Financially Constrained Servicers and Aggressive Foreclosures

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ABSTRACT

Financially constrained mortgage servicers destroyed substantial MBS investor value during the financial crisis through their management of delinquent mortgages. Servicers have an obligation to advance to investors monthly payments missed by borrowers. This paper shows that, to minimize this obligation to extend financing to distressed borrowers, constrained servicers aggressively pursued foreclosures and modifications at the expense of investors, borrowers, and future mortgage performance. IV regressions suggest that servicers' financial constraints caused 440,712 additional foreclosures. On average, a servicer's financial constraints were responsible for 20.51% of the total investor value destroyed per defaulted loan—causing aggregate investor value destruction of $84 billion.

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During the 2007-2008 financial crisis, a spike in mortgage default rates destabilized the entire U.S. financial system. This spillover was driven by the concentration of mortgage instruments (and hence, mortgage default risk) on the balance sheets of important financial institutions (Mian and Sufi, 2009; Diamond and Rajan, 2009). These institutions delegated to intermediaries—mortgage servicers—the management of delinquent loans. My paper shows that more financially constrained servicers modified and foreclosed more aggressively than their unconstrained counterparts and consequently destroyed a significant amount of investor value. A substantial fraction of the foreclosures initiated during the financial crisis period were driven by servicer financial constraints. The agency costs and economic destruction associated with the actions of important intermediaries when under considerable financial stress are of major concern.

An important feature of the contract between mortgage servicers and MBS investors is that servicers are required to advance the monthly principal and interest payments from borrowers to investors in the event borrowers do not make full payment. Thus servicers were obligated to provide short run financing to delinquent borrowers, allowing the borrowers an opportunity to recover on their own. Moreover, servicers had an obligation to maximize value on behalf of the mortgage owners. If the borrower could not bring himself current, or refinance or sell the property ("pay off" the loan), the servicer possessed authority to intervene by either modifying the terms of the note or foreclosing on the property on behalf of the investor. These interventions are designed to aid the investor, but they are directly beneficial to a servicer that is financially stressed; upon completion (the signing of the modification agreement or the sale of a foreclosed property) a servicer avoids having to advance additional delinquent payments and recovers all previously made advances on that loan, regardless of the proceeds or performance of the specific loan.

My paper shows that more financially constrained mortgage servicers were often less willing or less able to cover delinquent borrower shortfalls to mortgage investors. For every standard deviation increase in financial constrainedness, servicers were 14 percentage points more likely to either foreclose or modify (a nine and five percentage point increase each, respectively) after a borrower's first episode of delinquency—and consequently these borrowers were significantly less likely to pay off through their own efforts. Overall I find that the financial constraints of mortgage servicers caused 440,712 (16%) of the approximately 2.7 million foreclosures in my sample. Given the quasi-random assignment of servicer financial constraints detailed below, these are foreclosures where, in the absence of the effect of servicer financial constraints, the borrower would have self cured, refinanced, or sold the property.

In addition to studying the behavior of an important intermediary during the crisis, this paper also characterizes a particular agency cost that is directly related to the financial constrainedness of the agent. By aggressively and prematurely intervening in defaulted loans, and by mismanaging the default process once underway, mortgage servicers destroyed an immense amount of investor value. On average, a servicer's financial constraints were responsible for \$12,225 (20.51%) of the \$59,611 average total investor value destroyed per defaulted loan. In aggregate, the financial constrainedness of mortgage servicers destroyed at least \$84 billion of investor value on defaulted loans with original balances of \$1.72 trillion.

Even though constrained servicers modified and foreclosed on loans of better average quality (these borrowers were more likely to pay off if left alone), their performance conditional on intervention was worse than those performed by less constrained servicers. Foreclosure loss severities and modification redefault[1] rates were higher—4 and 7 percentage points respectively per standard deviation change in servicer financial constraints. Higher modification redefault is surprising given that modifications included an additional 2 percentage point reduction in interest rate per standard deviation increase in constraints. Constrained servicers offered generous terms to increase the likelihood of a borrower agreeing to modify. Overall, for each standard deviation increase in constraints, modifications and foreclosures performed worse—destroying \$7,015 and \$11,831 in investor value, respectively.

I utilize a largely unexplored dimension of existing mortgage performance data. I start with a rich dataset that follows the performance of approximately 90% of the mortgage loans sold into non-agency RMBS[2] transactions pre-crisis. In order to investigate servicer behavior and incentives on default outcomes, I condition on loans that defaulted and observe the outcome related to the first stretch of borrower delinquency.

In this paper, the amount of advances a mortgage servicer makes is used as an indicator of financial constraints. In March 2009 policymakers at the Federal Reserve began allowing mortgage servicers to include, as eligible collateral for TALF[3] lending, "asset-backed securities backed by mortgage servicing advances" (Housing Wire, 2009). This was "the latest attempt by government officials to free up capital among strapped servicing operations..." (ibid.) and was done in order to "improve the servicers' ability to work with homeowners

[1]A borrower redefaults when he becomes delinquent again after receiving a modification.

[2]Non-agency, also known as private-label, RMBS are publicly issued by financial institutions other than agencies such as Fannie Mae (FNMA), Freddie Mac (FHLMC), and Ginnie Mae (GNMA) and lack their guarantees.

[3]TALF, or Term Asset-Backed Securities Loan Facility, was a program by the Federal Reserve to spur consumer lending by lending to institutions and taking qualified asset-backed securities as collateral.

to prevent avoidable foreclosures" (Federal Reserve Board, 2009). This action demonstrates the belief that servicing advances are an important measure of constraints and posits a relationship between financial constraints and servicer loss mitigation actions.

A number of major econometric challenges confound the identification of a causal link between servicer financial constraints and default outcomes. First, this paper argues that observed results are consistent with financially constrained servicers acting to minimize their advance obligations. Servicer advance levels are endogenous to servicer actions. Second, increases in advances can be informative about the quality of the servicer or can inform the servicer about the quality of his assets. Finally, macroeconomic or regulatory conditions can influence the level of servicer advances, loan outcomes, optimal loss mitigation strategies, and the borrower's ability to refinance (Palmer, 2015).

I address these econometric issues and construct plausibly exogenous variation in servicer advances by instrumenting with a servicer's unique exposure to the timing of housing price returns in geographies far removed from the focal loan. A servicing-portfolio-balance-weighted average of zip-level housing price returns, excluding the Core-Based Statistical Area (an agglomeration of economically integrated counties) in which the focal loan resides, directly impacts the volume of advances a servicer makes. However, the servicer portfolio's housing price return, in geographies separate from the focal loan, should not influence loss mitigation decisions or outcomes except through its direct effect on the advances made by the servicer (Granja, Matvos, and Seru, 2017).

Variation in this instrument stems from local and regional variation in the footprint of servicer portfolios. Housing price returns are measured at a precise geographic level—the zip code of the property—and even national servicers have important variations in their lending behavior and experience distinct competitive environments at these (and even smaller) geographic levels (Aiello, Garmaise, and Natividad, 2017). This translates to important differences in the geographic diversity of their servicing portfolios. This instrument then measures the extent to which a particular servicer is exposed to exogenous housing price shocks. Finally, I include the housing price return for the zip code in which the loan resides as a control, as well as fixed effects at both the servicer level and an interaction between loan default year, property zip code, and borrower credit quality category (Prime, Alt-A, and Subprime). Estimates then compare loans that defaulted in the same zip code and year, and were of the same credit quality. Additional specifications reported in Appendix Section A.1 demonstrate the robustness of these results to various alternate specifications.

My results are subject to an important caveat in that I assume that unobservable borrower quality does not vary systematically with the level of servicer financial constraints. In order to provide evidence that this assumption holds, I demonstrate that both the length of time between origination and a borrower's first delinquency as well as a measure of unobservable borrower quality described in Aiello (2016) are not predicted by the financial constrainedness of the servicer at origination. These measures of quality, unobservable at origination, show that constrained servicers do not have loans that vary, even in unobservable ways, from those serviced by unconstrained ones—at least until the borrower goes delinquent and the servicer has the opportunity to (not) act.

Finally, in order to confirm that the servicer is responding to his financial constraints rather than to capacity or operational constraints and to control for any learning from previous exposure to defaults, I include as a control the change in the count of delinquencies in the servicer's portfolio over the 12-months preceding the default of the focal loan. Both of these alternate stories—capacity constraints and servicer learning—are likely to operate through the number of defaulted loans they have experienced rather than the magnitude of the advances the servicer has been required to make with respect to those defaulted loans.

While there exist large literatures related to financial constraints and to agency costs, the interaction between these two effects is largely understudied. Most similarly to this study, Chodorow-Reich and Falato (2017) demonstrate that commercial banks, in their lending activities to corporations, behaved similarly to the constrained mortgage servicers in this study: stressed banks were less likely to grant a waiver to corporations in violation of covenants and consequently increased the prevalence of renegotiation and forced accelerated repayment of the debt. Whited (1992) and Eisfeldt and Rampini (2007) provide models of financial-constraint-driven myopia that describes well the behavior of the mortgage servicers in this study. Previous literature on the financial constraints of intermediaries is largely limited to the observations that financial constraints increased intermediary risk taking during the savings and loan crisis (Kroszner and Strahan, 1996; Esty, 1997a,b) and the effects that regulatory induced financing constraints have on insurance companies (Lee, Mayers, and Smith, 1997; Ellul, Jotikasthira, and Lundblad, 2011; Merrill, Nadauld, Stulz, and Sherlund, 2014; Koijen and Yogo, 2014). This paper also attempts to directly measure the magnitude of a realized agency cost. Ang, Cole, and Lin (2000) followed by Singh and Davidson (2003) have attempted this within the context of corporations. While not directly related to an agency problem, Ang, Green, Longstaff, and Xing (2017) demonstrate that the short-term budgetary constraints of a municipality can lead it to take actions that destroy a significant amount value for itself. Agency conflicts in a mortgage servicer's contract have been studied previously (Cordell, Dynan, Lehnert, Liang, and Mauskopf, 2008; Herndon, 2017; Mooradian and Pichler, 2017; Huang and Nadauld, 2017) and a servicer's financial constraints are examined in Kim, Laufer, Pence, Stanton, and Wallace (2018). However, this paper is the first to demonstrate the relationship between a servicer's financial constraints and the realized agency costs borne by the investor.

This paper addresses the importance of the decision by a servicer to either intervene or provide an opportunity for a borrower to solve the problem himself—something unaddressed in the mortgage literature. Previous literature demonstrates a large number of channels that influence both the loss mitigation decisions and the outcomes related to delinquent borrowers. Agarwal, Amromin, Ben-David, Chomsisengphet, Piskorski, and Seru (2017) find that different quality servicers have varied appetites and ability to perform modifications while Chomsisengphet and Lu (2015) explores the role of servicer financial constraints in this decision. Regulators placed pressure on servicers to emphasize modifications over foreclosures in an attempt to minimize the spillovers of the foreclosure process to the larger economy (Gerardi, Lambie-Hanson, and Willen, 2013; Anenberg and Kung, 2014; Gupta, 2016). Recent evidence from Favara and Giannetti (2017) suggests that some servicers do internalize these foreclosure spillover effects, representing a channel relating foreclosures and servicer behavior that is complementary to, but separate from, that of regulatory pressure. The aggregate welfare benefits of policies that encourage modifications over foreclosures has been extensively studied (Mayer, Morrison, Piskorski, and Gupta, 2014; Mian, Sufi, and Trebbi, 2015; Gabriel, Iacoviello, and Lutz, 2016; Agarwal et al., 2017) and we have evidence that securitization itself either reduces the likelihood of modification (Wang, Young, and Zhou, 2002; Posner and Zingales, 2009; Piskorski, Seru, and Vig, 2010; Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff, 2011; Adelino, Gerardi, and Willen, 2013; Kruger, 2017)—or doesn't (Adelino, Gerardi, and Willen, 2014). Additionally, firms that service mortgages are usually also large originators of mortgages, and often continue to service the same mortgage loans that they originated. This could lead to a reputational effect where servicers are hesitant to become known as being aggressive to foreclose and are therefore more willing to modify in order to attract customers to their origination business lines (Riddiough and Wyatt, 1994). This paper examines, conditional on securitization, how a servicer's financial constraints influence the agency frictions related to managing a delinquent loan.

The remainder of the paper proceeds as follows. Section 1 introduces the data and Section 2 provides industry context. Section 3 elucidates the identification strategy and Section 4 examines my central findings. Section 5 concludes.

1 Data

The loan data in this paper describe 6,940,990 U.S. residential mortgage loans securitized into a non-agency mortgage backed security that defaulted in 2013 or before.[4] The data are sourced from BlackBox, which covers about 90% of pre-crisis privately securitized residential mortgage loans.

These loans have a total of 351 million monthly loan observations. These monthly records are collapsed to the loan level for all loans that went delinquent, entered bankruptcy, or were ever modified, foreclosed, or liquidated in a manner other than a borrower pay off in full. The loans in my sample are tracked beginning with their final timely payment. Resolution of a particular episode of borrower delinquency occurs through an action by either the borrower or the servicer. A borrower either self cures when he makes at least three[5] consecutive current payments with no servicer intervention, pays off the loan in full, or enters bankruptcy. The servicer ends an episode of delinquency by either modifying, foreclosing, repurchasing, or liquidating (generally either a charge-off or short sale) the loan. Focus is restricted to the first episode of delinquency.

Figure 1 provides an illustrative example of a qualified delinquent episode. Each box represents a monthly payment. Missed payments are gray and made payments are white. The highlighted set of boxes represents the focal episode for this loan. The second and third period are ignored because they represent delinquencies that occurred after the initial modification. The servicer's decision after already providing the borrower with a modification previously differs from the focal decision of this paper.

Restricting attention to only those defaulted loans with valid loan and borrower characteristic variables and servicer level advance and instrument values leaves 6,940,990 unique loans. The first column of Panel A of Table 1 contains the mean value for various loan level measures within the overall BlackBox population (with valid covariate and servicer values) for comparison to the remainder of the table, which deals with only loans in sample. The sample loans are selected primarily by conditioning on delinquency, as reflected in the comparison between the sample and BlackBox population measures. Defaulted loans are

[4]Appendix Section A.1.5 reports results demonstrating robustness to restricting attention to just the period beginning with the financial crisis as well as results relating to the period after the extension of TALF coverage. Delinquencies are observed in the data, in low numbers, beginning with the 2000 calendar year. During the early part of the decade the coverage of BlackBox is still increasing. In 2003 there were over 150,000 first delinquencies in the database.

[5]See Appendix Section A.1.6 for robustness results relating to the 3-month definition of self cure.

larger, were originated later, had lower credit scores and higher loan-to-value ratios, and were more likely to be adjustable rate. Panel B of Table 1 addresses the loss mitigation results that occurred in sample. Sample proportion statistics are mutually exclusive[6] and collectively exhaustive. They report the first event to occur post-default.[7] These outcomes are either borrower driven (self cure or pay off in full), servicer driven (modification, foreclosure, or liquidation), or due to something largely outside of the servicer's control (bankruptcy or repurchase). In addition to outcome proportions, the average and standard deviation of the months to completion[8] and the NPV of the action to the investor (see Section 3.4) are reported as well. Panel C of Table 1 reports the average values of loan and borrower characteristics for major sub-samples of the data, conditioned on the first episode of delinquency.

Servicer names are cleaned to remove differing entity name permutations and to collapse subsidiaries. Loans with servicer's listed as "Unknown" (8.9%) are removed from the analysis. Appendix Section A.2 reports summary statistics at the servicer level.

Geographic indicators are found at the zip code level within the BlackBox dataset. United States Postal Service, Census Bureau, and United States Department of Agriculture cross walk files are used to match zip codes to Core-Based Statistical Areas (CBSAs), Commuting Zones, and States.[9] CBSAs consist of a core urban area and surrounding territory that "has a high degree of social and economic integration with the core."[10] CBSAs are either the more well known Metropolitan Statistical Areas (MSAs) or smaller Micropolitan Statistical Areas (μSAs). Commuting Zones are derived from the United States Department of Agriculture's Economic Research Service and fulfill largely the same role as CBSAs, but are generally much larger in geographic area. Commuting Zones and States cover the entire geography of the United States. Rural counties that are not included in a CBSA are considered as separate "CBSA-like" geography observations.

[6]There are a small number of delinquencies that resulted in a simultaneous modification and foreclosure. All results are robust to excluding these loans, classifying them as one or the other, or both.

[7]Because this study focuses on the first episode of delinquency, these sample proportions are not representative of the ultimate outcomes. Self Cures or modifications that ultimately redefaulted could have had a second episode of delinquency (or a third, etc.) that ended in any of these possible outcomes. For example, only 24% of first delinquency episodes resulted in a foreclosure, but overall in sample 40% of defaulted loans were ultimately foreclosed.

