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

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Abstract

We study the role of mortgage servicers in implementing the CARES Act mortgage forbearance program during the COVID-19 pandemic. Despite universal eligibility, we document that a significant number of federally backed mortgage borrowers become delinquent during the pandemic without successfully entering into a forbearance program, and that the relative frequency of these "missing" forbearances varies significantly across mortgage servicers for otherwise identical loans. Forbearance outcomes are systematically related to servicer characteristics including size, liquidity and organizational form, consistent with the role of economic incentives in shaping servicer behavior. We also use servicer-level variation in forbearance outcomes to estimate the causal effect of forbearance on borrower outcomes. We find that assignment to a "high-forbearance" servicer translates to a significantly higher non-payment rate, and we find evidence that part of this additional household liquidity is used to pay down high-cost credit card debt.

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

JEL classification: G21, G23, G28

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1 Introduction

Financial intermediaries often play an important role in the transmission of public policy, particularly in the case of debt relief and emergency lending programs.[1] But misaligned incentives or other frictions may prevent policies from being implemented as intended "on the ground." For example Agarwal et al. (2017) finds that intermediary-specific factors significantly reduced the amount of government-sponsored debt renegotiation in the wake of the Great Recession.

In this paper we study the role of financial intermediaries in implementing a large new government debt relief program providing forbearance to mortgage borrowers during the COVID-19 pandemic. The program, authorized by the CARES Act, allows borrowers with federally backed mortgages to temporarily pause their mortgage payments without incurring fees, penalties or unscheduled interest and without negative effects on their credit history. The borrower simply needs to attest to a hardship related to the pandemic in order to qualify for forbearance; no documentation of income loss is required.

Despite this universal eligibility, we document that a significant number of federally backed mortgage borrowers become delinquent during the pandemic without successfully entering into a forbearance program, and that the relative frequency of these "missing" forbearances varies significantly across mortgage servicers for otherwise identical loans. Forbearance outcomes are systematically related to servicer characteristics including size, liquidity and organizational form, consistent with the role of incentives in shaping servicer behavior.

We then use servicer-level variation in forbearance outcomes to estimate the causal effect of forbearance on borrower outcomes. We find that assignment to a "high-forbearance" servicer translates to a significantly higher non-payment rate, and that part of this additional household liquidity is used to pay-down high-cost credit card debt.

Our analysis focuses on Federal Housing Administration (FHA) and Veterans Administration (VA) mortgages, the segment of the mortgage market which serves the borrowers with lowest incomes and the highest risk of default, and the segment where mortgage default poses the greatest risk to servicers due institutional factors described below. Using loan-level data from eMBS we estimate that the probability of entering forbearance con-

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

ditional on delinquency varies between 0.4 to 0.9 after controlling for loan and borrower characteristics, with a weighted interquartile range of 15 percentage points. We interpret these striking differences in outcomes as a reflection of the many ways that servicer actions can affect forbearance outcomes. For example, servicers vary significantly in terms of the ease of applying for forbearance, the type of information given to borrowers, and the ease of contacting the servicer.

We then investigate sources of these differences, and what they tell us about the role of servicer incentives and other frictions. We find that larger servicers, bank servicers, and servicers with more liquid assets make forbearance more accessible to borrowers. These findings are consistent with the hypothesis that economic incentives shaped servicer behavior. For example, mortgage delinquency is associated with significant liquidity risk because the servicer of an FHA or VA loan is required to finance payments to investors while borrowers are nonperforming — this liquidity risk is most significant for nonbanks without access to government backstops and insured deposits, and particularly for nonbanks with thin liquidity cushions.

In the second half of paper, we use variation in servicers' forbearance practices to examine the causal effect of forbearance on borrower outcomes. We classify servicers into high and low forbearance-availability groups, depending on whether the fraction of delinquent borrowers in forbearance at a servicer is above or below the median. Then we compare borrower-level outcomes at high- and low-availability servicers before and after the CARES Act in a difference-in-differences framework.

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

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

In summary, forbearance availability directly affects borrower decisions about whether to defer mortgage payments during the pandemic, at least for the substantial set of marginal borrowers whose forbearance outcomes are affected by servicer practices. Borrowers at servicers that made forbearance more accessible were able to have additional cash by deferring their payments without negatively impacting their credit scores. Effectively, the forbearance program provided a low-cost source of liquidity to mortgage borrowers, which in part allowed them to reduce other higher-cost sources of borrowing such as credit card debts.

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

1.1 Related literature

Our paper contributes to literature on the role of financial intermediaries in the mortgage market, and more specifically to research on the CARES Act forbearance programs. Cherry et al. (2021), An et al. (2021) and Zhao et al. (2020) present more general analysis of forbearance during the COVID pandemic, for example showing how forbearance rates vary with borrower characteristics and depending on the depth of the economic shock posed by COVID-19. Research also finds that borrowers in forbearance saw income declines (Zhao et al. (2020)), and that forbearance reduced inequality (An et al. (2021)).

Like us, these papers also document that a significant number of delinquent borrowers did not successfully enter a forbearance program. Cherry et al. (2021) also find that

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

non-banks offer forbearance at lower rates, studying variation in outcomes across large servicers for prime mortgages securitized through Fannie Mae.

We also contribute to a broader literature showing that studying financial frictions and incentives associated with mortgage intermediaries, most of which studies the period after the Great Recession. For example, prior research finds servicers were more likely to modify mortgages retained in their own portfolios compared to loans serviced for other investors (Agarwal et al. (2011) and Kruger (2018)). Servicers offered HAMP modifications at different rates, reflecting organizational structure and incentives (Agarwal et al. (2017)). More recently, Cherry et al. (2021) find that nonbanks offered forbearance at lower rates than banks among Fannie Mae loans.

2 Forbearance and the CARES Act

The CARES Act was signed into law on March 27, 2020, and included significant relief for mortgage borrowers. Homeowners with federally-backed mortgages became eligible for up to 180 days of forbearance, renewable for an additional 180 days upon request.[3,4] While in forbearance, borrowers can skip their mortgage payments without accruing unscheduled interest, late fees or penalties, or risking foreclosure. Missed payments are also not reported to credit bureaus and therefore do not affect the borrower's credit score.[5]

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

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

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

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

The CARES Act is silent about what should occur at the end of the forbearance period. In the weeks after the passage of the Act, however, regulators and the mortgage agencies stated that a range of options would be available, and borrowers would not be required to repay missed payments in a lump sum (e.g., Freddie Mac, 2020). In April 2020, the FHA announced a National Emergency Partial Claim program, under which most borrowers that re-perform after exiting forbearance can transfer accumulated missed payments into a subordinate interest-free note which is not due until the termination of the mortgage through a property sale, refinancing or payoff (Department of Housing and Urban Development, 2020a,b).[6] Fannie Mae and Freddie Mac announced a similar payment deferral option in May (Federal Housing Finance Agency, 2020). Since missed payments do not accrue interest, deferral effectively provides a zero-interest loan to the borrower.

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

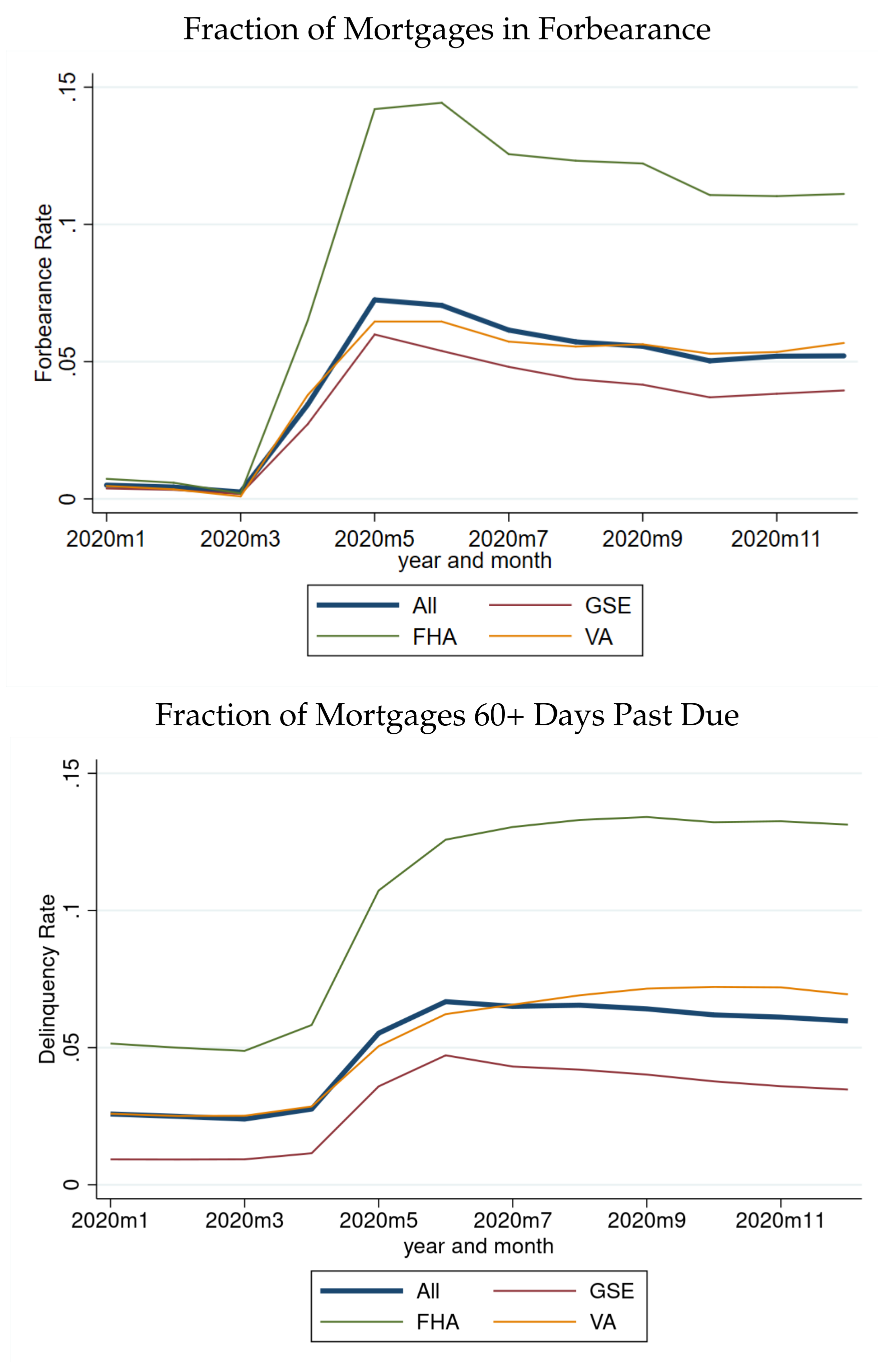
The analysis in this paper focuses on the $2 trillion of "government" mortgages insured by the FHA and VA. This segment of the mortgage market is of particular interest because it disproportionately serves low-income and high-risk borrowers, and because FHA loans in particular have a much higher forbearance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

2.1 Forbearance trends

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

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

Figure 1: Forbearance Rate and Delinquency Rate Over 2020



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

The aggregate forbearance rate peaked in May at 7.3 percent, and then declined slowly over the remainder of 2020 (to 5.2 percent as of December).[7] Delinquency, as measured by 60+ days past due (bottom panel) follows a similar shape.[8] At an individual level however, not all delinquent borrowers entered forbearance, and conversely some borrowers in forbearance continued making some or all of their scheduled mortgage payments.[9]

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

2.2 Forbearance implementation and the role of servicers

The mortgage servicers that implemented the CARES Act forbearance programs on the ground vary widely in terms of size, regulation, funding, profitability and other characteristics. One might assume that servicers play a limited and passive role, given the essentially universal eligiblity for forbearance among agency borrowers and lack of documentation requirements. In practice however, borrowers and regulators report a wide range of servicer-related issues, including misinformation, processing errors, and communication difficulties, suggesting that servicer practices may indeed significantly affect borrower outcomes.

