower characteristics by servicer type: eMBS-CRISM matched sample.** Summary statistics measured as of January 2020 for high- and low-forbearance servicers using the merged eMBS-CRISM data. We define "high-forbearance" servicers as those with above-median servicer fixed effects (estimated as described in Section 4, using the merged eMBS-CRISM data). Column (3) reports differences in characteristics between high- and low-forbearance servicers, and column (4) reports standard errors of the differences clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer	(3) Diff. (High − Low)	(4) Std. Err.
Unpaid mortgage balance	184,736.49	165,272.18	-19,464.31*	(10,042.07)
Auto loan balance	16,103.48	15,331.09	-772.39	(506.78)
Credit card balance	8,951.05	8,740.05	-210.99	(253.21)
12-month change in CNTY unemp rate (Aug 2020)	6.07	5.86	-0.20*	(0.12)
FHA	0.69	0.70	0.01	(0.06)
Updated credit score (FICO V5)	694.22	703.49	9.27	(6.31)
Original LTV	93.94	94.28	0.34	(0.31)
Loan age (year)	4.50	6.01	1.51*	(0.82)
N. Obs.	1,270,977	1,626,621		

Table A.6: **Ex ante borrower characteristics by servicer type and origination year: eMBS-CRISM matched sample.** Summary statistics measured as of January 2020 for high- and low-forbearance servicers using the merged eMBS-CRISM data. We define "high-forbearance" servicers as those with above-median servicer fixed effects (estimated as described in Section 4, using the merged eMBS-CRISM data). Column (3) reports differences in characteristics between high- and low-forbearance servicers, and column (4) reports standard errors of the differences clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

(a) Origination year up to 2013

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer	(3) Diff. (High − Low)	(4) Std. Err.
Unpaid mortgage balance	136,335.32	137,011.41	676.10	(3,365.34)
Auto loan balance	13,399.83	13,955.28	555.46***	(171.36)
Credit card balance	9,167.34	8,856.06	-311.28**	(138.04)
12-month change in CNTY unemp rate (Aug 2020)	6.16	5.87	-0.29**	(0.14)
FHA	0.83	0.77	-0.06***	(0.02)
Updated credit score (FICO V5)	711.80	707.34	-4.46	(2.97)
Original LTV	93.66	93.67	0.00	(0.23)
Loan age (year)	8.52	8.66	0.13	(0.22)
N. Obs.	350,093	741,283		

(b) Origination year from 2014 to 2017

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer	(3) Diff. (High − Low)	(4) Std. Err.
Unpaid mortgage balance	185,845.28	180,704.64	-5,140.64	(9,035.48)
Auto loan balance	16,547.14	16,564.76	17.62	(375.89)
Credit card balance	9,320.18	8,996.56	-323.62	(298.79)
12-month change in CNTY unemp rate (Aug 2020)	6.11	5.88	-0.23	(0.17)
FHA	0.71	0.68	-0.03	(0.04)
Updated credit score (FICO V5)	696.65	702.02	5.37	(4.51)
Original LTV	93.92	94.92	1.00***	(0.25)
Loan age (year)	4.62	4.79	0.18	(0.12)
N. Obs.	363,104	553,867		

(c) Origination year since 2018

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer	(3) Diff. (High − Low)	(4) Std. Err.
Unpaid mortgage balance	221,930.34	209,119.38	-12,810.96	(13,571.26)
Auto loan balance	17,511.62	16,346.45	-1,165.17**	(568.28)
Credit card balance	8,574.99	8,052.02	-522.97	(453.44)
12-month change in CNTY unemp rate (Aug 2020)	5.98	5.81	-0.17	(0.14)
FHA	0.59	0.59	0.00	(0.14)
Updated credit score (FICO V5)	681.59	697.33	15.73	(13.09)
Original LTV	94.11	94.58	0.47	(0.59)
Loan age (year)	1.90	2.12	0.22***	(0.07)
N. Obs.	557,780	331,471		

Table A.7: **Ex ante borrower characteristics by servicer type and origination year: eMBS sample.** Summary statistics measured as of January 2020 for high- and low-forbearance servicers using the eMBS sample. We define "high-forbearance" servicers as those with above-median servicer fixed effects (estimated as described in Section 4, using the eMBS sample). Column (3) reports differences in characteristics between high- and low-forbearance servicers, and column (4) reports standard errors of the differences clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

(a) Origination year up to 2013

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer	(3) Diff. (High − Low)	(4) Std. Err.
Unpaid mortgage balance	114,464.79	118,119.20	3,654.41	(4,835.10)
12-month change in CNTY unemp rate (Aug 2020)	5.95	5.91	-0.04	(0.12)
FHA	0.80	0.77	-0.02	(0.03)
Original credit score	699.49	705.85	6.37	(4.11)
Original LTV	92.62	92.67	0.06	(0.38)
Loan age (year)	10.26	10.11	-0.15	(0.48)
N. Obs.	1,039,878	1,893,974		