[8]The average months to completion are the number of months between first default and the month of the borrower's third consecutive current payment, the pay off date, modification effective date, foreclosure sale date, liquidation date, bankruptcy petition filing date, or the date of repurchase as applicable.

[9]In all cases where multiple possible matches exist between any level of geography, the match that had the highest percentage overlap of residential addresses was used.

[10]`https://www.census.gov/topics/housing/housing-patterns/about/core-based-statistical-areas.html`

2 Introduction to Mortgage Servicers and Advances

Servicing a mortgage is the process of turning borrower cashflow claims into a uniform mortgage asset. A mortgage servicer is an entity that owns a mortgage servicing right. When a loan is originated two separable assets are created, the note itself and a mortgage servicing right. The servicing right is either sold alongside the note to another party ("servicing released") or retained by the originator ("servicing retained"). For securitized loans, the note is placed in an off-balance sheet special purpose entity of the issuer.[11] The servicing right, however, could be retained by the originator or transferred to the issuer's captive primary servicer.[12] The owner of this servicing right is referred to as the "servicer." The servicer is responsible for all borrower facing activities including payment collection, managing loan and escrow accounts, and providing loss mitigation services in the case of default.

Loss mitigation activities consist of encouraging delinquent borrowers to make their payments, working out repayment plans, providing modifications or other loss mitigation alternatives such as deed-in-lieu of foreclosure or short sales, and managing the foreclosure process. Servicers undertake these activities in compliance with the relevant securitization guidelines and are obligated to act in the best interest of the investor. The assumption that modification is always better than foreclosure, even from the investor's perspective, while ubiquitous in the literature, is not accurate. Maturana (2014) shows that it is true on the level of an average effect, but it should be self-evident that, locally, it is often better to seize a borrower's home rather than provide a hopeless modification.

Appendix Figure A.1 presents a general overview of the loss mitigation process. The diagram begins with the left-most arrow, in green, labeled "Delinquent Loan" and flows through to either the blue box which represents a reperforming current mortgage loan, or the red box representing a liquidation of the investor's interest in the property and note. If a borrower fails to self cure a delinquent loan the servicer generally has three options: a modification, a foreclosure, or a loss mitigation alternative such as a Deed-In-Lieu of Foreclosure or a Short Sale. A modification can be requested by the borrower or the servicer himself can solicit a modification. It is ultimately approved or rejected, with approved modifications can succeeding or failing. A failure results in a "redefault." The foreclosure

[11] The other alternative is that the note is held, either for investment or sale, on the balance sheet of an entity such as a bank.

[12] A third, and fairly common, result is the servicing right being owned by a party that intermediated between the originator and the issuer. Those loans are then primary serviced by an entity unaffiliated with the issuer but which is not itself the originator of the loan.

process ends with the sale of the property to a third party, in which case the loan liquidates, or to the securitization trust wherein the investor now owns a Real Estate Owned (REO) property. An REO property is then either sold or "charged off" as a complete investor loss.

When a borrower fails to make his mortgage payment, generally the servicer is obligated to advance the principal and interest to the investor out of its own funds. This creates a receivable on the balance sheet of the servicer. If the borrower makes his past due payment, the receivable is cleared on the servicer's balance sheet. Upon completion of a modification agreement or the sale of a foreclosed property, a mortgage servicer has the first and highest claim on any cashflows from that related loan to recover his advances. To the extent that these cashflows are insufficient to reimburse the servicer for his previous advances, he has first priority claim on all cashflows related to any other loan in the securitization. If the servicer were to modify the loan, they capitalize all outstanding advances into the investor's loan balance and the servicer recovers his advances from the investor by reducing pool cashflows in the month of modification.[13] In the event of a foreclosure the servicer recovers advances outstanding from the proceeds of the sale of the property or, if that is insufficient, from pool cash flows in the month of foreclosure sale. Ultimately, the servicer is always made whole.

Figure 2 presents illustrative examples of the interplay between the balance sheets of the borrower, servicer, and investor. The numbers used in the examples represent the principal portion of the mortgage debt. In the first example, where the borrower self cures his delinquency, the borrower begins with an outstanding loan balance of \$100. He makes his January payment of \$1 that goes directly to the investor who writes down his receivable by that same amount. His February through April payments, however, are not made and are instead advanced to the investor by the servicer. The servicer increments a receivable account as he makes the advances to the investor. In May the borrower self cures by making all three of his past due payments as well as his May monthly payment. The servicer receives \$3 to clear his receivable, and the investor gets forwarded just the single payment he is owed.

In the second example, in May, a modification agreement is made wherein the borrower's three past due payments are added to his outstanding loan balance.[14] The investor

[13]Modifications always bring the paid-to-date of a loan to current. This is accomplished either through a capitalization as discussed, forgiveness of the borrower's debt, or a loan workout agreement where partial payments are made until the borrower is caught up. What matters from the point of view of the servicer is that once the paid-to-date is brought current, the servicing advance receivable is cleared.

[14]The increase in borrower loan balance is simplified in these scenarios. I have abstracted away from interest accrual differences between the investor loan balance and the borrower loan balance as well as from the impact the modification has on the amortization term or monthly loan payment.

"buys" more of that borrower's loan and pays[15] the servicer who recovers his advances. The borrower then proceeds to make his scheduled monthly payments.

The final two examples cover two different foreclosure outcomes. In both, the borrower stops making his payments after the January payment. Following the November due payment the borrower has missed ten payments, and the servicer accrued \$10 in servicing advance receivables. In December, in the bottom-left scenario, the home is sold at foreclosure auction, and proceeds of \$50 are realized from the sale. The servicer has the first and highest claim on these proceeds, net of foreclosure expenses, from which it reimburses itself for the advances. The investor receives the remaining \$40 from the foreclosure proceeds and suffers a \$49 loss. In the bottom-right scenario, the home is sold but generates no proceeds. In this case, the servicer reimburses its outstanding advances from cashflows on other loans in the pool causing the investor to suffer an additional loss, for a total of \$99.

2.1 Servicer Advances Calculation

A loan has an outstanding servicing advance when both its paid-to-date is less than the monthly activity date and its scheduled balance is less than the actual balance. The loan level servicing advance outstanding amount is calculated by summing all monthly Principal and Interest (P&I) constants for each paid-to-date currently outstanding.[16] Because of data quality issues, the loan-month outstanding advance distribution is winsorized (right tail only) at the 0.01% level. Appendix Section A.1.7 reports robustness results relating to the winsorization assumptions.

These loan level servicing advances are summed, for each month, to the servicer level[17]

[15] In practice this payment from the investor to the servicer is accomplished by simply reducing the amount owed to the investor in the month of capitalization. This allows the servicer to reimburse himself for previously made advance amounts from the cashflows on the entire pool that contains the loan in question. The servicer may only do this when a qualifying event, in this case a modification, occurs. During periods of particularly high modification volume it was possible that the cashflows for a particular month would have been insufficient to cover the reimbursements. In these cases, the servicer was required to hold off reimbursing until the following month. However, the risk that the pool would ultimately have insufficient cashflows to cover the servicer's advances is negligible. There was no reported instance of this occurring throughout the financial crisis

[16] Missing P&I constants are imputed using an average of the P&I constant before and after the stretch of missing values.

[17] Advances on delinquent loans serviced on behalf of private mortgage portfolios or agency securitizations are unavailable in the data. While these possibly represent a significant portion of a servicer's portfolio by loan count, they are likely to have significantly lower levels of delinquency overall than the non-agency portfolio and so represent a smaller relative share of the total outstanding servicing advances. Additionally, because loans in agency securitizations are guaranteed by a Government Sponsored Entity (e.g. FNMA or

to calculate $Advances_{t,s}$, representing the outstanding servicing advances in month t for servicer s.[18] $Advances_{t,s}$ is then scaled by the total portfolio outstanding actual loan balance for servicer s at time t, $PortfolioBalance_{t,s}$, to calculate the ratio of the outstanding advances to the outstanding portfolio balance,

$$AdvFrac_{t,s} = \frac{Advances_{t,s}}{PortfolioBalance_{t,s}} \tag{1}$$

Actual balance scaled servicer-month outstanding servicing advances, $AdvFrac_{t,s}$, are then winsorized at the 1% level in the right tail. Appendix Section A.1.7 reports robustness results relating to the winsorization assumptions.

The principal variable of interest throughout this study and the main measure of the financial constrainedness of a servicer, "1-Year Change in Advances as a Percentage of Loan Portfolio Balance", is calculated by taking the difference in levels between the scaled value $AdvFrac_{t,s}$ in the month preceding loan default and the scaled value one year prior,

$$\begin{aligned} \Delta AdvFrac_{t,s} &= AdvFrac_{t-1,s} - AdvFrac_{t-12,s} \\ &= \frac{Advances_{t-1,s}}{PortfolioBalance_{t-1,s}} - \frac{Advances_{t-12,s}}{PortfolioBalance_{t-12,s}} \end{aligned} \tag{2}$$

I standardize $\Delta AdvFrac_{t,s}$, separately for each regression, by subtracting out the mean and dividing by the standard deviation (Cookson and Niessner, 2016).

FHLMC), they are purchased from the securitization after the fourth missed payment, at which point the servicer stops advancing (Cordell et al., 2008).

[18]The servicer-loan match is static in the data and represents the servicer of the loan at the time of securitization. Changes in servicer are not reported in any available datasets relating to this loan population. Mayock and Shi (2018) provide evidence that servicing transfer activity picked up significantly beginning in 2011. Robustness results in Appendix Section A.1.5 demonstrate that a servicer's financial constraints played a significant role largely prior to this.

3 Empirical Strategy

The principal empirical specification of this paper involves two types of outcome variables: a servicer's action decisions in regards to a delinquent loan and the loan outcomes that occur following a servicer's decision. These outcomes are examined within the framework of two dimensions of fixed effects. First, a fixed effect at the servicer level removes the average effect of the servicer, held constant over time. Second, an interacted fixed effect dimension restricts attention to loans that first defaulted in the same calendar year, are located in the same zip code, and are of the same general credit quality (Prime, SubPrime, or Alt-A).[19] Additionally, all relevant loan and borrower characteristics are included as controls.

Included within this framework is a measure of servicer financial constrainedness that is an economically and statistically significant predictor of both servicer actions and loan outcomes. From the standpoint of the investor the optimal servicer action should not be influenced by the balance sheet of the servicer. The fact that it is, however, is indicative of an agency friction relating to the conflict between the servicer's objective function and his obligation to maximize investor value.

A servicer's financial constraints are measured through the amount of borrower monthly payments the servicer has been required to advance in the immediate past, scaled by the servicer's portfolio size. Specifically, this is measured as the change, over the 12-months preceding loan default, in the ratio of a servicer's outstanding advances to the outstanding actual principal balance of the servicer's portfolio. This calculation is detailed in Section 2.1.

The servicer securitizes the servicing advances themselves into privately placed servicing advance facilities. The setup and use of these facilities are immensely costly for the servicer.[20] The servicing advances pledged to the facility carry an implicit guarantee from the servicer. Consequently, a sharp increase in the amount that a servicer is forced to draw on a facility creates a leverage constraint. Due to the fixed cost and effort associated with the setup of these funding facilities, the short run change in advances, rather than the absolute level, is what is important. This paper measures the level of the financial constrainedness of the servicer by looking at the increase over time in the ratio of his advances outstanding to the loan portfolio balance. The amount of cash he has recently been forced to disgorge

[19] Appendix Section A.1.8 details the robustness of the main results to various alternate fixed effects structure, including the use of Servicer-Year interacted fixed effects.

[20] Appendix Section A.1.5 demonstrates robustness results restricting attention to subsamples of just the largest servicers, and then separately the largest servicers that were subsidiaries of broader financial institutions.

measures the proximity to his contemporary leverage constraint.

This paper endeavors to estimate the causal impact of a servicer's financial constraints on a servicer's actions. However, the actions that a servicer takes in regards to its delinquent loan portfolio is going to have a direct impact on the amount of servicing advances that it has to make. Advances are endogenous to servicer actions. Additionally, changes in advance levels can be informative about the quality of the servicer or can inform the servicer about the quality of his assets, consequently changing our interpretation of these behaviors or prompting the servicer to adjust his actions accordingly. Finally, the level of servicer advances, loan outcomes, optimal loss mitigation strategies, and the borrower's ability to refinance can all be influenced by macroeconomic or regulatory conditions. For these reasons, I instrument outstanding advances by measuring a servicer portfolio's unique exposure to housing price returns over the 12-months preceding loan default. The calculation of this instrument is detailed in Section 3.1. This instrument is relevant because housing price declines in a particular geographic region are strongly associated with increased delinquencies, which will in turn cause a servicer to make additional advances. By utilizing the two stage least squares approach detailed in Section 3.2 I am able to test this. These first stage results are reported in detail in Section 3.3 and demonstrate that the instrument is both strongly predictive of servicer advances and encompasses a meaningful level of the variation in those advances.

In order for this instrument to satisfy the exclusion restriction it must be true that housing prices do not directly impact a servicer's actions or loan outcomes. In the case of my instrument, I exclude the portion of a servicer's portfolio in the Core-Based Statistical Area immediately surrounding the focal loan and include as a control the relevant zip code level housing price return for the 12-months preceding loan default. Thus my exclusion restriction—as satisfied by assumption—is that, conditional on the local zip-code housing price return, the servicer portfolio housing price return (in geographies separate from the loan) does not influence loss mitigation decisions and outcomes except through their effect on servicing advances outstanding and the balance sheet of the servicer. Consequently, the manner in which a servicer's unique exposure to far away housing prices, conditional on a local housing price, impairs his balance sheet provides me with plausibly exogenous variation in a servicer's financial constraints.

Of particular concern is the possibility that unobservable borrower characteristics are correlated to the measure of financial constraints. That this is not true remains an identifying assumption. Section 4.7 reports results that suggest that the unobservable quality of the borrower did not vary systematically with the level of servicer financial constraints.

While time-invariant servicer characteristics are removed throughout this paper with a fixed effect, the type or size of the servicer may still be important for the interpretation of the results. Appendix Section A.1.5 demonstrates that the effect remains largely the same when the sample is restricted to only the largest servicers as well as to servicers that are subsidiaries of large financial institutions rather than specialized, mortgage only, entities. Additionally, time varying servicer characteristics are removed in Appendix Section A.1.8 through the use of a Servicer-Year interacted fixed effect.

A concern remains that servicers with earlier exposure to loan defaults may behave differently than servicers that did not have similar exposure, not because of lasting balance sheet impacts, but rather because they have learned more (or differently) about the behavior of borrowers. Murfin (2012) demonstrates that, in the commercial loan market, banks that have recently experienced higher numbers of defaults in their loan portfolio are more likely to write stricter contracts with future borrowers. The dataset utilized in this paper is updated on a monthly basis and is widely available to all market participants in real time. A servicer's ability for marginal learning from his direct experience with defaults in a particular geography is not likely to be relevant conditional on the learning he can glean from industry-wide and nation-wide defaults, which are controlled for throughout this paper with a year fixed effect. To the extent a concern remains, I include in specifications throughout the paper (with robustness discussed in Section A.1.4) a measure of the change in the count of delinquent loans in a particular servicer's portfolio over the twelve months immediately preceding the loan's default. Any learning on the part of the servicer is likely to be a function of the volume of delinquencies with which he has experience (as opposed to the dollar amount of advances made on those delinquencies). Additionally, financial constraints operate predominantly through the servicer's most recently experienced defaults. In contrast, a servicer's learning is likely to be strongly influenced by the experiences two or three years prior to loan default. Consequently, Section A.1.4 also discusses robustness results relating to differing specifications of the way the total delinquency count for a particular servicer has evolved. Finally, Section A.1.4 also contains details of a specification that includes interacted Servicer-Year fixed effects, which would effectively control for any servicer's learning through time.

Additionally, the possible existence of a servicer operational constraint could confound the causal interpretation of this instrument. As a servicer's portfolio realizes worse housing price returns their advance volume increases and they suffer from an increase in delinquent mortgages. As operational capacity constraints are reached the servicer may behave differently, adversely impacting the investor's interests. I address this through the inclusion of the change in the count of portfolio delinquencies, as a measure of capacity constraints (see Section A.1.3 for robustness). Operational constraints bind on the basis of loan count volume not loan balance. That is, the difference in effort to modify or foreclose on a small loan instead of a large loan is insignificant. While contamination of my mechanism from operational constraints is relevant, my main finding—that constrained servicers are more likely to take a loss mitigation action in order to reduce their constraint—rules out the importance of this effect.