Consumer Financial Protection Bureau (2021a) presents systematic qualitative evidence regarding issues with servicers based on the observations of CFPB supervisors. The report highlights the logistical challenges faced by servicers, stating that *"Many servicers reported operational constraints, resource burdens, and service interruptions. Many servicers also*

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

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

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

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

moved employees from other duties to respond to forbearance requests." It also documents a range of deficient practices by servicers including:

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

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

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

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

v.) Enrolling borrowers in automatic or unwanted forbearance;

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

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

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

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

Not all borrowers experienced problems, however, and many servicers took significant steps to streamline the forbearance process, such as providing a prominent button or link on their website to a simple online application. We have also heard numerous anecdotes from practitioners about servicers that have engaged proactively with borrowers to explain forbearance and make them aware of their options (e.g., one large servicer contacts delinquent borrowers not in forbearanceat a daily frequency). Taken together, the qualitative evidence suggests there has been a wide range of servicer practices, which in turn could lead to significant variation in borrower outcomes.

2.3 The role of servicer characteristics

We now discuss factors relating to financial constraints, regulation and organizational form that may lead to systematic variation in forbearance practices and outcomes across servicers. We study the importance of these different factors empirically in section 4.1.

1. Liquidity constraints. Mortgage servicers are required to temporarily advance scheduled payments on delinquent mortgages to investors and other parties, including principal, interest, taxes and insurance. Servicers facing more binding liquidity constraints may therefore wish to discourage borrowers from entering forbearance, if forbearance then induces borrowers to pause their payments.[12]

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

2. Regulation and legal risk. Mortgage servicers face stricter regulation and supervi-

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

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

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

3. Capitalization and risk-shifting. Decisions about servicing practices involve a trade-off between risk and reward. Actions such as enabling easy access to forbearance, or investing heavily in servicing technology or staff training, are likely to be costly in the short run but may reduce the likelihood of future regulatory or legal action and also perhaps improve customer satisfaction and retention. Undercapitalized servicers may thus have weaker incentives to provide high-quality servicing, in line with the classic risk-shifting hypothesis of Jensen and Meckling (1976).

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

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

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

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

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

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

3 Data and summary statistics

Our analysis combines loan-level data on mortgage characteristics and performance, FHA forbearance records, and regulatory data on the characteristics and financial condition of mortgage servicers. The datasets we use are described below.

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, delinquency 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 but are backfilled to the start of the pandemic. They have subsequently been updated on a monthly basis.[18]

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

Black Knight McDash and CRISM. Black Knight McDash (hereafter "McDash") includes loan characteristics and performance for the servicing portfolios of the largest 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, in-

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

cluding information on other forms of debt (e.g., credit cards, junior liens, and student loans) for primary borrowers and all co-borrowers on the McDash mortgages.

FRBY Consumer Credit Panel / Equifax Data (CCP). The CCP is a representative panel of the credit history of an anonymous 5% sample of the U.S. adult population (see Lee and der Klaauw (2010) for details of the dataset). Narrative codes in the CCP together with scheduled payment variables allow us to measure the incidence of mortgage forbearance. The CCP does not include loan performance data for mortgages in forbearance plans, since that information is not reported to credit bureaus. We use the CCP to calculate forbearance rates for the overall mortgage market (Figure 1), and to cross-validate the forbearance information in the Ginnie Mae data.

3.1 eMBS-CRISM merge

Unlike eMBS, CRISM does not include servicer identities. We are however able to merge CRISM with a vector of anonymous servicer identifiers by undertaking a fuzzy match between CRISM/McDash with eMBS loan-level data based on mortgage balance at origination, origination year-month, mortgage rate, credit score, whether a loan is an FHA or VA loan, and state.[19]

This matched dataset allows us to trace out the effects of servicer variation in forbearance practices on other borrower outcomes (e.g., total household debt and the performance of non-mortgage debt). It also enriches the set of available borrower-level characteristics relative to the eMBS-only dataset (e.g., since CRISM/McDash includes finer 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, whereas in eMBS we essentially are able to observe the entire universe of FHA and VA mortgages.

3.2 Summary statistics

Table 1 presents summary statistics for the eMBS loan-level sample, which reflects the population of FHA and VA loans in Ginnie Mae securities as of February 2020. The

[19]Note that the Federal Reserve's terms of use agreement with Black Knight does not permit us to retain servicer characteristics in this merged dataset. We are able to retain an anonymized servicer identifier, however.

dataset includes 10.3 million mortgages, of which about 70% are FHA loans. FHA loans have higher loan-to-value (LTV) ratios, higher debt-to-income (DTI) and lower average credit scores, reflecting the disproportionately low-income, high-risk FHA borrower population.

Table 1: Summary Statistics

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

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

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

4 Servicer variation in forbearance outcomes

We measure variation in servicing practices by using eMBS loan-level data to estimate a linear probability model of the form

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

The dependent variable is a dummy equal to one if a mortgage i entered forbearance between March-December 2020, X_i is a set of loan characteristics to control for differences in borrower demand for forbearance, and $\xi_{servicer}$ is a vector of servicer fixed effects, which measure cross-servicer variation in outcomes for otherwise equivalent mortgages.

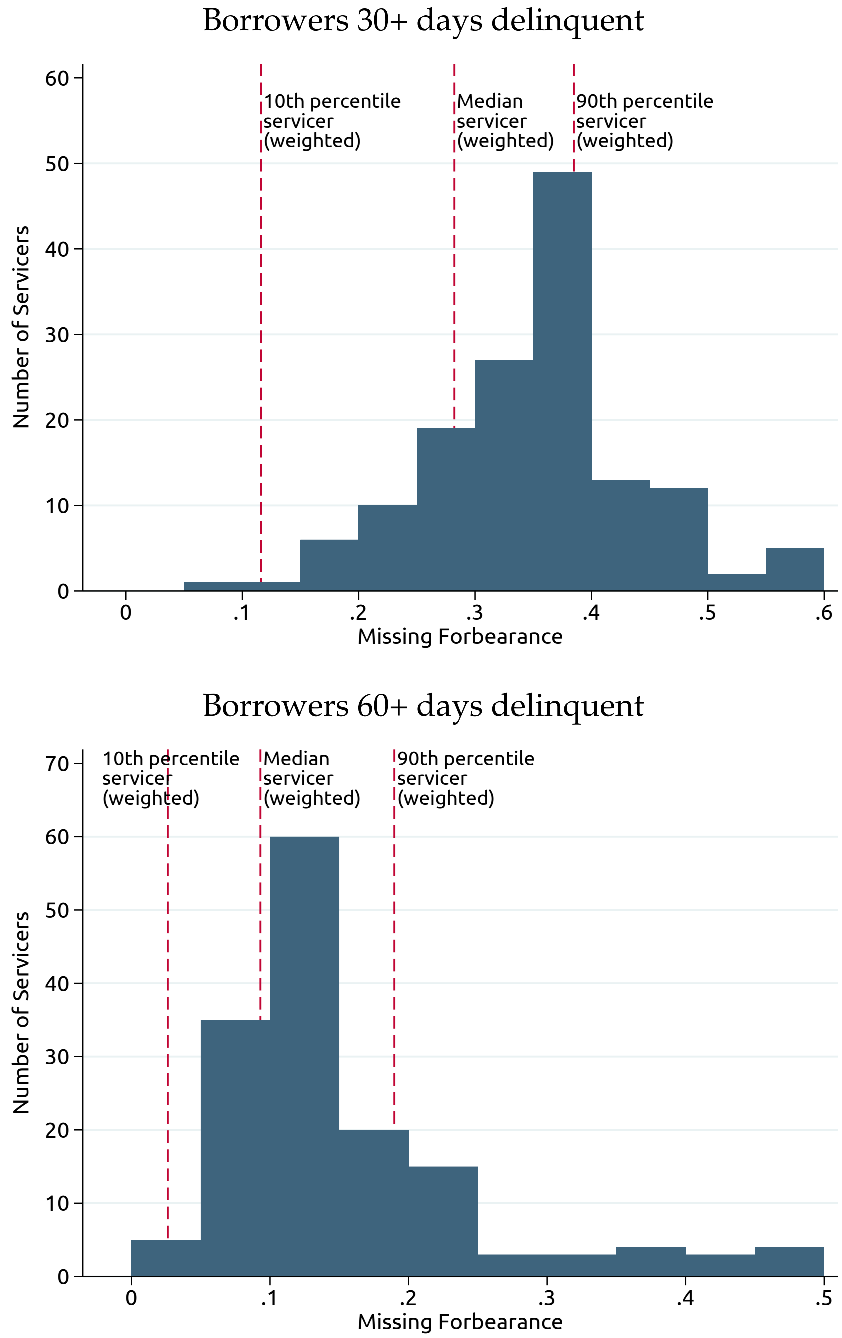
Our baseline approach is to estimate this model for borrowers that were current in January 2020 but missed at least one payment between March and December. This sample of borrowers would unambiguously benefit from forbearance, but as we have discussed, a significant number of them became delinquent without successfully entering into a forbearance plan. Our results therefore estimate how the incidence of "missing" forbearances varies across servicers.

Figure 2 presents the distribution of the estimated servicer fixed effects from equation 1. For the purposes of the figure we normalize the fixed effects to show the probability that a delinquent mortgage does *not* enter into a forbearance plan, varying only the servicer identity but holding the controls fixed at their sample average values.[20]

The figure shows that across servicers, the fraction of delinquent borrowers who "fall through the cracks" and do not receive a forbearance spans from under 10% to almost

[20] Although not our primary object of interest, coefficient estimates on loan and borrower characteristics are reported in section B of the Internet Appendix.

Figure 2: P(no forbearance | COVID delinquency)



Note: Calculated from estimates of servicer fixed effects (from equation 1, estimated using eMBS data).

60%. This dispersion is not simply a result of disparate outcomes among very small servicers. Weighting by loan count, the probability of no forbearance is around 40% for a servicer at the 90th percentile of the distribution, almost 30 percentage points higher than for a servicer at the 10th percentile.

The bottom panel of Figure 2 presents the same histogram conditioning on more serious delinquency (60 days or more past due). Although the share of missing forbearances is smaller for this group, there is still a significant gap in the probability of entering forbearance between the 10th percentile and 90th percentile servicer, of around 15 percentage points. Proportionately, the likelihood of not receiving forbearance is four times higher for a "low-forbearance-availability" servicer at the 90th percentile of the distribution compared to a "high-forbearance" servicer at the 10th percentile.

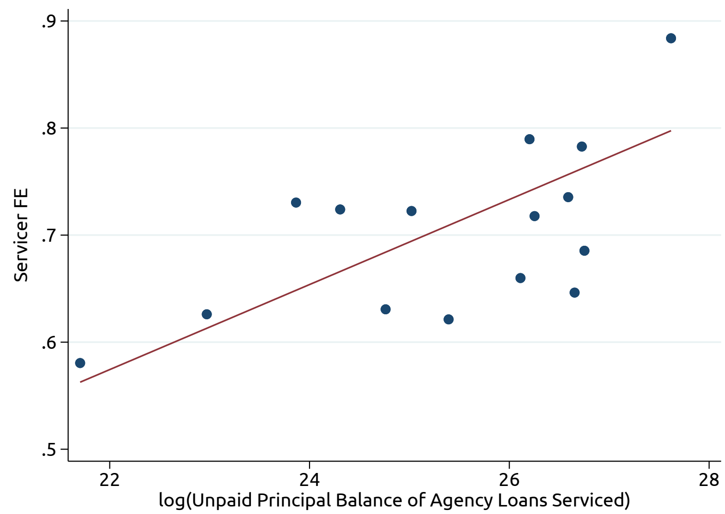
4.1 Servicer characteristics and forbearance availability

Now we study how a servicer's "forbearance propensity," as measured by its fixed effect in Section 4, varies with servicer characteristics. The goal of this analysis is to shed light on whether forbearance outcomes vary systematically with economic factors that may shape servicers' incentives or organizational effectiveness (as discussed in section 2.3).

