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Three Essays Concerning the Financial Economics of Mortgage Markets

A dissertation submitted in partial satisfaction
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by

Darren James Aiello

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Abstract of the Dissertation

Three Essays Concerning the Financial Economics of Mortgage Markets

by

Darren James Aiello

Doctor of Philosophy in Management

University of California, Los Angeles, 2018

Professor Mark J. Garmaise, Chair

In the first chapter of this dissertation, I find that financially constrained mortgage servicers destroyed substantial MBS investor value during the financial crisis through their management of delinquent mortgages. Servicers have a contractual obligation to advance to the investors any monthly payments missed by borrowers. This chapter shows that, in order to minimize this obligation to extend financing to distressed borrowers, constrained servicers aggressively pursued additional foreclosures and modifications at the expense of MBS investors, borrowers, and future mortgage performance. IV regressions suggest that servicers' financial constraints caused 440,712 additional foreclosures. A one standard deviation increase in servicer financial constraints led to an average reduction in investor value of $22,298 per loan—causing aggregate investor value destruction of $84 billion.

In the second chapter of this dissertation, I describe an important borrower risk factor observed privately by the issuer of non-agency RMBS. The private information available to the issuer is drawn from behavioral cues exhibited early in the life of the loan. Mortgage borrowers that make their first six payments at least a day prior to the due date are 14.8 percentage points less likely to become delinquent (equivalent to a 91-point increase in FICO score). This effect is persistent, unobservable at loan origination, and privately observed by

the issuer prior to securitization. Both the credit rating agencies and the investor do not appear to be aware of this risk factor. Surprisingly, issuers are quicker to securitize loans with positive private signals rather than less promising loans.

In the final chapter of this dissertation (with Mark J. Garmaise and Gabriel Natividad), we analyze competitive dynamics in the mortgage market. Using discontinuities in mortgage acceptance models to generate shocks to a bank's current local lending, we show that future applicants are attracted to growing lenders. Local mortgage markets resemble tournaments: a bank's originations are reduced by the lending of its quickest-growing competitors, not that of its overall competitors nor of its largest competitors. Moreover, future lending activity is convex in current originations. Tougher competition leads a bank to charge higher interest rates, partially due to the increased risk of its loans, and results in worse mortgage performance.

The dissertation of Darren James Aiello is approved.

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2018

To Mandy,

I could not ask for a better partner, friend, or wife than who you have proven yourself to be;

to James, Peter, John, Charlotte, and Madison,

for your sacrifices, your respect, and—above all—your love;

and to my mother and father,

for laying the best foundation, and providing the most support, I could ask for.

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CHAPTER 1

Value Destruction and Aggressive Foreclosures: The Behavior of Financially Constrained Mortgage Servicers

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. This chapter 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.

This chapter 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 of the approximately 2.7 million U.S. homes foreclosed in my sample, or about 16%. These are foreclosures performed on borrowers that, in the absence of the effect of servicer financial constraints, would have self cured or refinanced or sold the property.

In addition to studying the behavior of an important intermediary during the crisis, this chapter 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. For every one standard deviation increase in mortgage servicer financial constraints at the time of borrower first delinquency, $22,298 in investor value was destroyed per defaulted loan with average balances of $243,996 at default. The financial constrainedness of mortgage servicers destroyed at least $84 billion of investor value on defaulted loans with original balances totaling $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 servicer financial constraints. Constrained servicers offered generous terms to increase the likelihood of a borrower agreeing to modify. Overall, for each standard deviation increase in servicer financial 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 chapter, 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 undertaken in order to "improve the servicers' ability to work with homeowners to prevent avoidable foreclosures" (Federal Reserve Board, 2009). This action shows that the Fed believed servicing advances to be an important measure of constraints and posits a relationship between financial constraints and the loss mitigation actions of servicers.

A number of major econometric challenges confound the identification of a causal link

[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.

between servicer financial constraints and default outcomes. First, this chapter 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 both the level of servicer advances as well as 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.

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, Mark J. 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.

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.

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; Esty, 1997b) and the effects that regulatory induced financing constraints have on insurance companies (Lee, Mayers, and Smith, 1997; Ellul, Jotikasthira, and Lundblad, 2011; Merrill et al., 2014; Koijen and Yogo, 2014). This chapter also attempts to directly measure the magnitude of a realized agency cost. J. S. 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, A. Ang et al. (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 (L. Cordell et al., 2008; Herndon, 2017; Mooradian and Pichler, 2017; Huang and Nadauld, 2017). However, this chapter is the first to demonstrate the relationship between a servicer's financial constraints and the realized agency costs borne by the investor.

This chapter 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. 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 P. S. 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 et al., 2014; Mian, Sufi, and Trebbi, 2015; S. A. Gabriel, Iacoviello, and Lutz, 2016; Agarwal, Amromin, Ben-David, Chomsisengphet, Piskorski, 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 P. S. Willen, 2013; Kruger, 2017)—or doesn't (Adelino, Gerardi, and P. 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 chapter examines, conditional on securitization, how the financial constrainedness of the servicer influences the agency frictions associated with its decisions in regards to a delinquent borrower.

The remainder of the chapter proceeds as follows. Section 1.1 introduces the data and Section 1.2 provides industry context. Section 1.3 elucidates the identification strategy and Section 1.4 examines my central findings. Section 1.5 concludes.

1.1 Data

The loan data in this chapter 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 1.1 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 chapter.

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

[4]Appendix Section 1.6.4 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 1.6.5 for robustness results relating to the 3-month definition of self cure.

loans. The first column of Panel A of Table 1.1 contains the mean value for various loan level measures within the overall BlackBox population 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 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 1.1 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 1.3.4) are reported as well. Panel C of Table 1.1 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 1.7 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

[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.

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.

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[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

1.2 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 1.4 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

[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.

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 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.

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.[14]

[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]Appendix Section 1.6.4 demonstrates robustness result restricting attention to subsamples of just the largest servicers, and then separately the largest servicers that were subsidiaries of broader financial institu-

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 chapter 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 measures the proximity to his contemporary leverage constraint.

Figure 1.2 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.[15] The investor "buys" more of that borrower's loan and pays[16] the servicer who recovers his advances. The borrower

tions.

[15]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.

[16]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

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.

1.2.1 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.[17] Because of data quality issues, the loan-month outstanding advance distribution is winsorized (right tail only) at the 0.01% level. Appendix Section 1.6.6 reports robustness results relating to the winsorization assumptions.

These loan level servicing advances are summed, for each month, to the servicer level[18] to

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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

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

[18]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

calculate $Advances_{t,s}$, representing the outstanding servicing advances in month t for servicer s.[19] $Advances_{t,s}$ 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,

$$AdvFrac_{t,s} = \frac{Advances_{t,s}}{PortfolioBalance_{t,s}} \tag{1.1}$$

Actual balance scaled servicer-month outstanding servicing advances, $AdvFrac_{t,s}$, are then winsorized at the 1% level in the right tail. Appendix Section 1.6.6 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,

$$\begin{aligned} \Delta AdvFrac_{t,s} &= AdvFrac_{t-1,s} - AdvFrac_{t-12,s} \\ &= \frac{Advances_{t-1,s}}{PortfolioBalance_{t-1,s}} - \frac{Advances_{t-12,s}}{PortfolioBalance_{t-12,s}} \end{aligned} \tag{1.2}$$

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 (L. Cordell et al., 2008).

[19]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.

1.3 Empirical Strategy

The principal empirical specifications of this chapter examines the effect that a change in a servicer's advance balance over the prior year has on decisions made by the servicer and the results of those decisions. Endogeneity concerns relating to this question are detailed below.

First, this chapter argues that the observed servicer behavior is consistent with a servicer acting to minimize his servicing advance obligation. Reverse causality is a concern in that a servicer that is implementing a policy to actively minimize its advances will have lower advances. Thus an OLS specification showing that a servicer that has more advances but is also intervening more aggressively will tend to understate the causal channel from advances to policy. In short, the servicer's level of advances are endogenous to servicer actions.

Second, a change in servicing advances is likely to be informative to the servicer about the quality of his portfolio and cause him to adjust his behavior as he learns about his type. Similarly, a servicer's burgeoning advance obligation provides possible information regarding the quality of the servicer himself, inferring outcomes related to his behavior and loss mitigation performance.

Finally, an omitted variable of a particular macroeconomic or regulatory condition could drive the advances outstanding for a particular servicer as well as impact the ideal loss mitigation strategy (or the effectiveness thereof) for a particular loan.

I construct plausibly exogenous variation in servicer financial constraints by utilizing servicer portfolio housing price returns in geographies far removed from the focal loan. The overall housing price return of a servicing portfolio forms a large part of the variation in advances outstanding. In order for the exclusion restriction to hold, the instrument will ignore the portion of the servicer's portfolio in the Core-Based Statistical Area where the focal loan resides. The housing price return for the zip code of the focal loan, as well as zip-year-credit category and servicer level fixed effects are included as controls. Exogenous variation in servicing advances is then driven by servicers experiencing higher exposure to exogenous housing price returns.

Given the interacted fixed effect, the empirical specification compares two loans that defaulted in the same zip code in the same calendar year and were of the same credit quality (Prime, SubPrime, Alt-A), that differed only in the amount of servicing advances made by the loan's servicer(s) over the prior year. A servicer's propensity towards taking default actions and it's average ex-post performance level, irrespective of its time-varying level of financial constrainedness, is also removed from the analysis via a second dimension of fixed effects at the servicer level.

The identifying assumption can then be stated as: 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 default outcomes except via its effect on the servicing advances outstanding and balance sheet of the servicer. A violation of the exclusion restriction would require that, when examining loan outcomes or loss mitigation decisions that the servicer makes for a loan in a particular locality, the housing price return in a geography far removed from the focal loan where this particular servicer happens to have a large servicing presence is informative above and beyond the housing price return in the particular zip code in which the focal loan resides.