Finally, it is possible that a servicer is also one of the many investors in some of the securitizations it services. When this is the case however, it is likely that he owns an equity (or subordinate) tranche. Consequently, he is more likely to make decisions that support the short term cash flow of the securitization at the expense of the bulk of the investors (Huang and Nadauld, 2017). In order for these "servicer-investors" to represent a violation of the exclusion restriction in my study, it would be necessary that a servicers equity ownership level is negatively correlated with the housing price returns it would later experience—a servicer would hold more equity in worse mortgage pools.

3.1 Construction Of Instrument

Log housing price returns for zip code z in month t, $ZipHPRet_{t,z}$, are gathered from the Zillow Home Value Index (All Homes). The index uses a hedonic regression framework that updates the value of every home within a particular region in response to every transaction (Hartman-Glaser and Mann, 2016).

The zip log housing price returns, $ZipHPRet_{t,z}$, are weighted by the outstanding scheduled[21] balance of the servicer's total mortgage portfolio available in BlackBox, $SvcrPortSchedBal_{t,z,s(i)}$. This represents the unique exposure of a particular servicer $s(i)$ to housing price returns in month t for geographies outside of a particular CBSA $g(i)$, and is calculated by

[21]The portfolio scheduled balance, rather than the actual balance, is used because it is a better proxy for the current and future advance obligation that could arise from a particular geography.

$$OneMonthSvcrPortHPR_{t,g(i),s(i)} = \frac{\sum_{z \notin g(i)} ZipHPRet_{t,z} \cdot SvcrPortSchedBal_{t,z,s(i)}}{\sum_{z \notin g(i)} SvcrPortSchedBal_{t,z,s(i)}}, \quad (3)$$

where $OneMonthSvcrPortHPR_{t,g(i),s(i)}$ is the one month servicer portfolio balance weighted log housing price return for all zip codes in month t for servicer $s(i)$ outside of the CBSA, $g(i)$, associated with focal loan i.

The values of $OneMonthSvcrPortHPR_{t,g(i),s(i)}$ over the twelve months preceding the month of default, t, are then summed, as

$$SvcrPortHPR_{t,g(i),s(i)} = \sum_{n=1}^{12} OneMonthSvcrPortHPR_{t-n,g(i),s(i)}, \quad (4)$$

where $SvcrPortHPR_{t,g(i),s(i)}$ is then the instrument used throughout the principal empirical specifications, "1-Year Servicer Portfolio Housing Price Return (Excluding Loan CBSA)".

3.2 Empirical Approach

The empirical strategy follows a two-stage least squares regression framework. In the first stage, I regress the 1-Year Change in Advances as a Percentage of Loan Portfolio Balance on the 1-Year Servicer Portfolio Housing Price Return (Excluding Loan CBSA). The regressions include a set of loan and borrower characteristic controls and fixed effects at both the servicer and zip-year-credit category level. For loan i, defaulting in month t, located in zip code $z(i)$, CBSA $g(i)$, and serviced by servicer $s(i)$,

$$\begin{aligned} \Delta AdvFrac_{t,s(i)} = \beta_{FS} \cdot SvcrPortHPR_{t,g(i),s(i)} + \gamma_1 \cdot ZipHPRet_{t,z(i)} \\ + \gamma_2 \cdot \Delta DQCount_{t,s(i)} + \gamma_3 \cdot controls_i + \epsilon_i \end{aligned} \quad (5)$$

where $\Delta AdvFrac_{t,s(i)}$ is the change in advances outstanding as a percentage of loan portfolio balance for servicer $s(i)$ over the 12-month period ending with month t and $SvcrPortHPR_{t,g(i),s(i)}$ is the balance weighted average housing price return of servicer $s(i)$ over the 12-month period ending in month t, excluding the CBSA $g(i)$.[22] Controls

[22] This is the instrument used in the principal empirical specifications throughout this paper. Robustness to various aspects of instrument design are examined in Appendix Section A.1.2.

include the housing price return of zip code $z(i)$ for the 12-month period preceding month t, $ZipHPRet_{t,z(i)}$, and the change in the volume of delinquencies at servicer $s(i)$ over the 12-month period preceding month t, $\Delta DQCount_{t,s(i)}$. Additionally, servicer level fixed effects and a threefold interaction of fixed effects for the year and zip code of default and the broad credit category (Prime, Alt-A, and SubPrime)[23] of the loan are included. Finally, a vector of loan and borrower controls is included that consists of: FICO, original note rate, original loan-to-value, original loan balance, lien position, percentage of mortgage insurance coverage, as well as indicators for whether the loan was an adjustable rate mortgage, owner occupied, a purchase loan, for a single family property, fully income documented, interest only, or had mortgage insurance or balloon features. Standard errors are clustered separately at the servicer and zip code level.[24]

This first stage regression yields the variation in servicing advances attributable to the housing price movements in geographies removed from the focal loan. I estimate the reduced form equation,

$$\begin{aligned} Y_i = \beta_{RF} \cdot SvcrPortHPR_{t,g(i),s(i)} + \gamma_7 \cdot ZipHPRet_{t,z(i)} \\ + \gamma_8 \cdot \Delta DQCount_{t,s(i)} + \gamma_9 \cdot controls_i + \mu_i. \end{aligned} \tag{6}$$

This measures the direct relationship between an outcome variable of interest for loan i, Y_i, and the instrument, servicer portfolio housing price variability.

To estimate the causal impact of financial constraints on servicer behavior and loan outcomes I estimate the second stage regression,

$$\begin{aligned} Y_i = \beta_{IV} \cdot \Delta \widehat{AdvFrac}_{t,s(i)} + \gamma_4 \cdot ZipHPRet_{t,z(i)} \\ + \gamma_5 \cdot \Delta DQCount_{t,s(i)} + \gamma_6 \cdot controls_i + \nu_i. \end{aligned} \tag{7}$$

Here $\Delta \widehat{AdvFrac}_{t,s(i)}$ is the fitted value from Equation 5 representing the variation in servicing advances attributable to housing price movements in geographies removed from focal loan i. The coefficient β_{IV} estimates the causal impact of principal interest. Alternatively, I combine the first stage and reduced form estimators from Equations 5 and

[23] A fixed effect structure utilizing FICO bins (of width ten) interacted with zip code and year yields results similar in magnitude but with more statistical significance than the baseline specification utilizing Credit Category.

[24] I utilize the estimator of Correia (2016) in order to account for the multiple dimensions of fixed effects and clustered standard errors.

6 respectively, to obtain,

$$\beta_{IV} = \frac{\beta_{RF}}{\beta_{FS}} \tag{8}$$

The outcomes of interest, represented by Y_i in the above equations, vary throughout the paper. Sections 4.1, 4.2, and 4.5 utilize binary indicators, Y_i, for whether or not the servicer undertook a loss mitigation action, whether the loan was ultimately foreclosed, and whether a modification redefaulted within a particular time frame, respectively. Both the instrumental variables and reduced form specifications are estimated with OLS, despite the binary form of the outcome variables, due to the large number of fixed effects on multiple dimensions that are also included. Fixed effects that increase in number with the number of observations create an incidental parameters problem within maximum likelihood methods, as described in Abrevaya (1997), leading logit and probit to no longer be consistent estimators. Linear probability models, such as the one herein, are utilized in similar approaches such as Card, Dobkin, and Maestas (2008), Matsudaira (2008), Friedman and Schady (2013), Garmaise (2015), and Aiello (2016).

The primary concern regarding estimating ordinary least squares with a binary outcome variable is related to the in-sample fitted values lying outside of the $[0, 1]$ interval interpretable as probabilities. As demonstrated by Horrace and Oaxaca (2006), the OLS estimator bias under this specification is related to the probability of the fitted values falling outside of this interval. Of the 6,868,451 observations utilized in Table 4 (column two), 93.19% lay within the proper interval.[25] Horrace and Oaxaca (2006) suggest a trimmed sample estimation procedure. Appendix Section A.1.9 reports the results of this procedure as applied to the regression specification in column two of Table 4. Results from the trimmed sample estimator remain significant and are larger in magnitude than reported results utilizing the untrimmed LPM estimator. Regardless of these technicalities, Wooldridge (2010) says "If the main purpose of estimating a binary response model is to approximate the partial effects of the explanatory variables, averaged across the distribution of $\mathbf{x}$, then the LPM often does a very good job.... The fact that some predicted probabilities are outside the unit interval need not be a serious concern."

[25] 394,878 (5.75%) such that $\hat{y} < 0$ and 73,081 (1.06%) such that $\hat{y} > 1$.

3.3 First Stage Results

The first column of Table 2 presents results relating to the first stage estimate of Equation 5 in the sample appropriate for the regression estimates used throughout this paper. The estimator, β_{FS}, is negative at -8.146 and significant with a t-statistic of -5.22. The negative coefficient implies what we expect from the economic motivation underlying this choice of a first stage setup—that a reduction in housing prices at the servicer portfolio level is associated with an increase in servicing advances over the same time period. Also reported is the incremental adjusted R^2, the increase in the adjusted R^2 associated with adding the instrument into the regression estimated with Equation 5, of 2.6%. This implies that the instrument is driving a meaningful portion of the variation in my measure of financial constraints and is evidence that the instrument relevance requirement of an IV framework is satisfied.

The first stage result in column one of Table 2 is at the defaulted loan observation level. The dependent variable and the independent variable of interest, change in advances and servicer portfolio housing price return, are better thought of however, as servicer level variables. Accordingly, I test the first stage of the instrumental variables framework at a servicer-month level, to ensure that the relationship between advances and housing price returns is general. In the loan level specification the instrument includes a geographic holdout surrounding the focal loan. For the servicer-month specification a generalized instrument with no geographic holdout is used. Additionally, there are no loan or borrower characteristic controls and the fixed effects are done separately at the servicer and year level. Standard errors are clustered at the servicer level. The estimated first stage coefficient with this setup is -2.161 and is significant, with a t-statistic of -3.97 (see Table 2). While Equation 8 would allow for the use of this first stage estimate in the calculation of my causal estimate, I utilize the loan level first stage estimates reported in column one Table 2 primarily because it allows for the exclusion of housing price returns in geographies surrounding the focal loan as well as because its larger magnitude results in more conservative estimates of the underlying causal mechanisms.

3.4 NPV Calculation

The monthly loan performance data provides a rich opportunity to observe actual net present value outcomes of mortgage servicer decisions for the investor.[26] The net present value to the investor of a servicer's action is calculated by discounting the monthly loan level cashflows to the investor back to the last current payment before the qualifying delinquent episode.[27] Monthly investor cashflows at the loan level are calculated by adding the monthly interest payment[28] to the change in the loan's scheduled balance and subtracting any current period loss amounts. These cashflows are discounted at a rate equal to the note rate on the particular loan at origination (see Appendix Section A.1.1 for discussion and robustness results). For loans still active as of the end of sample in December 2015, the remaining outstanding payments due, at the P&I constant in December 2015, are treated as an annuity. If the loan is Delinquent, is in Bankruptcy or Foreclosure, or is an REO Property, a haircut of 50% is applied to the annuity value (see Appendix Section A.1.10 for robustness results.).

Figure 3 provides illustrative examples of cashflow streams for various servicer decisions and loan outcomes. In all scenarios, the white box represents the last cashflow associated with a current borrower payment. Any cashflows projected to be received after December 2015 are accounted for as an annuity and are represented by gray boxes. Blue boxes represent either borrower payments or servicing advances, both of which are received by the investor as cashflows. In the top scenario, labeled "Self Cure" the borrower first misses the payment associated with the first blue box. This payment is advanced to the investor by the servicer and there is no interruption in the cashflows to the investor. At some point the borrower begins making payments again (and makes all previously delinquent payments), and the servicer takes no action. This scenario mirrors the top left scenario of Figure 2. In the second scenario in Figure 3, labeled "Foreclosure," the borrower again misses the payment associated with the first blue box, and the servicer continues advancing the payment to the investor until the loan is liquidated. The red box represents a net loss to the investor as the servicer reimburses himself for advances previously made. This scenario mirrors the bottom

[26]The NPV to the investor remains the focus of this paper due to data limitations. The cashflows to the servicer are largely opaque. Government cash incentives to modify, late fees from the borrower, foreclosure management fees and REO marketing fees as well as the costs of different loss mitigation techniques, (amongst many other examples) are unobservable. In addition, the haircuts and costs of borrowing relating to the funding of the servicing advance obligation is unavailable.

[27]Cashflows associated with the last current payment are not considered in the calculation of investor net present value.

[28]The monthly interest payment is calculated as the loan balance owned by the investor at the beginning of the month (the beginning scheduled balance) times the interest rate net of servicing fees, divided by 12. If the rate net of all servicing fee strips is not available then the gross rate is used instead.

right scenario of Figure 2. The net present value calculated in this case recognizes that the investor benefited from the time value of money from the servicer's advances. The third and fourth scenarios, labeled "Successful Modification" and "Failed Modification" respectively, represent two different modification outcomes. Both scenarios mirror, at the beginning, the top right panel of Figure 2. In the successful modification scenario, the loan is capitalized, resulting in a negative cashflow to the investor as the servicer recovers his previously made advances. The borrower then continues to makes his (lower) monthly payment. In the failed modification scenario the loan is capitalized, but the loan is ultimately foreclosed on after the borrower redefaults. Determining whether or not the failed modification undertaken in the fourth scenario was beneficial to the investor can be addressed through this framework of analyzing the impact of constraints on the net present value of these decisions.

4 Results

In this section, I examine the actions that a servicer takes in response to an increase in his financial constrainedness. A servicer has significant latitude in its ability to perform its obligations towards the MBS investor but is contractually obligated to act in the investor's best interests. The actions taken under financial constraints have the potential to have a significant impact on the value of the asset to the investor. A servicer's obligation to advance principal and interest payments to the investor in the event of borrower delinquency represents a significant burden on its balance sheet. A financially constrained servicer faces increased incentives to relieve or avoid its advance obligation. When a borrower becomes delinquent, the servicer faces a choice—either give the borrower an opportunity to self cure or initiate a default intervention such as a modification or a foreclosure. Given that the decision by a servicer to allow the borrower more time to self cure involves the servicer effectively extending financing to the delinquent borrower, it is likely that a financially constrained servicer would be less willing or less able to do so. Sections 4.1 and 4.2 demonstrate exactly this effect. More financially constrained servicers are more likely to modify and foreclose on delinquent borrowers, and, consequently, these borrowers are significantly less likely to pay off their loan on their own. The financial constrainedness of mortgage servicers caused 440,712 foreclosures—foreclosures that would have not occurred during the life of a particular loan had servicers been less constrained or had their constraints not mattered to the extent that they did. The impact of hundreds of thousands of foreclosures, through a spillover effect on the economy, represents a tremendously important indirect cost of financial distress.

These outcomes, while undesirable from a social welfare perspective, may have been to the benefit of the investor. In order to quantify the value of a particular servicer's actions to the investor, I measure the net present value of all cashflows to the investor subsequent to that action. The net present value of loan cashflows is useful as a measure of loan outcome because it provides a single unit of measure that is common to and meaningful for both modifications and foreclosures. Additionally, it is appropriate because it is the measure that the servicer is contractually required to maximize for the investor when making loss mitigation decisions on his behalf. This framework allows for the examination of whether or not the impact that financial constraints have on particular servicer actions are beneficial or harmful to the investor. Consequently, Section 4.3 regresses the net present value of the realized cashflows of the delinquent mortgage loans on the level of servicer financial constraints. Overall, more financially constrained servicers took actions that were costly to the investor.

Sections 4.4 and 4.5 demonstrate the impact that a servicer's level of financial constrainedness has on the performance of his default interventions, conditional on a particular action being taken. Loss severities associated with foreclosures are higher for financially constrained firms than for unconstrained firms. Financially constrained servicers, in order to induce uptake of modification agreements, offer more generous terms in the form of larger interest rate reductions. Modifications performed by financially constrained firms redefault at higher rates than those of unconstrained firms, despite the lower interest rates charged by them. Returning to investor net present value, a more precise measure of investor benefit, Section 4.6 demonstrates that individual modifications and foreclosures performed by more financially constrained servicers are, on average, worse. These investor net present value impacts, conditional on outcome, are significantly smaller than those that are unconditional on servicer action or loan outcome (reported in Section 4.3). What financially constrained servicers did that was most harmful to investors was to intervene at all.

Finally, Section 4.7 demonstrates that the unobservable quality of borrowers at the time of origination is not correlated with the financial constrainedness of the servicer at origination—the loans in the sample look identical up until the first payment is missed (conditional on my regression specification). The differences being measured only exist once the loan goes delinquent and the servicer has the opportunity to (not) act.

Reported throughout are coefficients associated with the housing price return over the twelve month period preceding loan delinquency for the zip code in which the loan resides as well as the servicer level change in the count of delinquencies over those same twelve months.