(b) Origination year from 2014 to 2017

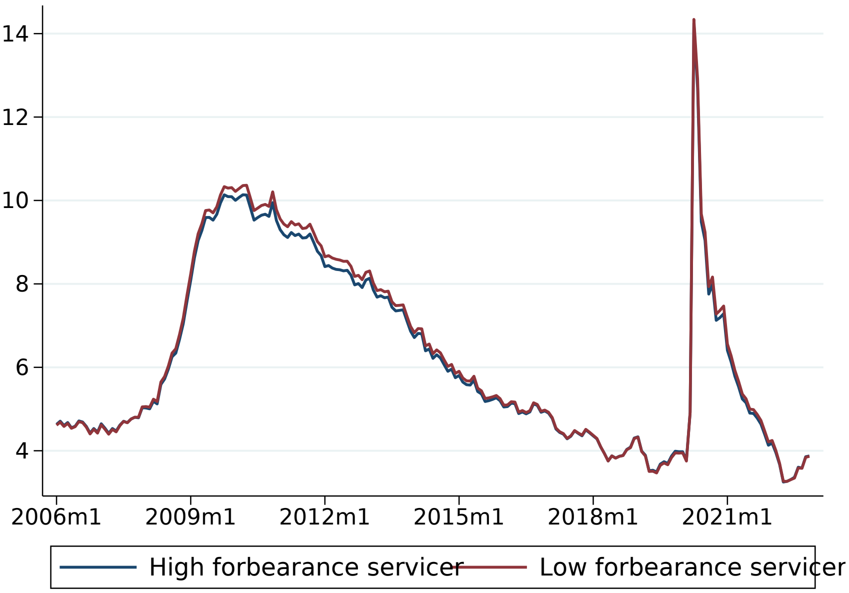
	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer	(3) Diff. (High − Low)	(4) Std. Err.
Unpaid mortgage balance	178,017.12	175,241.83	-2,775.30	(8,074.62)
12-month change in CNTY unemp rate (Aug 2020)	6.09	5.87	-0.22	(0.13)
FHA	0.69	0.61	-0.08	(0.05)
Orig credit score	690.85	702.36	11.51***	(3.31)
Orig LTV (%)	93.38	93.06	-0.31	(1.03)
Loan age (year)	4.62	4.71	0.09	(0.08)
N. Obs.	1,150,984	1,200,757		

(c) Origination year since 2018

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer	(3) Diff. (High − Low)	(4) Std. Err.
Unpaid mortgage balance	216,955.67	203,721.30	-13,234.37	(8,647.42)
12-month change in CNTY unemp rate (Aug 2020)	6.15	5.77	-0.38***	(0.12)
FHA	0.69	0.58	-0.11*	(0.06)
Orig credit score	683.56	696.60	13.04**	(6.27)
Orig LTV (%)	94.56	93.46	-1.10	(1.33)
Loan age (year)	2.05	2.12	0.08	(0.05)
N. Obs.	1,843,638	1,326,624		

G Macroeconomic conditions by servicer type

Figure A.5: **History of county-level unemployment rate: high- vs low-forbearance servicer portfolios.** Historical time series evolution of the county unemployment rate for loans in high- and low-forbearance servicers' portfolios as of January 2020.



H Pre-CARES Act loan performance by servicer type

Figure A.6: **Delinquency transition probabilities around pandemic onset: high- vs low-forbearance servicers.** Difference in monthly transition probability from current to 30+ days past due between borrowers matched to high-forbearance vs low-forbearance servicers (estimates of β coefficients from Equation 3), estimated using the eMBS-CRISM sample. y-axis indicates the fraction of newly past due mortgages, defined as loans that are past due in month *t* but current in month *t-1*. Specification includes same borrower and loan controls as our main eMBS-CRISM specification (reported in table A.2). Standard errors are clustered by servicer.