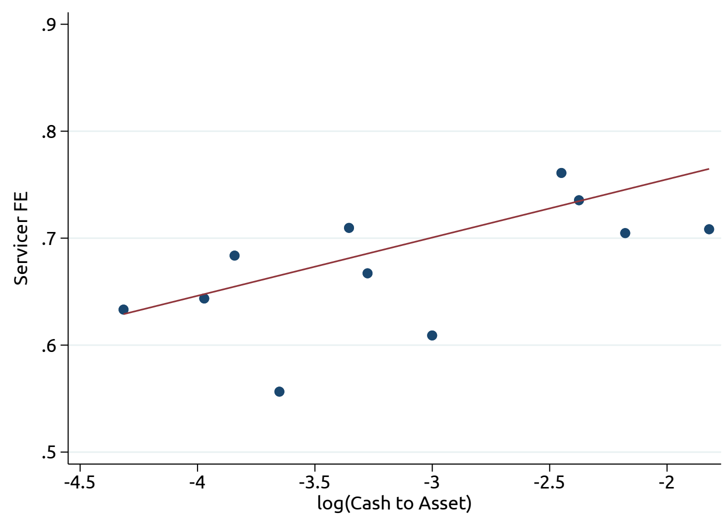
We begin our analysis by visually examining how the servicer fixed effect is related to servicer size and liquidity. Figure 3(a) shows that the conditional forbearance rate tends to be higher for servicers with a large agency servicing portfolio size. As we mentioned earlier, larger servicers may enjoy scale economies likely because of fixed costs involved in offering forbearance such as technology investments. They are also likely to have more resources to train servicing staff and thus provide more accurate information about the forbearance program. Finally, large servicers may also be targeted more intensively by regulators.

Figure 3(b) shows that the conditional forbearance rates for nonbank servicers are positively correlated with their cash holdings relative to total assets, measured as of March 2020. This finding is consistent with the hypothesis that servicer behavior was influenced by the liquidity risk associated with forbearance. This channel is likely more salient for nonbank servicers, which rely primarily on short-term wholesale funding and do not have access to government backstops such as the Federal Reserve discount window and Federal Home Loan Bank system advances.

Figure 3: **Servicer characteristics and conditional forbearance rates** This figure displays binned scatter plots between the servicer fixed effects and servicer characteristics. Each dot represents averages of the characteristics and fixed effects of servicers in each bin, not data points for an individual servicer. Each observation (each servicer) is weighted by the number of borrowers that were current in January 2020 but missed at least one payment between March and December.



(a) Servicer Size



(b) Nonbank servicer liquidity

We estimate a simple cross-sectional regression of servicer fixed effects on servicer characteristics. Results are reported in table 2. The estimates for servicer size and nonbank liquidity are consistent with Figure 3 even when we include other servicer characteristics. Further, estimates for additional variables included in the regression are consistent with the proposed mechanisms described earlier. Nonbank servicers tend to have lower forbearance availability, reflecting their liquidity cost and/ or regulatory environments facing them. Forbearance availability is also lower for servicers who relied more on servicing transfers instead of loan originations for their growth.[21] One possibility is that these servicers may not have enough servicing staff to deal with forbearance demand because of their rapid growth. Additionally, servicing transfers may present operational challenges around data management and integration, which Agarwal et al. (2017) found to be important for earlier mortgage relief programs.

Table 2: **Regression of conditional forbearance rates on servicer characteristics**: Each observation (each servicer) is weighted by the number of borrowers that were current in January 2020 but missed at least one payment between March and December. Columns (1) through (4) are estimated with the sample of all servicers. Columns (5) through (8) are estimated only with the subsample that include only nonbank servicers.

	All Servicers				Nonbanks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nonbank Servicer	-0.109**			-0.087***				
	(0.046)			(0.025)				
log(Total agency servicing book size)		0.040***		0.035***				0.028***
		(0.012)		(0.006)				(0.006)
Growth rate of svc book size from 2019 to 2020			-0.134**	-0.038				-0.009
			(0.058)	(0.038)				(0.046)
log(Cash to Total Asset)					0.055***			0.051***
					(0.019)			(0.013)
Capital ratio						0.211		0.036
						(0.132)		(0.104)
log(svc staff wage to servicing book size)							0.002	-0.001
							(0.005)	(0.003)
Constant	0.067	-1.037***	0.050	-0.842***	0.137**	-0.086**	-0.020	-0.597***
	(0.041)	(0.289)	(0.041)	(0.168)	(0.065)	(0.041)	(0.060)	(0.143)
N. Obs.	155	155	150	150	92	102	90	86
Adj. R^2	0.22	0.32	0.16	0.50	0.22	0.03	-0.01	0.44

Although we cannot separately identify which mechanism is more relevant for explaining the variation in a servicer's forbearance practice, our findings are consistent with the servicer incentives we noted in Section 2.3: servicers with observably more binding liquidity and operational constraints appear to restrict access to forbearance. As a result,

[21] Borrowers whose loans have been transferred in the past may have lower forbearance rates because they may not know which servicers to contact to obtain forbearance. We also separately control for whether a loan has been transferred to a different servicer when estimating the servicer fixed effect in Equation (**??**).

some borrowers may have found forbearance difficult to access for reasons unrelated to their own need for forbearance. In the next section, we show that our results are robust to alternative samples, specifications, and measures of forbearance availability.

4.2 Robustness checks

We show in section D of the Internet Appendix that estimates of servicer fixed effects are highly correlated across alternative methods of estimating them. We compare our baseline estimates of X_i to five alternative estimates based on

(i) retaining only loans that became 60+ days past due during the pandemic (corresponding to the distribution in the lower panel of Figure 2, rather than 30+ days;

(ii) including all loans in the sample, rather than just those that became past due[22];

(iii) restricting the estimation sample only to borrowers that became delinquent in February or March, prior to the passage of the CARES Act;

(iv) including *lender* fixed effects in the set of controls X_i — in this model, servicer fixed effects are identified only from loans where servicing rights were sold or otherwise transferred from the originator.

(v) retaining only loans in our matched CRISM-eMBS sample. We compare servicer FE estimated using variables available in eMBS with servicer FE estimated using variables available in CRISM and eMBS.

Figure A.3 shows the correlation between the servicer fixed effects estimated using our main specification with the alternative fixed effects estimated using these alternative approaches. In all five cases, our scatter plots show that the resulting fixed effect estimates are highly positively correlated with our main estimates from the top panel of Figure 2. This suggests that our main findings are robust to alternative specifications and speaks against the story that our measure of servicers' forbearance policies is endogenous to their portfolio composition.

[22] We also present the histogram of these fixed effects in the Internet Appendix, which similar to our main estimates shows that there is economically significant dispersion in conditional forbearance rates across servicers.

Table 3 reports estimates of the relationship between these alternative servicer fixed effect estimates and servicer characteristics. Although some coefficient estimates become statistically insignificant with the alternative fixed effects, many estimates are consistent with our main estimate reported in Table 2. Thus, the qualitative finding that some servicers restrict forbearance access in response to economic incentives still holds under these alternative approaches for measuring servicers' forbearance practices.

Table 3: **Alternative Servicer FE and characteristics:** Dependent variables for regression estimates in this table are the alternative servicer fixed effects. For columns (1) and (2), we consider the servicer fixed effects estimated with the sample of loans that became 60+ days past due during the pandemic. For columns (3) and (4), we consider the servicer fixed effects estimated with all loans. For columns (5) and (6), we consider the servicer fixed effects estimated with the sample of borrowers that became delinquent in February or March 2020. For columns (7) and (8), we consider the servicer fixed effects estimated with a regression that includes lender fixed effects. The number of observations is lower for columns (7) and (8) because we only consider servicer who ever acquired servicing rights of loans originated by another lender. Each observation (each servicer) is weighted by the number of borrowers in the sample used to estimate servicer fixed effects.

	DQ 60+ since Mar		All loans		DQ in Feb or Mar		Lender FE	
	(1) All Servicers	(2) Nonbanks	(3) All Servicers	(4) Nonbanks	(5) All Servicers	(6) Nonbanks	(7) All Servicers	(8) Nonbanks
Nonbank Servicer	-0.016		-0.030***		-0.008		-0.077	
	(0.015)		(0.011)		(0.028)		(0.069)	
log(Total agency servicing book size)	0.027***	0.030***	0.009***	0.004	0.034***	0.029***	0.035*	0.038***
	(0.004)	(0.006)	(0.003)	(0.004)	(0.007)	(0.009)	(0.017)	(0.011)
Growth thru servicing transfer	-0.183**	-0.261***	-0.008	0.013	-0.198***	-0.188***	-0.156	-0.112*
	(0.071)	(0.076)	(0.026)	(0.034)	(0.059)	(0.059)	(0.097)	(0.060)
log(Cash to Total Asset)		0.016**		0.012		0.037		0.065***
		(0.008)		(0.009)		(0.023)		(0.012)
Capital ratio		0.115		0.119**		0.321***		0.189
		(0.122)		(0.050)		(0.112)		(0.122)
Constant	-0.666***	-0.735***	-0.224***	-0.093	-0.848***	-0.680***	-0.843**	-0.810**
	(0.096)	(0.167)	(0.067)	(0.068)	(0.168)	(0.200)	(0.402)	(0.289)
N. Obs.	155	92	157	93	153	91	35	23
Adj. R^2	0.33	0.40	0.37	0.23	0.29	0.40	0.14	0.62

4.3 Servicer effects or omitted borrower characteristics?

Our interpretation is that this dispersion in outcomes is driven by variation in servicer practices. But an alternative explanation is that it is due to unobserved variation in forbearance *demand* (conditional on observable loan and borrower characteristics).

We offer three forms of evidence that our identification assumption is plausible.

1. Figure A.6 and Tables A.10 - A.13 in Internet Appendix Section H show that there is little systematic difference in delinquency flows for borrowers at high versus low availability servicers prior to the start of the pandemic.[23] If anything, pre-pandemic delinquency flows are slightly *lower* at high-forbearance servicers, although the difference is economically small. Under an "omitted risk" explanation, we would expect borrowers at high-forbearance servicers to have higher non-payment rates not just during the pandemic, but also prior to it.[24]

2. In Internet Appendix Tables A.2 - A.4 we show that measured servicer forbearance availability ($\xi_{servicer}$) is not strongly correlated with observable borrower characteristics measured either at origination or just prior to the pandemic. We also show in Internet Appendix Table A.11 that pre-pandemic and that pre-pandemic credit card delinquencies did not vary across servicer type. Table A.12 shows that auto loan delinquencies were slightly lower at high-forbearance servicers, but the magnitude of the difference is economically small. [25]

3. We showed in Section 4.2 that the servicer fixed effects are robust to a number of different specifications and samples. Notably, the estimates are stable as we introduce more granular geographic controls and borrower characteristics like updated credit score and non-mortgage borrowing. The robustness of these estimates to additional borrower-level controls suggests that portfolio composition does not drive variation in forbearance policy. Additionally, restricting our sample to borrowers that are at some point delinquent, and therefore observably stressed, limits important sources of unobservable variation in demand for forbearance.

[23] We focus on flows into delinquency rather than the delinquency rate for two reasons. First, servicer quality may be correlated both with forbearance policies and with the ability to cure delinquent borrowers. Second, because our sample is comprised of loans that were in securities as of early 2020, servicers with the same delinquency flows may have different delinquency rates, depending on whether they buy delinquent loans out of Ginnie securities. Within our sample, we require loans to be current in January 2020, to remove this source of variation in forbearance takeup. Flows into delinquency are therefore the cleanest pre-pandemic risk measure in our sample.