4.1 Default Intervention

This section analyzes the impact of a servicer's financial constraints on the ability and willingness of the servicer to provide financing to a delinquent borrower. By modifying or foreclosing on a delinquent borrower, the servicer avoids advancing the monthly payments to the investor. This denies the borrower the opportunity to either bring himself current or to pay off the loan in full. This change in behavior can be observed through an increase in the likelihood of a default intervention amongst more constrained servicers.

Table 3 reports results relating to exactly that increased likelihood. An indicator for whether the servicer intervened in the loan default, "Default Intervention," is one when the servicer either completed a modification or liquidation (generally either a Short Sale or a Charge-Off) or initiated a foreclosure in response to a borrower's first episode of delinquency, and is zero otherwise. This indicator is regressed directly on the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" as well as a vector of controls and a series of fixed effects in an OLS specification in column one. The coefficient is positive and significant, implying that an uninstrumented increase in advances is associated with an increase in the likelihood of servicer default interventions. Controls include a series of loan and borrower characteristic controls, as well as the housing price return over the year prior to delinquency for the zip code of the focal loan and the change in the count of delinquencies in the servicer's portfolio over that same time frame.

The second column of Table 3 reports results relating to the estimation of Equation 6 with the default intervention indicator as an outcome variable. This reduced form estimate is negative and significant, implying that an increase in the portfolio housing price return for a particular servicer is associated with a decrease in its propensity to intervene with a distressed borrower. The third column of Table 3 reports the IV estimate as in Equation 7 of 0.141 with a t-stat of 5.30. This implies that a one standard deviation increase in the financial constrainedness of the servicer is associated with a 14.1 percentage point increase in the probability of that servicer performing a default intervention.

This increase is relative to the servicer continuing to finance the borrower in his delinquency, allowing the borrower to pay off the loan in full or to make at least three consecutive current payments, becoming current again. In sample, the servicer performed a default intervention for the first delinquent episode of a particular borrower 31.35% of the time.

The rightmost portion of Table 3, columns four through seven, present instrumental variables specifications regressing indicator variables for the major outcomes in the dataset. A one standard deviation increase in the financial constrainedness of the servicer increases not only the probability of foreclosure by 8.97 percentage points (t-statistic 4.40), but also the probability of modification by 5.43 percentage points (t-statistic 1.84). Given that the servicer initiates, after the first borrower delinquency, a foreclosure on 24.04% of the sample and a modification on only 7.13%, the similar magnitude of the impact of financial constrainedness on both options is surprising. While foreclosures increase in absolute terms more than modifications, a constrained servicer performs relatively more modifications than foreclosures. This is likely driven largely by the timing differential of the two options. Panel B of Table 1 shows that the average months from delinquency to completion of modification (at which point a servicer is able to recover 100% of his outstanding advances) is only 8.31 months. Alternatively, the average foreclosure liquidation occurs 24.51 months after the borrower's first delinquency.[29] This difference of 493 days means that, on average, a modification returns a servicer's outstanding advances 2.95 times faster than a foreclosure. This fact, in addition to the lessened advancing obligation due to the shorter time frame, leads a financially constrained servicer to prefer modification over foreclosure.

Columns six and seven of Table 3 demonstrate the borrower outcomes that are being substituted for when the servicer intervenes. The probabilities that a borrower pays off his loan in full or brings his loan current are reduced by 9.47 and 3.73 percentage points, respectively. The coefficient on the reduction in probability of a loan paying off in full is statistically significant with a t-statistic of -2.94, but the self cure coefficient is not significant, even at the 10% level (t-statistic of -1.58). Delinquent borrowers that were given more time by the unconstrained servicers were ultimately able to pay off their loan or bring themselves current. The investors contracted with the mortgage servicer; designating them to be the entity that provides this financing to delinquent borrowers. When mortgage servicers became more constrained, however, they were either unwilling or unable to extend financing and consequently, more borrowers experienced foreclosures and modifications immediately after going delinquent.

4.2 Ultimate Outcomes

Section 4.1 demonstrated that a constrained servicer intervenes more aggressively in the event of a borrower delinquency. The unit of observation for that specification was the first episode of delinquency on any particular loan. But does the impact of a servicer's financial constraints on a borrower's outcome survive past just the first opportunity for the servicer to intervene? This section investigates the impact that a servicer's financial constraint has on a borrower's ultimate outcomes—were they ever foreclosed on, did they ever receive a modification, or were they ever able to pay their loan off in full?

Table 4 utilizes an indicator variable in the first three columns, "Ultimately Foreclosed", that is 1 for loans that where the servicer initiated foreclosure proceedings at any point in the life of the loan, and 0 otherwise. This indicator is then regressed, in column one of Table 4, directly on the measure of servicer financial constrainedness at the time of the borrowers first

[29] Both of these statistics are related only to the actions the servicers took on the borrower's first delinquency. A foreclosure is measured at the time the servicer first places a loan into foreclosure. A foreclosure liquidation is when a previously foreclosed loan is eventually sold, either at a foreclosure auction or through the REO process. A foreclosure liquidation is distinct from a charge-off or short sale liquidation which are generally labeled as unqualified "liquidations" throughout this paper.

delinquency and the standard controls. As column one shows, the OLS coefficient is small but significant, demonstrating a positive relationship between the financial constrainedness of a servicer and his probability of initiating foreclosure.

Instrumenting these servicing advances with the "1-Year Servicer Portfolio Housing Price Return (Excluding Loan CBSA)" per Section 3, column two reports results relating the estimation of Equation 6 with the Ultimately Foreclosed outcome indicator on the left hand side. The housing price return for loans in a servicer's portfolio that exist in geographies outside of the focal loan's CBSA is negatively associated with the likelihood of a loan being foreclosed. Column three estimates the causal impact of the servicer's financial constraints at the time of borrower delinquency on whether or not the servicer foreclosed on the borrower. Overall in sample, 39.86% of defaulted loans were ultimately foreclosed on, and column three demonstrates that a one standard deviation increase in the financial constrainedness of a servicer caused him to increase the probability of life-of-loan foreclosure by 11.7 percentage points (t-statistic of 5.45).

Out of the 6,868,451 defaulted loans in the Table 4 sample, 2,737,712 (39.86%) were ultimately foreclosed.[30] Utilizing the average level of financial constrainedness in sample (0.00423557 unstandardized), the number of in sample foreclosures caused by servicer financial constraints was 440,712. These foreclosures demonstrate that a loan serviced by a financially constrained servicer had a significantly higher hazard rate of foreclosure and that, in fact, there were at least 440,712 foreclosures that would not have happened during the life of that particular loan had the servicer been less constrained or had their constraint not been as important as it was.

Additionally, a financially constrained servicer increased the rate at which loans were modified by 6.28 percentage points (t-statistic of 1.94) per standard deviation increase in constrainedness. The increase in foreclosures was ultimately at the expense of the loan being able to eventually pay off in full, which saw a reduction of 9.41 percentage points (t-statistic of -2.94) per standard deviation change in constrainedness.

In all, a servicer's financial constrainedness inflicted over 440,000 extra foreclosures on the economy at large. These foreclosures were avoidable in the sense that if the mortgages had instead been serviced by an unconstrained servicer (or if the servicer's financial constraints had not mattered to the extent it did), the borrower would have been able to pay off

[30] According to Kruger (2017), 5.3 million U.S. homes were foreclosed from the beginning of the financial crisis period through the end of 2016.

his loan in full, or bring himself current.[31] The magnitude of the foreclosure externality itself, the neighborhood spillover effect, is not accounted for in my analysis. The causal estimator, by leaving out the impact of a large geographic area around the focal loan, avoids measuring any spillover effects, as well as any endogeneity introduced through a servicer internalizing those costs as in Favara and Giannetti (2017). In all, this leads these estimates of ultimate outcomes to understate the devastating impact that a mortgage servicer's financial constraints had on the economy at large during the recent financial crisis.

4.3 Investor Value

In order to characterize the actions of a financially constrained servicer as pinning down an agency cost, I now turn to determining their decision's impact on the net present value (at the time of first delinquency) of the future cashflows to the investor. Section 3.4 details the methodology of these calculations. Because precise data relating to the investor cashflows is available subsequent to default, the exact impact of a servicer's level of financial constrainedness can be determined. The outcomes observed, while representing an ex-post outcome, are an agency cost in the sense that they would not have been incurred had the servicer been less financially constrained.[32] The magnitude of this realized agency cost, however, is also influenced by the poor state realization of the economy.

Table 5 reports results relating to the overall impact that a financially constrained servicer's action or inaction had on investor value. A servicer's decision to push a modification or a foreclosure on a borrower that would have been able to self cure or pay-off, in addition to a servicer's poor handling of foreclosures and modifications themselves, destroys an immense amount of value for its principal. The first column of Table 5 regresses, in an OLS specification, the net present value of the loan cashflows after default, on a measure of the financial constrainedness of the servicer. As discussed in Section 3, in order to measure the causal effect an instrumental variables specification must be found. The

[31] Because data limitations prevent me from tracking borrowers across multiple loans, some of the borrowers that were able to pay off in full likely did so through a refinancing channel (as opposed to exiting the market and becoming a renter). I am unable to address whether these borrowers, in their next loan, were able to avoid foreclosure completely. However, given the near-comprehensive coverage of the private label mortgage backed securities market enjoyed by this data, these new loans likely ended up as an additional observation in my sample (except in the unlikely event that a delinquent borrower was able to refinance into a conforming mortgage).

[32] Even considering that an investor might prefer sacrificing some NPV in order to keep a struggling mortgage servicer afloat, the servicer's financial constrainedness itself is still imposing a loss that represents an agency cost.

second and third columns of Table 5 estimate Equations 6 and 7 respectively with the net present value of the future investor cashflows as the outcome variable.

The instrumental variables coefficient is negative and significant, and implies that a financially constrained servicer destroyed \$22,298 (t-statistic of -4.01) of investor value per loan, for every standard deviation increase in the level of financial constrainedness. Loans in sample had an average balance at the time of default of only \$243,996 (see Table 1). Therefore, a one standard deviation increase in constrainedness reduces investor value by 9.13% of the outstanding principal value of the loan at the time of default. Because the expected net present value of a defaulted loan has to be less than its outstanding principal balance, this represents a theoretical lower bound on the actual loss percentage suffered by an investor due solely to the level of financial constrainedness observed for the servicer at the moment of first delinquency. The average net present value for the investor in this sample, at the time of first delinquency, is \$185,130. Thus it is likely that the true percentage loss figure is closer to 12.03% per standard deviation increase in the financial constrainedness of the servicer.

The total issuance balance of the securities that contain at least one loan included in the sample used in Table 5 is \$4.65 trillion, 36.99% (\$1.72 trillion) of which had qualified delinquent episodes and values for all of the relevant covariates and measurement variables, and were thus included in this specification. The coefficient for the regression that is equivalent to Table 5 equation (3) without standardizing the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" is -2,886,796.5. The average level of the increase in the servicing advances measure of financial constraints is 0.00423557, implying a per-loan average of \$12,227.24 in investor value destruction, or \$83.98 billion in aggregate investor value destruction across all 6,868,451 loans in sample. The average loan, conditional on delinquency has an investor NPV of only \$184,385 on a balance at the time of first delinquency of \$243,996. This implies that investors lost \$59,611 per defaulted loan in investor value, 20.51% of which (\$12,227.24) was directly the result of the servicer's financial constraints.

In all, investors that purchased a total of \$4.65 trillion in private label mortgage backed securities prior to the financial crisis suffered an \$83.98 billion realized agency cost (accounting for 20.51% of all investor value losses) associated with hiring an agent that, in the presence of financial constraints, would intervene aggressively in the event of default rather than providing the financing (and the time) the borrower needed to help themselves.

4.4 Foreclosures

Conditional on a servicer undertaking a foreclosure, does his financial constrainedness impact his performance? There are many dimensions under which a servicer can influence the performance of foreclosures once the foreclosure has begun (the "first legal date"). Examples include the speed at which the servicer is able to get the loan to the foreclosure auction, the price the servicer receives at auction, and the expenses the servicer incurs during the process. Many of these items are difficult to disentangle subject to data limitations and their jointly determined nature.[33] A simple measure of the performance of the servicer, conditional on foreclosure, is the loss severity suffered by the investor. Dividing the loss taken on the loan (sale proceeds less servicer expenses) in liquidation by the outstanding principal balance[34] at the time of foreclosure sale is an oft-used metric in industry. While this metric is naive in that it does not account for the discounting of subsequent proceeds (or expenses) months after the property has sold, in practice the majority of cashflows are realized almost immediately after the sale.

Table 6 regresses the foreclosure liquidation loss severity for loans where the servicer successfully foreclosed on the borrower after the first episode of delinquency on a measure of the servicer's financial constrainedness at the time of first delinquency. For every one standard deviation increase in the financial constrainedness of the servicer, the loss severity on the loan increased by 4.34 percentage points (t-statistic of 2.52). The average loss severity in sample is 68.03%, representing the average percentage of the outstanding principal balance that the investor was forced to write-off because of the foreclosure.

While this result is suggestive of a particular form of investor value destruction conditional on the servicer initiating a foreclosure, Section 4.6 will investigate this more rigorously by utilizing the investor net present value calculated at the time of first default. This method will encompass all potential aspects of value destruction that a financially constrained mortgage servicer's decisions can entail.

[33]While Section 3 rules out the causal channel of capacity constraints for the main results in this paper, it is possible that a financially constrained servicer, precisely because he is intervening so aggressively has fewer operational resources to devote to the managing of foreclosures once they have begun. This could be the primary channel through which the results in this section operate.

[34]The balance utilized is the scheduled (investor) balance, not the actual balance owed on the loan.

4.5 Modifications

A constrained servicer is able to minimize his future servicing advance obligation and more quickly recover outstanding advances by increasing the rate at which he modifies loans. In order to increase the rate of modification, the servicer increases the benefits of modification to the borrower by offering better terms. An interest rate reduction, while costly to the investor,[35] is beneficial to both the borrower and the servicer. The borrower benefits from a lower rate, and the servicer has lowered the monthly interest payment that he is obligated to advance in the event the modified loan redefaults (which is also likely to be reduced given a larger interest rate reduction). An interest rate reduction does not impact the servicer's monthly fee strip.

Columns one and two of Table 7 report results relating to the impact that financial constraints have on the terms of modifications that are completed. Conditional on a fixed rate mortgage being modified,[36] column one estimates Equation 8 where the dependent variable is the percentage point reduction in interest rate after the modification. The average modification reduces the borrower's rate by 1.16%, and, for every standard deviation increase in the financial constrainedness of the servicer, the borrower receives an additional 1.70 percentage point decrease (t-statistic of 2.98) in his mortgage rate.

The first column of Table 7 reports the impact of financial constraints on modification interest rate reduction, conditional only on modification. The second column additionally conditions on the modification including an interest rate reduction component. In this case, conditional on a modification with an interest rate reduction, the average interest rate reduction is 3.05%, and a one standard deviation increase in the constrainedness of the servicer implies a decrease in the post-modification rate of an additional 0.72 percentage points (t-statistic of 1.89).

While a financially constrained servicer makes more modifications and provides the borrower with a lower monthly principal and interest payment, it is unclear whether or not this is beneficial to the ultimate owner of the loan, the MBS investor. The standard measure of the success of a particular modification is whether or not the borrower redefaulted within a specified time frame. Redefault is defined as the borrower missing at least one payment within the specified time window after the modification is completed. It is the standard

[35] There is likely to be some level of interest rate reduction on some set of modifications that is beneficial to the investor in the sense that it makes the borrower re-perform and reduces the likelihood of redefault.

[36] I exclude adjustable rate mortgage loans as well as ARM-to-Fixed rate conversion modifications for the purposes of the first two columns of Table 7.

measure of modification quality in both industry and the academic literature. The average redefault rate is, as expected, increasing in the redefault window. 34.98% of modified loans in sample went delinquent within three months after the completion of the modification. By 6-months post-modification 43.81% were, again, delinquent, and 54.26% a year after the modification closed. While these estimates seem generally indicative of poorly designed loss mitigation strategies on behalf of the servicers, the estimates are in line with existing literature (An and Cordell, 2017) for modification success rates during the crisis.

The third, fourth, and fifth columns of Table 7 measure the impact that the financial constrainedness of a servicer has on the effectiveness of his modifications by implementing the instrumental variables framework of Equation 8 at the level of a modified loan utilizing a binary[37] indicator of whether the loan redefaulted. Columns three, four, and five use a 3-month, 6-month, and 12-month redefault rate, respectively, as the dependent variable. All coefficients are positive, significant, qualitatively similar and suggest that for every one standard deviation increase in the financial constrainedness of the servicer, the redefault rate increases by 7.17, 6.12, and 6.38 percentage points (t-statistics of 2.03, 1.68, and 1.86) at 3-month, 6-month, and 12-month horizons, respectively.