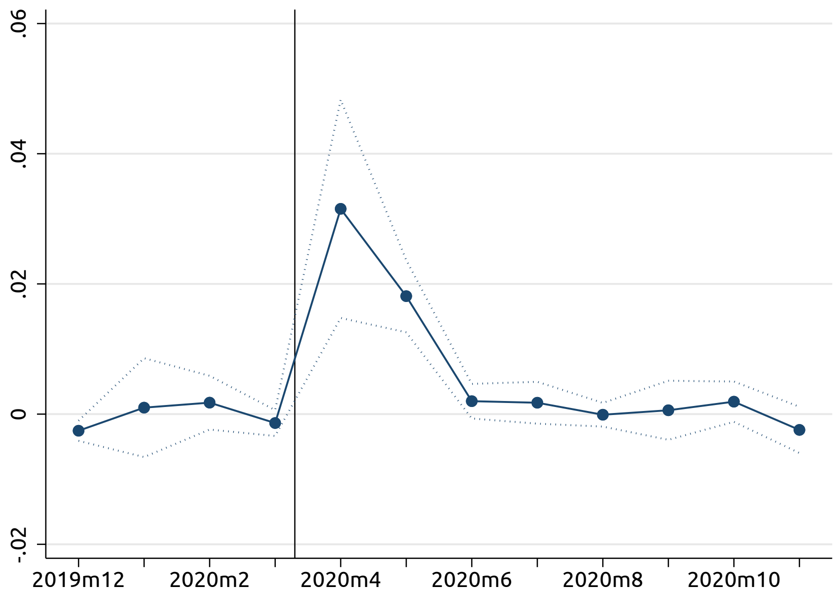


Table A.8: **Pre-CARES Act loan performance.** Relationship between high-forbearance servicer dummy and measures of pre-pandemic loan delinquency. eMBS data from December 2019 and January 2020 are used to estimate panel (a), and the matched eMBS-CRISM data from December 2019 and January 2020 are used to estimate panels (b), (c), and (d). Dependent variable for panels (a) and (b) is a dummy equal to 1 if the loan transitions from current to 30+ days delinquent. Dependent variables for panels (c) and (d) are whether a borrower has a delinquent credit card and auto loan account, respectively. eMBS controls include an FHA dummy, loan size, dummy for first-time homebuyer, LTV, credit score, DTI, and dummy for purchase loans. CRISM controls include updated credit scores and a borrower's age. Standard errors clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

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

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

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

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

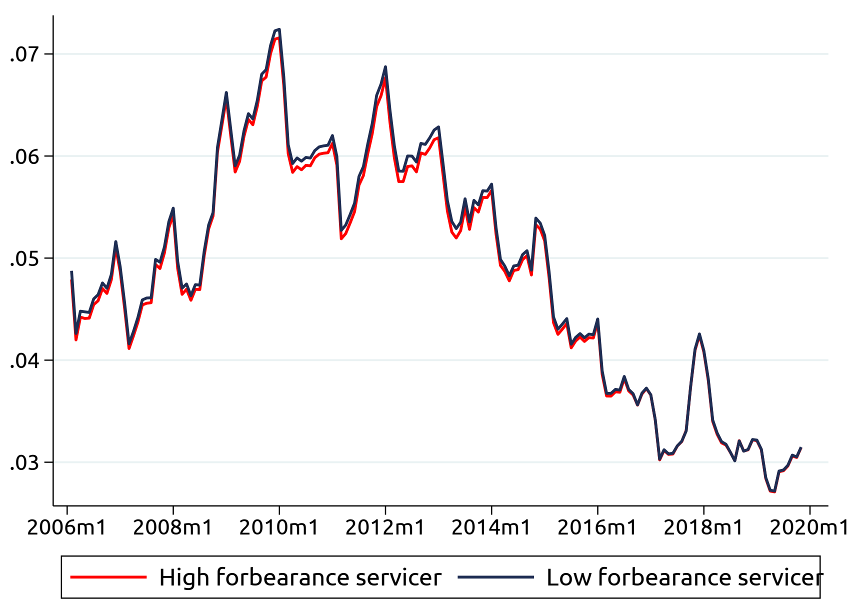
(c) Credit card delinquencies (eMBS-CRISM match)

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

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

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

Figure A.7: **Pre-CARES Act evolution of mortgage delinquency rates: high- vs low-forbearance servicer portfolios.** Historical time series evolution of the zipcode-level 60+ day delinquency rates for loans in high- and low-forbearance servicers' portfolios as of January 2020.



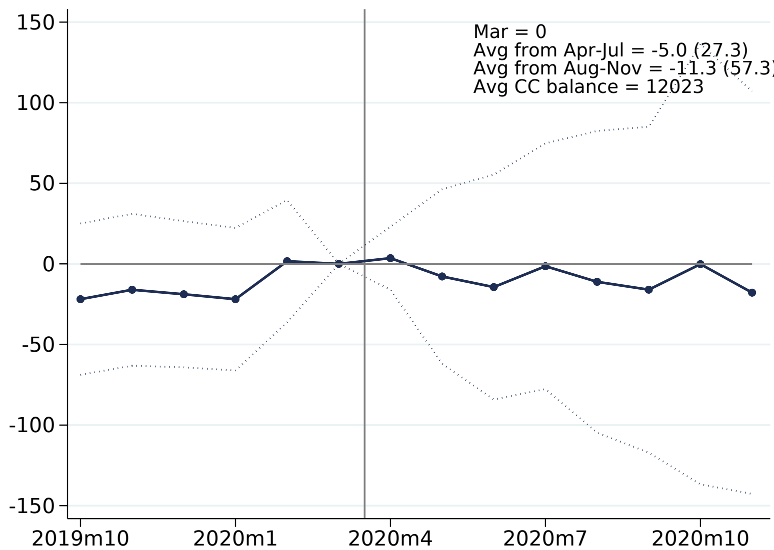
I Additional nonmortgage results

Table A.9: **Nonmortgage results.** Estimates of the average effect of assignment to a high-forbearance servicer on various nonmortgage outcomes measured in CRISM. Estimates reported in columns (1), (3) and (5) are the average coefficient on the high-forbearance-servicer $\times$ time dummies (estimates of β_t from equation 3) over three phases of the pandemic: a pre-pandemic period (October 2019-February 2020); early pandemic (April-July 2020) and later pandemic (August-November 2020), along with the associated standard error of each mean. For context, columns (2), (4) and (6) report the unconditional mean of the dependent variable at low-forbearance servicers during the period referenced. For outcome variables related to auto loans, we report "NA" during the early pandemic period because the CRISM data on auto loans for the period is of low quality due to a temporary reporting error. Standard errors are clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