[24] Fuster et al. (2021a) show that along observable dimensions of mortgage risk, this is exactly what does happen; borrowers with low credit scores, for example, experience a larger increase in delinquency during the pandemic. This fact is also apparent in Figure 1, which shows that the pandemic amplified pre-existing differences in delinquency rates across different segments of the mortgage market.

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

Thus, remaining variation in forbearance outcomes across servicers among such borrowers is unlikely driven by demand-side factors but by servicer-related factors. The orthogonality of servicer forbearance policies and borrower characteristics provides a quasi-experimental setting within which we can explore the impact of forbearance availability on borrowers. We undertake this analysis in the next section.

4.4 Summary

To sum up the results of this section, we find that a significant fraction of FHA and VA borrowers entitled to forbearance under the CARES Act do not in fact enter forbearance, and we find significant variation in the fraction of "missing forbearance" across mortgage servicers after controlling for detailed loan and borrower characteristics. The propensity to place borrowers in a forbearance plan is lower for smaller servicers, nonbanks, servicers with smaller liquidity buffers, and servicers which have grown their servicing book through servicing transfers. These results point to the role of financial constraints, regulation and possibly scale economies in shaping forbearance outcomes for borrowers.

5 Does forbearance cause nonpayment?

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

For this portion of the analysis, we rely primarily on the CRISM-eMBS merge described in Section 3.[26] Usage restrictions on the CRISM dataset prevent us from retaining servicer information in the merged eMBS-CRISM dataset, but the merge does allow us to retain anonymous servicer identifiers. We use these identifiers to estimate servicer-level

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

fixed effects using the same methodology as in the prior section. We then use the fixed effects as a source of plausibly exogenous variation in forbearance availability to trace the effects of forbearance on other borrower outcomes.

The key identification assumption underlying this approach is that servicer forbearance fixed effects are orthogonal to unobserved borrower characteristics which would affect outcomes during the pandemic (conditional on mortgage characteristics measured in CRISM). This is the same identification assumption required for our analysis in Section 4.3, where we present evidence of its validity.

5.1 Regression specification

We use a difference-in-difference approach to compare outcomes and behavior of borrowers at servicers with more- and less-generous forbearance practices. We define "high-forbearance" servicers as those with above-median servicer fixed effects (estimated as described in Section 4, using the merged eMBS-CRISM data). We use the 6 month period preceding the March 2020 passage of the CARES Act to establish the absence of different pre-existing trends between high- and low-forbearance servicers. We attribute differences in borrower outcomes and behavior after March 2020 to differences in the accessibility of forbearance.

We estimate the following regression:

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

where Y_{it} is a borrower outcome such as nonpayment; S_i^H is an indicator variable equal to 1 for high-forbearance servicers; Z_{it} is a vector of loan and borrower characteristics which may affect mortgage delinquency, including mortgage characteristics at origination, the borrower's updated credit score (measured by the Equifax Risk Score) as of January 2020, updated principal balance, loan age, borrower age, updated LTV, and loan type (FHA vs. VA); α_s is a vector of servicer fixed effects, which account for persistent differences in borrower outcomes across servicers; and α_{zt} is a vector of zipcode x month x origination month FE to account for the time-varying geographic effects of the pandemic separately for loans originated in different times. We cluster standard errors at the servicer level. Note that our zip x month x origination month FE absorb any general equilibrium effects of the program.

5.2 Results

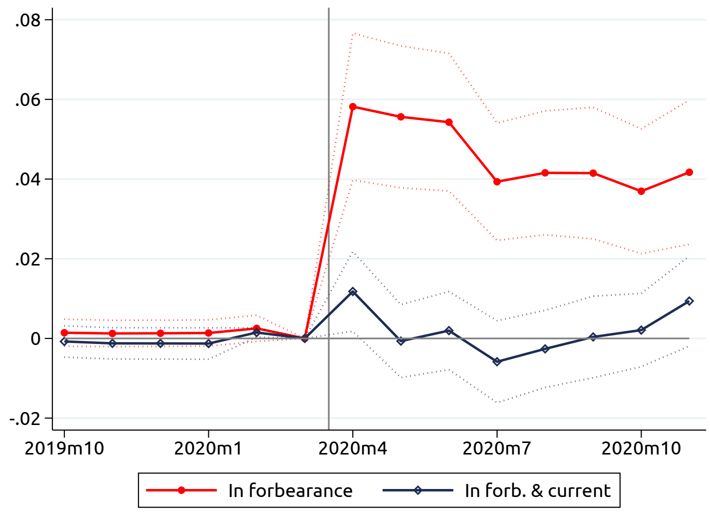
First, we confirm that the path of forbearance rates is actually higher among servicers we have categorized as high-forbearance-availability servicers. Figure 4(a) plots the estimates of β_τ from Equation 2 using a forbearance dummy as the outcome variable. The coefficients can be interpreted as the difference in the probability that a borrower is in a forbearance plan at a high-forbearance servicer vs. at low-forbearance servicer in a given month, all else equal.

Figure 4(a) confirms that forbearance rates are higher at high-forbearance servicers throughout the pandemic. At the peak in April, the share of borrowers in forbearance at high-forbearance servicers was about 5 percentage points (about 30%) higher than at low-availability servicers. The difference begins to diminish from May onwards, even as overall forbearance rates continue to rise, perhaps reflecting that low-forbearance-availability servicers partially "catch up" in their policies and practices. However the difference in forbearance rates remains high throughout the pandemic.

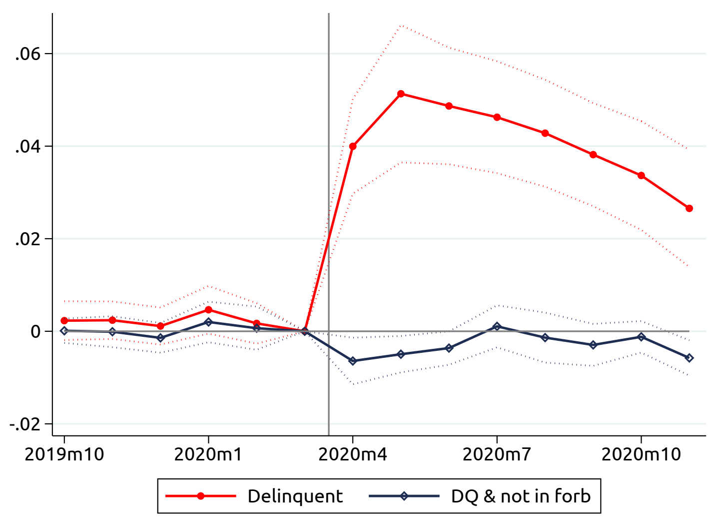
Next, we examine whether forbearance availability *causes* mortgage nonpayment. Given that forbearance significantly reduces the cost of missing mortgage payments, it seems reasonable to expect that the delinquency rates will rise disproportionately at servicers that make it easier for borrowers to enter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

Figure 4(b) reports the monthly difference in the probability a borrower is past-due (i.e., has missed at least one payment) at high-forbearance servicers relative to low-forbearance servicers. We find that the probability that a borrower is past-due is significantly higher for borrowers at high-forbearance servicers, by as much as 5 percentage points at the peak in May 2020. Moreover, the estimates for the probability that a borrower is past-due are similar to the estimates for the forbearance probability in Figure 4(a). This result indicates that effectively *all* of the additional forbearance at high-forbearance servicers drives borrower nonpayment. In other words, marginal forbearance recipients at high-forbearance servicers would not have missed payments had forbearance been more difficult to access.

Figure 4: **Forbearance and Delinquency.** Estimates of the effect of assignment to a "high-forbearance" servicer on the likelihood of forbearance and missed payments.



(a) In forbearance



(b) Past due

Figure 4(a) confirms that this sharp increase in delinquencies is driven entirely by borrowers who are in forbearance plans. Conversely, there is also no difference in delinquency rates outside of forbearance among high-vs-low availability servicers (shown in the blue line in Figure 4(b)).

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

6 Non-mortgage effects

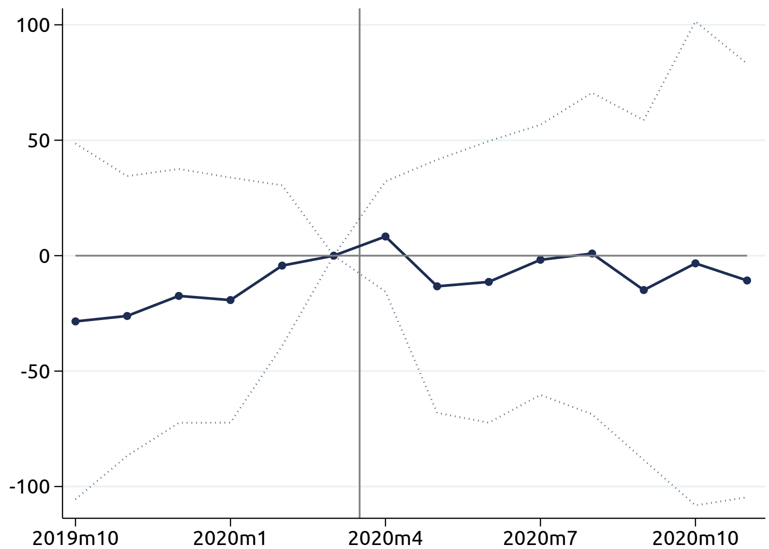
Our results so far show that assignment to a "high-forbearance-availability" servicer induces borrowers to obtain forbearance and also to defer their mortgage payments. This deferral puts a significant amount of additional cash in the borrower's pocket. We now examine how borrowers use this additional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

We estimate these effects using the same methodology, but replacing the dependent variable in Equation 2 with various nonmortgage outcomes. Results are presented in Figures 5 and 6.

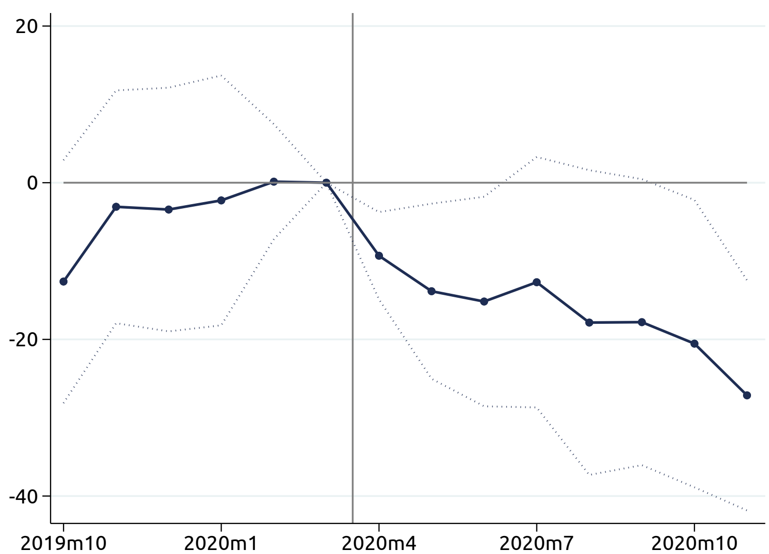
Figure 5 shows that forbearance availability induced some borrowers to pay down credit card balances. Borrowers with below-median credit card balances at high-forbearance servicers paid off around $20 relative to borrowers at low-availability servicers (Figure 5(b)). Because the forbearance rate is higher by 5 percentage points for borrowers at high-forbearance servicers, the result implies that marginal borrowers who received forbearance as a result of assignment to a high-forbearance servicer reduced their credit card balances by about $400. This difference is about a quarter of the average forbearance-driven savings in mortgage payments of those borrowers at high-forbearance servicers. We do not find robust evidence that higher-balance borrowers paid down credit cards, and the standard errors on these specifications are much larger (Figure 5(a)).