This increase in redefault rate comes in spite of the more generous terms provided to the borrower through an interest rate reduction. This suggests some additional component regarding the modification terms provided or actions performed by financially constrained servicers that remains unobserved.[38] Table 8 measures the impact of financial constraints on the investor net present value, conditional on modification, which will account for the totality of a constrained servicer's impact on investor outcomes. In all, the results in Tables 3 and 7 suggest a hierarchy in the actions of a constrained servicer that is consistent with a financial constraints motivation. Constrained servicers are more aggressive in performing foreclosures, at the expense of loans that would have paid off. Then, because modifications recover advances faster on average than do foreclosures, some modifications are performed that would have been better off as foreclosures from the perspective of investors. While

[37]See Section 3.2 for a discussion of the challenges inherit in the estimation of a linear probability model.

[38]On average a more constrained servicer is less likely to modify with a debt forgiveness component (By simply forgiving past due payments, a servicer forgoes future servicing fee strips on the forgiven balance, but reduces the potential future advance obligation) and is more likely to instead capitalize arrearages (A capitalization adds past due payments to the balance of the loan, increasing the potential future servicing advance obligation, as well as the future servicing fee strip). The ambiguous desirability of the capitalization vs. debt forgiveness decision, from the perspective of the servicer, means that neither of these observed average differences are significantly different from zero. A modification of either type, however, always results in a loan being "brought current" and the servicer recovering 100% of his outstanding servicing advances on that loan.

Table 3 shows that, in total, more foreclosures are performed than modifications due to servicer financial constraints, in relative terms the increase in modifications is much greater.

4.6 Conditional Investor Value

Given that a constrained servicer is modifying and foreclosing on loans that, had they been left alone, would have paid-off or self cured, it is reasonable to expect that overall performance, conditional on either foreclosure or modification, would improve. However, Sections 6 and 4.5 demonstrated that the actions of a servicer, under financial stress, have a deleterious impact on the specific performance of both foreclosures and modifications—foreclosures suffer greater losses and modifications redefault at higher rates.[39] This section demonstrates that, conditional on a loan being either foreclosed or modified, greater levels of servicer financial constrainedness at the time of loan first delinquency drastically reduce investor net present value. Despite the fact that constrained servicers are modifying and foreclosing on loans that are in some sense "better," their actions in and handling of the loss mitigation process were so poor due to their financial constraints, they still destroyed value on average. Panels B and C of Table 1 relates summary statistics conditional on various loan outcome dimensions.

Table 8 reports results relating to the causal impact of servicer financial constraints on investor net present value, conditional on the action the servicer took. Section 4.4 demonstrated that foreclosures by financially constrained servicers had higher overall loss severity than those done by unconstrained servicers. The first column of Table 8 demonstrates that, conditional on foreclosure, a financially constrained servicer performed significantly worse than an unconstrained one from the perspective of the investor. For every standard deviation increase in the financial constrainedness of the servicer the investor net present value of the foreclosure was reduced by $11,831 ($t$-statistic of -3.14). The average foreclosure in sample had a net present value of $123,560, implying a 9.6% reduction in average net present value per standard deviation increase in servicer financial constraints.

Section 4.5 reported the result that, despite the borrower receiving generally more favorable terms in the form of increased interest rate reduction amounts, modifications made by financially constrained servicers were more likely to redefault. This implied that the

[39]This paper focuses on the change in investor net present value, rather than modification redefault, as the more accurate indicator of whether a particular modification was justified. A modification that results in the borrower making all past due payments but then redefaulting immediately post-mod could very well be to the benefit of the investor.

modifications made by those servicers were not as effective as those made by unconstrained servicers, but was only suggestive of investor value destruction. The second column of Table 8 demonstrates that, conditional on modification, a financially constrained servicer performed modifications that had worse investor net present value outcomes than those performed by an unconstrained one. Regressing investor net present value on an instrumented measure of financial constraints results in per standard deviation value destruction of \$7,015 (t-statistic of -2.09) on average across all modifications. The average modification in sample had a net present value to the investor of \$168,093, thus a one standard deviation increase in servicer financial constrainedness resulted in an 4.2% reduction in investor value.

The final column of Table 8 shows that the financial constrainedness of the servicer had little impact on the performance outcomes of Short Sale and Charge-Off type liquidations. This is consistent with the notion that, beyond deciding which loss mitigation tactic to take,[40] the outcome of these types of liquidations is largely invariant to the particular actions of the servicer.

4.7 Unobservable Borrower Quality

My identification strategy is subject to the important caveat that unobservable characteristics of the borrower and loan at origination look the same across servicers that will experience different levels of financial constrainedness during the crisis and pre-crisis period. The observation that a particular servicer is servicing a particular loan might provide information as to the borrower's unobserved type, which in turn could influence the appropriate value maximizing decision on the part of the servicer.[41] In order to address this identifying assumption, I propose two tests which are ultimately suggestive of there being no relationship between the financial constrainedness of the servicer at origination and the unobservable quality of the borrower at the time of origination.

The first column of Table 9 regresses the number of months between the loan's note date and the month of borrower first delinquency on the financial constrainedness of the servicer at the time of loan origination and the standard controls (measured at the time of loan origination, not delinquency, where applicable). There is no statistically significant

[40] Additionally, it is important to note that the constrainedness of the servicer has no significant impact on the probability of a borrower receiving a Short Sale or a Charge-Off.

[41] DeMarzo (2005), Aiello (2016), Begley and Purnanandam (2017), and Adelino, Gerardi, and Hartman-Glaser (2017) all have important results relating to the nature of the information asymmetries associated with the pooling and tranching of mortgages.

relationship between the length of time it took for a borrower to go delinquent and the level of financial constrainedness the servicer bore at origination. The servicer has little to no opportunity to influence the time it takes for a borrower to go delinquent. Conditional on the fixed effect structure, loans serviced by financially constrained servicers look identical to those serviced by unconstrained servicers up until the first borrower missed payment. They only become different once they go delinquent and the servicer has the opportunity to react.

Aiello (2016) shows that a borrower that makes her initial few monthly payments at least one business day before her actual due date (generally the first of the month) on a regular basis has a sharply reduced likelihood of ever going delinquent in the future. This propensity to pay an obligation before it is due, "borrower diligence," is unobservable at origination. Aiello (2016) further demonstrates that windows of varying size (including three and six month windows) and beginning at various times after origination (including immediately on the first payment due and starting with the fourth payment due) are all predictive of future delinquency performance. Starting the window later generally results in increasing the sample size as it allows for loans that were securitized after one or two payments to be included in the sample. Lengthening the observation window slightly reduces the sample size as loans become delinquent.

Following this idea, I measure the number of payments made before they were due during an early period of the life of the loan and regress this on the level of financial constrainedness of the servicer at loan origination. Columns two, three, and four of Table 9 report these results. There exists no statistically significant relationship between the financial constrainedness of the servicer at the time of origination and a measure of the borrower's unobservable quality, as inferred by observing initial payment habits.

Both of these measures, the time to borrower first delinquency and the borrower's payment habits, are measures of quality that have nothing to do with the servicer. The fact that these unobservable characteristics did not vary systematically with my quasi-random assignment of servicer constrainedness is reassurance that my identification strategy is sound.

5 Conclusion

This paper analyzes the important relationship between financial constraints and agency costs by exploiting an important detail relating to the institutional setting of mortgage securitizations. A financial intermediary, the mortgage servicer, is obligated to advance to the investor monthly payments on behalf of delinquent borrowers. Advances represented a significant source of financial stress for servicers during the financial crisis.

Mortgage servicers entered the financial crisis with contracts in place that obligated them to bear a significant portion of the short term risk in the event of large scale mortgage defaults. As agents wholly responsible for the management of mortgages, they were positioned to have immense influence on the value of a large volume of assets owned by major systemic institutions. The destruction of tens of billions of dollars in investor value and the infliction of hundreds of thousands of foreclosures on the economy is of enormous concern, particularly when caused by little more than a mortgage servicer acting myopically because of his balance sheet. These servicers traded their reputations for short term liquidity.

A mortgage servicer faces a decision relating to how quickly he should modify or foreclose in the event of delinquency. In waiting, a servicer is forced to finance the borrower until he self cures. I find that constrained servicers were either unwilling or unable to provide that financing and consequently modified and foreclosed at higher rates as compared to unconstrained servicers.

Policymakers at the Fed acted in 2009 to relieve these constraints in a manner that was likely effective at accomplishing its stated goal of "prevent[ing] avoidable foreclosures." The policy response to the financial crisis was largely an attempt to prevent foreclosures and increase modifications. However, this study shows that relieving a servicer's financial constraints, while effective at reducing foreclosures, is not likely to increase loan modifications. Relief would instead lead to something even better—an increased opportunity for a borrower to become current or pay off through his own efforts.

The agency costs and economic destruction associated with the actions of important intermediaries under considerable financial stress are important to study. Both investors and servicers, while likely aware of potential distortionary influences related to servicer financial constrainedness, were unlikely to have appreciated the true magnitude of value destruction that could stem from these decisions. Likewise regulators, in acting to extend TALF coverage to servicing advance obligations in 2009, were too late to avoid the swathes of foreclosures that were caused by servicers' financial constraints.

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Table 1
Summary Statistics

This table reports summary statistics relating to the loan population utilized in this paper. The first column of Panels A and B report results relating to the population of BlackBox loans with valid covariate and servicer values. The remainder of the columns relate to the loans that experienced at least one qualifying delinquent episode. Panel A reports summary statistic data. Panel B reports performance statistics at the loss mitigation outcome level associated with the first delinquent episode. Panel C replicates Panel A statistics grouping by loss mitigation outcomes.

Panel A

	BlackBox Mean	Mean	Median	Sample Std. Dev.	10^{th}%	90^{th}%
Original Loan Amount	248,454	248,798	188,800	221,908	50,250	504,400
Loan Amount at Default		243,996	185,311	219,018	48,386	499,861
Note Date	3/5/2005	5/23/2005	9/1/2005	19mos, 9 days	6/1/2003	12/1/2006
Default Date		8/13/2007	7/1/2007	25mos, 3 days	3/1/2005	3/1/2010
Original Note Rate	7.32%	7.32%	7.13%	2.59%	4.75%	10.65%
Credit Score	674.37	668.84	670.00	68.64	576.00	761.00
LTV	71.19	72.02	80.00	22.44	26.70	95.00
Adjustable Rate	0.60	0.63				
Owner Occupied	0.82	0.82				
Purchases	0.41	0.41				
Single Family	0.71	0.70				
Full Documentation	0.31	0.31				

Panel B

	BlackBox Proportion	Sample Proportion	Average Months to Completion	SD of Months to Completion	Average NPV	SD of NPV
Defaulted	0.782				184,385	202,589
Self Cure		0.263	7.07	5.09	153,749	179,134
Paid-In-Full		0.396	2.37	1.87	251,460	231,944
Modified		0.071	8.31	9.03	161,797	179,350
Foreclosed		0.240	24.51	19.38	122,774	149,536
Liquidation		0.002	12.03	13.01	45,737	112,863
Bankruptcy		0.028			120,481	133,593
Repurchased		0.000			208,398	211,931

Panel C

	Self Cure	Paid-In-Full	Modified	Foreclosed	Liquidated
Average Original Loan Amount	220,250	263,701	272,545	255,020	116,405
Average Loan Amount at Default	217,057	253,211	273,511	255,714	114,245
Average Note Date	5/4/2005	11/17/2004	2/6/2006	1/22/2006	1/28/2009
Average Default Date	6/18/2007	2/9/2007	10/23/2007	3/5/2008	1/24/2009
Average Original Note Rate	7.41%	7.05%	7.24%	7.66%	8.87%
Average Credit Score	656.77	679.32	666.36	665.91	691.10
Average LTV	71.52	69.94	75.14	75.17	39.03
Proportion, Adjustable Rate	0.58	0.66	0.62	0.67	0.57
Proportion, Owner Occupied	0.83	0.84	0.88	0.77	0.76
Proportion, Purchases	0.39	0.39	0.40	0.46	0.44
Proportion, Single Family	0.71	0.71	0.71	0.68	0.61
Proportion, Full Documentation	0.38	0.27	0.37	0.29	0.19

Table 2
First Stage

This table reports regression results relating to the first stage estimates obtained by regressing a measure of servicer financial constraints, the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance," on the instrument, the "1-Year Servicer Portfolio Housing Price Return," both measured at the time of borrower first delinquency, and a vector of controls. The first column is done at a loan level and is the specification used as the first stage in the two stage least squares setup that underlies all of the instrumental variables results in the paper. The second column performs the same regression at the servicer level. First stage coefficient estimates from the servicer level are smaller than at the loan level, implying that the use of the loan level specification results in a more conservative IV estimate. The instrument utilized at the loan level is the housing price variation of the servicer's portfolio for geographies outside of the CBSA in which the loan resides, while the servicer level specification utilizes no geographic holdout. Servicer level "1-Year Change in Delinquency Count" and fixed effects are included in both specifications. Additionally, the servicer level specification has year fixed effects while the loan level specification includes the "1-Year Zip Housing Price Return" for the zip code where the loan resides, as well as a vector of loan and borrower characteristic controls and an interacted zip-year-credit category fixed effect. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1-Year Change in Advances as a Percentage of Loan Portfolio Balance	
	Loan	Servicer
	(1)	(2)
1-Year Servicer Portfolio Housing Price Return (Excluding Loan CBSA)	-8.146***	
	(-5.22)	
1-Year Servicer Portfolio Housing Price Return (No Geo Holdout)		-2.161***
		(-3.97)
1-Year Zip Housing Price Return	1.250***	
	(2.90)	
1-Year Change in Delinquency Count	-3.62e-06**	-1.60e-06
	(-2.13)	(-1.44)
Loan/Borrower Characteristic Controls	Yes	
Servicer FE	Yes	Yes
Zip-Year-CreditCat FE	Yes	
Year FE		Yes
Servicer Clustering	Yes	Yes
Zip Clustering	Yes	
N	6,868,451	18,528
adj. R^2	0.436	0.103
Incremental adj. R^2	0.026	0.013

Table 3

Default Intervention

This table reports results related to the estimation of a linear probability model regressing a series of loan outcome binary indicators (calculated relative to the outcome of the borrower's first episode of delinquency) on an instrumented "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measured at the time of borrower first delinquency, as well as a vector of controls and fixed effects. Column one additionally reports an uninstrumented version of column three, while column two reports the commensurate reduced form regression ("Default Intervention" indicator directly on to the instrument). A default intervention is defined as either a foreclosure (column four), a modification (column five) or a liquidation. The coefficient estimate in column three is predominantly relative to the counterfactuals of Paid-In-Full and Self Cure that are utilized in columns six and seven respectively. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Intervention			Foreclosure	Modification	Paid-In-Full	Self Cure
	OLS	Reduced Form	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	0.0111***		0.141***	0.0897***	0.0543*	-0.0947***	-0.0373
	(2.66)		(5.30)	(4.40)	(1.84)	(-2.94)	(-1.58)
1-Year Servicer Portfolio Housing Price Return (Excluding Loan CBSA)		-1.150***					
		(-7.82)					
1-Year Zip Housing Price Return	-0.722***	-0.293***	-0.470***	-0.370***	-0.0977**	0.381***	0.119**
	(-15.93)	(-6.88)	(-10.70)	(-7.41)	(-2.03)	(4.89)	(1.98)
1-Year Change in Delinquency Count	-1.04e-07	-1.13e-07	3.99e-07*	-5.83e-08	4.79e-07**	6.70e-08	-4.16e-07***
	(-0.54)	(-0.61)	(1.91)	(-0.28)	(2.34)	(0.32)	(-3.00)
Loan/Borrower Characteristic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Year-CreditCat FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Servicer and Zip Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,868,451	6,868,451	6,868,451	6,868,451	6,868,451	6,868,451	6,868,451
adj. R^2	0.260	0.262	0.213	0.169	0.122	0.282	0.108
Dependent Variable Average	0.3135		0.3135	0.2404	0.0713	0.3961	0.2618