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

Figure A.8: **Effects of forbearance availability on level of credit card balances.** Estimates and 95% confidence intervals of the effects of assignment to a high-forbearance servicer on the dollar level of credit card debt for borrowers with above- and below-median credit card utilization. Utilization is measured over the period from October 2019 to March 2020; the median average utilization is calculated for each cohort of borrowers with the same mortgage origination year. Estimated using the eMBS-CRISM matched sample. Standard errors are clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

(a) High utilization borrowers ($)



(b) Low utilization borrowers ($)

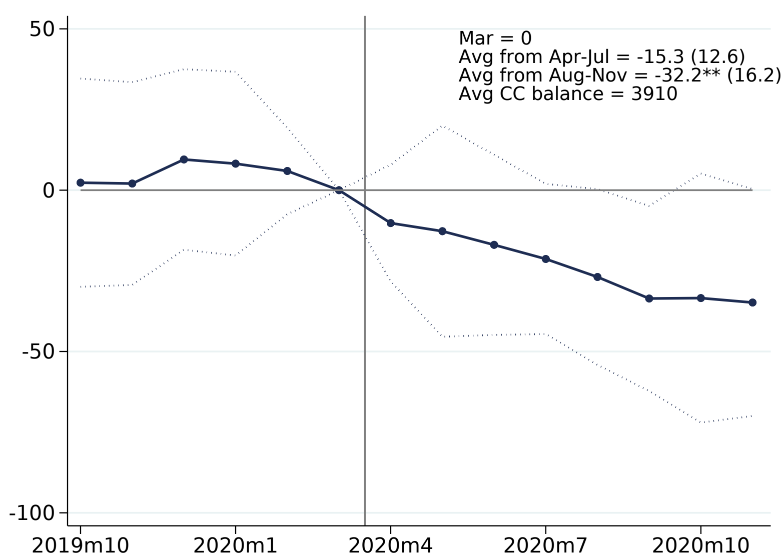
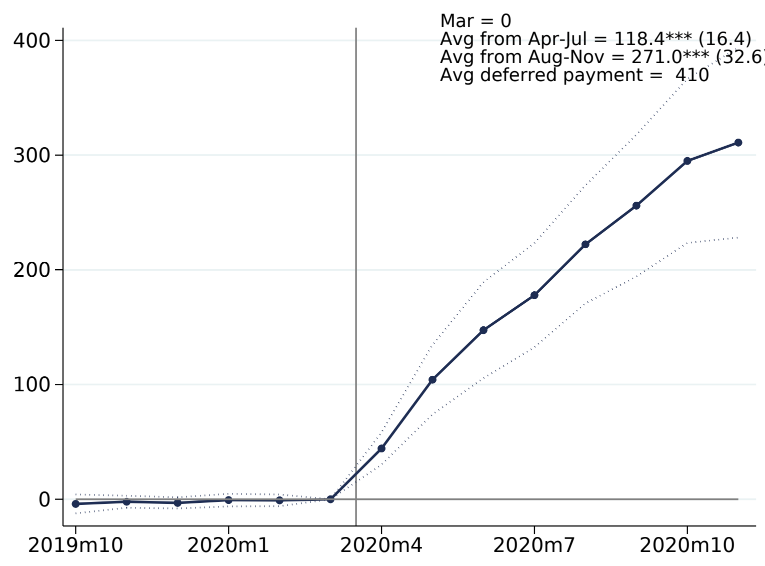


Figure A.9: **Forbearance availability and cumulative deferred mortgage payments.** Estimates and 95% confidence intervals of effect of assignment to a high-forbearance servicer on cumulative deferred mortgage payments (measured in dollars). Estimated as β coefficients from Equation 3 in a model where the dependent variable measures total cumulative borrowing through forbearance: the number of missed payments times the monthly mortgage payment inclusive of taxes and insurance. The coefficients can be interpreted as the average difference in cumulative deferred payments among borrowers at high- vs low-forbearance servicers. To construct this dependent variable, we assume that taxes and insurance sum to equal 30% of the principal and interest payment, which is the average among FHA loans. (This is an approximation, because we cannot directly observe whether borrowers make partial payments or continue to pay taxes and insurance.) We assume that loans that exit forbearance do not immediately repay their deferred balances; we do not directly observe borrowers' repayment plans. Standard errors are clustered at the servicer level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.



J Characteristics of borrowers in forbearance

Table A.10: **Characteristics of borrowers in forbearance: high- vs low-forbearance servicers.** Summary statistics measured as of January 2020 for borrowers that ever entered forbearance during our sample period, comparing borrowers at high- vs low-forbearance servicers. Constructed from merged eMBS-CRISM data.

	(1) Low-Forbearance Servicer	(2) High-Forbearance Servicer
Months in forbearance (as of Nov 2020)	5.73	6.60
Ever exited forbearance	0.35	0.31
Unpaid mortgage balance	196,713.93	172,327.63
Auto loan balance	18,242.10	17,765.52
Credit card balance	10,841.62	11,487.21
12-mo change in CNTY unemp rate (Aug 2020)	6.61	6.36
FHA	0.83	0.82
Updated credit score (FICO V5)	648.79	663.06
Original LTV	94.22	94.77
Loan age (year)	3.89	5.60
N. Obs.	140,001	237,422

K Alternative estimates controlling for lender fixed effects

Table A.11 and figures A.10 and A.11 presented below re-estimate several of our main results based on servicer fixed effects that are estimated conditional on *originator* fixed effects. In this case, servicer effects are identified based on transfers of servicing rights, since for these observations the servicer and lender are different organizations. (Please refer to section 4 for further discussion of the strengths and weaknesses of this approach.)