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 1.4.7 reports results that lessen the likelihood of this being true.

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 1.6.3 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.

It is likely 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.

It is also true that strategic defaulters, borrowers that are defaulting in response to their property being underwater in order to receive a modification, are possibly driving my first stage effect. It is not true that my effect is local to a servicer's response to a strategic defaulter due to the geographic holdout nature of my instrument. The instrument is providing variation in servicer advances from borrowers in a different geography than the focal loan. The only remaining channel is the possibility that a servicer, upon observing a high incidence of strategic default elsewhere in his portfolio is learning about the likelihood of dealing with a strategic defaulter in either his portfolio or in general. Given that a strategic defaulter, by definition has a higher ability to repay his mortgage than a non-strategic defaulter, and most likely owes more than the property is worth, we would expect to see a servicer's rational response to a strategic defaulter to be an increase in modifications and a reduction in foreclosures. Given that my principle result is driven largely by a significant increase in the hazard rate of foreclosure, it is unlikely that this is a story about servicer's responses to strategic default.

1.3.1 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[20] 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

$$OneMonthSvcrPortHPR_{t,g(i),s(i)} = \frac{\sum_{z \notin g(i)} ZipHPRet_{t,z} \cdot SvcrPortSchedBal_{t,z,s(i)}}{\sum_{z \notin g(i)} SvcrPortSchedBal_{t,z,s(i)}}, \tag{1.3}$$

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

$$SvcrPortHPR_{t,g(i),s(i)} = \sum_{n=1}^{12} OneMonthSvcrPortHPR_{t-n,g(i),s(i)}, \tag{1.4}$$

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)".

1.3.2 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

[20] 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.

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 $s(i)$,

$$\begin{aligned} \Delta AdvFrac_{t,s(i)} = \beta_{FS} \cdot SvcrPortHPR_{t,g(i),s(i)} + \gamma_1 \cdot ZipHPRet_{t,z(i)} \\ + \gamma_2 \cdot \Delta DQCount_{t,s(i)} + \gamma_3 \cdot controls_i + \epsilon_i \end{aligned} \tag{1.5}$$

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 $g(i)$.[21] Controls 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) 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.[22]

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

[21] This is the instrument used in the principal empirical specifications throughout this chapter. Robustness to various aspects of instrument design are examined in Appendix Section 1.6.2.

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

form equation,

$$Y_i = \beta_{RF} \cdot SvcrPortHPR_{t,g(i),s(i)} + \gamma_7 \cdot ZipHPRet_{t,z(i)} + \gamma_8 \cdot \Delta DQCount_{t,s(i)} + \gamma_9 \cdot controls_i + \mu_i. \tag{1.6}$$

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,

$$Y_i = \beta_{IV} \cdot \Delta \widehat{AdvFrac}_{t,s(i)} + \gamma_4 \cdot ZipHPRet_{t,z(i)} + \gamma_5 \cdot \Delta DQCount_{t,s(i)} + \gamma_6 \cdot controls_i + \nu_i. \tag{1.7}$$

Here $\Delta \widehat{AdvFrac}_{t,s(i)}$ is the fitted value from Equation 1.5 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 1.5 and 1.6 respectively, to obtain,

$$\beta_{IV} = \frac{\beta_{RF}}{\beta_{FS}} \tag{1.8}$$

The outcomes of interest, represented by Y_i in the above equations, vary throughout the chapter. Sections 1.4.1, 1.4.2, and 1.4.5 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), Mark J 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 1.4 (column two), 93.19% lay within the proper interval.[23] Horrace and Oaxaca (2006) suggest a trimmed sample estimation procedure. Appendix Section 1.6.7 reports the results of this procedure as applied to the regression specification in column two of Table 1.4. 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."

1.3.3 First Stage Results

The first column of Table 1.2 presents results relating to the first stage estimate of Equation 1.5 in the sample appropriate for the regression estimates used throughout this chapter. 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

[23] 394,878 (5.75%) such that $\hat{y} < 0$ and 73,081 (1.06%) such that $\hat{y} > 1$.

the instrument into the regression estimated with Equation 1.5, 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 1.2 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 1.2). While Equation 1.8 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 1.2 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.

1.3.4 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.[24] The net present value to the investor of a servicer's action is calculated by discounting the monthly loan level cashflows

[24]The NPV to the investor remains the focus of this chapter 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.

to the investor back to the last current payment before the qualifying delinquent episode.[25] Monthly investor cashflows at the loan level are calculated by adding the monthly interest payment[26] 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 1.6.1 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 1.6.8 for robustness results.).

Figure 1.3 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 1.2. In the second scenario in Figure 1.3, 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 right scenario of Figure 1.2. 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

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

[26]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.

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 1.2. 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.

1.4 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 1.4.1 and 1.4.2 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 1.4.3 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 1.4.4 and 1.4.5 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 1.4.6 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 1.4.3). What financially constrained servicers did that was most harmful to investors was to intervene at all.

Finally, Section 1.4.7 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.

1.4.1 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 1.3 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 1.3 reports results relating to the estimation of Equation 1.6 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 1.3 reports the IV estimate as in Equation 1.7 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 1.3, 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 1.1 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.[27] 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 1.3 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,

[27]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 chapter.

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.

1.4.2 Ultimate Outcomes

Section 1.4.1 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 1.4 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 1.4, directly on the measure of servicer financial constrainedness at the time of the borrowers first 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 1.3, column two reports results relating the estimation of Equation 1.6 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 1.4 sample, 2,737,712 (39.86%) were ultimately foreclosed.[28] 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 his loan in full, or bring himself current.[29] The magnitude of the foreclosure externality

[28] 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.

[29] 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

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.

1.4.3 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 1.3.4 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.[30] The magnitude of this realized agency cost, however, is also influenced by the poor state realization of the economy.

Table 1.5 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 1.5 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 1.3, in order to measure the

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).

[30]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.

causal effect an instrumental variables specification must be found. The second and third columns of Table 1.5 estimate Equations 1.6 and 1.7 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 1.1). 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 1.5 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. For these 6,868,451 loans the average level of the increase in the servicing advances measure of financial constraints is 0.00423557, implying \$83.98 billion in aggregate investor value destruction.

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 (1.8%) 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.

1.4.4 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.[31] 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[32] 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 1.6 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 1.4.6 will investigate this more rigorously by utilizing the investor net present value calculated at the time of first default. This method will

[31] While Section 1.3 rules out the causal channel of capacity constraints for the main results in this chapter, 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.

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

encompass all potential aspects of value destruction that a financially constrained mortgage servicer's decisions can entail.

1.4.5 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,[33] 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 1.7 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,[34] column one estimates Equation 1.8 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 1.7 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

[33] 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 reperform and reduces the likelihood of redefault.

[34] 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 1.7.

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 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 L. R. Cordell, 2017) for modification success rates during the crisis.

The third, fourth, and fifth columns of Table 1.7 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 1.8 at the level of a modified loan utilizing a binary[35] 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

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[35] See Section 1.3.2 for a discussion of the challenges inherit in the estimation of a linear probability model.

regarding the modification terms provided or actions performed by financially constrained servicers that remains unobserved.[36] Table 1.8 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 1.3 and 1.7 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 Table 1.3 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.

1.4.6 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 1.6 and 1.4.5 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.[37] This section demonstrates that, conditional on a loan being either foreclosed or modified, greater levels

[36] 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.

[37] This chapter 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.

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 1.1 relates summary statistics conditional on various loan outcome dimensions.

Table 1.8 reports results relating to the causal impact of servicer financial constraints on investor net present value, conditional on the action the servicer took. Section 1.4.4 demonstrated that foreclosures by financially constrained servicers had higher overall loss severity than those done by unconstrained servicers. The first column of Table 1.8 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 1.4.5 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 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 1.8 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 1.8 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,[38] the outcome of these types of liquidations is largely invariant to the particular actions of the servicer.

1.4.7 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.[39] 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 1.9 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 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

[38]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.

[39]DeMarzo (2005), Begley and Purnanandam (2017), Aiello (2016), 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.

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 1.9 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.

1.5 Conclusion

This chapter 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.

1.6 Robustness Appendix

1.6.1 Discount Rate Sensitivity

Throughout this chapter, 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, S. 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 1.10 reports results from a series of instrumental variable specifications each similar to that found in Table 1.5, 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 chapter 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 1.5. The top portion of Appendix Table 1.10 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 1.10 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.

1.6.2 Geographic Holdout Sensitivity

The instrument used in the main specifications throughout the chapter 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 1.11 demonstrate robustness of the instrumental variables specifications found throughout the chapter 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 1.7 and column one of Table 1.8. Overall, these results support the notion that a holdout at some geographic level is important for a well-functioning instrument.

1.6.3 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 1.3 this remains unlikely due to the direction of my main results (i.e. Table 1.3), I include throughout the chapter the change in the count of servicer portfolio delinquencies for the year prior to loan delinquency as a control.

Appendix Table 1.12 demonstrates robustness to excluding this control by replicating column three of Tables 1.3, 1.4, and 1.5 in columns one, three, and five, respectively. Columns two, four, and six of Appendix Table 1.12 then duplicate these results excluding the control. 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 these 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.

1.6.4 Sample Definition

Regression specification (E) in Appendix Table 1.11 tests the major results of the chapter (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 1.11 tests the major results of the chapter, 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 1.11. 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 1.11 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.

Regression specification (H) in Appendix Table 1.11 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 or larger financial institutions. The fact that these servicers still responded to their financial constraints in the manner described in the chapter suggests that local subsidiary level, internal capital market, constrainedness is important to the decision making process of those managers.

1.6.5 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 1.11 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.

1.6.6 Winsorization

In Section 1.2.1 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 1.11

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.

1.6.7 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 1.13 duplicates the results of the instrumental variables specification, Equation 1.7, of the third column of Table 1.4. The second column of Appendix Table 1.13 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.