This finding shows that forbearance essentially provided a low-cost source of liquidity to households, partially replacing expensive credit card debts. Households with lower

Figure 5: **Effects of forbearance availability on credit card balances**. Figure plots estimates of the effects of assignment to a high-forbearance servicer on credit card debt for borrowers with above- and below-median outstanding credit card balances as of April 2020.

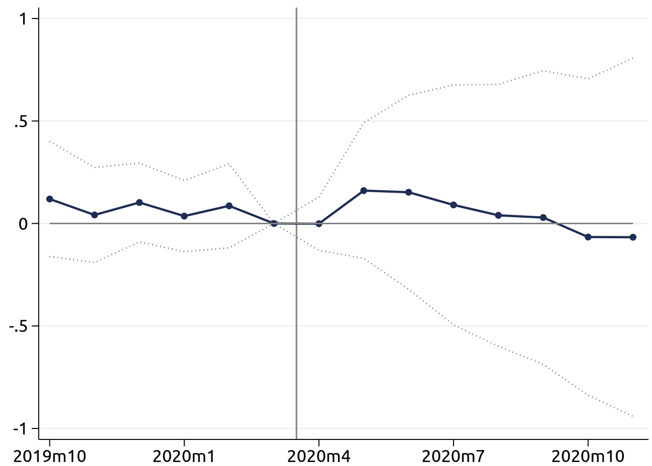


(a) Credit card balance among high-credit-card-balance borrowers ($)



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

Figure 6: **Effects of forbearance availability on updated credit score (FICO Score version 5)**. Figure plots estimates of the effects of assignment to a high-forbearance servicer on the borrower's credit score (Equifax Risk Score 3.0), as measured in CRISM.



credit card balances before the pandemic may be less liquidity-constrained than high-balance borrowers, which may explain why they were more willing to use the additional funds to pay down credit card debt rather than for consumption or to increase liquid assets.

We note that our estimates for credit card pay-down among low-balance borrowers are somewhat sensitive to the set of fixed effects used in the regression, with estimates ranging from about $20 to about $50, and the standard errors are quite wide. We present the results several alternative specifications in Figure A.7.

We find no evidence that borrowers used forbearance to pay down other sources of debt like auto loans, student debt, or junior liens (Table A.15). This is perhaps unsurprising, as these forms of borrowing are much cheaper than credit card debt, making them a lower priority for payoff. (Additionally, our analysis in this section relies on a relatively small absolute difference in forbearance rates across servicer-types, so we are unlikely to have sufficient power to measure small changes in average balances.) We also do not find that households assigned to higher-forbearance servicers purchased more cars (Table A.16). We find no effect on the delinquency rates of non-housing debt, though the availability of other forbearance programs may have affected these outcomes as well (Table A.17).

Figure 6 shows that although borrowers at high-forbearance servicers are more likely to miss mortgage payments, their credit scores (FICO Score 5)[27] did not decrease as a result, because nonpayment during forbearance is not reported to the credit bureaus. In fact, credit scores for the high-forbearance group of borrowers actually increase slightly (perhaps reflecting their paydown of credit card balances and/or avoiding delinquency on non-mortgage debt), although the effect is estimated with a large standard error once we include servicer fixed effects.

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

7 Moral Hazard

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

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

Our data are not particularly well-suited to estimate the extent of moral hazard, because we do not have access to high-frequency dynamic income and employment data for our sample. Even so, several pieces of evidence suggest that most borrowers who skipped payments in forbearance did so as a result of negative income shocks. First,

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

Table A.18 shows that the characteristics of borrowers in forbearance are comparable between high- and low-availability servicers, suggesting that easier access did not draw observably less-risky borrowers on the margin. For example, the average non-mortgage balances and average credit scores are very similar between the two groups. Borrowers at high-forbearance servicers tend to be in forbearance longer and less likely exit forbearance, but the differences between the two groups are quantitatively small. If moral hazard were the main channel driving nonpayments, we might instead expect high-financial-literacy borrowers at high-forbearance servicers to use the program more intensively: to miss more payments and to remain in forbearance longer.

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

A final point is that in aggregate only a relatively small proportion of borrowers used forbearance to skip mortgage payments. In principle, many borrowers could have acted in an opportunistic manner to take advantage of the generous repayment terms offered through the forbearance program. But it is clear that the vast majority of borrowers who were able to make their mortgage payments did not do so.

A separate question is whether restricting forbearance access was the "right" ex post decision for resource-constrained servicers. Theoretically, offering forbearance can be pareto improving for servicers and borrowers. Servicing and foreclosing on delinquent loans is costly; if forbearance reaches borrowers who would miss payments anyway and also prevents foreclosure, servicers' interests may align with public policy objectives. But our results suggest that additional access to the program induced nonpayment, on net. In fact, easier access to forbearance increased nonpayment in tandem, suggesting that almost none of the additional borrowers in forbearance at high-forbearance servicers would have missed payments absent the program. This level of induced nonpayment would likely discourage resource-constrained servicers from voluntarily expanding forbearance access. [28]

[28] This is not a complete cost-benefit analysis for servicers during this time period. Idiosyncratic dynamics in

8 Conclusion

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

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

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

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

Overall, the CARES Act mortgage forbearance program has been successful in enrolling a large number of borrowers in a short period of time, and significantly mitigating the negative shock of the COVID-19 pandemic on household liquidity. The low aggregate

the secondary market may have counteracted any costs from additional induced nonpayment for high-liquidity servicers, since servicers could purchase 90-day-delinquent loans out of pools and resecuritize the cured loans at great profit early in the program. The terms of the resecuritization for these loans became less favorable after June 2020.

level of nonpayment suggests that despite a high rate of induced delinquency among forbearance users, the program was well-targeted to households that experienced hardship. Even so, our results show that idiosyncratic differences across servicers played a significant role in the rollout of the program and shaped household outcomes. Policymakers may wish to consider whether future debt relief programs can include features (e.g., auto-enrollment) that overcome servicer reluctance and mitigate variation in outcomes that is unrelated to borrower fundamentals.

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Internet Appendix for:

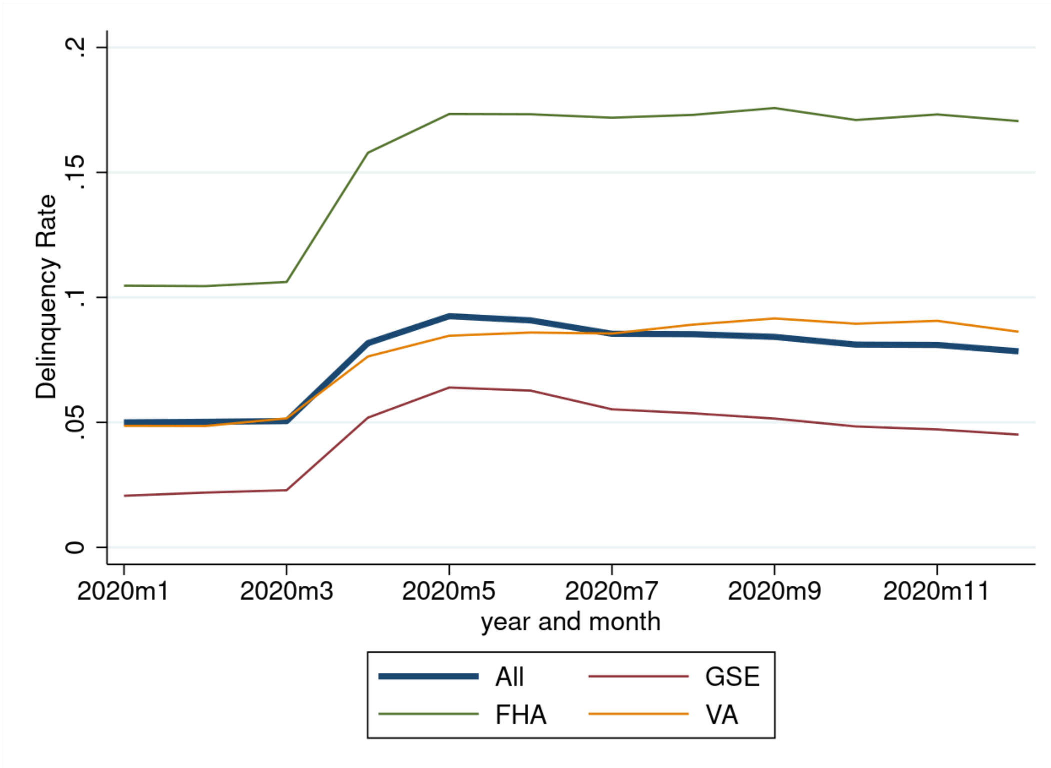
"Intermediation Frictions in Debt Relief: Evidence from CARES Act Forbearance"

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

September 7, 2021

A Mortgages 30+ days past due, by segment

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



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

B Loan-level estimates: eMBS

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

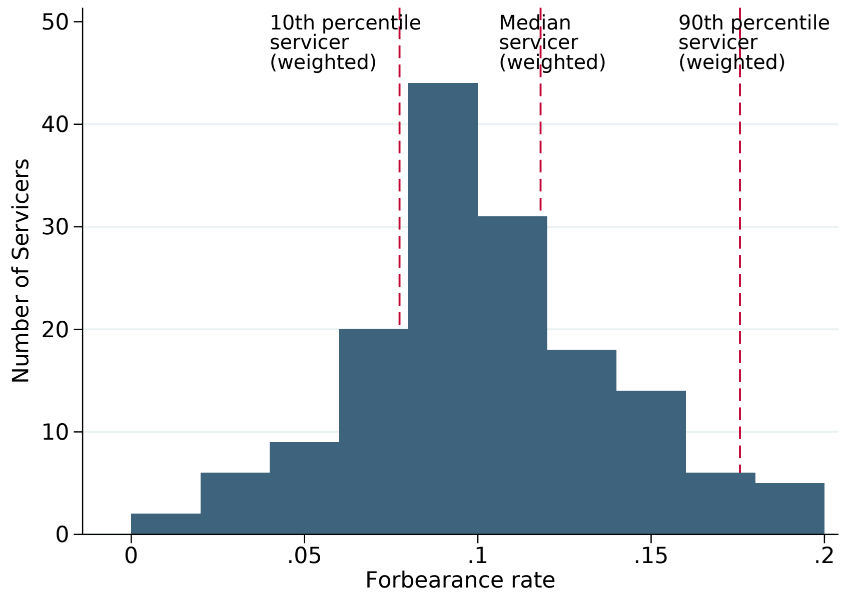
	(1) Ever delinquent sample	(2) Full sample
Ever servicer change	-0.031***	0.002***
	(0.002)	(0.000)
Months since last servicer change	0.001***	-0.000***
	(0.000)	(0.000)
First-time homebuyer	0.030***	0.022***
	(0.001)	(0.000)
DTI at orig:		
$25 < \text{dti} \leq 50$	0.043***	0.028***
	(0.002)	(0.000)
$\text{dti} > 50$	0.083***	0.072***
	(0.002)	(0.001)
Loan age (year)	-0.017***	-0.006***
	(0.000)	(0.000)
Loan age (year) × Loan age (year)	0.000***	0.000***
	(0.000)	(0.000)
Ln(Current UPB)	0.097***	0.033***
	(0.001)	(0.000)
CS at orig:		
$620 < \text{orig cs} \leq 680$	0.018***	-0.020***
	(0.001)	(0.001)
$680 < \text{orig cs} \leq 740$	0.027***	-0.066***
	(0.002)	(0.001)
$\text{orig cs} > 740$	0.010***	-0.101***
	(0.002)	(0.001)
Loan purpose:		
refinace	0.043***	0.003***
	(0.002)	(0.000)
LTV at orig:		
$80 < \text{LTV} \leq 95$	0.023***	0.006***
	(0.002)	(0.000)
$95 < \text{LTV} \leq 100$	0.030***	0.016***
	(0.002)	(0.000)
$\text{LTV} > 100$	0.015***	0.019***
	(0.003)	(0.001)
FHA	0.063***	0.067***
	(0.001)	(0.000)
30+ days delinquent in Feb 2020		-0.311***
		(0.011)
Servicer FE	Y	Y
State FE	Y	Y
N. Obs.	1,193,794	9,069,971

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

C Servicer fixed effects estimates: unconditional sample

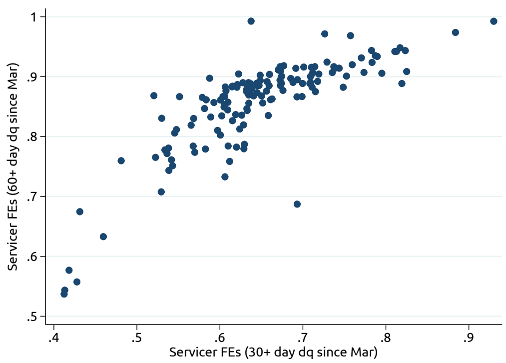
The figure below reports the estimated distribution of servicer fixed effects from regressing a forbearance dummy on loan characteristics and servicer dummies using the full sample of FHA and VA loans (rather than restricting the sample to mortgages that enter delinquency during the pandemic, as we do in the main text).