Here we document that this alternative approach produces generally similar estimates to the baseline results in the main text. In particular:

(i) We still find that large servicers, banks, and nonbanks with high liquid asset buffers are more likely to provide forbearance (table A.11). One minor difference from our main results is that the coefficient on nonbank capital is also now statistically significant (although quantitatively fairly small);

(ii) Easier access to forbearance increases the number of past-due borrowers, close to 1:1, as in our main estimates (figure A.10);

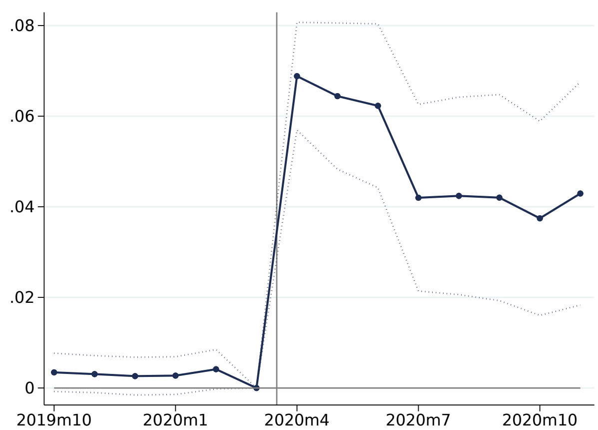
(iii) Easier access to forbearance is associated with lower credit card debt, concentrated among low-utilization borrowers (figure A.11), although here the results, while similar in magnitude, are estimated less precisely and are only individually statistically significant in two months (and marginally so in those cases). This lower power reflects the fact that we lose a significant number of servicers from the sample under the "originator fixed effects" approach because only a subset of servicers are active in the servicing transfer market for Ginnie Mae loans (this limitation is also discussed in section 4). For the same reason we are no longer able to estimate a credit union dummy in table A.11, because credit unions typically retain their FHA and VA servicing rights.

Table A.11: **Determinants of servicer effects: controlling for originator fixed effects.** Servicer-level regression of servicer forbearance fixed effects on characteristics drawn from bank and nonbank call reports and eMBS. Servicer fixed effects are estimated controlling for originator fixed effects. Column 1 is based on all servicers including banks, credit unions and nonbanks. Columns 2-4 reflect nonbank mortgage company servicers only. Columns 5-7 reflect bank servicers only. Weighted least squares, weighted by number of borrowers that were current in January 2020 but past due between March and November. Robust standard errors. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	All	Nonbank mtg companies			Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Servicer characteristics							
log(Servicing assets)	0.037***	0.040***	0.041***		0.035**	-0.035	
	(0.008)	(0.010)	(0.010)		(0.012)	(0.064)	
log(Assets)				0.037***			-0.048
				(0.006)			(0.040)
Cash / assets			0.941***	1.261***		-0.166	1.527
			(0.346)	(0.274)		(1.661)	(1.726)
Securities / assets			-0.101	-0.022		3.454	3.592**
			(0.165)	(0.097)		(2.605)	(1.670)
Capital / assets			0.146	0.281**		0.945	-0.428
			(0.142)	(0.124)		(2.617)	(2.201)
Servicing growth	0.034	0.014	0.030	-0.003	0.092	0.320	0.335
	(0.065)	(0.071)	(0.062)	(0.055)	(0.152)	(0.299)	(0.281)
Servicer type							
Nonbank mortgage company	-0.089**						
	(0.036)						
Credit union	0.000						
	(.)						
N. Obs.	92	71	71	71	21	21	21
Adj. R^2	0.40	0.34	0.45	0.49	0.08	0.18	0.26

Figure A.10: **Forbearance access and mortgage payment behavior: controlling for originator fixed effects.** Estimates and 95% confidence intervals of the effects of assignment to a "high-forbearance" servicer on the overall probability of being in forbearance (top panel) and probability of being past due (bottom panel). A servicer is defined as a high-forbearance servicer if its servicer forbearance fixed effect, estimated controlling for originator fixed effects, is above the median. Standard errors clustered at the servicer level. Sample includes loans that were current and active as of January 2020.