1.6.8 Terminal Value Haircut Sensitivity

In the calculation of investor net present value, as detailed in Section 1.3.4, 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 1.14 details results relating to the sensitivity of the headline NPV result of the third column of Table 1.5 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 chapter 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 1.14) 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.

1.7 Servicer Summary Statistics Appendix

Appendix Table 1.15 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 1.3, 1.4, and 1.5. 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 1.15 demonstrates the significant level of heterogeneity in the size, risk profile, and geographic dispersion of the mortgage servicers in sample.

Table 1.1
Summary Statistics

This table reports summary statistics relating to the loan population utilized in this chapter. The first column of Panels A and B report results relating to the population of BlackBox loans. 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	Sample Mean	Median	Std. Dev.	10^{th}%	90^{th}%
Original Loan Amount	221,328	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	5/14/2004	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	7.62%	7.32%	7.13%	2.59%	4.75%	10.65%
Credit Score	670.26	668.84	670.00	68.64	576.00	761.00
LTV	70.21	72.02	80.00	22.44	26.70	95.00
Adjustable Rate	0.53	0.63				
Owner Occupied	0.79	0.82				
Purchases	0.38	0.41				
Single Family	0.70	0.70				
Full Documentation	0.30	0.31				

Panel B

	BlackBox Proportion	Sample Proportion	Average Months to Completion	SD of Months to Completion	Average NPV	SD of NPV
Defaulted	0.812				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 1.2

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 chapter. 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 1.3

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 1.4

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 1.5
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 1.6

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 1.7

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 1.8

Conditional Investor Value

This table reports instrumental variable regression results similar to that of column three in Table 1.5 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 1.9

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

Table 1.10

Discount Rate Sensitivity

This table reports results similar to that of column three in Table 1.5 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 chapter. 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 1.11
Robustness

This table contains robustness results relating to various specification changes for the major results of the chapter. Row (A) contains the baseline specification utilized throughout the chapter. Columns one through eight report the results related to column three of Tables 1.3, 1.4, and 1.5, column one of Tables 1.6 and 1.7, column three of Table 1.7, and columns one and two of Table 1.8, respectively. See Appendix Section 1.6 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	Fixed Rate Mods, Interest Rate Reduc.	Modification 3mo Redefault	Foreclosure Investor NPV	Modification 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)
		Dep. Var. 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)
		Dep. Var. 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)
		Dep. Var. 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)
		Dep. Var. 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	-21163.0	0.286*	-0.300	-0.722	-49147.7*	-1538.1
		t-stat	(0.81)	(0.85)	(-0.99)	(1.85)	(-0.10)	(-1.60)	(-1.85)	(-0.51)
		Dep. Var. 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)
		Dep. Var. 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)
		Dep. Var. 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)
		Dep. Var. 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)
		Dep. Var. 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)
		Dep. Var. 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)
		Dep. Var. 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)
		Dep. Var. Avg.	0.3130	0.3980	185,333	67.94%	1.16%	0.3497	123,885	168,153

Table 1.12

Capacity Constraints

This table reports, in columns one, three, and five, regressions identical to the third column of Tables 1.3, 1.4, and 1.5, respectively. The second, fourth, and sixth columns mimic the first, third, and fifth 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. 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
	(1)	(2)	(3)	(4)	(5)	(6)
1-Year Change in Advances as a Percentage of Loan Portfolio Balance	0.141***	0.140***	0.117***	0.117***	-22,298**	-21,548***
	(5.30)	(5.16)	(5.45)	(5.46)	(-4.01)	(-3.60)
1-Year Zip Housing Price Return	-0.470***	-0.474***	-0.401***	-0.402***	59,198***	61,838***
	(-10.70)	(-10.45)	(-5.47)	(-5.50)	(3.29)	(3.47)
1-Year Change in Delinquency Count	3.99e-07*		9.49e-08		-0.225**	
	(1.91)		(0.38)		(-2.52)	
Loan/Borrower Characteristic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Year-CreditCat FE	Yes	Yes	Yes	Yes	Yes	Yes
Servicer and Zip Clustering	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
adj. R^2	0.213	0.214	0.237	0.237	0.825	0.825

Table 1.13

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 1.4, 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 1.14

Terminal Value Haircut Sensitivity

This table reports results similar to that of column three in Table 1.5 but varying the haircut methodology utilized for the calculation of the investor net present value. 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 chapter, reported in bold in specification (6), utilizes a 50% haircut for all default buckets. Specifications (1) through (11) report various fixed haircuts applied uniformly across all default buckets. The remainder of the specifications, (12) through (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 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.

	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 1.15

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 chapter. 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

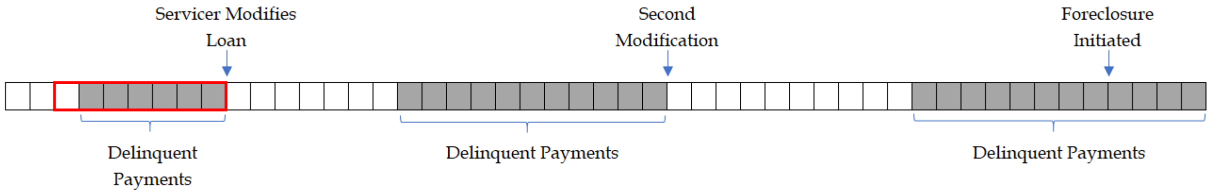

Figure 1.1. Illustrative Payment String in Data

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 1.4.2, 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 1.2. 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.

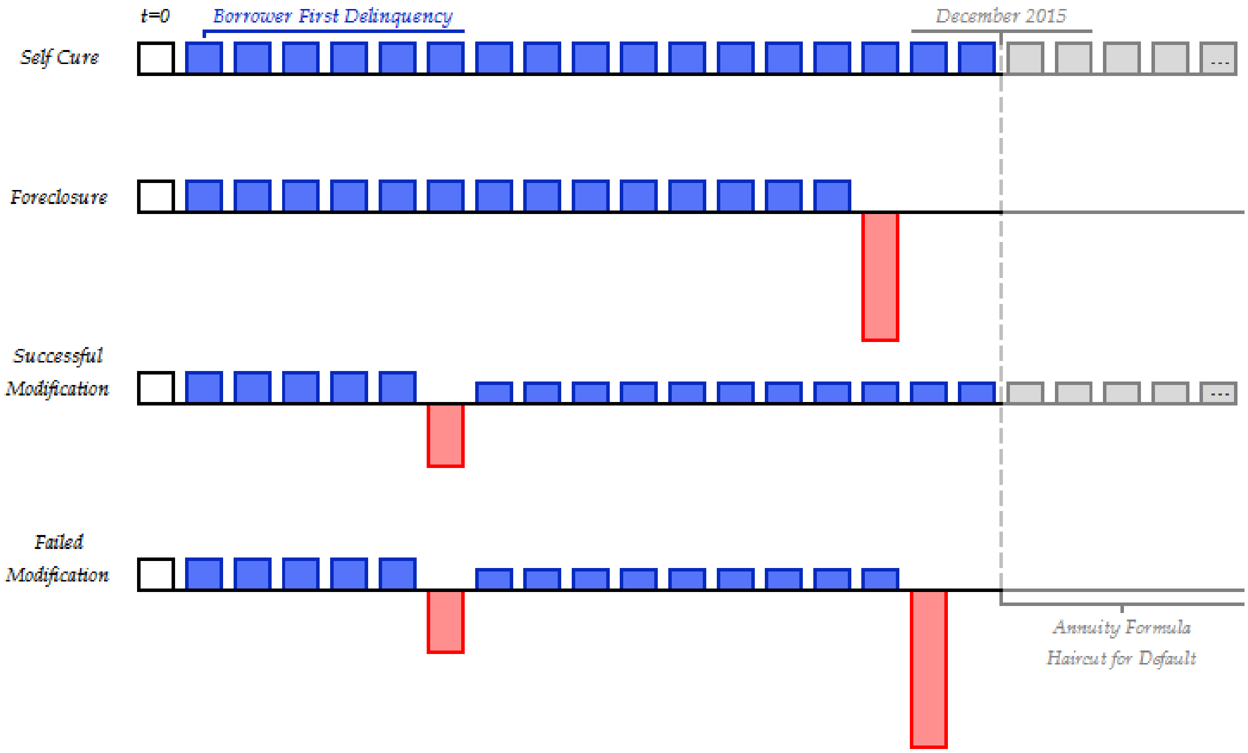

Figure 1.3. NPV Calculations

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.