Table 4

Ultimate Outcomes

This table reports results related to the estimation of a linear probability model regressing a series of loan outcome binary indicators on an instrumented "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measured at the time of borrower first delinquency, as well as a vector of controls and fixed effects. Column one additionally reports an uninstrumented version of column three, while column two reports the commensurate reduced form regression ("Default Intervention" indicator directly on to the instrument). Outcome indicators utilized in this table are calculated in reference to ultimate outcomes on the loan. That is, regardless of the initial result of the borrower's first episode of delinquency, was this loan *ever* placed into foreclosure (column three), modified (column four), or pay off in full (column five). Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ultimately Foreclosed			Ultimately Modified	Ultimately Paid-In-Full
	OLS	Reduced Form	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	0.0148***		0.117***	0.0628*	-0.0941***
	(3.50)		(5.45)	(1.94)	(-2.94)
1-Year Servicer Portfolio Housing Price Return (Excluding Loan CBSA)		-0.953***			
		(-7.92)			
1-Year Zip Housing Price Return	-0.598***	-0.254***	-0.401***	-0.184***	0.382***
	(-7.42)	(-3.77)	(-5.47)	(-4.07)	(4.90)
1-Year Change in Delinquency Count	-3.01e-07*	-3.29e-07**	9.49e-08	7.74e-07***	7.08e-08
	(-1.89)	(-2.26)	(0.38)	(2.92)	(0.34)
Loan/Borrower Characteristic Controls	Yes	Yes	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes	Yes	Yes
Zip-Year-CreditCat FE	Yes	Yes	Yes	Yes	Yes
Servicer and Zip Clustering	Yes	Yes	Yes	Yes	Yes
N	6,868,451	6,868,451	6,868,451	6,868,451	6,868,451
adj. R^2	0.262	0.263	0.237	0.216	0.282
Dependent Variable Average	0.3986		0.3986	0.1646	0.3963

Table 5

Investor Value

This table reports results demonstrating the causal impact of a servicer's financial constraints, as measured at the time of borrower first delinquency by the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance," on the net present value for the investor. The first column reports the coefficient estimate for an uninstrumented OLS specification, the second the reduced form specification wherein "Investor NPV" is regressed directly on the instrument "1-Year Servicer Portfolio Housing Price Return (Excluding Loan CBSA)," and the third utilizes an instrumental variables framework to report the causal estimate. The standard controls and fixed effects are utilized throughout. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Investor NPV		
	OLS	Reduced Form	IV
	(1)	(2)	(3)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	-2,254**		-22,298***
	(-2.32)		(-4.01)
1-Year Servicer Portfolio Housing Price Return (Excluding Loan CBSA)		181,641***	
		(5.10)	
1-Year Zip Housing Price Return	98,010***	31,327	59,198***
	(6.06)	(1.54)	(3.29)
1-Year Change in Delinquency Count	-0.148**	-0.145**	-0.225**
	(-2.32)	(-2.49)	(-2.52)
Loan/Borrower Characteristic Controls	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes
Zip-Year-CreditCat FE	Yes	Yes	Yes
Servicer and Zip Clustering	Yes	Yes	Yes
N	6,868,451	6,868,451	6,868,451
adj. R^2	0.830	0.831	0.825
Dependent Variable Average	185,130		185,130

Table 6

Foreclosures

This table reports results relating to the regressing, conditional on a loan being foreclosed on during its first episode of delinquency, the "Foreclosure Liquidation Loss Severity" on an instrumented measure of servicer financial constraints, the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measured at the time of borrower first delinquency, and the standard controls and fixed effects. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Foreclosure Liquidation Loss Severity
	IV
	(1)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	0.0434**
	(2.52)
1-Year Zip Housing Price Return	-0.107***
	(-3.35)
1-Year Change in Delinquency Count	4.69e-07
	(1.54)
Loan/Borrower Characteristic Controls	Yes
Servicer FE	Yes
Zip-Year-CreditCat FE	Yes
Servicer and Zip Clustering	Yes
N	1,353,649
adj. R^2	0.220
Dependent Variable Average	68.03%

Table 7

Modifications

This table reports results relating to the performance and characteristics of modifications performed on loans following their first episode of delinquency. Columns one and two regress the percentage point reduction in interest rate associated with the modification on an instrumented measure of servicer financial constraints, the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measured at the time of borrower first delinquency, and the standard controls and fixed effects. Columns three through five regress indicators of whether the loan again became delinquent three, six, and twelve months respectively, after the modification brought the loan current on the measure of servicer financial constraints and the standard controls and fixed effects. All columns are conditional on the loan being modified as a result of the first episode of delinquency. Additionally, columns one and two condition on the loan being a fixed rate loan both prior and subsequent to the modification. Column two further conditions on the modification performed containing some interest rate reduction component. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Modification Interest Rate Reduction		3mo Redefault	6mo Redefault	12mo Redefault
	Fixed Rate Mods	FR Int Rt Red.	Mod Only	Mod Only	Mod Only
	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	1.704***	0.716*	0.0717**	0.0612*	0.0638*
	(2.98)	(1.89)	(2.03)	(1.68)	(1.86)
1-Year Zip Housing Price Return	-0.762	0.176	-0.0756	-0.0789	-0.0809
	(-1.17)	(0.55)	(-1.24)	(-1.14)	(-1.00)
1-Year Change in Delinquency Count	4.09e-06	1.20e-06	8.24e-07***	8.06e-07***	8.75e-07***
	(0.89)	(0.72)	(3.88)	(3.55)	(3.72)
Loan/Borrower Characteristic Controls	Yes	Yes	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes	Yes	Yes
Zip-Year-CreditCat FE	Yes	Yes	Yes	Yes	Yes
Servicer and Zip Clustering	Yes	Yes	Yes	Yes	Yes
N	110,219	33,325	440,921	440,921	440,921
adj. R^2	0.297	0.641	0.138	0.169	0.195
Dependent Variable Average	1.16%	3.05%	0.3498	0.4381	0.5426

Table 8

Conditional Investor Value

This table reports instrumental variable regression results similar to that of column three in Table 5 with further conditioning based on the servicer action taken after the first episode of borrower delinquency. Columns one, two, and three condition on foreclosure, modification, and liquidation (generally a charge-off or a short sale) respectively. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Investor NPV		
	FC Only IV	Mod Only IV	Liq Only IV
	(1)	(2)	(3)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	-11,831***	-7,015**	-290.2
	(-3.14)	(-2.09)	(-0.10)
1-Year Zip Housing Price Return	12,006	-32,793*	5,332
	(1.55)	(-1.92)	(0.26)
1-Year Change in Delinquency Count	-0.189**	-0.139**	-0.0215
	(-2.07)	(-2.05)	(-0.55)
Loan/Borrower Characteristic Controls	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes
Zip-Year-CreditCat FE	Yes	Yes	Yes
Servicer and Zip Clustering	Yes	Yes	Yes
N	1,592,194	440,921	7,306
adj. R^2	0.758	0.780	0.826
Dependent Variable Average	123,560	168,093	33,610

Table 9

Unobservable Borrower Quality

This table regresses various measures of unobservable borrower quality on an instrumented measure of servicer financial constraints, the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance," measured at the time of loan origination. Column one regresses the number of months between loan origination and the borrower's first delinquency on the servicer's financial constraints at the time of loan origination. Columns two through four instead utilize a measure of unobservable borrower quality related to the frequency with which the borrower makes his monthly payment at least a day before it is due. This measure has been established in the literature as highly correlated with future loan delinquency and default outcomes and is, crucially, unobservable at the time of loan origination. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Months To First DQ	Early Payments, Mos 1-6	Early Payments, Mos 4-6	Early Payments, Mos 4-9
	IV	IV	IV	IV
	(1)	(2)	(3)	(4)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance At Origination	-3.588	-4.742	-0.720	-2.698
	(-1.56)	(-1.04)	(-1.03)	(-1.20)
1-Year Zip Housing Price Return At Origination	3.794*	6.627	-0.0176	0.0260
	(1.75)	(0.98)	(-0.06)	(0.04)
1-Year Change in Delinquency Count At Origination	-2.38e-05	5.47e-06	-2.84e-06	-3.78e-06**
	(-1.29)	(0.30)	(-1.66)	(-2.01)
Loan/Borrower Characteristic Controls	Yes	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes	Yes
Zip-Orig. Year-CreditCat FE	Yes	Yes	Yes	Yes
Servicer and Zip Clustering	Yes	Yes	Yes	Yes
N	6,315,297	2,478	2,514,099	2,227,485
adj. R^2	0.217	-3.003	-0.097	-0.807
Dependent Variable Average	25.33	1.87	0.93	1.84

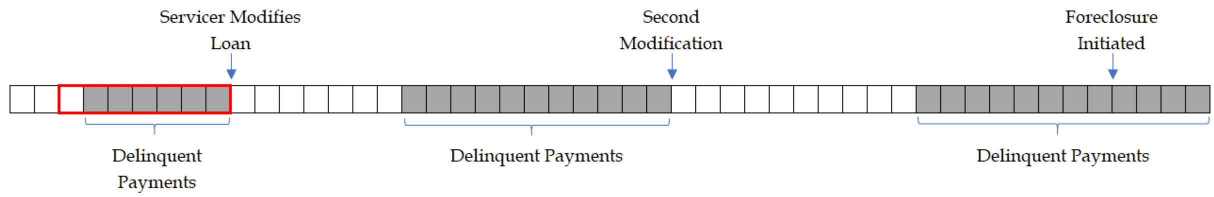

Figure 1. Illustrative Payment String in Data This figure illustrates an hypothetical series of borrower payments. Made payments are in white and missed payments are in gray. This borrower receives a modification, redefaults, receives a second modification, and then the servicer initiates a foreclosure after the second redefault. For all results except those relating to ultimate outcomes in Section 4.2, this example loan would be treated as a modification pursuant to the result relating to the first, highlighted, episode of delinquency.

Borrower Self Cure

	Borrower Loan Payable		*Servicer Advance Receivable*		*Investor Loan Receivable*	
		100	0		100	
Jan	1		0			1
Feb	0		1			1
Mar	0		1			1
Apr	0		1			1
May	4			3		1
Jun	1		0			1
		94	**0**		**94**	

Modification

	Borrower Loan Payable		*Servicer Advance Receivable*		*Investor Loan Receivable*	
		100	0		100	
Jan	1		0			1
Feb	0		1			1
Mar	0		1			1
Apr	0		1			1
Mod	0			3	3	
May	1		0			1
Jun	1		0			1
		97	**0**		**97**	

Foreclosure

	Borrower Loan Payable		*Servicer Advance Receivable*		*Investor Loan Receivable*	
		100	0		100	
Jan	1		0			1
Feb	0		1			1
Mar	0		1			1
Apr-Nov	0		8			8
Dec	50			10		40
		49	**0**		**49**	

Foreclosure

	Borrower Loan Payable		*Servicer Advance Receivable*		*Investor Loan Receivable*	
		100	0		100	
Jan	1		0			1
Feb	0		1			1
Mar	0		1			1
Apr-Nov	0		8			8
Dec	0			10	10	
		99	**0**		**99**	

Figure 2. Recoveries of Servicing Advances This figure presents, for four stylized examples, the T accounts associated with the borrower's loan payable, the servicer's outstanding advance receivable, and the investor's loan receivable. Change to the accounts over time represent the inflows and outflows associated with the various loan scenarios and borrower or servicer actions. These illustrate the mechanisms by which servicer advances are made and recovered and their impact on investor cashflows.

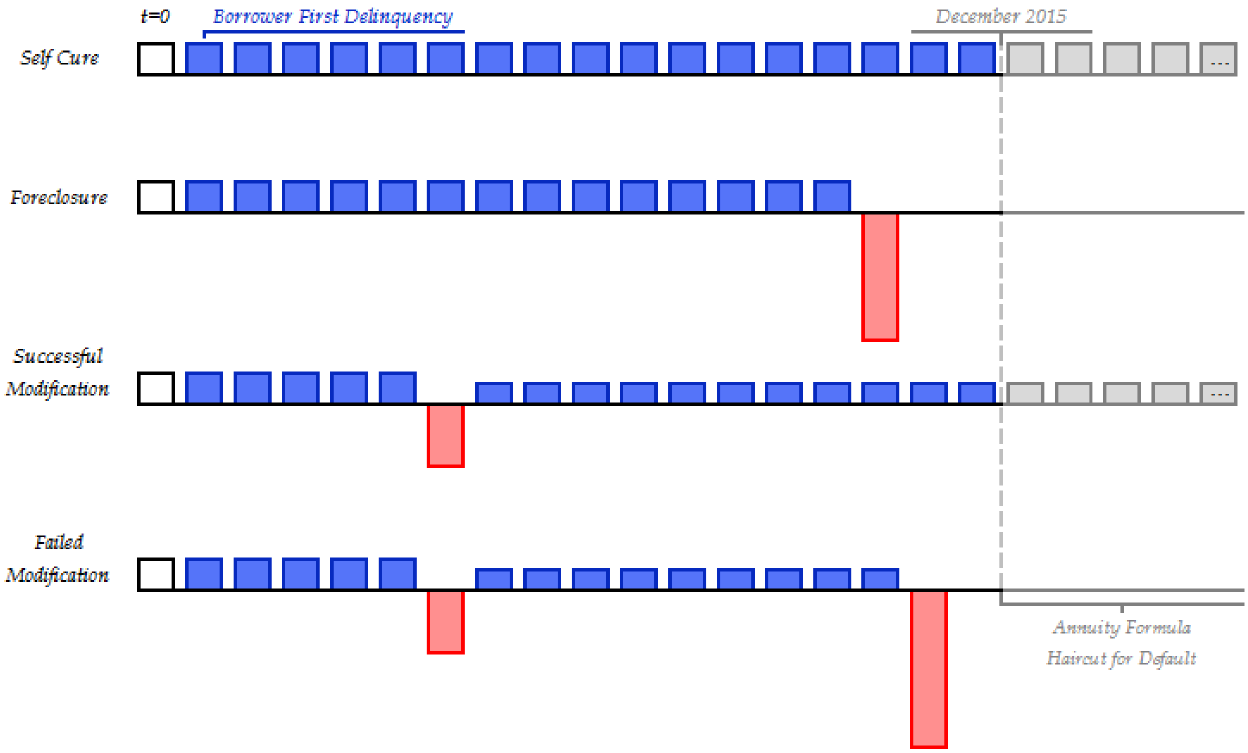

Figure 3. NPV Calculations This figure presents illustrative graphical representations of the investor cashflows associated with various loan outcomes. The last current payment by the borrower, at $t = 0$ is represented by the white box. The borrower's first delinquent payment, which is advanced by the servicer is represented by the first blue box. Red boxes represent negative cashflows to the investor where cashflows from other loans in the pool are used to reimburse the servicer for outstanding advances (and expenses in the case of a foreclosure). Gray boxes occurring after December 2015 are imputed based on an annuity formula and an haircut associated with the loan status at the end of the sample period. All investor cashflows represented by blue, red, or gray boxes are discounted back to the $t = 0$ period.

Appendix

A.1 Robustness

A.1.1 Discount Rate Sensitivity

Throughout this paper, the calculation of the net present value of loan cashflows is discounted at the original note rate on the loan. Existing literature remains silent on the correct discount rate methodology to use, and innovation here is not within the scope of this study. However, we can generally make use of broad guidance on the nature of the riskiness of these cashflows. The correct discount rate should account for the undiversifiable (Cotter, Gabriel, and Roll, 2014) portion of the variability of mortgage loan cashflows. Default and prepayment risk remain important things to consider. Discounting using the treasury rate at the time of loan default only accounts for the time varying nature of the risk free component of the theoretically correct discount rate. The component associated with the risk premium became incredibly important during the crisis, but remains difficult to estimate without a better understanding of the nature of the marginal investor during the crisis.

The note rate at which the loan was closed remains an important leverage point in the analysis and should, unconditionally, represent a theoretical ceiling for an appropriate discount rate at the time of origination. However, because the loans in sample have all defaulted, it is likely that the appropriate discount rate is higher, rather than lower, than the note rate. As magnitude estimates are increasing in the fixed discount rate chosen (see below), the note rate is selected as a conservative estimate for the principal empirical specification.

Appendix Table A.1 reports results from a series of instrumental variable specifications each similar to that found in Table 5, each varying the discount rate methodology utilized. The table reports the IV coefficient estimate and its significance. Additionally, the dependent variable average and the effect of a one standard deviation increase in financial constraints are reported. The principal empirical specification of this paper utilizes the original note rate of the loan, and is reported in the first row of the table. Reported results are identical to the IV specification in Table 5. The top portion of Appendix Table A.1 reports other results related to discount rate methodologies other than fixed rates. The second and third rows use the 2-year and 10-year Treasury rate, respectively, at the time of loan default. The coefficient estimates are largely invariant to this choice, although the treasury rate schemes are amongst the most significant, but smallest in magnitude. The bottom portion of Appendix Table A.1 varies a fixed discount rate between 2% and 10%. The coefficient estimates are largely insensitive to this choice and are increasing in magnitude with the discount rate.

As these robustness results demonstrate, the short time line along which the majority of the cashflows relating to a defaulted loan are realized means that the specific choice of discount rate utilized in the analysis is of vanishing importance for the effect of financial constraints.