(a) Forbearance



(b) Past due

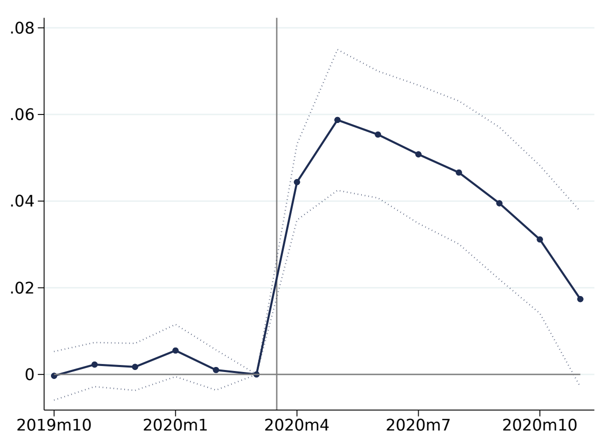
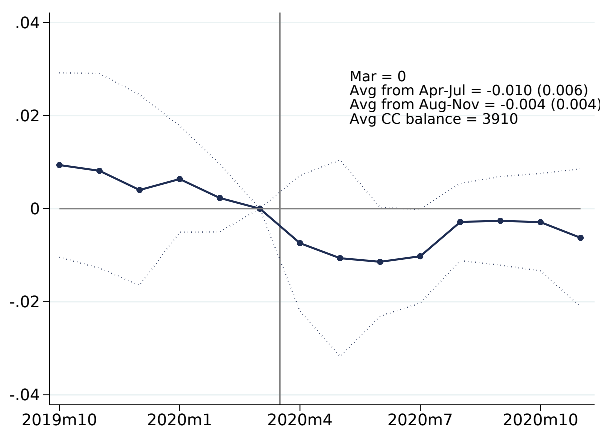
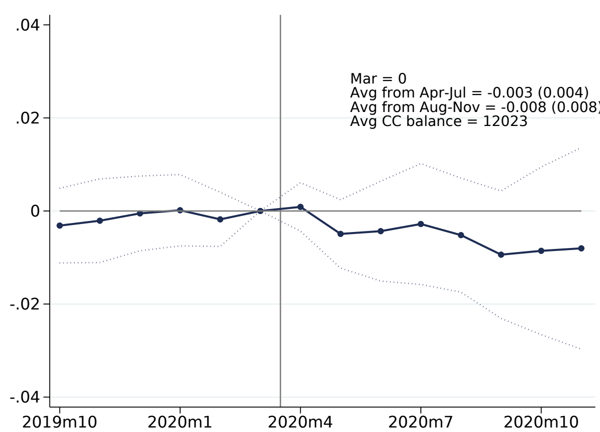


Figure A.11: **Forbearance access and credit card balance: controlling for originator fixed effects.** Estimates and 95% confidence intervals of the effects of assignment to a high-forbearance servicer on log(total credit card debt). A servicer is defined as a high-forbearance servicer if its servicer forbearance fixed effect, estimated controlling for originator fixed effects, is above the median. The top (bottom) panel shows estimates for borrowers with below (above) median credit card utilization (measured ex ante between October 2019 and March 2020). The median average utilization is calculated separately for each cohort of borrowers based on mortgage origination year. Standard errors are clustered at the servicer level.

(a) Low utilization borrowers



(b) High utilization borrowers



L Credit constraints and credit card utilization

Statistics below show that credit card utilization is higher for lower-income and more financially-constrained individuals, both before and during the pandemic. Table A.12 shows that utilization is monotonically and significantly decreasing in household income at the zipcode level. Table A.13 shows that high-utilization households have lower credit scores and higher delinquency rates on credit cards, mortgages and auto loans.

Table A.12: **Credit card utilization rate by IRS zipcode income.** Source: Author calculations based on data from IRS and Federal Reserve Bank of New York Consumer Credit Panel / Equifax.

IRS Average Income At Zipcode Level	(1) January 2020	(2) June 2020
Less than $30K	35%	32%
$30K - $40K	30%	28%
$40K - $50K	27%	25%
$50K - $60K	25%	23%
$60K - $70K	24%	21%
$70K - $80K	22%	20%
$80K - $90K	21%	19%
$90K - $100K	21%	18%
Higher than $100K	19%	16%

Table A.13: **Credit card utilization rate and credit performance.** Source: Author calculations based on Federal Reserve Bank of New York Consumer Credit Panel/ Equifax.

(a) As of January 2020

CC Utilization Rate	(1) Average Credit Score	(2) Credit Card Delinquency	(3) Mortgage Delinquency	(4) Auto Loan Delinquency
Less than 20%	784	0.56%	0.52%	1.4%
20% - 40%	740	2.77%	0.95%	2.64%
40% - 60%	701	6.66%	2.48%	4.87%
60% - 80%	662	12.25%	4.21%	7.54%
Higher than 80%	586	40.05%	11.28%	25.72%

(b) As of June 2020

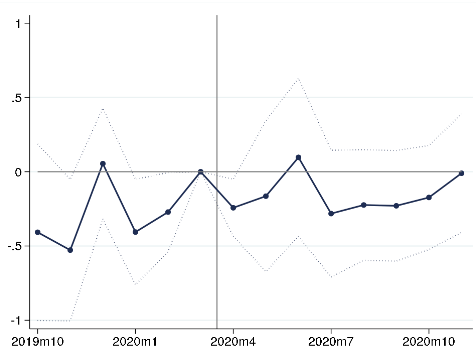
CC Utilization Rate	(1) Average Credit Score	(2) Credit Card Delinquency	(3) Mortgage Delinquency	(4) Auto Loan Delinquency
Less than 20%	782	0.56%	0.38%	1.74%
20% - 40%	732	3.19%	0.79%	3.08%
40% - 60%	694	7.16%	1.50%	5.60%
60% - 80%	659	12.76%	2.38%	8.37%
Higher than 80%	591	44.87%	6.78%	24.23%