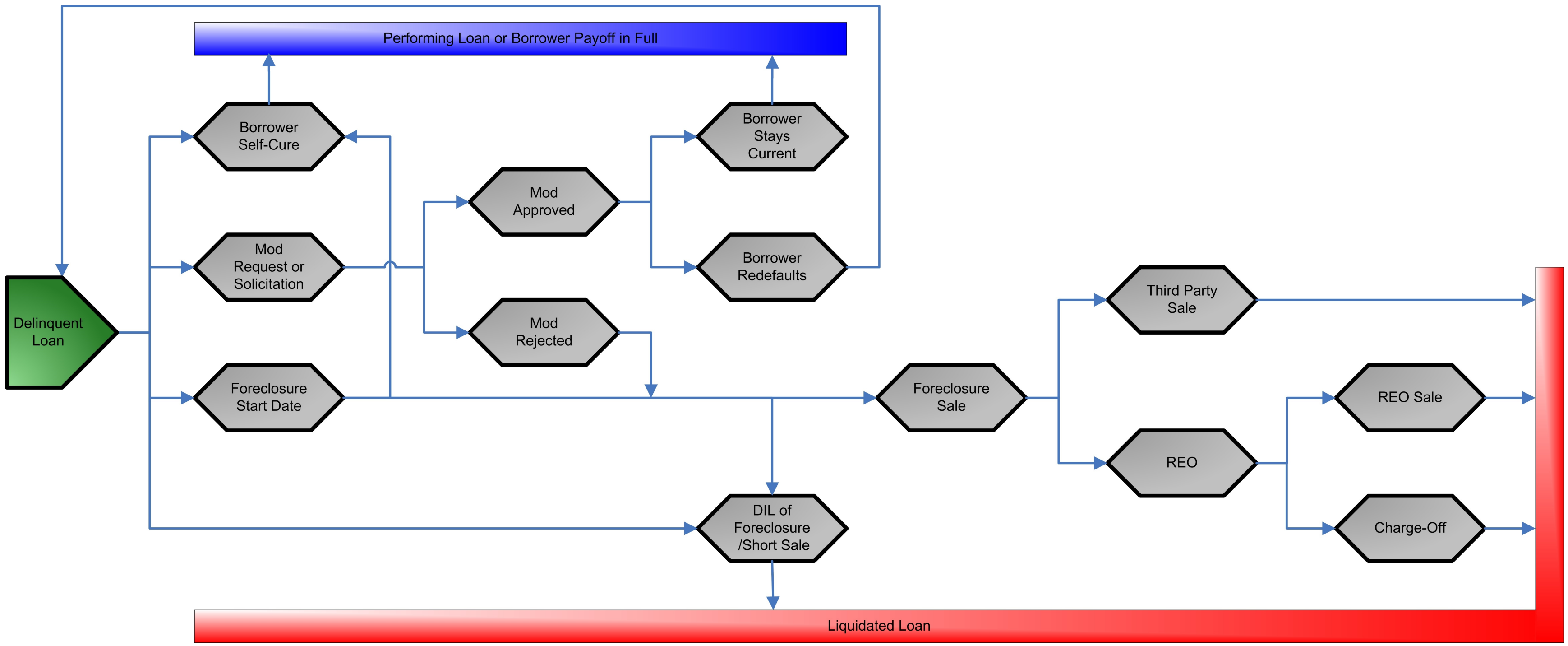

Figure 1.4. Loss Mitigation Process

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.

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CHAPTER 2

Information Exploitation? A Pre-Crisis RMBS Issuer's Private Information

Empirical studies describing the impact that asymmetric information has on the formation of contracts and the design of securities are relatively uncommon. In this chapter, I study the role of asymmetric information in the market for non-agency residential mortgage backed securities issued during the pre-crisis period. The prevailing opinion regarding pre-crisis RMBS issuers' expected behavior is that they happily exploited any available informational advantage. Their informational advantage stems largely from their proximity to the origination process and the richness of their data sources. I find evidence suggesting that we should consider more carefully the role that reputational concerns play in mitigating these asymmetric information problems.

The data in this study are from a U.S. financial institution that was engaged in the structuring and issuance of non-agency residential mortgage backed securities. Both loan and securitization level information contained in the disclosures to the investors prior to sale as well as post-issuance performance data are analyzed. Included loans have first payment due dates between January 1^{st}, 2004 and October 1^{st}, 2007 and cover a broad range of nonconforming credit qualities, mortgage instruments and geographies. Loan performance data is observed through the December 1^{st}, 2014 payment and is consistent with the performance of collateral of this quality and time period.

I begin by studying mortgage borrower behavior as it relates to the timing of when the borrower makes his payment. A borrower payment received by the mortgage servicer at least a day prior to the day on which it is actually due is strongly predictive of positive ex-post delinquency and default outcomes. Mortgage borrowers that make all of their first six payments in such a manner are 14.8 percentage points less likely to become delinquent than those that made none of them early. This is equivalent to a 91 point increase in FICO score.

This effect is extremely persistent. Those same first six payments are predictive of delinquency outcomes far into the future, even after conditioning on more than six years of consecutive current payments on the part of the borrower. This early payment behavior is consistent with the notion of an underlying borrower characteristic I call "diligence." I demonstrate that diligence is unobservable at origination and is observed privately by the issuer, via early payment behavior, prior to the loan being placed into a securitization. The exact timing of borrower payments is not a part of the information disclosed by the issuer to potential investors.

I then turn to the question of what the issuer did with this private information. I show that the issuer did not signal his private information by retaining a larger equity tranche in securitizations that exhibited higher levels of early payment behavior. Nor does it appear that the issuer was able to charge more for loans that exhibited this early payment behavior. In fact I am able to demonstrate that price is insensitive to the overall retention level, suggestive of an issuer that has a high reputation of honesty (Hartman-Glaser, 2013).

The issuer does, however, securitize loans faster that exhibit a pattern of early payment behavior, decreasing the time these loans spend in the warehouse. As these loans have demonstrated a decreased level of credit risk, this behavior is inconsistent with the image of an issuer driven to maximal exploitation of his informational advantage. Instead it appears that reputational concerns have led the issuer to make an asset selection decision in the interests of the investor.

I conclude my analysis of the impact of this private information by showing that credit rating agencies, who in principle could have observed this important signal of loan default outcomes, did not factor it into their ratings. Thus the ratings, intended to characterize the default likelihood of the underlying assets, did not adequately account for an important characteristic correlated with ex-post outcomes and did not appear to play an influential role in enforcing the "good behavior" of the issuer.

Theoretical models relating to asymmetric information begin with the description of the lemons problem in Akerlof (1970) and proceed to the signaling model of Leland and Pyle (1977). P. DeMarzo and Duffie (1999) and then P. M. DeMarzo (2005) extend this concept to security design in the context of securitization. Downing, Jaffee, and Wallace (2009) investigate specifically the incentives under which an issuer of residential mortgage backed securities operates, while An, Deng, and Gabriel (2011) investigate the particular role asymmetric information plays in the securitization process and Hartman-Glaser, Piskorski, and Tchistyi (2012) derive the optimal securitization contract in the presence of moral hazard. Following in the spirit of Kaplan and Stromberg (2000) and Garmaise and Moskowitz (2004) I attempt to investigate empirically the role that asymmetric information plays in the theoretical framework provided in the previous literature.

The empirical strategies employed in this chapter were guided in their application to mortgage data largely following studies such as Garmaise (2015) for loan level and A. C. Ghent, Torous, and Valkanov (2014) and Begley and Purnanandam (2017) for deal level data. Non-mortgage studies providing examples of similar empirical strategies include Card, Dobkin, and Maestas (2008), Matsudaira (2008), and Friedman and Schady (2013). Technical literature utilized include Abrevaya (1997), Horrace and Oaxaca (2006), Wooldridge (2010), and Cameron, Gelbach, and Miller (2012).

Studies of the behavior of households and their attitudes toward indebtedness include Hirad and Zorn (2001) who look at the effectiveness of pre-purchase homeownership counseling, Gerardi, Goette, and Meier (2010) who investigate financial literacy, Garmaise (2013) who looks at financial flexibility in regards to mortgages, Meissner (2014) who investigate the role of debt aversion, An, Deng, and Gabriel (2015) who looks at the optionality of borrower default, and Chernov, Dunn, and Longstaff (2017) who investigate the underlying macroeconomic drivers of prepayment risk.

Digman (1997) and Nicholson et al. (2005) describe frameworks of personality traits and O'Donoghue and Rabin (1999) describe procrastination. Thaler and Benartzi (2004) and Levi (2014) demonstrate the power that individual consumer decisions have on overall household outcomes.

Information and incentive problems on the part of the issuer of securitizations are studied in the commercial and residential MBS markets by Titman and Tsyplakov (2010) and Piskorski, Seru, and Witkin (2015) respectively and on the part of lenders by Keys et al. (2010). Erel, Nadauld, and Stulz (2013) study the behavior of RMBS investors during the relevant time period and shed interesting insight into the complex interplay between issuers and investors. Finally, the roles and incentives of credit rating agencies have been exhaustively studied in papers such as Benmelech and Dlugosz (2009), Benmelech and Dlugosz (2010), Ashcraft, Goldsmith-Pinkham, and Vickery (2010), He, Qian, and Strahan (2012), Griffin and Tang (2012), and Flynn and A. Ghent (2015).

The rest of this chapter will proceed as follows. Section 2.1 describes the institutional setting in which this study takes place. Section 2.2 describes the data utilized and the identification of early payment behavior. Section 2.3 describes the early payment behavior and provides evidence of its import for ex-post loan outcomes, its persistence across time, and its unobservability at origination. Section 2.4 details the impact this private information has on the securitization process by examining issuer signaling, pricing, and asset selection decisions as well as the role the credit rating agencies played in mitigating the informational frictions in this market. Section 2.5 concludes.

2.1 U.S. Non-Agency Residential Mortgage Backed Securities

A Residential Mortgage Backed Security (RMBS) is a collection of structured claims on a pool of residential mortgage assets. Non-agency[1] 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.[2] Non-agency RMBS securitization issuance effectively stopped with the onset of the subprime mortgage crisis in late 2007. Prior to this, however, it accounted for a substantial portion of the total domestic mortgage market. Total mortgage debt outstanding in non-agency RMBS transactions peaked in 2007 at $2.95 Trillion.[3] This section will provide an overview of the complex process of securitizing mortgages, the related securities, and servicing of the mortgage asset post-issuance.

2.1.1 Securitization

Securitization is the process of collecting assets (in this case residential mortgages), pooling them and then designing and selling security claims on them. Figure 2.1 displays a stylized timeline of the stages of the securitization process. When a potential borrower approaches an originator looking for a mortgage loan, the underwriting process begins. The originator evaluates the borrower's creditworthiness as well as the characteristics of the proposed loan and property. When the loan closes, a mortgage note is created and the date the note enters into effect is known as the note date. The first payment date is the date on which the borrower owes his first payment. This is typically the first of the month[4] immediately

[1] Also known as "private-label."

[2] The Federal National Mortgage Association (FNMA) and the Federal Home Loan Mortgage Corporation (FHLMC) are government sponsored enterprises (GSEs) and the Government National Mortgage Association (GNMA) is wholly owned by the U.S. Federal Government and managed by the Department of Housing and Urban Development.