Figure A.2: Forbearance rate: full sample

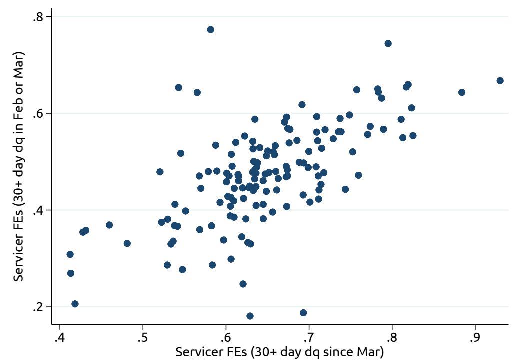


D Comparison of fixed effects across approaches

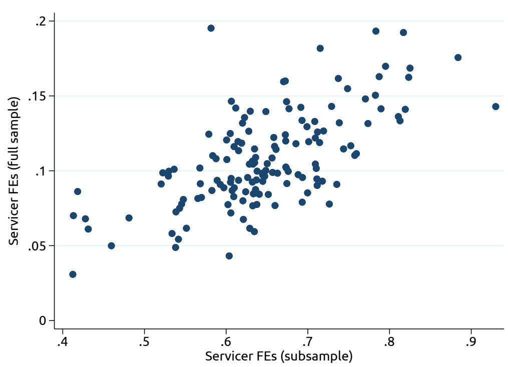
Figure A.3: **Correlation between servicer fixed effects from different specifications**: These figures show correlations between the baseline servicer fixed effect estimates and three alternative sets of estimates, based on: (i) using the subsample of loans which became at least 60 days delinquent (DQ) after March 2020 (panel a); (ii) using the subsample of borrowers who missed at least a payment in February or March 2020 (panel b); using the entire sample for estimation, rather than just borrowers that became delinquent (panel c); include lender fixed effects in the model, so that identification of servicer fixed effects is based on servicing transfers (panel d).



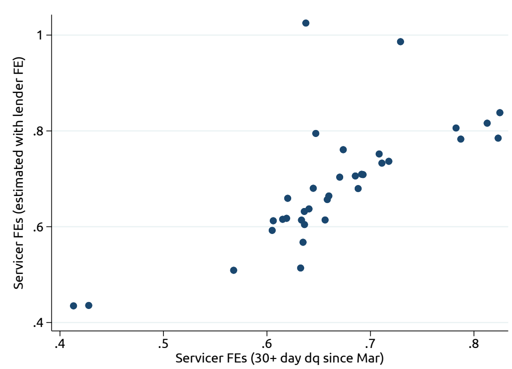
(a) 60+ day past due post-March 2020



(b) Missed payment in Feb/Mar 2020

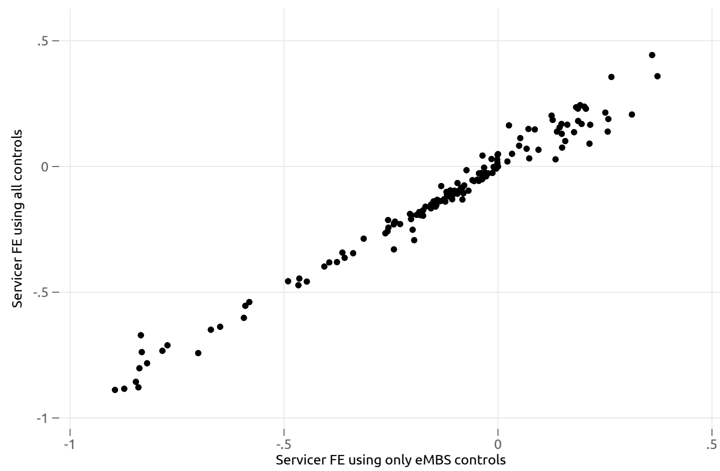


(c) include all loans in sample

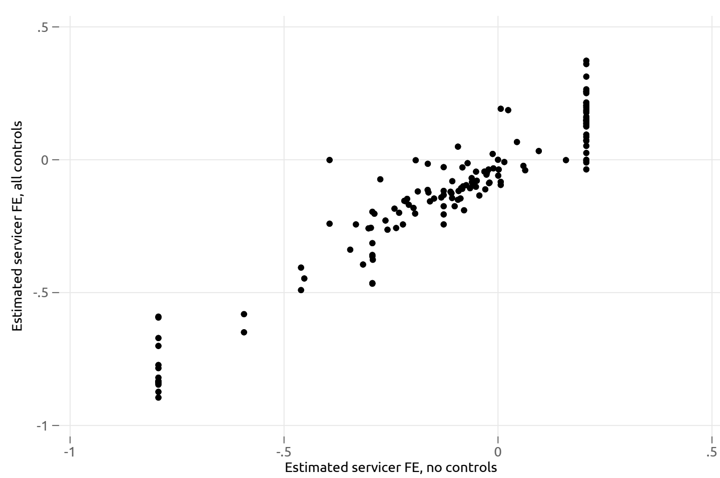


(d) include lender fixed effects

Figure A.4: **Robustness of Servicer FE Estimates.** Panel (a) shows the correlation between servicer FE estimated using borrower and servicer characteristics available only in eMBS and servicer FE estimated using borrower and servicer characteristics available in CRISM. Panel (b) shows the correlation between servicer FE estimated without controls and servicer FE estimated using all controls available in the CRISM-eMBS merge.



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



(b) Servicer FE Estimated using all available controls and no controls

E Borrower Characteristics by Servicer Type

Table A.2: Borrower Characteristics across Servicers (measured as of Feb 2020)

	(1) Low-Availability Servicer	(2) High-Availability Servicer
30+ days delinquent in Feb 2020	0.02	0.02
60+ days delinquent in Feb 2020	0.00	0.00
Current Mortgage Balance	184,319.36	163,433.68
Non-First-Mortgage Balance	42,375.87	40,664.19
Auto Loan Balance	16,101.49	15,254.14
Credit Card Balance	8,970.18	8,710.08
Student Loan Balance	10,319.28	9,563.49
CES + HELOC	2,661.43	2,981.82
Pre-Cares Act DQ in Non-First-Mortgage	0.12	0.11
12-mo change CNTY UR (8/20)	6.02	5.80
FHA	0.67	0.70
Riskscore	706.85	716.59
LTV at origination	93.92	94.22
Loan age (year)	4.49	6.04
N. Obs.	1,242,931	1,521,057

Table A.3: **Borrower characteristics across servicers by origination year (CRISM-eMBS match)**

(a) Origination year up to 2013

	(1) Low-Availability Servicer	(2) High-Availability Servicer
Current Mortgage Balance	135,381.09	136,305.65
12-mo change CNTY UR (8/20)	6.15	5.82
FHA	0.83	0.77
Riskscore	727.17	721.57
LTV at origination	93.59	93.64
Loan age (year)	8.52	8.63
Auto Loan Balance	13,323.63	13,931.55
Credit Card Balance	9,137.77	8,821.67
N. Obs.	330,688	709,149

(b) Origination year from 2014 to 2017

	(1) Low-Availability Servicer	(2) High-Availability Servicer
Current Mortgage Balance	184,134.60	178,100.39
12-mo change CNTY UR (8/20)	6.06	5.81
FHA	0.68	0.68
Riskscore	709.56	714.79
LTV at origination	94.05	94.82
Loan age (year)	4.59	4.82
Auto Loan Balance	16,509.47	16,469.37
Credit Card Balance	9,324.62	8,966.90
N. Obs.	383,516	499,196

(c) Origination year since 2018

	(1) Low-Availability Servicer	(2) High-Availability Servicer
Current Mortgage Balance	220,673.50	206,800.80
12-mo change CNTY UR (8/20)	5.92	5.75
FHA	0.57	0.59
Riskscore	692.16	708.16
LTV at origination	94.02	94.60
Loan age (year)	1.90	2.11
Auto Loan Balance	17,542.96	16,313.49
Credit Card Balance	8,608.26	8,047.07
N. Obs.	528,727	312,712

Table A.4: **Borrower characteristics across servicers by origination year (eMBS)**

(a) Origination year up to 2013

	(1) Low-Availability Servicer	(2) High-Availability Servicer
Ever in forbearance	0.09	0.12
Current Mortgage Balance	114,314.50	117,761.95
12-mo change CNTY UR (8/20)	5.95	5.91
FHA	0.80	0.78
Orig credit score	696.70	704.44
Orig LTV (%)	92.66	92.71
Loan age (year)	10.26	10.13
N. Obs.	1,099,416	1,962,228

(b) Origination year from 2014 to 2017

	(1) Low-Availability Servicer	(2) High-Availability Servicer
Ever in forbearance	0.13	0.15
Current Mortgage Balance	177,486.62	174,668.33
12-mo change CNTY UR (8/20)	6.09	5.87
FHA	0.70	0.62
Orig credit score	688.00	700.56
Orig LTV (%)	93.47	93.14
Loan age (year)	4.62	4.71
N. Obs.	1,240,481	1,258,138

(c) Origination year since 2018

	(1) Low-Availability Servicer	(2) High-Availability Servicer
Ever in forbearance	0.16	0.17
Current Mortgage Balance	216,244.11	202,969.29
12-mo change CNTY UR (8/20)	6.15	5.77
FHA	0.70	0.59
Orig credit score	680.73	694.65
Orig LTV (%)	94.65	93.56
Loan age (year)	2.06	2.13
N. Obs.	1,987,328	1,389,321

F Alternative specifications: Role of servicer characteristics in forbearance policy

Table A.5: Servicer FEs (conditional on 60+ dq)

	All Servicers				Nonbanks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nonbank Servicer	-0.042			-0.019				
	(0.028)			(0.017)				
log(Total agency servicing book size)		0.026***		0.021***				0.019***
		(0.005)		(0.005)				(0.006)
Growth rate of svc book size from 2019 to 2020			-0.096***	-0.053				-0.049
			(0.035)	(0.040)				(0.051)
log(Cash to Total Asset)					0.039***			0.036***
					(0.015)			(0.012)
Capital ratio						0.159		-0.083
						(0.130)		(0.134)
log(svc staff wage to servicing book size)							-0.001	-0.006*
							(0.003)	(0.003)
Constant	0.025	-0.661***	0.035*	-0.520***	0.111**	-0.050	-0.023	-0.396***
	(0.024)	(0.128)	(0.018)	(0.126)	(0.045)	(0.035)	(0.046)	(0.143)
N. Obs.	155	155	150	150	92	102	90	86
Adj. R^2	0.06	0.24	0.15	0.30	0.14	0.02	-0.01	0.32