M Crowding-out effects of forbearance on lending

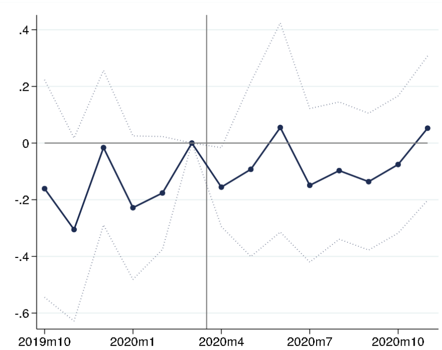
M.1 Agency mortgage originations

Figure A.12: **Agency mortgage originations: high- vs low-forbearance servicers.** Estimates and 95% confidence intervals of the proportionate difference between mortgage origination volumes at high vs low-forbearance servicers, normalized to zero in March 2020. Estimated using a poisson regression, via the PPMLHDFE Stata package of Correia et al. (2020). A servicer is defined as a high-forbearance servicer if its servicer forbearance fixed effect is above the median. Standard errors are clustered at the servicer level. Panels on the left (a and c) are weighted by the servicer's origination volume in February 2020. Panels on the right (b and d) are unweighted. The top two panels show all mortgages securitized into agency MBS. The bottom two panels focus on Ginnie Mae loans only. All specifications include interactions between month and two servicer characteristics: a nonbank dummy and servicing volume (defined as in column 1 of table 3). The data source is eMBS. Several banks merged during the time period shown. We set pre-merger origination volumes at these servicers to missing.

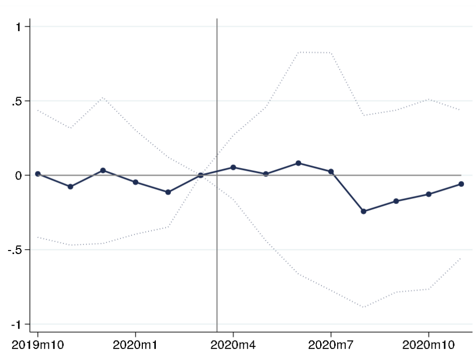
(a) Agency originations, weighted



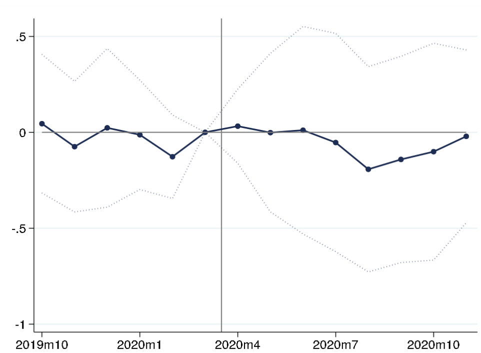
(b) Agency originations, unweighted



(c) GNMA originations, weighted



(d) GNMA originations, unweighted

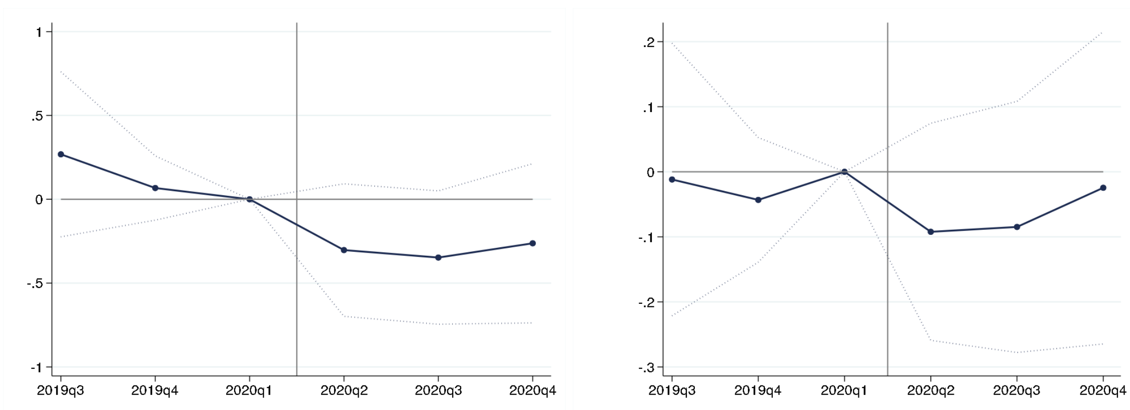


M.2 Quarterly nonbank originations

Figure A.13: **Originations by nonbanks: high- vs low-forbearance servicers.** Estimates and 95% confidence intervals of the proportionate difference between mortgage origination volumes at high vs low-forbearance servicers, normalized to zero in 2020:Q1. Estimated using a poisson regression, via the PPMLHDFE Stata package of Correia et al. (2020). A servicer is defined as a high-forbearance servicer if its servicer forbearance fixed effect is above the median. Standard errors are clustered at the servicer level. The panel on the left (a) is weighted by the servicer's origination volume in 2019:Q4. The panel on the right (b) is unweighted. The estimates include servicer fixed effects and the statistically-significant controls from column 3 of table 3 interacted with quarter dummies. The data source is CSBS. Origination volumes are winsorized at the 98th percentile to limit the influence of outliers.