[3] See Statistical Supplement to the Federal Reserve Bulletin, 2008 Table 1.54, Mortgage Debt Outstanding.

[4] 94.5% of the loans in this study have payments that are due on the 1^{st} of the month. The remainder of the loans are referred to as "odd due day" loans. For all subsequent loan level analysis, attention is restricted to loans due on the first of the month.

following a full calendar month after the note date.[5]

For loans that end up in non-agency RMBS transactions, the note is purchased by the issuer[6] of the securitization either directly from the originator or through a chain of intermediaries. Once a loan is closed, while the securitization is being designed, the loan is "warehoused." Payments made by the borrower during the warehousing stage are generally owned by the issuer.[7] The issuer places loans into pools and, working with a consortium of investment bankers, designs a security to meet the particular investment appetites of specific investors. These investors express preferences for classes with particular payment and rating characteristics (see Section 2.1.2). These classes generally become senior, or Class A, certificates. The issuer then provides the details of the underlying mortgage pool as well as the senior class characteristics to one or more credit rating agencies who dictate the level of subordination required in order to give prime (AAA or Aaa) ratings to the senior classes.[8]

Once the security has been designed, the credit rating agencies have provided preliminary ratings, and a majority of the classes have been sold, the securitization is closed. The pooling and servicing agreement[9] is the principal governing document of the transaction and is finalized at closing. This document defines the cut-off date, specifying that all payments due on or after that date are owned by the securitization. This cut-off date delineates the

[5]This window differs in length depending on the amount of interest the borrower paid at closing.

[6]The term "issuer" will be used in this chapter as a synonym for the more precise term "sponsor," which refers to the financial institution that is driving the securitization process. The more precise term "issuing entity" refers to a particular off-balance-sheet entity owned by the sponsor, referred to in this chapter as the "shelf."

[7]Payments made prior to the issuer taking possession of a particular mortgage are owned by either the originator or an intermediary. This chapter will abstract from that aspect as once the issuer takes possession (and even during the sale process) he is given full access to all servicing data in order to "board the loan." This implies that he has the same information set regardless of the amount of time he actually owns the loan during warehousing.

[8]Numerous studies, such as Benmelech and Dlugosz (2010), Ashcraft, Goldsmith-Pinkham, and Vickery (2010), He, Qian, and Strahan (2012), and Griffin and Tang (2012), have provided evidence of perverse incentives on the part of credit rating agencies. In totality they show the oversight ability of pre-crisis credit rating agencies to have been severely compromised. Generally, this will serve to strengthen the later results of this chapter.

[9]See, as a reference, the series supplement for RALI Series 2007-QS6 (2007a).

end of the warehousing stage and the loan is then considered to be securitized. The number of payments made by a borrower into the warehouse (warehouse payments or warehouse seasoning) is then a function of the particular pool in which the issuer decides to place a loan.

2.1.2 Security Design

A single securitization is divided into multiple ownership classes. The structure of the claims on the underlying pool, or the security design, varies greatly depending on the risk appetites of individual investors and the characteristics of the underlying mortgage collateral. Figure 2.2 presents a stylized example of the class listing of a broad classification of securitizations with senior-subordinated (senior-sub) structures.[10]

The senior classes, which are generally designed specifically for a particular investor, are termed Class A certificates and usually receive a prime rating (the highest rating available from a particular credit rating agency). The mezzanine classes (Class M Certificates) provide subordination to the senior certificates and receive a lower rating than the senior certificates (although still, generally, an investment grade rating). The junior certificates, or Class B Certificates, either receive a junk rating or are not rated at all.[11]

In general, cashflows from the mortgage pool work their way down this class list, whilst default losses work their way up. Senior class interest has highest priority (generally always pro-rata amongst all senior classes), followed closely by senior class principal paid according to a complex cashflow "waterfall" described in detail in the relevant governing documents.[12] Each mezzanine and junior class then has individual priority claim on any

[10] The senior-subordinated structures in the issuances looked at in this chapter are generally associated with higher quality collateral. The alternative is known as an overcollateralized (OC) structure. The difference as it relates to this analysis is discussed in Section 2.4.

[11] The mappings from senior-mezzanine-junior classes to particular ratings bands are only generalizations. In the data utilized in this chapter there are examples of junk ratings being assigned to mezzanine classes and investment grade ratings being assigned to senior and junior classes

[12] The example provided in Figure 2.2 has A-P and A-V classes, which are principal-only and interest-only strips, respectively.

remaining cashflows for its individual interest and then principal payment in descending order. The first default losses to be realized on the mortgage pool are applied to the principal balance of the most junior outstanding class (known as the "first loss piece," B-3 in the example provided). The most junior outstanding class is then the most sensitive to any private information the issuer may have about the default performance of the mortgage pool.

Figure 2.2 is representative of a common table detailing the class structure. It is placed at the front of a securitization's prospectus supplement[13], which is the offering document provided to potential investors. The classes that are offered for sale publicly under the prospectus supplement are termed the offered certificates. "Information presented for the non-offered certificates is," according to the prospectus supplement, "provided solely to assist [the investors'] understanding of the offered certificates." These non-offered certificates constitute the first classes to take default losses on the pool and were either held for investment by the issuer or sold in a market that was much less informationally sensitive than the public offering of the offered certificates.[14] While the offered certificates always receive a rating from at least one credit rating agency, the non-offered certificates differ widely both in the level and existence of a rating.

2.1.3 Mortgage Servicing

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 loans destined for securitization the note ultimately ends up in an off-balance sheet special purpose entity of

[13] A good reference prospectus supplement is for RALI Series 2007-QS6 (2007b).

[14] In general one of three things happens to the non-offered certificates. They are either: 1. Retained by the issuer. 2. Bundled with non-offered certificates from other securitizations into a CDO which is than privately placed as a Rule 144A exempt transaction. 3. Sold directly to a special servicer that, in exchange for purchasing the most default-sensitive class, also receives the right to service any loans in the underlying pool that enter default.

the issuer.[15] The servicing right, however, could be retained by the originator or transferred to the issuer's captive primary servicer.[16] The owner of this servicing right is referred to as the "primary servicer." The primary server is responsible for all borrower facing activities including collecting payments, managing loan and escrow accounts, and in the event of a default, providing loss mitigation services.[17]

An individual securitization contains loans that are primary serviced by many different entities. For this reason the issuer acts in a role known as the "master servicer." The master servicer is a party to the securitization documents (whilst the primary servicers, generally, are not) and is responsible for overseeing and aggregating the servicing activities of all of the primary servicers. The master servicer, as a subsidiary of the issuer, acts as the overall administrator of the securitization post issuance. They are responsible for all loan accounting, default oversight, cashflow calculations, and reporting. The master servicer fulfills this role on behalf of the issuer during the warehousing stage, in addition to once the loan has been securitized.

Borrower payments collected within a calendar month are tabulated, reported, and remitted from the primary servicer to the master servicer at the beginning of the following calendar month. Consider a borrower payment that is due on April 1st. Whenever that borrower payment is received by the primary servicer the loan is considered to be "paid-to" April 1st. Payments are collected throughout the month but the master servicer distribu-

[15]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.

[16]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.

[17]Loss mitigation activities primarily 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 itself. These activities are undertaken under the supervision of the master servicer who ensures compliance with the relevant securitization guidelines.

tes to investors[18] at a particular, fixed,[19] point of the month. Consequently the agreement between the primary servicer and the master servicer[20] defines an "accounting cycle cut-off date" which is the last day for which payments received by borrowers can be included in the monthly reporting forwarded to the master servicer. For all of the securitizations in this study this date is defined as "the last business day of the month before the month for which a remittance is being calculated" (Ocwen Master Servicing, 2014). This means that the paid-to-date in the primary servicer's system as of the close of business on the last business day of a calendar month is what will be reported to the investor as the delinquency status of the loan three weeks later on the 25^{th}. Most importantly for the identification of early pay behavior, a payment received by the servicer on the 1^{st} of a calendar month will not be reported to the investor until the following distribution.

For loans due on the 1^{st} of the month, a borrower who makes his payments exactly on the day they are due will appear to investors to be consistently "behind" in his payments. Continuing the previous example, for the borrower that made his April 1^{st} payment exactly on April 1^{st}, the investor will observe a paid-to-date of March 1^{st} when he receives the April 25^{th} reporting. Because of this delay, the industry standard is to consider a March 1^{st} paid-to-date as "current" for the April 25^{th} investor distribution. A payment is then only considered delinquent if the payment still had not been received by the end of the calendar month on which it was due.[21] Payments received by the servicer at least a business day prior to the day on which they are due will be reflected as a having a later paid-to-date to the

[18] The master servicer calculates all bond payments, remits cash, and sends investor reports (see RALI Series 2007-QS6 (2007c)) to the trustee two business days before the 25^{th} of the month. Actual disbursement to the investors is done by the trustee.

[19] For all securitizations in this study, this occurs on the 25^{th} calendar day (or next business day) of the month.

[20] For the securitizations in this study this is known as the Servicing Guide. A recent version of this document can be accessed at Ocwen Master Servicing (2014)

[21] This method is generally referred to as the MBA (Mortgage Bankers Association of America) method. For lower quality collateral the OTS (The Office of Thrift Supervision) method is utilized, which ultimately results in an extra month of "forgiveness," i.e. a loan that is two months delinquent under MBA is only considered one month delinquent under OTS. For the purposes of this study the MBA method is utilized throughout, even when the securitization document calls for OTS reporting.

investor. For example, if the previously described borrower had made his April 1^{st} payment on March 31^{st} then the April 25^{th} investor report will reflect a paid-to-date of April 1^{st}.[22] Thus both a paid-to-date of March 1^{st} and April 1^{st} are considered to be current and are generally not distinguishable from each other in most industry reporting.[23]

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[22]Regardless of the paid-to-date of the loan, for the April 25^{th} investor distribution the master servicer remits the April 1^{st} borrower payment. If that payment had not been received by the primary servicer prior to the accounting cycle cut-off date the payment is advanced to the investor.