A.1.2 Geographic Holdout Sensitivity

The instrument used in the main specifications throughout the paper holds out the Core-Based Statistical Area (CBSA) surrounding the focal loan from the calculation of servicer portfolio housing price returns. Specifications B, C, and D of Appendix Table A.2 demonstrate robustness of the instrumental variables specifications found throughout the paper to different levels of geographic holdout. Both the magnitude and significance of the default intervention and investor NPV results are largely unchanged when varying the geographic holdout level between Core-Based Statistical Area, Commuting Zone, and (at the highest level) the entire State. With no holdout the significance is mildly diminished whilst the magnitude slightly increases.

The only material changes are that, when the instrument includes no geographic holdout (specification B) the impact of financial constraints on modifications' 3-month redefault rate and investor NPV are attenuated and consequently no longer significant. These results are suggestive that the OLS bias stemming specifically from the housing price realizations of geographies close to the focal loan tends to exaggerate the magnitude of the effect of servicer financial constraints on both the loss mitigation decision as well as the loan outcome overall, but attenuates the effects specific to modification outcomes. In other words, low local housing price returns imply better modification performance overall. This is largely consistent with the sign on the "1-Year Zip Housing Price Return" coefficients in column three of Table 7 and column one of Table 8. Overall, these results support the notion that a holdout at some geographic level is important for a well-functioning instrument.

A.1.3 Capacity Constraints

One possible challenge to the interpretation of my causal mechanism as being related to the financial constrainedness of the mortgage servicer is the fact that a financially constrained servicer is also likely operationally constrained. An influx of delinquent loans in his servicing portfolio not only requires a large outflow of cash in the form of servicing advances, but also necessitates a significant operational commitment in order to appropriately handle these loans. Although, as discussed in Section 3, this remains unlikely due to the direction of my main results (i.e. Table 3), I include throughout the paper the change in the count of servicer portfolio delinquencies for the year prior to loan delinquency as a control.

Appendix Table A.3 demonstrates robustness to excluding this control by replicating column three of Tables 3, 4, and 5 in columns one, four, and seven, respectively. Columns two, five, and eight of Appendix Table A.3 then duplicate these results excluding the control. Finally, columns three, six, and nine of Appendix Table A.3 replace the control with the count of delinquencies in the servicer's portfolio at the time of loan delinquency as well as at year lags up to three years prior to loan delinquency. In general the results remain unchanged. However, consistent with the notion of a generally attenuating endogeneity problem in the uninstrumented specification, the slight decrease in magnitude of the uncontrolled results, though not statistically significant, suggests that a servicer's capacity, or operational, constraint works in the opposite direction of the measured financial constraints. A servicer that is more capacity constrained has less ability to be more aggressive in intervening, and is forced to provide the delinquent borrower with advance financing, and consequently, destroys less investor value.

A.1.4 Servicer Learning

One potential challenge to the exogeneity of the housing price shocks with respect to servicer behavior is the concern that a servicer may have learned differentially about how to respond to defaulted loans by being exposed to high-default geographies early in the crisis. This would then provide the servicer with differential experience and could lead to differential loan treatment or outcomes. This potential issue is largely mitigated by the nature of information that is revealed to the servicers in this market. The data utilized in this study is published on a monthly basis in real-time, and is generally available to all market participants. Consequently, a servicer has the ability to "learn" from the market as a whole and this effect is controlled for in my baseline specifications through time fixed effects.

In order to address any residual concern, I include in my baseline specifications a measure of the change in delinquency count the servicer has experienced over the twelve month period immediately preceding the loan default. A servicer will learn from his previous experiences in a manner consistent with the count of delinquent loans he has managed. Additionally, Appendix Table A.3 demonstrates robustness to a restructuring of this covariate as a measure of the level of delinquencies in the servicer's portfolio as well as lags at every year out to three years in the past. The path taken to the current situation is a better measure of learning than the current financial constraint.

To further strengthen these arguments, regression specification (N) in Appendix Table A.2 demonstrates the robustness of the main specifications to the inclusion of a Servicer-Year fixed effect. By only comparing loans serviced by the same servicer in the same year, these specifications have conditioned on any potential learning done by a particular servicer at the precision of a calendar year.

A.1.5 Sample Definition

Regression specification (E) in Appendix Table A.2 tests the major results of the paper (duplicated for reference in line (A) of the same table), for loans that first went delinquent in 2005 or earlier. During this period a servicer experiencing a significant outlay of servicing advances was not as restricted from access to liquidity as would happen later during the crisis. Consequently, servicer's experiencing higher levels of financial constraints, as measured by servicing advances, do not respond in the manner they do during the crisis. The coefficients estimated in this sample are largely insignificant and most are substantially smaller in magnitude than their full sample counterparts.

Regression specification (F) in Appendix Table A.2 tests the major results of the paper, restricting attention to just the crisis period, defined here as a borrower first delinquency in 2006 or later. For comparison the baseline specification is ran on line (A) of Appendix Table A.2. The results are qualitatively identical, with only slightly diminished significance in some cases—consistent with the reduction in sample size. The net present value impact of the servicer's financial constrainedness is the most reduced in magnitude.

Regression specification (G) in Appendix Table A.2 tests whether loans that first went delinquent after the extension of TALF eligibility to servicing advances were differentially treated by servicers. Because coefficient magnitudes are similar in most cases to the baseline specification reported in row (A), it is difficult to disentangle the impact TALF might have had on servicer behavior from the reduction in statistical power related to the sub-sampling.

Because the type or size of the servicer may be important for the interpretation of the results, regression specifications (H) and (I) in Appendix Table A.2 test the principal results of the paper on important sub samples of the servicer population. Specification (H) reports results relating to just the largest decile servicers (by defaulted loan observation count). These results reject the hypothesis that the behavior exhibited by financially constrained servicers in this study is driven only by smaller, and thus less robust, entities. Row (I) further restricts attention just to the servicers amongst the largest decile that were subsidiaries of larger financial institutions. The fact that these servicers still responded to their financial constraints in the manner described in the paper suggests that subsidiary level internal capital market constrainedness is important to the decision making process of those managers.

A.1.6 Self Cure Definition

I define a delinquency as being a "Self Cure" if the borrower makes at least three consecutive current payments without servicer intervention. I choose this specification for two reasons. First, some modifications are structured as "workouts," meaning that the modified terms of the loan are conditional on the borrower being able to bring his loan current via an agreed upon repayment plan. In these cases, the modification flag in the data does not appear until after the borrower has appeared to have brought himself current. By waiting to observe three consecutive current payments before classifying as a self cure, I am able to correctly categorize workout modifications as being modifications, rather than self cures. Second, a borrower that is delinquent and then makes a small number of current payments before relapsing into delinquency, is not likely to be treated significantly differently by the servicer in relation to his loss mitigation efforts. A servicer that has begun the process of treating the borrower as being distressed is not likely to completely clear him that quickly.

Regression specifications (J) and (K) of Appendix Table A.2 demonstrate robustness to changing the self cure definition to require either two months of consecutive current payments or simply a single current payment, respectively. Results, compared to specification (A), are largely insensitive to these changes. In the 1-Month Self Cure specification, however, it looks like modifications in general perform much worse. This suggests that workout type modifications, as discussed above, are generally better performing compared to traditional modifications as these are likely to be misclassified here as self cures.

A.1.7 Winsorization

In Section 2.1 the loan-month level outstanding advance distribution is winsorized (right tail only) at the 0.01% level to reduce the effect of extreme outlier advance amounts (likely driven by data quality issues) have on drawn inferences. Once these advances are aggregated to the servicer-month level and scaled by the outstanding portfolio actual balance, these values are again winsorized (right tail only) at the 1% level. In order to demonstrate robustness to these winsorization assumptions, regression specification (L) in Appendix Table A.2 reports results relating to the exclusion of these outlier values rather than their truncation. Results, as compared to the baseline specification in line (A), are qualitatively identical, with only a slight reduction in significance in a few areas.

A.1.8 Alternate Fixed Effect Structures

Regression specifications (M), (N), and (O) of Appendix Table A.2 demonstrate robustness to differing fixed effect structures of the main specifications used in this paper.

A servicer with a particularly aggressive risk appetite may endogenously select into servicing loans within geographies that are likely to experience more volatile housing price returns. The separate servicer fixed effect included in the main specifications controls for any unobserved servicer type. Additionally, as reported in specification (M) of Appendix Table A.2, utilizing an interacted Servicer-Zip Code-Credit Category alongside a separate Year Fixed Effect dimension shows that the main effects hold even within Servicer-Zip Codes.

Regression specification (N) includes a Servicer-Year fixed effect dimension separate from a Zip Code-Credit Category dimension. The main results are robust to this restructuring of the fixed effects. See Section A.1.4 for a complete discussion of these results.

Regression specification (O) includes a fixed effect dimension for the issuer of the securitization in which the loan resides. These specifications demonstrate the robustness of the main findings to any concerns related to the heterogeneity of particular pooling and servicing agreements, as these are likely to predominantly vary along securitization issuer lines.

A.1.9 Trimmed Sample Linear Probability Model

The use of a linear probability model is, at times, problematic. Horrace and Oaxaca (2006) suggest a trimmed sample estimation procedure wherein an LPM specification is estimated and observations whose fitted values lie outside of the unit interval are discarded. The process is then iterated until all fitted values are contained in [0,1] and are thus correctly interpretable as probabilities. Column one of Appendix Table A.4 duplicates the results of the instrumental variables specification, Equation 7, of the third column of Table 4. The second column of Appendix Table A.4 then reports results of the final IV estimate after the iterative trimming procedure was performed. Trimming slightly increased the magnitude and significance of the coefficient of interest, suggesting that in this setting the Horrace and Oaxaca (2006) Linear Probability Model Bias is attenuating my coefficient estimates.

A.1.10 Terminal Value Haircut Sensitivity

In the calculation of investor net present value, as detailed in Section 3.4, cashflows subsequent to December 2015 are unavailable. When a loan is still active as of December 2015, an annuity paying the monthly principal and interest payment for a number of months equal to the remaining term is calculated. In the baseline specification, if the loan is Delinquent, is in Bankruptcy or Foreclosure, or is currently an REO Property at the end of sample, a haircut of 50% is applied to the annuity value. Appendix Table A.5 details results relating to the sensitivity of the headline NPV result of the third column of Table 5 to this assumption.

Specifications (1) through (11) use a fixed haircut across all loan statuses that ranges from fully excluding any future cashflows (line 1) to no haircut at all (line 11). The baseline specification used throughout the paper is presented in bold on line (6). The next set of specifications assume a general rule that the haircut should be strictly monotonic in the severity of the loan status—Delinquency is not as bad for the investor as Bankruptcy, which is not as bad as Foreclosure, which is not as bad as properties directly owned by the investor (REO). Specifications (12) through (28) present a plethora of different specifications. The net present value of a defaulted loan (final column of Appendix Table A.5) varies with the haircut schema chosen as expected. The reported IV coefficient (and its significance level), reporting the per standard deviation impact of financial constrainedness on average investor value per defaulted loan, does not meaningfully vary with the haircut assumption utilized.

A.2 Servicer Summary Statistics

Appendix Table A.6 presents average summary statistics at the servicer level for both the 231 servicers contained in sample as well as the 210 servicers that appear in the regressions of Tables 3, 4, and 5. The 21 excluded servicers are dropped because the fixed effect estimation procedure of Correia (2016) drops all observations in singleton fixed effect cells in order to avoid overstating the statistical significance of coefficient estimates.

Appendix Table A.6 demonstrates the significant level of heterogeneity in the size, risk profile, and geographic dispersion of the mortgage servicers in sample.

Table A.1
Discount Rate Sensitivity

This table reports results similar to that of column three in Table 5 but varying the discount rate methodology utilized for the calculation of the investor net present value. The top, bolded, line discounts investor cash flows at the note rate on the loan at origination. This matches the primary methodology used throughout the paper. Lines two and three utilize the 2-yr and 10-yr U.S. treasury rates at the time of loan default respectively. The remaining specifications utilize a fixed discount rate that ranges in percentage point increments from two to ten percent, inclusive. IV coefficients and t-stat values relate to the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure and have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and separately clustered at the servicer and zip level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Discount Rate Methodology	IV Coefficient	t-stat	Dependent Variable Average
Original Note Rate	**-22,298*** **	**(-4.01)**	**185,130**
2-yr Treasury at Default	-20,221***	(-4.70)	205,035
10-yr Treasury at Default	-21,825***	(-4.57)	195,850
2%	-21,961***	(-4.82)	206,191
3%	-22,415***	(-4.63)	199,748
4%	-22,793***	(-4.46)	194,197
5%	-23,110***	(-4.31)	189,371
6%	-23,378***	(-4.19)	185,140
7%	-23,606***	(-4.08)	181,401
8%	-23,801***	(-4.00)	178,070
9%	-23,969***	(-3.93)	175,082
10%	-24,114***	(-3.87)	172,384

Table A.2
Robustness

This table contains robustness results relating to various specification changes for the major results of the paper. Row (A) contains the baseline specification utilized throughout the paper. Columns one through eight report the results related to column three of Tables 3, 4, and 5, column one of Tables 6 and 7, column three of Table 7, and columns one and two of Table 8, respectively. See Appendix Section A.1 for descriptions of the various rows. IV coefficients and *t*-stat values relate to the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure and have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported *t*-statistics in parentheses are heteroskedasticity-robust and separately clustered at the servicer and zip level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

			Default Intervention	Ultimate Foreclosure	Investor NPV	FC Liq Loss Severity	Interest Rate Reduc.	Mod 3mo Redefault	FC Investor NPV	Mod Investor NPV
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A)	Main Specification	IV Coef.	0.141***	0.117***	-22,298***	0.0434**	1.704***	0.0717**	-11,831***	-7,015**
		t-stat	(5.30)	(5.45)	(-4.01)	(2.52)	(2.98)	(2.03)	(-3.14)	(-2.09)
		D.V. Avg.	0.3135	0.3986	185,130	68.03%	1.16%	0.3498	123,560	168,093
(B)	No Geographic Holdout	IV Coef.	0.152***	0.118***	-22,743***	0.0421**	1.491**	0.0219	-11,596***	-1,685
		t-stat	(5.24)	(5.36)	(-3.96)	(2.48)	(2.47)	(0.65)	(-3.07)	(-0.36)
		D.V. Avg.	0.3136	0.3988	185,133	68.03%	1.16%	0.3498	123,568	168,093
(C)	Commuting Zone Geographic Holdout	IV Coef.	0.140***	0.117***	-22,204***	0.0435**	1.761***	0.0742**	-11,758***	-8,549***
		t-stat	(5.36)	(5.48)	(-4.08)	(2.51)	(3.12)	(2.08)	(-3.17)	(-2.83)
		D.V. Avg.	0.3135	0.3986	185,132	68.03%	1.16%	0.3498	123,560	168,096
(D)	State Geographic Holdout	IV Coef.	0.141***	0.119***	-22,331***	0.0455**	1.853***	0.0752**	-11,771***	-9,696***
		t-stat	(5.48)	(5.42)	(-4.18)	(2.52)	(3.46)	(2.21)	(-3.12)	(-3.39)
		D.V. Avg.	0.3135	0.3986	185,130	68.03%	1.16%	0.3498	123,562	168,094
(E)	Pre-Crisis Period, 2005 and Earlier, Only	IV Coef.	0.0350	0.0604	-21,163	0.286*	-0.300	-0.722	-49,148*	-1,538
		t-stat	(0.81)	(0.85)	(-0.99)	(1.85)	(-0.10)	(-1.60)	(-1.85)	(-0.51)
		D.V. Avg.	0.0976	0.1748	186,365	41.47%	0.07%	0.4205	97,168	52,184
(F)	Crisis Period, 2006 and Later,Only	IV Coef.	0.150***	0.122***	-19,429***	0.0455***	1.701***	0.0754**	-10,063**	-6,215*
		t-stat	(4.57)	(5.12)	(-3.87)	(2.65)	(2.92)	(2.02)	(-2.60)	(-1.82)
		D.V. Avg.	0.3623	0.4492	184,851	69.36%	1.16%	0.3484	125,049	170,375
(G)	Post TALF Extension, 2009 and Later, Only	IV Coef.	0.170	0.232**	-23,339**	0.0213	1.274	0.200	-6,041	11,809
		t-stat	(1.63)	(2.28)	(-2.12)	(0.74)	(0.53)	(1.12)	(-1.10)	(0.22)
		D.V. Avg.	0.4547	0.4241	223,662	63.10%	0.90%	0.2430	154,641	218,978
(H)	Largest Decile Servicers Only	IV Coef.	0.138***	0.116***	-22,532***	0.0454**	1.734**	0.0815*	-12,602***	-7,974**
		t-stat	(4.93)	(5.06)	(-3.69)	(2.38)	(2.40)	(1.96)	(-3.06)	(-2.11)
		D.V. Avg.	0.3158	0.4020	182,464	68.06%	1.12%	0.3524	122,816	168,722
(I)	Largest Decile Subsidiary Servicers Only	IV Coef.	0.126***	0.111***	-19,201**	0.0314*	2.055*	0.103	-8,632***	-10,860**
		t-stat	(4.19)	(3.49)	(-3.13)	(2.11)	(1.87)	(1.56)	(-3.69)	(-2.43)
		D.V. Avg.	0.2900	0.3686	197,739	66.98%	1.06%	0.3236	130,879	172,974
(J)	2-Month Self Cure	IV Coef.	0.140***	0.116***	-22,461***	0.0426**	1.917***	0.0882**	-11,689***	-7,970**
		t-stat	(5.32)	(5.39)	(-4.00)	(2.47)	(2.82)	(2.24)	(-2.97)	(-2.09)
		D.V. Avg.	0.2898	0.3980	184,870	67.99%	1.13%	0.3372	124,840	172,284
(K)	1-Month Self Cure	IV Coef.	0.138***	0.115***	-22,679***	0.0388**	2.247**	0.114**	-11,297***	-9,592**
		t-stat	(5.33)	(5.29)	(-4.00)	(2.34)	(2.60)	(2.45)	(-2.79)	(-2.09)
		D.V. Avg.	0.2569	0.3967	184,299	67.96%	1.07%	0.3182	127,014	178,181
(L)	Exclusion not Winsorization	IV Coef.	0.126***	0.104***	-19,900***	0.0348**	1.724**	0.0713**	-9,665***	-6,924**
		t-stat	(5.37)	(5.46)	(-4.02)	(2.54)	(2.88)	(2.03)	(-3.16)	(-2.07)
		D.V. Avg.	0.3130	0.3980	185,333	67.94%	1.16%	0.3497	123,885	168,153
(M)	Srvcr-Zip-CreditCat and Year FE	IV Coef.	0.108***	0.0667***	-15,874***	0.0401**	1.225**	0.0691	-8,255**	710.7
		t-stat	(3.84)	(3.17)	(-3.92)	(2.23)	(2.16)	(1.45)	(-2.04)	(0.11)
		D.V. Avg.	0.3145	0.3992	185,112	67.90%	1.09%	0.3393	122,675	170,431
(N)	Srvcr-Year and Zip-CreditCat FE	IV Coef.	0.115***	0.0710**	-18,313***	0.0378**	1.760***	0.0669*	-4,615	145.3
		t-stat	(3.34)	(2.09)	(-3.60)	(2.04)	(3.56)	(1.69)	(-1.22)	(0.03)
		D.V. Avg.	0.3129	0.4894	184,432	67.38%	1.22%	0.3463	122,917	162,563
(O)	Issuer Fixed Effects	IV Coef.	0.132***	0.105***	-19,442***	0.0377**	1.684***	0.0511*	-9,955***	-9,530***
		t-stat	(5.04)	(4.87)	(-3.99)	(2.30)	(3.84)	(1.97)	(-2.79)	(-3.02)
		D.V. Avg.	0.3135	0.3986	185,130	68.03%	1.16%	0.3498	123,560	168,094