Table A.6: Servicer FEs (controlling for lender FEs)

	All Servicers				Nonbanks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nonbank Servicer	-0.029			-0.075				
	(0.045)			(0.048)				
log(Total agency servicing book size)		0.021		0.027*				0.033**
		(0.016)		(0.016)				(0.012)
Growth rate of svc book size from 2019 to 2020			-0.083*	-0.074				-0.006
			(0.048)	(0.049)				(0.056)
log(Cash to Total Asset)					0.076***			0.075***
					(0.019)			(0.012)
Capital ratio						0.246		0.170
						(0.202)		(0.135)
log(svc staff wage to servicing book size)							0.003	-0.000
							(0.005)	(0.003)
Constant	0.012	-0.563	0.029	-0.606	0.234***	-0.070	0.009	-0.674**
	(0.037)	(0.396)	(0.036)	(0.389)	(0.064)	(0.064)	(0.070)	(0.301)
N. Obs.	35	35	34	34	23	26	22	22
Adj. R^2	-0.02	0.06	0.08	0.16	0.40	0.02	-0.04	0.57

Table A.7: Servicer FEs (conditional on becoming dq in Feb or Mar 2020)

	All Servicers				Nonbanks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nonbank Servicer	-0.033			-0.020				
	(0.044)			(0.032)				
log(Total agency servicing book size)		0.030***		0.028***				0.022**
		(0.008)		(0.008)				(0.009)
Growth rate of svc book size from 2019 to 2020			-0.073*	-0.037				0.014
			(0.043)	(0.043)				(0.048)
log(Cash to Total Asset)					0.054*			0.060**
					(0.028)			(0.023)
Capital ratio						0.366***		0.139
						(0.130)		(0.154)
log(svc staff wage to servicing book size)							-0.006	-0.007*
							(0.005)	(0.004)
Constant	0.023	-0.764***	0.029	-0.684***	0.170*	-0.085**	-0.058	-0.470**
	(0.038)	(0.196)	(0.028)	(0.193)	(0.099)	(0.041)	(0.069)	(0.191)
N. Obs.	153	153	148	148	91	101	89	85
Adj. R^2	0.02	0.21	0.06	0.23	0.16	0.09	0.02	0.35

Table A.8: Servicer FEs (full sample including current loans)

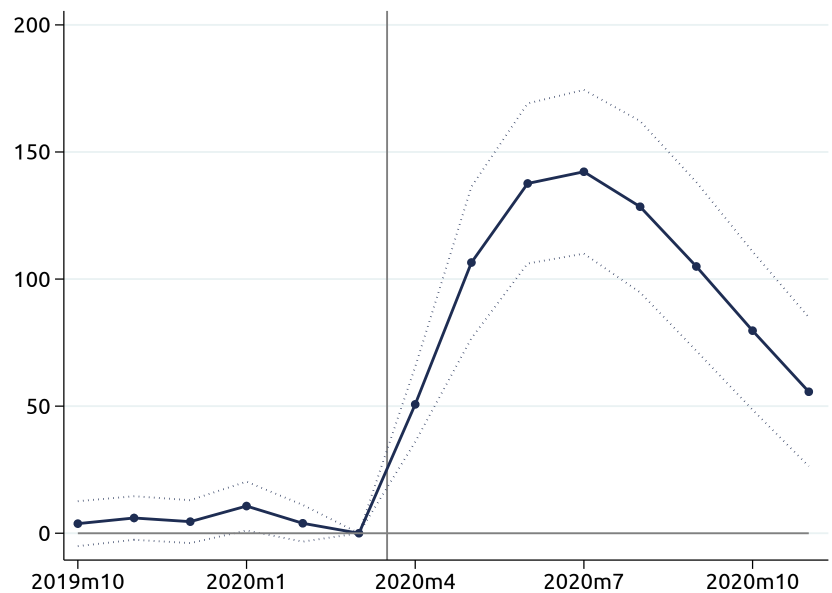
	All Servicers				Nonbanks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nonbank Servicer	-0.033**			-0.032***				
	(0.016)			(0.012)				
log(Total agency servicing book size)		0.010**		0.010***				0.005
		(0.004)		(0.003)				(0.003)
Growth rate of svc book size from 2019 to 2020			-0.023	0.005				0.029*
			(0.021)	(0.015)				(0.017)
log(Cash to Total Asset)					0.011			0.014
					(0.011)			(0.009)
Capital ratio						0.133***		0.140**
						(0.042)		(0.053)
log(svc staff wage to servicing book size)							-0.001	0.001
							(0.002)	(0.002)
Constant	0.020	-0.257**	0.008	-0.230***	0.022	-0.041***	-0.024	-0.134**
	(0.013)	(0.109)	(0.016)	(0.067)	(0.038)	(0.015)	(0.027)	(0.063)
N. Obs.	157	157	151	151	93	103	91	86
Adj. R^2	0.21	0.18	0.04	0.37	0.06	0.14	0.00	0.31

Table A.9: Bank servicer

	(1)	(2)	(3)	(4)
log(Cash to Asset)	0.055*			0.028
	(0.029)			(0.026)
Capital ratio		-1.948**		-1.048**
		(0.854)		(0.486)
log(Bank Total Asset)			0.028**	-0.032
			(0.012)	(0.021)
log(Total agency servicing book size)				0.061**
				(0.023)
Growth rate of svc book size from 2019 to 2020				-0.080
				(0.048)
Constant	0.190**	0.268**	-0.488**	-0.712**
	(0.088)	(0.105)	(0.236)	(0.304)
N. Obs.	39	40	40	38
Adj. R^2	0.04	0.18	0.21	0.51

G Deferred payments

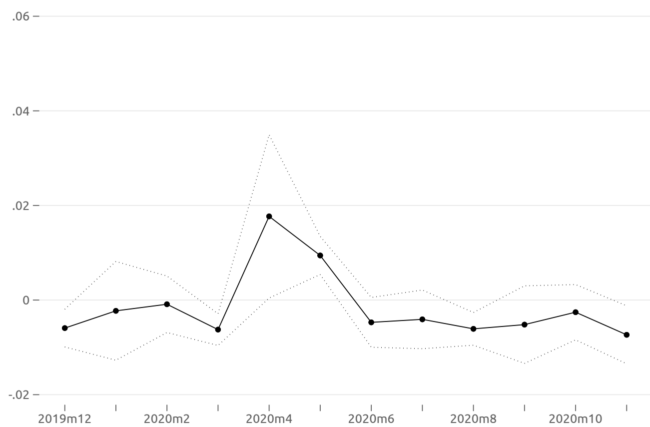
Figure A.5: **Deferred payments** This shows the results of the coefficients from Equation 2, where the dependent variable is a measure of the total borrowing through forbearance: the number of missed payments times the monthly mortgage payment (including taxes and insurance). This is an estimate, as we cannot directly observe whether borrowers make partial payments or continue to pay taxes and insurance. The coefficients can be interpreted as the average difference in cumulative deferred payments among borrowers at high- vs. low servicers.



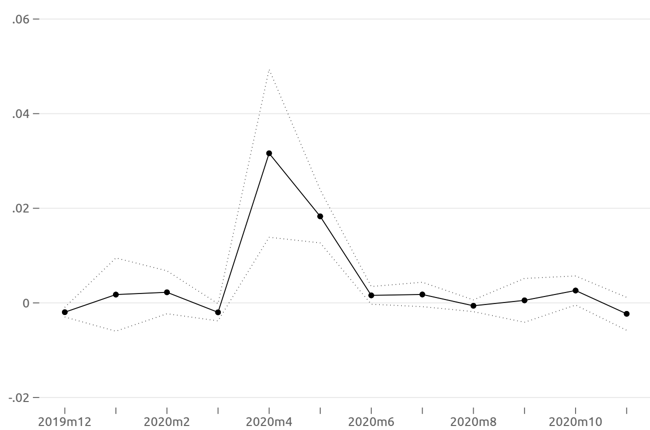
(a) Carried mortgage balance ($)

H Pre-CARES Act delinquencies

Figure A.6: **New 30-day delinquencies.** These two panels show the results of the coefficients from Equation 2. The dependent variable is new delinquency, which is equal to 1 if a delinquent loan was current in the previous period 0 if a current loan remains current. The graphed values can be interpreted as the difference in the new delinquency rates at high vs. low servicers. Panel (a) does not add borrower or servicer controls, and panel (b) uses the same controls as our main specifications. Errors are clustered by servicer.



(a) No controls



(b) Controls used in Figure 4

Table A.10: New 30-day delinquencies

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.003*	-0.001	-0.001*	-0.001*
	(0.002)	(0.001)	(0.001)	(0.001)
FHA		0.004***	0.002***	
		(0.000)	(0.000)	
Ln(Current UPB)		0.000	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
First-time homebuyer		0.002***	0.001	0.001*
		(0.000)	(0.000)	(0.000)
LTV at orig:				
$80 < LTV \leq 95$		0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
$95 < LTV \leq 100$		0.001***	0.000	0.000
		(0.000)	(0.000)	(0.000)
$LTV > 100$		0.002***	0.000	0.000
		(0.000)	(0.000)	(0.000)
CS at orig:				
$620 <$ orig cs ≤ 680		-0.008***	-0.004***	-0.004***
		(0.001)	(0.001)	(0.001)
$680 <$ orig cs ≤ 740		-0.016***	-0.007***	-0.007***
		(0.001)	(0.001)	(0.001)
orig cs > 740		-0.019***	-0.007***	-0.008***
		(0.001)	(0.001)	(0.001)
DTI at orig:				
$25 <$ dti ≤ 50		0.002***	0.001**	0.001*
		(0.000)	(0.000)	(0.000)
dti > 50		0.004***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
Loan purpose: refinace		-0.001***	-0.001***	-0.000
		(0.000)	(0.000)	(0.000)
Riskscore:				
$620 <$ updated cs ≤ 680			-0.019***	-0.019***
			(0.002)	(0.002)
$680 <$ updated cs ≤ 740			-0.027***	-0.027***
			(0.002)	(0.002)
updated cs > 740			-0.029***	-0.029***
			(0.001)	(0.001)
Borrower age:				
$30 <$ age ≤ 45			0.000	0.000
			(0.000)	(0.000)
$45 <$ age ≤ 60			-0.001**	-0.001*
			(0.000)	(0.000)
age > 60			-0.002***	-0.002***
			(0.000)	(0.000)
Zipcode FE		Y	Y	Y
Orig Year-Month FE		Y	Y	Y
FHA x Zipcode x Orig Year-Month FE				Y
N. Obs.	2,884,554	2,715,301	2,711,403	2,598,267
Adj. R^2	0.00	0.01	0.02	0.01