[23]Loans occasionally have paid-to-dates well in advance of even the early pay date. A paid-to-date of May 1^{st} or later for the April 25^{th} investor payment indicates either a data quality issue or a borrower that has made a block of payments at a time (perhaps in expectation of going on vacation). When considering whether a borrower made an early payment, loans that are "paid ahead" to such an advanced degree are excluded.

2.2 The Data

The loan data in this chapter describe 878,385 U.S. residential mortgage loans which were securitized into one of 284 private label residential mortgage backed securities transactions with General Motors Acceptance Corporation, Residential Funding Company (GMAC-RFC), a U.S. financial institution, acting as sponsor.[24] Each securitization is master serviced by the sponsor and has a diversity of borrower facing primary servicers. A large portion of the primary servicing is performed by a subsidiary of the sponsor. Loans were originated through a wide array of channels and entities, with a portion of originations occurring through the sponsor's own channels.[25]

In May 2012 GMAC-RFC (then doing business as a subsidiary of Ally Financial Inc. as GMAC Rescap) filed for Chapter 11 bankruptcy protection. The assets of the bankrupt entity were purchased by Ocwen Loan Servicing in February 2013, from which point Ocwen became the master servicer, largely acting as the successor sponsoring entity. Loan data is drawn from two publicly available sources, accessible at the investor website maintained by Ocwen in their role as master servicer.[26] First, loan level snapshot files provided to investors at the issuance of the securitization detail the origination characteristics of the loan as well as their current status immediately preceding securitization. Monthly performance files, covering January 2004 through December 2014, supplement the issuance files with over a decade of performance data. Monthly payment observations begin with the later of the January 1st, 2004 borrower payment or the first payment owned by the securitization the loan was placed into. Monthly performance data ends with the earlier of the December 1st,

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[24] The sponsor, GMAC-RFC, utilized four different special purpose vehicles as the issuer of record for these transactions. They are Residential Funding Mortgage Securities I, Inc (RFMSI), Residential Accredit Loans, Inc. (RALI), Residential Asset Mortgage Products, Inc. (RAMP), and Residential Asset Securities Corp. (RASC).

[25] Origination and primary servicing is not necessarily provided by the same company, although in many cases it is.

[26] https://www.vision.ocwen.com/

2014 payment or the liquidation or payoff date of the loan.[27]

2.2.1 Early Payments

As detailed in Section 2.1.3, the primary servicer reports to the master servicer the paid-to-date in his system as of the close of business of the last business day of a calendar month. For a loan due on the first of the month this field has information content beyond simply allowing an investor to calculate a delinquency status. Consider the borrower payment due April 1st. If the paid-to-date reported as of the close of business on March 31st is April 1st then the borrower made his payment at least a day before it was due. This behavior is referred to as an *early payment.* If the paid-to-date instead reflects March 1st the borrower, while still current, will make a normal (non-early) payment. If the April 1st payment is not received by the end of April, the borrower then becomes delinquent.

While the files provided to the investor at issuance contain a paid-to-date field, this is the paid-to-date of the loan as of the cut-off date of the securitization (the point when the loan changes ownership from the issuer to the investor). Because historical paid-to-dates for payments made while the loan was in the issuer's warehouse are not provided to the investor, the investor is unable to observe the early payment behavior of the loan prior to securitization. The issuer privately observes this behavior during the securitization process.

The principal measure of early payment behavior utilized in this study is the number of times a borrower made an early payment for the first six payments due on his loan. The data utilized in this study are from publicly available sources, provided by the issuer for the benefit of the investor. Because of this, the early payment behavior of these loans is only observable while the loan is owned by a securitization. The principal empirical specification of Section 2.3.1 will utilize a smaller loan set of 109,818 loans for which the early pay behavior for the first six months of the life of the loan is observable. The original 878,385 loans securitized are pared down to 109,818 via the following exclusions. 343,988 loans made

[27] Payoff refers to a borrower prepayment in full. Liquidation refers to a third party sale, REO disposition, short payoff, or charge-off.

their first payments into the issuer's warehouse. 52,158 loans made their first payments prior to December 1, 2003 (the issuer only began reporting monthly performance data in January 2004). The first payments for 334,974 loans, while owned by the securitization, were made exactly on the cut-off date of the securitization. Their second payments were made prior to the first reporting date of the securitization. As such the early payment behavior of the first payment on these loans was observed privately by the issuer, but after the closing of the securitization. Of the remaining loans, 7,938 were odd due day loans, 13,638 had significant gaps in their performance histories,[28] 14,255 loans went delinquent in their first six months,[29] while 1,593 loans were significantly paid ahead at some point in the first six months. FICO information for 23 of the then remaining loans is missing, and these loans are also excluded.[30]

2.2.2 Summary Statistics

The 109,818 loans utilized in the principal empirical specification of Section 2.3.1 cover a broad cross-section of various non-conforming borrower credit qualities including Subprime, High-LTV, Alt-A, and Jumbo. They are geographically diverse; the data include observations in every state (and Washington, D.C.) and over 15,000 zip codes. Table 2.1 primarily details the at issuance characteristics of these loans. The mean borrower FICO credit score is 687.58, and the mean Debt-To-Income ratio is 38.96%. Only 56% of loans were originated with full documentations of assets and income, the remainder were stated documentation loans.

Monthly payment observations begin with reporting of the January 1$^{\text{st}}$, 2004 borrower

[28]Performance history gaps are largely due to mistaken liquidation or payoff codings that took time for the servicer to reverse.

[29]This study focuses attention on the distinction between an early payment and a non-early payment *that is otherwise current*. Including delinquent payments as non-early observations rather than excluding them altogether would give an unfair advantage to estimates of the performance impact of loans that paid early.

[30]In additional results available upon request I explore the sensitivity of the principal empirical results to many of these exclusions by varying the early payment observation window specification. If only the initial three mortgage payments are considered, rather than the initial six, the requirement that the loan remain current for a period of time at the beginning of its life is relaxed. Results are robust through all specifications including to consideration of only the first mortgage payment due. Additionally by starting the analysis later, such as examining the second through seventh mortgage payments, the effects are shown to be robust to an expanding set of loans with greater levels of warehouse seasoning.

payment and end with the December 1st, 2014 payment. Consistent with the quality of the collateral and the market conditions associated with this time frame, the securitizations experienced a high level of delinquencies and defaults. Over the eleven observed years, 49% of the loans made at least one delinquent payment and 27% entered foreclosure, REO, or were liquidated (other than a borrower prepayment in full). 49% of the loans ultimately paid-off (irrespective of whether they were current, delinquent, or in foreclosure).

2.3 Borrower Diligence

The behavior of interest for this study is the propensity for a borrower to make his payments before they are actually due. I interpret this behavior as characteristic of a particular borrower trait I am calling "diligence" which can be thought of as a measure of responsibility, conscientiousness, or dutifulness as it relates to managing their household finances.

A propensity to make an early monthly payment is not likely to be the only indicator of diligence. Future drafts of this study will also look at curtailments[31] at mortgage loan outset as well as behavior in relation to non-mortgage debt. Furthermore, Section 2.3.4 investigates whether there were other, non early payment, indicators of diligence that may have been observable to the originator prior to the closing of the mortgage loan.

The loans for which early payment behavior is observable were all placed into a public securitization. This means that access to demographic descriptors is extremely limited. Future drafts of this study will explore linkages between these loans and the dataset available under the Home Mortgage Disclosure Act, allowing for a closer look at certain borrower demographics and geographies. Borrowers are more likely to exhibit early payment behavior when they have high FICO scores, lower Loan-To-Value ratios, and lower Debt-To-Income ratios. The correlation between these observable borrower traits and the early payment behavior is just that, correlation. It is most likely the case that borrowers exhibiting diligent behavior today exhibited it in the past, leading to higher FICO's, more liquidity for a down payment, and a lower propensity to take on high levels of debt relative to their incomes. Additionally, mortgages on Owner Occupied properties are more likely to be paid early than ones on vacation and investment properties. Later work will investigate whether wealthier individuals are more likely to pay early as they likely bear a less proportional cost to doing so.

Nicholson et al. (2005) examine risk taking in the context of the "Big Five" personality measures (see Digman (1997)). Elements of conscientiousness, and perhaps neuroticism or

[31] A curtailment is a partial paydown of the principal balance of a mortgage loan by a borrower.

fastidiousness, are likely to be associated with diligent behavior. The propensity for individuals to procrastinate is well described in O'Donoghue and Rabin (1999) and experimental studies such as Thaler and Benartzi (2004) and Levi (2014) show the importance of thinking about this aspect of behavioral economics. Borrower diligence exists in direct counterpoint to the concept of procrastination and can be thought of as the opposite pole along this particular behavioral dimension. Meissner (2014) finds evidence for debt aversion in the context of a stochastic dynamic optimization problem, suggesting an unwillingness to become a borrower. Early payment of a mortgage is suggestive of a similar motivation within the context of an agent that has already become a debtor, and perhaps indicates a desire to be seen as responsible in the eyes of the mortgage servicer.

Making a mortgage payment before the due date, especially when considering the often generous grace period of 10-15 days required by state laws before the incurrence of late fees, can be viewed as evidence of a lack of financial sophistication on the part of the borrower. While this is possible, the low return associated with marginal household dollars over a time frame measured in weeks implies that the costs associated with an early payment are not likely to be significant. Future drafts of this study will also look at the time series variation in returns on checking and savings accounts for an influence on early payment behavior.

The hypotheses with which the remainder of this section is principally concerned examine ex-post loan outcomes and how they are associated with the degree to which the borrower exhibited early payment behavior during the initial payments of the loan. These outcomes include delinquency, default, and prepayment in full. Before turning to the empirical specification, Table 2.2 shows that in the cross-section of early payment behaviors, both delinquency and default rates are monotonically decreasing in the number of early payments made by the borrower on the initial six monthly payments. Figure 2.3 and Figure 2.4 graphically depict the cumulative hazard functions for delinquency and default, respectively.