(a) Weighted

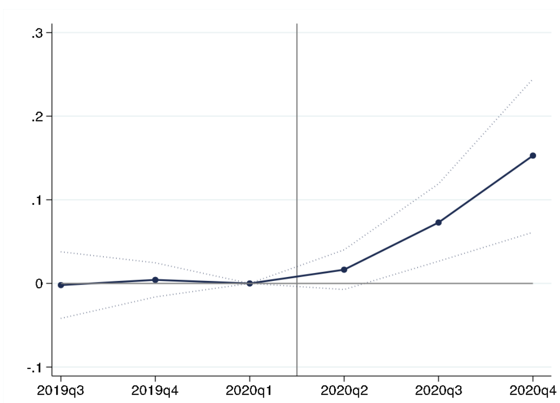
(b) Unweighted



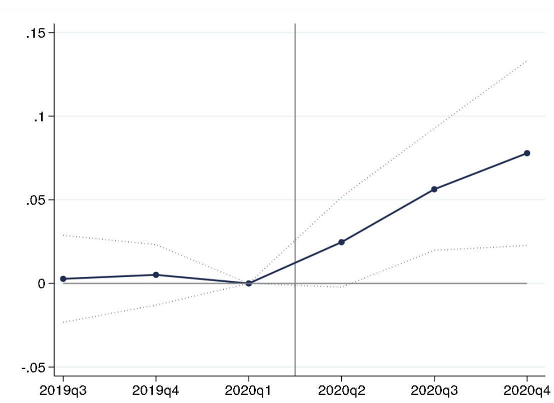
M.3 Bank lending

Figure A.14: **Lending by banks: high- vs low-forbearance servicers.** Estimates and 95% confidence intervals of the proportionate difference between mortgage origination volumes at high vs low-forbearance servicers, normalized to zero in 2020:Q1. Estimated using a poisson regression, via the PPMLHDFE Stata package of Correia et al. (2020). A servicer is defined as a high-forbearance servicer if its servicer forbearance fixed effect is above the median. Standard errors are clustered at the servicer level. Panels on the left (a and c) are weighted by the servicer's total loan volume in 2019:Q4. Panels on the right (b and d) are unweighted. The top two panels show total loan volume outstanding. The bottom two panels show commercial and industrial (C&I) loans outstanding. All regressions include servicer fixed effects and total outstanding servicing volume (measured before the pandemic, as in table 3) interacted with quarter dummies. The data are from FR Y-9C and call reports. Several banks merged during the time period shown. We treat pre-merger loan volumes as missing. We dropped two banks from the sample due to the fact their mergers occurred during the pandemic event period (2020:Q2 and 2020:Q4).

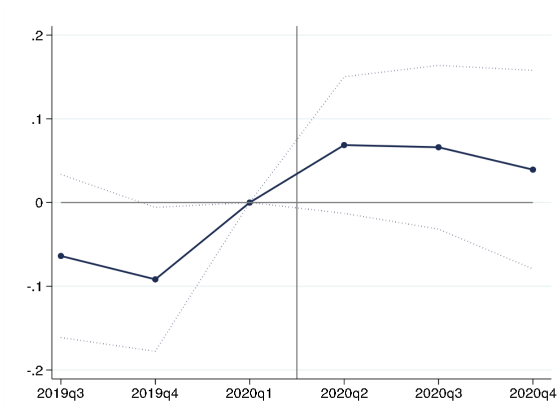
(a) Total loan volume, weighted



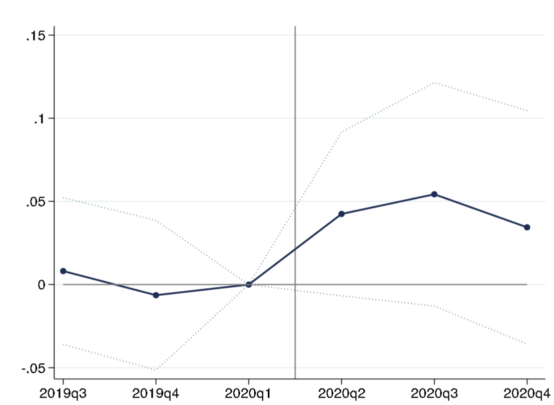
(b) Total loan volume, unweighted



(c) C&I loan volume, weighted



(d) C&I loan volume, unweighted



M.4 GNMA lending volume: alternative loan-level specification

Figure A.15: **Ginnie Mae originations: market share of high-forbearance servicers.** Dependent variable is equal to 1 if the lender is a high-forbearance servicer; this variable is regressed on a set of month dummies which are plotted in the figure below, as well as loan-level controls (loan purpose, FHA dummy, DTI, LTV, credit score, first time home buyer flag, loan origination channel indicator, and loan origination amount) and lender characteristics (bank and credit union dummies, log of total assets, and log of total servicing unpaid balance). Dummy for March 2020 is omitted to normalize the share of high-forbearance servicers to zero in that month. Regression sample consists of the population of new FHA and VA mortgage originations. 95% confidence intervals shown. Standard errors are clustered at the servicer level.