Table A.3
Capacity Constraints and Servicer Learning

This table reports, in columns one, four, and seven, regressions identical to the third column of Tables 3, 4, and 5, respectively. The second, fifth, and eighth columns mimic the first, fourth, and seventh respectively, leaving out only the control variable associated with the "1-Year Change in Delinquency Count" measured at the servicer level at the time of borrower first delinquency. The third, sixth, and ninth columns also mimic the first, fourth, and seventh respectively, but replace the "1-Year Change in Delinquency Count" measured at the servicer level at the time of borrower first delinquency with the count of Delinquent loans in the servicer's portfolio at the time of loan first delinquency, and at 1-year lags going out to three years. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Intervention			Ultimately Foreclosed			Investor NPV		
	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	0.141***	0.140***	0.141***	0.117***	0.117***	0.135***	-22,298**	-21,548***	-22,043***
	(5.30)	(5.16)	(5.12)	(5.45)	(5.46)	(4.86)	(-4.01)	(-3.60)	(-4.28)
1-Year Zip Housing Price Return	-0.470***	-0.474***	-0.462***	-0.401***	-0.402***	-0.453***	59,198***	61,838***	53,426***
	(-10.70)	(-10.45)	(-8.84)	(-5.47)	(-5.50)	(-6.83)	(3.29)	(3.47)	(2.79)
1-Year Change in Delinquency Count	3.99e-07*			9.49e-08			-0.225**		
	(1.91)			(0.38)			(-2.52)		
Servicer Delinquency Count At Loan First DQ			4.66e-07			2.03e-07			-0.218***
			(1.15)			(0.80)			(-3.25)
Servicer Delinquency Count One Year Prior to First DQ			-6.51e-07			-8.85e-07**			0.141**
			(-1.10)			(-2.47)			(2.30)
Servicer Delinquency Count Two Years Prior to First DQ			4.16e-07			-2.36e-07			0.0773
			(1.35)			(-0.59)			(0.75)
Servicer Delinquency Count Three Years Prior to First DQ			-1.73e-07			6.09e-07***			-0.0280
			(-0.79)			(2.70)			(-0.31)
Loan/Borrower Characteristic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Year-CreditCat FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Servicer and Zip Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,868,451	6,868,451	6,490,005	6,868,451	6,868,451	6,490,005	6,868,451	6,868,451	6,490,005
adj. R^2	0.213	0.214	0.212	0.237	0.237	0.224	0.825	0.825	0.822

Table A.4

Trimmed Sample Linear Probability Model

This table reports regression results from an alternative procedure for estimating a linear probability model that reduces the bias associated with fitted value lying outside of the unit interval. The first column reports exactly the result from column three of Table 4, while column two reports the result related to iteratively excluding all observations associated with fitted values that lie outside of $[0, 1]$ and re-estimating the instrumental variables specification until all fitted values lie within the interval correctly interpretable as a probability. Values of the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure have been standardized for the sample utilized in each regression so that coefficient estimates are in units per standard deviation change in servicer financial constraints. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ultimately Foreclosed	
	Full IV	Trimmed IV
	(1)	(2)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	0.117***	0.128***
	(5.45)	(5.46)
1-Year Zip Housing Price Return	-0.401***	-0.476***
	(-5.47)	(-5.65)
1-Year Change in Delinquency Count	9.49e-08	1.74e-08
	(0.38)	(0.06)
Loan/Borrower Characteristic Controls	Yes	Yes
Servicer FE	Yes	Yes
Zip-Year-CreditCat FE	Yes	Yes
Servicer and Zip Clustering	Yes	Yes
N	6,868,451	5,913,869
adj. R^2	0.237	0.166
Dependent Variable Average	0.3986	0.4372

Table A.5

Terminal Value Haircut Sensitivity

This table reports results similar to that of column three in Table 5 but varies the haircut methodology utilized for the calculation of the investor NPV. When a loan is still active as of the end of the sample period, December 2015, remaining investor cashflows are calculated utilizing the present value of an annuity of the principal and interest payment due in the final observable month for the number of payments remaining in the life of the loan. A haircut is applied if the loan is delinquent, in bankruptcy or foreclosure, or has been previously foreclosed and is thus in a "real estate owned" status. The principal specification of the paper, reported in bold in specification (6), utilizes a 50% haircut for all default buckets. Specifications (1)-(11) report various fixed haircuts applied uniformly across all default buckets. The remainder of the specifications, (12)-(28), vary the haircut across default buckets, maintaining a strictly increasing relationship in the haircut with the severity of the default status. IV coefficients and *t*-stat values relate to the "1-Year Change in Advances as a Percentage of Loan Portfolio Balance" measure and have been standardized for the sample utilized in each regression. Reported *t*-statistics in parentheses are heteroskedasticity-robust and separately clustered at the servicer and zip level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Terminal Value Haircut				IV		Dependent
	DQ	BK	FC	REO	Coefficient	t-stat	Variable Average
(1)	100%	100%	100%	100%	-23,170***	(-3.89)	182,400
(2)	90%	90%	90%	90%	-22,996***	(-3.91)	182,946
(3)	80%	80%	80%	80%	-22,821***	(-3.94)	183,492
(4)	70%	70%	70%	70%	-22,647***	(-3.96)	184,038
(5)	60%	60%	60%	60%	-22,473***	(-3.98)	184,584
(6)	**50%**	**50%**	**50%**	**50%**	**-22,298*** **	**(-4.01)**	**185,130**
(7)	40%	40%	40%	40%	-22,124***	(-4.03)	185,677
(8)	30%	30%	30%	30%	-22,647***	(-3.96)	184,038
(9)	20%	20%	20%	20%	-22,473***	(-3.98)	184,584
(10)	10%	10%	10%	10%	-22,298***	(-4.01)	185,130
(11)	0%	0%	0%	0%	-22,124***	(-4.03)	185,677
(12)	0%	10%	20%	30%	-21,681***	(-4.10)	187,171
(13)	10%	20%	30%	40%	-21,855***	(-4.08)	186,625
(14)	20%	30%	40%	50%	-22,030***	(-4.05)	186,079
(15)	30%	40%	50%	60%	-22,204***	(-4.03)	185,533
(16)	40%	50%	60%	70%	-22,378***	(-4.01)	184,987
(17)	50%	60%	70%	80%	-22,553***	(-3.98)	184,441
(18)	60%	70%	80%	90%	-22,727***	(-3.96)	183,894
(19)	70%	80%	90%	100%	-22,901***	(-3.93)	183,348
(20)	0%	20%	40%	60%	-21,935***	(-4.07)	186,481
(21)	10%	30%	50%	70%	-22,099***	(-4.05)	185,986
(22)	20%	40%	60%	80%	-22,284***	(-4.03)	185,389
(23)	30%	50%	70%	90%	-22,458***	(-4.00)	184,843
(24)	40%	60%	80%	100%	-22,633***	(-3.98)	184,297
(25)	0%	30%	60%	90%	-22,190***	(-4.05)	185,792
(26)	10%	40%	70%	100%	-22,364***	(-4.02)	185,246
(27)	0%	25%	50%	75%	-22,063***	(-4.06)	186,137
(28)	25%	50%	75%	100%	-22,498***	(-4.00)	184,771

Table A.6

Servicer Summary Statistics

This table reports summary statistics at the servicer level. The left half of the table reports results relating to the 231 servicers contained in the sample of BlackBox loans that went delinquent, while the right half relates to the 210 servicers that are present in the main regressions specifications of the paper. Servicers are excluded because the fixed effect estimation procedure utilized drops singleton fixed effect observations. With the exception of Loan Count, Total Loan Amount, State Count, and Zip Count, all statistics are reported measures relating to the average value at the servicer level.

	Full Sample (231 Servicers)					Regression Sample (210 Servicers)				
	Mean	Median	St. Dev.	10^{th}%	90^{th}%	Mean	Median	St. Dev.	10^{th}%	90^{th}%
Loan Count	82,237	175	322,774	8	143,061	91,560	268	337,469	10	161,614
Total Loan Amount	18.9 billion	17.1 million	75.2 billion	507,750	28.5 billion	20.8 billion	57.5 million	78.7 billion	666,462	35.3 billion
Average Loan Amount	193,965	139,351	169,286	45,136	416,275	194,424	150,258	160,363	46,631	413,330
Avg Note Date	10/1/2004	10/30/2005	27 mos, 9 days	6/23/2001	1/24/2006	9/2/2004	9/28/2005	28 mos, 6 days	3/27/2001	1/24/2006
Avg Note Rate	9.23%	8.72%	2.82%	5.74%	12.90%	9.11%	8.59%	2.75%	5.71%	12.69%
Avg Credit Score	692.54	700.37	40.46	627.62	739.69	691.84	699.68	39.27	628.65	735.39
Avg LTV	81.70	77.85	15.19	66.22	98.55	81.00	76.68	15.15	65.83	98.49
Avg Adjustable Rate	0.32	0.17	0.35	0.00	0.84	0.34	0.24	0.35	0.00	0.85
Avg Owner Occupied	0.48	0.67	0.42	0.00	0.94	0.50	0.70	0.41	0.00	0.94
Avg Purchases	0.25	0.24	0.25	0.00	0.56	0.26	0.27	0.24	0.00	0.56
Avg Single Family	0.63	0.67	0.20	0.36	0.84	0.64	0.67	0.19	0.36	0.83
Avg Full Documentation	0.17	0.03	0.24	0.00	0.49	0.17	0.05	0.23	0.00	0.49
Avg Prime	0.65	0.72	0.30	0.17	0.99	0.64	0.71	0.29	0.18	0.97
Avg Alt-A	0.15	0.13	0.12	0.00	0.32	0.15	0.14	0.12	0.00	0.31
Avg Subprime	0.16	0.02	0.26	0.00	0.57	0.16	0.02	0.25	0.00	0.57
State Count	24.5	15.0	21.0	2.0	51.0	26.7	20.5	20.8	2.5	51.0
Zip Count	3,914	120	6,805	7	14,705	4,304	189.5	7,020	9	15,892

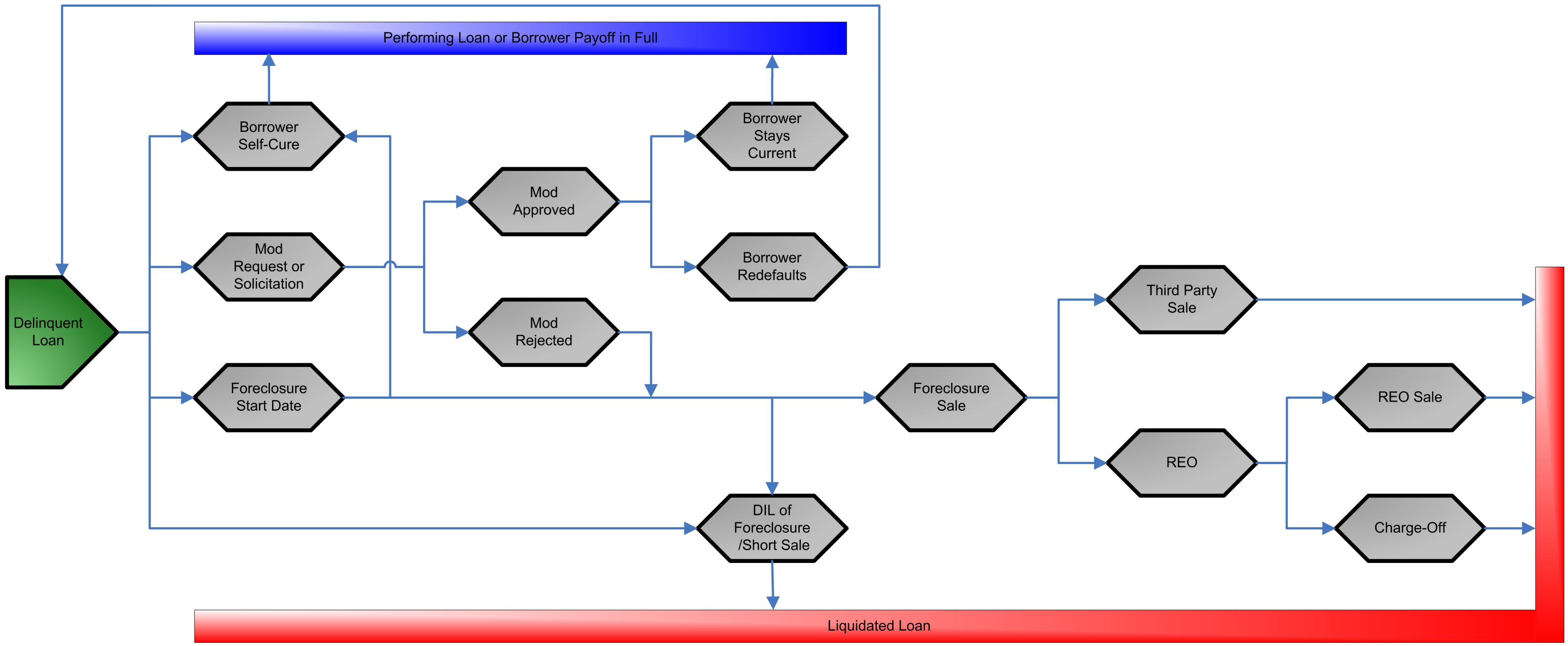

Figure A.1. Loss Mitigation Process This figure presents a flowchart representation of the loss mitigation process. The flow starts on the far left with the green arrow labeled "Delinquent Loan." A loan that is delinquent eventually ends up either becoming current again, represented by the blue box, or being liquidated, represented by the red box.