2.3.1 Empirical Specification

The following empirical analysis is principally focused on determining whether early payment behavior at loan outset is correlated with subsequent loan outcomes. The primary test examines the hypothesis that borrowers who exhibit higher levels of early payment behavior in their first six monthly payments are less likely to become delinquent throughout the life of the loan. To analyze this hypothesis I estimate the following model:

$$Delinquent_{m,i} = \alpha + \beta_1 E_{t,n,i} + \gamma * controls_i + \lambda_{s(i)} + \varepsilon_i, \tag{2.1}$$

where $Delinquent_{m,i}$ is an indicator as to whether loan i ever became delinquent,[32] $E_{t,n,i}$ is the count of early payments made between loan payments t and $t + n - 1$ (inclusive), $controls_i$ is a vector of loan and property characteristics as well as pool and zip code fixed effects, $\lambda_{s(i)}$ is a month of first payment due fixed effect, and ε_i is the error term.

The coefficient of central interest is β_1, which measures the impact of a marginal month of early payment behavior on the probability of eventual delinquency. Under the null hypothesis of no correlation between early payment behavior and loan outcomes, $\beta_1 = 0$ should be observed. Under the maintained hypothesis that borrowers exhibiting early payment behavior are less likely to become delinquent, it is expected that $\beta_1 < 0$.

Equation 2.1 is estimated with OLS, despite the binary form of *Delinquent*, due to the large number of fixed effects on multiple dimensions that are also included. This creates an incidental parameters problem within maximum likelihood methods described in Abrevaya (1997) leading to logit and probit no longer being consistent estimators. A linear probability model is utilized in similar approaches such as Card, Dobkin, and Maestas (2008), Matsudaira (2008), Friedman and Schady (2013), and Garmaise (2015). Logit and probit specifications, similar to Equation 2.1, result in correlations between the (in-sample) fitted

[32] $Delinquent_m$ is defined as the event where a borrower's payment has not been received by the end of the business day immediately preceding the date of the *second* next due payment, ever enters foreclosure or REO status, is liquidated (except through borrower pay in full), or passes m consecutive payment due days in which the immediately preceding payment due has not been received.

values of the LPM and logit, and the LPM and probit of 0.996 and 0.997 respectively.

The primary concern regarding estimating ordinary least squares with a binary outcome variable is related to 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 this interval. Of the 109,818 observations utilized in Table 2.3 (column 2), 99.76% lay within the proper interval.[33] Of secondary concern is the heteroskedasticity of the error terms resulting from the binary nature of the dependent variable. All results follow allowing for heteroskedasticity-robust standard errors. 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."

2.3.2 Results

I begin by estimating Equation 2.1 in order to test the hypothesis that borrowers who exhibit greater levels of early payment behavior in their first six monthly payments are less likely to become delinquent throughout the life of the loan. Results are reported in Table 2.3.

The first column of Table 2.3 regresses an indicator of Delinquency on the observed count of early payments made by the borrower during the initial six payments on the mortgage, a discrete variable that runs from zero to six. The resulting coefficient is significant and shows that, for every early payment made, the borrower exhibits a 3.39 percentage point (t-statistic of -35.50) decrease in the resulting likelihood of delinquency. The second column includes standard mortgage risk characteristics, as well as characteristics relating to the loan structure, underwriting standards, property characteristics, as well as fixed effects for month of first payment due, pool, and property zip code. While the magnitude of the coefficient is diminished to 2.36 percentage points, early payment behavior remains a highly

[33] 177 (0.16%) such that $\hat{y} < 0$ and 91 (0.08%) such that $\hat{y} > 1$.

significant predictor of delinquency (t-statistic of -23.32). This specification is not attempting to establish a causal relationship between early payment behavior and ex-post delinquency. Instead it is simply demonstrating a correlation between a behavioral cue and ultimate performance.

The result detailed in column 2 of Table 2.3 are robust to many additional specifications. Clustering at the zip code level as well as double clustering by both zip and pool following Cameron, Gelbach, and Miller (2012) are shown to have similar results. Additionally, by varying the window of observed early payment information, the sample can be expanded along two dimensions. By shortening the overall window, inference relies less on a high level of conditioning on consecutive current payments at loan outset. Additionally, because early payment behavior is only observable when the payment was made into a securitization, by delaying the observation window (to, for example, months four through nine) the number of observations increases significantly. Coefficient estimates are similar and remain statistically significant at comparable levels to those found in Table 2.3 for all specifications.[34]

Additionally, by converting the discrete counter variable of the number of early payments observed for the initial six months into a factor, the difference in levels for a borrower that made all six initial payments early (compared to one that made none early) is a 14.8 percentage point decrease in the likelihood of ultimate delinquency (with a t-statistic of -20.05). Furthermore, the coefficient estimate for the effect of a single observed early payment is roughly constant at around 11 percentage points for at least the first 18 monthly payments.

In column 3 of Table 2.3 the dependent variable is changed to an indicator as to whether the loan ever entered default. Default here is defined as the loan entering into foreclosure, being acquired as an REO, or being liquidated (REO disposition, third party sale, or write-off) in a manner that is not a borrower prepayment in full. The resulting coefficient on the early payments in months one through six shows that for every early payment made the

[34]Coefficient estimates for windows of length different than six months vary in magnitude proportionate to the number of months they are estimated for. For example, the coefficient estimate for the early payment behavior of the first three monthly payments is approximately twice that of the coefficient estimate reported in column 2 of Table 2.3 for six monthly payments.

borrower exhibits a 1.17 percentage point (t-statistic of -14.37) decrease in the likelihood of default. Results are robust to varying degrees of delinquency severity between the two extremes of columns 2 and 3 of Table 2.3. $Delinquent_m$ is defined as the event where a borrower's payment has not been received by the end of the business day immediately preceding the date of the *second* next due payment, ever enters foreclosure or REO status, is liquidated (except through borrower pay in full), or passes m consecutive payment due days in which the immediately preceding payment due has not been received. Results in columns 1 and 2 of Table 2.3 are related for $Delinquent_1$. Results for $Delinquent_2$, $Delinquent_3$, and $Delinquent_4$ hold. These results demonstrate that the definition of a delinquency event can be relaxed and the effect of early payment behavior remains significant both economically and statistically.

Column 4 of Table 2.3 demonstrates that for every additional early payment the borrower makes in the initial six months of the life of the loan, there is a 1.09 percentage point increase (t-statistic of 11.97) in the likelihood of that borrower ultimately paying off the loan balance in full prior to the maturity date. This result is consistent with the previous discussion of the behavioral foundations of diligence. It will, however, complicate the interpretation of subsequent results as a borrower that exercises his prepayment option more optimally increases the investor's exposure to extension and contraction risk. This necessitates the evaluation of all originator, issuer, and investor decisions concerning borrowers that are making early payments to be examined as possessing both a positive (increased likelihood of delinquency and default) and a negative (increased likelihood of prepayment in full) characteristic.

Most notable of the effect demonstrated in column 2 of Table 2.3 in various borrower cross-sections is that, while the effect is significant for all levels of FICO score, for borrowers with a low-FICO score the effect is stronger. This implies that for a low-FICO borrower, making early payments may be a signal that they are attempting to turn their financial situation around or perhaps that their low-FICO score is due to episodes of bad luck in their financial history.

2.3.3 Persistence of Effect

I am only able to observe the calendar month in which a borrower makes his payment. Therefore payments made on the due date (the 1st of the month), just before the incurrence of late fees (i.e. the 15th of the month), or extremely late but not quite delinquent (31st of the month) are fundamentally indistinguishable.[35] Borrowers that make a payment two or three weeks after it is due are, quite uncontroversially, more likely to go delinquent in the near future. Their behavior can be interpreted as evidence of liquidity hoarding. As such, it is possible that the main results of Table 2.3 are driven by the comparison between an early payment and these two or three week late payments, which are included with and indistinguishable from, the borrowers making their payments on or just after the due date. This effect would not be of particular interest were it found to be the main driver of these results.

In order to provide evidence contrary to this concern, Figure 2.5 reports the change in the coefficient of interest in column 2 of Table 2.3 as the regression sample is conditioned on increasing levels of current payments at the beginning of the life of the loan. For example, consider a loan originated in at the end of 2006 for which the early payment behavior of the first six payments at the beginning of 2007 are observed. Conditional on five years of current payments (examine the value of 5 on the horizontal axis of Figure 2.5), we can see the effect of regressing delinquency outcomes in year six and after on the early payment behavior for those initial six payments. This coefficient estimate is negative and significantly different from zero at the 5% level. This means that for a borrower that remained current from 2007-2011 (inclusive), a period covering the worst of the financial crisis, the early payment behavior observed in the first half of 2007 is still predictive of ex-post delinquency rates from 2012-2014 (also inclusive). This effect remains conditioning through 6 years and 2 months of current payments.

This provides strong evidence against the effect observed in column 2 of Table 2.3 being

[35]Late fees are paid directly to the primary servicer and are not required to be reported or accounted for to the master servicer. Consequently they too are unobservable.

driven by comparing early payments against liquidity hoarders. Borrowers making their payment two or three weeks late are likely to enter delinquency imminently. It is unlikely that paying two or three weeks late for the first handful of payments on a loan has any correlation with delinquency seven and eight years later, *conditional on having been current on every payment for six years.*[36]

2.3.4 Observability

Early payment behavior is only one possible observable indicator of borrower diligence. Table 2.4 investigates whether the originator was able to observe this borrower characteristic through some other channel. If the originator observed that a potential borrower was likely to exhibit diligence and thus be less of a credit risk, it is likely that this would result in the borrower receiving a lower note rate reflective of this risk. This hypothesis is test through estimation of the following model:

$$NoteRate_i = \alpha + \beta_2 E_{t,n,i} + \gamma * controls_i' + \lambda_{s(i)} + \varepsilon_i, \tag{2.2}$$

where $NoteRate_i$ is the note rate at origination for loan i expressed as percentage points, $E_{t,n,i}$ is the count of early payments made between loan payments t and $t+n-1$ (inclusive), $controls_i'$ is a vector of loan and property characteristics (exclusive of controls that were co-determined with the note rate) as well as zip code fixed effects, $\lambda_{s(i)}$ is a month of first payment due fixed effect, and ε_i is the error term.