Table A.11: Credit card delinquencies

	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.009	-0.002	0.000	0.001
	(0.009)	(0.003)	(0.001)	(0.001)
FHA		0.016***	-0.004***	
		(0.003)	(0.001)	
Ln(Current UPB)		-0.009***	0.004***	0.004***
		(0.001)	(0.001)	(0.000)
First-time homebuyer		0.014***	-0.003***	-0.004***
		(0.001)	(0.001)	(0.001)
LTV at orig:				
$80 < \text{LTV} \leq 95$		0.003***	-0.001	-0.001
		(0.001)	(0.001)	(0.001)
$95 < \text{LTV} \leq 100$		0.013***	-0.001	-0.002
		(0.001)	(0.001)	(0.001)
$\text{LTV} > 100$		0.013***	-0.003	-0.001
		(0.002)	(0.002)	(0.002)
CS at orig:				
$620 < \text{orig cs} \leq 680$		-0.064***	0.010***	0.009***
		(0.007)	(0.002)	(0.003)
$680 < \text{orig cs} \leq 740$		-0.134***	0.022***	0.021***
		(0.008)	(0.002)	(0.003)
$\text{orig cs} > 740$		-0.172***	0.021***	0.020***
		(0.008)	(0.003)	(0.003)
DTI at orig:				
$25 < \text{dti} \leq 50$		0.026***	0.001	0.001
		(0.001)	(0.001)	(0.001)
$\text{dti} > 50$		0.048***	0.006***	0.006***
		(0.002)	(0.001)	(0.001)
Loan purpose:				
refinace		-0.004**	0.004***	-0.001
		(0.002)	(0.000)	(0.001)
Riskscore:				
$620 < \text{updated cs} \leq 680$			-0.399***	-0.404***
			(0.009)	(0.008)
$680 < \text{updated cs} \leq 740$			-0.489***	-0.495***
			(0.004)	(0.003)
$\text{updated cs} > 740$			-0.511***	-0.517***
			(0.003)	(0.003)
Borrower age:				
$30 < \text{age} \leq 45$			0.009***	0.008***
			(0.001)	(0.001)
$45 < \text{age} \leq 60$			0.009***	0.008***
			(0.001)	(0.001)
$\text{age} > 60$			0.002*	0.002
			(0.001)	(0.002)
Zipcode FE		Y	Y	Y
Orig Year-Month FE		Y	Y	Y
FHA x Zipcode x Orig Year-Month FE				Y
N. Obs.	2,884,719	2,715,317	2,711,419	2,598,284
Adj. R^2	0.00	0.04	0.36	0.36

Table A.12: Auto loan delinquencies

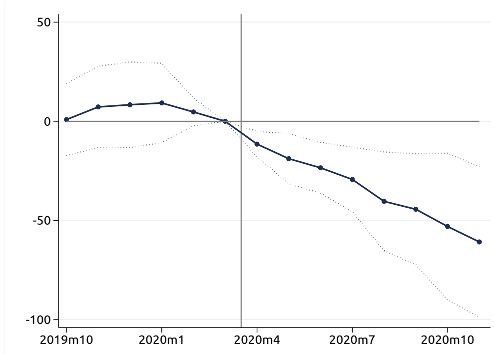
	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.006*	-0.002**	-0.002***	-0.002***
	(0.004)	(0.001)	(0.000)	(0.001)
FHA		0.002	-0.003***	
		(0.002)	(0.001)	
Ln(Current UPB)		-0.003***	0.001	0.001
		(0.001)	(0.001)	(0.001)
First-time homebuyer		0.006***	0.001	0.000
		(0.001)	(0.000)	(0.001)
LTV at orig:				
$80 < \text{LTV} \leq 95$		0.002***	0.001**	0.000
		(0.000)	(0.000)	(0.000)
$95 < \text{LTV} \leq 100$		0.006***	0.002***	0.002***
		(0.001)	(0.000)	(0.000)
$\text{LTV} > 100$		0.006***	0.001***	0.001**
		(0.001)	(0.000)	(0.001)
CS at orig:				
$620 <$ orig cs ≤ 680		-0.036***	-0.014***	-0.014***
		(0.004)	(0.002)	(0.002)
$680 <$ orig cs ≤ 740		-0.062***	-0.017***	-0.017***
		(0.004)	(0.002)	(0.002)
orig cs > 740		-0.072***	-0.016***	-0.016***
		(0.004)	(0.002)	(0.002)
DTI at orig:				
$25 <$ dti ≤ 50		0.010***	0.002***	0.003***
		(0.001)	(0.001)	(0.001)
dti > 50		0.019***	0.007***	0.007***
		(0.001)	(0.001)	(0.001)
Loan purpose:				
refinace		-0.004***	-0.002***	-0.002***
		(0.001)	(0.000)	(0.000)
Riskscore:				
$620 <$ updated cs ≤ 680			-0.120***	-0.121***
			(0.004)	(0.004)
$680 <$ updated cs ≤ 740			-0.147***	-0.147***
			(0.003)	(0.002)
updated cs > 740			-0.151***	-0.151***
			(0.002)	(0.002)
Borrower age:				
$30 <$ age ≤ 45			-0.000	-0.001
			(0.001)	(0.001)
$45 <$ age ≤ 60			0.000	-0.000
			(0.001)	(0.001)
age > 60			-0.000	-0.000
			(0.001)	(0.001)
Zipcode FE		Y	Y	Y
Orig Year-Month FE		Y	Y	Y
FHA x Zipcode x Orig Year-Month FE				Y
N. Obs.	2,884,719	2,715,317	2,711,419	2,598,284
Adj. R^2	0.00	0.02	0.10	0.10

Table A.13: New mortgage delinquencies: eMBS only

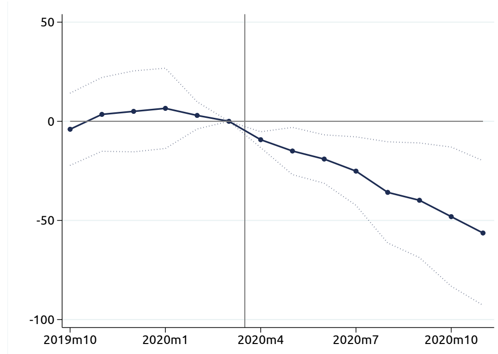
	(1)	(2)	(3)	(4)
High-forbearance servicer	-0.004***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
FHA		0.003***		
		(0.000)		
Nonbank Servicer		0.002***	0.002***	
		(0.001)	(0.001)	
Ln(Current UPB)		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
First-time homebuyer		0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
LTV at orig:				
$80 < \text{LTV} \leq 95$		0.000**	0.000**	0.000**
		(0.000)	(0.000)	(0.000)
$95 < \text{LTV} \leq 100$		0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
$\text{LTV} > 100$		0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
CS at orig:				
$620 < \text{orig cs} \leq 680$		-0.010***	-0.010***	-0.010***
		(0.001)	(0.001)	(0.001)
$680 < \text{orig cs} \leq 740$		-0.019***	-0.019***	-0.019***
		(0.001)	(0.001)	(0.001)
$\text{orig cs} > 740$		-0.023***	-0.023***	-0.023***
		(0.001)	(0.001)	(0.001)
DTI at orig:				
$25 < \text{dti} \leq 50$		0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
$\text{dti} > 50$		0.004***	0.003***	0.003***
		(0.000)	(0.000)	(0.000)
Loan purpose: refinace		-0.002***	-0.002***	-0.002***
		(0.000)	(0.000)	(0.000)
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
N. Obs.	10,427,090	9,552,659	9,552,603	9,552,471
Adj. R^2	0.00	0.00	0.00	0.00

I Alternate specifications: Credit card debt

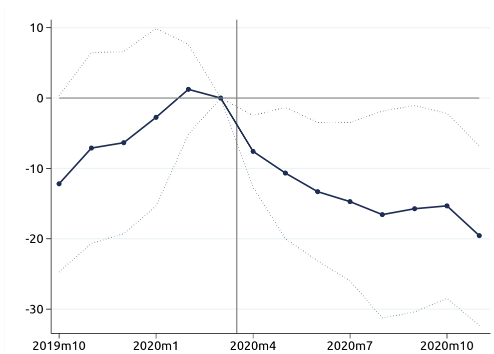
Figure A.7: **Credit card balances.** Robustness of estimates of the effect of assignment to high-type servicer.



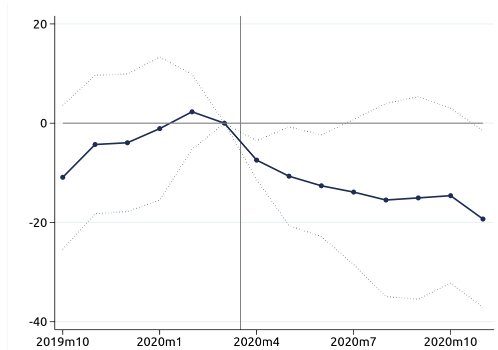
(a) Controls: Servicer FE and zipcode x current year-month FE



(b) Controls: Servicer FE, zipcode FE, origination year-month FE, and current year-month FE



(c) Controls: servicer FE, zipcode FE x current year-month FE, and origination year-month x current year-month FE



(d) Controls: servicer FE, zipcode FE, and origination year-month x current year-month FE

J Additional non-mortgage results

Table A.14: Balance (level)

	(1) Auto	(2) Credit card	(3) Other consumer credit	(4) Any consumer credit
1[t $\geq$ 2020:m4] $\times$ High-forb servicer	29.6	7.4	-12.9	38.9
	(20.0)	(21.1)	(10.8)	(52.3)
Servicer FE	Y	Y	Y	Y
Zipcode x Month x Orig Month FE	Y	Y	Y	Y
N. Obs.	29,416,301	29,406,384	29,424,562	29,417,235
Adj. R^2	0.07	0.08	0.03	0.09

Table A.15: Balance (log)

	(1) Auto	(2) Credit card	(3) Other consumer credit	(4) Any consumer credit
1[t $\geq$ 2020:m4] $\times$ High-forb servicer	0.00484	-0.01194**	-0.00935*	-0.00029
	(0.00407)	(0.00538)	(0.00543)	(0.00425)
Servicer FE	Y	Y	Y	Y
Zipcode x Month x Orig Month FE	Y	Y	Y	Y
N. Obs.	29,766,361	29,766,361	29,766,361	29,766,361
Adj. R^2	0.06	0.05	0.05	0.07

Table A.16: DQ transition

	(1) Auto	(2) Credit card	(3) Other consumer credit	(4) Any consumer credit
1[t $\geq$ 2020:m4] $\times$ High-forb servicer	0.00017***	0.00008	0.00006	0.00028
	(0.00005)	(0.00024)	(0.00007)	(0.00029)
Servicer FE	Y	Y	Y	Y
Zipcode x Month x Orig Month FE	Y	Y	Y	Y
N. Obs.	27,732,165	27,732,165	27,732,165	27,732,165
Adj. R^2	0.01	0.01	0.00	0.01

Table A.17: Others

	(1) Monthly prepayment	(2) New auto loan	(3) Updated credit score
$1[t \geq 2020{:}m4] \times$ High-forb servicer	-0.0004	-0.0006	-0.0206
	(0.0006)	(0.0004)	(0.3425)
Servicer FE	Y	Y	Y
Zipcode x Month x Orig Month FE	Y	Y	Y
N. Obs.	29,766,361	29,766,361	29,766,361
Adj. R^2	0.01	0.01	0.80

Note: "Updated credit score" refers to FICO Score 5.

K Characteristics of Borrowers in Forbearance

Table A.18: Comparing Characteristics of Borrowers in Forbearance across Servicers (as of Feb 2020)

	(1) Low-Availability Servicer	(2) High-Availability Servicer
Months in forbearance (as of Nov 2020)	4.88	5.86
Ever exited from forebarance	0.34	0.31
Ever 30+ days delinquent	0.84	0.88
Ever 60+ days delinquent	0.70	0.76
30+ days delinquent in Feb 2020	0.05	0.04
60+ days delinquent in Feb 2020	0.00	0.00
Current Mortgage Balance	197,640.46	171,094.07
Non-First-Mortgage Balance	50,310.54	50,810.03
Auto Loan Balance	18,309.95	17,717.73
Credit Card Balance	10,917.91	11,514.90
Student Loan Balance	13,405.42	13,234.00
CES + HELOC	2,866.27	3,482.11
Pre-Cares Act DQ in Non-First-Mortgage	0.24	0.21
12-mo change CNTY UR (8/20)	6.58	6.32
FHA	0.79	0.81
Riskscore	657.84	672.99
LTV at origination	94.30	94.73
Loan age (year)	3.89	5.61
N. Obs.	152,809	234,116