The coefficient of central interest is β_2, which measures the correlation between a marginal month of early payment behavior on the note rate the borrower received at origination. Under the null hypothesis of no correlation between early payment behavior and note rate, $\beta_2 = 0$ should be observed. Under the maintained hypothesis that borrower early payment behavior was priced into the loan at origination, it is expected that $\beta_2 < 0$.

[36] It is possible to interpret a borrower paying two or three weeks late as evidencing procrastination or "anti-diligence." This would likely be correlated with negative long term delinquency outcomes. However, drawing a distinction between early payments and this interpretation of the opposing behavior is an acceptable, albeit less satisfying, interpretation of these results.

Equation 2.2 is estimated in column 1 of Table 2.4. I am unable to reject the null hypothesis (t-statistic of -0.31), implying that the originator was unable to observe diligence and price the loan accordingly.[37]

Diligent behavior is also associated with an increased propensity to prepay in full. A loan with a higher likelihood of prepayment is less desirable as an investment (see Downing, Jaffee, and Wallace (2009)) and as such would likely require a higher note rate at origination. Given that accurate pricing of diligent behavior could lead to a lower note rate through one channel (reduced credit risk) and a higher note rate through another (increased prepayment risk), the net effect on the note rate may be indeterminate. Column 2 of Table 2.4 addresses this concern by replicating Equation 2.2 for only the adjustable rate loans in the sample.[38] Because the interest rate paid on an adjustable rate loan varies with a reference rate such as LIBOR or Treasury yield, the reinvestment risk of these loans is negligible. Consequently, only default risk should play a role in setting the margin on these loans. While the effect is mildly significant (t-statistic of -2.44) the magnitude is irrelevant, the difference between all six payments made early over none early is only a 6.4bp reduction to the ARM margin. The average ARM margin in the sample used in this specification is 5.41%, suggesting early payment behavior has no material impact. Column 3 of Table 2.4 demonstrates that early payment behavior is associated with better ex-post delinquency outcomes in the adjustable rate subsample as well.

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[37]I am not able to conclusively rule out the "originate-to-distribute" model that would have the originator unconcerned with accurately pricing default risk in the market conditions prevalent during the time period under consideration. However, many loans in my analysis were originated directly by the issuer or were sold to the issuer with significant levels of information sharing under very established underwriting channels. It is unlikely that blatant originate-to-distribute behavior was pervasive in the observed loan population.

[38]Rather than note rate, the margin for the ARM over the applicable index is used as the dependent variable, also expressed in percentage points.

2.4 Private Information

Section 2.3 demonstrated the valuable information content contained in early payment behavior. In order to differentiate an early payment from a non-early payment, the paid-to-date for each payment must be observed. The files provided to the investor at issuance contain only the most recent paid-to-date of the loan. Consequently, the early payment behavior of loans while they were in the warehouse is observed privately by the issuer and is unobservable to the investor. This section will turn to the question of what the issuer did with this private information.

Because the early payment behavior in the warehouse is unobservable in the data available for this study, a proxy for what this information contained must be created. For loans whose first payment was made directly to the securitization (zero warehouse seasoning), there is a .65 correlation (conditional on all observables) between the number of early payments observed in payments 1 through 3 and in payments 4 through 6. The persistence in early payment behavior by an individual borrower across time periods is a robust feature of the time series data. Relying on this correlation and restricting attention to loans that had a warehouse seasoning strictly greater than zero (the issuer was able to observe at least one payment in the warehouse), the information measure "early payments observed in private information, proxy" can be constructed by counting the number of early payments made by the borrower on the first three loan payments made into the securitization (the first three payments I observe). This measure will serve as a proxy for the private information available to the issuer at the time of the securitization. Use of this proxy in the subsequent regressions introduces an attenuation bias in my estimated coefficients. This implies my coefficients will be biased towards zero, strengthening my ultimate conclusion.

Section 2.1.1 introduced the loan level measure of warehouse seasoning. Warehouse seasoning and the proxy for the early payments observed by the issuer can be aggregated to the deal level by taking an issuance balance weighted average for all loans where each measure is observable. Table 2.5 presents summary statistics relating to these measures at the loan level as well as when aggregated to the deal level. Both the loan level and the deal level measures will be used in the regressions presented in this section.

2.4.1 Issuer Signaling

The private information possessed by the issuer gives him an information advantage over the investor. One possible result of this is that the issuer signals the content of his private information through the retention of equity. As discussed in Section 2.1.2 the proportion of the pool that was designated as "non-offered" at the time of securitization is a useful measure of the retained interest the issuer held in the most default information sensitive tranches (first, second, third, etc. loss pieces). Table 2.6 reports results that suggest the issuer's retention decisions were not driven by the early payment information he observed in the warehouse. These regressions are all at the deal level.

Column 1 of Table 2.6 shows an apparent unconditional correlation between retention and early payment behavior, with more early payments observed leading to less retention. This result, if not poorly specified, would suggest that the early payment behavior of the borrower was publicly observed. However, column 2 includes only one additional covariate: the average FICO of the loans in the deal. The coefficient on the early payment information is insignificant in this specification at -0.006 (t-statistic of -1.20), suggesting that the effect observed in column 1 was only through the component of early payment behavior that was correlated with the observables.

If observing borrower payments privately, as the issuer does in the warehouse, was a valuable source of private information (not just as it related to early payment behavior) then it can be expected that increased warehouse seasoning (or an increase in either the support or precision of the private signal the issuer receives) would be associated with an increase in retention. Column 3 of Table 2.6 demonstrates this effect. Column 4 of Table 2.6 demonstrates that the conclusions drawn in columns 2 and 3 are robust to the inclusion of a large set of observable deal level characteristics.

The coefficient observed in column 4 of Table 2.6, relating warehouse seasoning and retention, is 0.00377 (t-statistic of 2.59) and is economically significant. A one standard deviation change in average warehouse seasoning (0.50 months) implies an increase of 0.189 percentage points in the proportion of the pool not offered or 10.414% of the mean proportion. While the issuer does signal via equity retention based on the overall level of private information he could possibly have received (average warehouse seasoning), it does not appear that he signals the early payment behavior content of this information.

2.4.2 Securitization Pricing

The securitizations being investigated in this chapter are not sponsored by an agency and as such, while a secondary market does exist, they are thinly traded and price information is largely non-existent. The price the investor paid at issuance is of principal interest in examining whether or not the investor was aware of the early payment behavior demonstrated in the warehouse. Unfortunately this information is not available either. Consequently, following A. C. Ghent, Torous, and Valkanov (2014), I use the margin on adjustable-rate tranches as a proxy for the issuance price.

Restricting attention to only prime (AAA or Aaa) rated adjustable-rate tranches, the original tranche balance weighted average of the margins over LIBOR are taken at the deal level. Column 1 of Table 2.7 demonstrates that there is no significant relationship (coefficient of 0.0477, t-statistic of 0.49) between this measure of price and the early payment behavior observed by the issuer in the warehouse. This result suggests that the investor was ultimately unaware of the information (validating it as issuer private information) and consequently the issuer was unable to extract a higher price for those deals containing a higher concentration of early paying loans.

Table 2.7 also reports coefficients for the average level of warehouse seasoning and the proportion of the pool that was not offered. The insignificance of these coefficients suggests that the pricing of the securitization was insensitive to both the support of the private information the issuer received and his retention level.

2.4.3 Early Paying Loans Securitized Faster

If a loan in the warehouse of an issuer goes delinquent it is, generally, unable to be placed into a securitization.[39] Given this execution risk it should be expected that early payment behavior in the warehouse would be generally associated with a longer time in the warehouse as the urgency to securitize would be lessened.

Table 2.8 presents evidence that this issuer behaved in exactly the opposite manner. Specifically, a loan making early payments into the warehouse is associated with a *shorter* stay in the warehouse. The warehouse seasoning of individual loans is regressed on the proxy for the early payment behavior observed in the issuer's private information as well as a vector of loan level controls. Column 1 of Table 2.8 shows that one additional early payment observed (support for the proxy variables is from 0 to 3) is associated with a -0.0364 month decrease (t-statistic of -11.24) in time spent in the warehouse. Because early payment behavior is only observable by the issuer if the borrower made at least one payment into the warehouse, warehouse seasoning in this sample is always strictly greater than 0.

Warehouse seasoning is perfectly collinear with the month the borrower's first payment was due and the pool it was placed into. Consequently, Table 2.8 presents specifications with various permutations of those covariates excluded. Column 1 leaves them both out whilst columns 2 and 3 leave out the first payment due month and pool fixed effects respectively. Coefficients in all specifications are of similar significance and magnitude.

This behavior on the part of the issuer, faster securitization of loans he privately observes to be of lesser credit risk, is contrary to the baseline intuition of what would be in his best interests. As discussed in Section 2.4.2, the price of the securitization was insensitive to the level of signaling the issuer exhibited. Hartman-Glaser (2013) presents a model suggesting that this is associated with a high issuer reputation for honesty. This behavior is then

[39] While generally true, most securitizations in the sample contained a small portion of loans that briefly went delinquent but then immediately became current again. Some subprime securitizations had loans that were securitized in a delinquent state, although these were generally repurchased if they did not quickly begin performing again. GMAC-RFC issued a number of "scratch and dent" and "re-performing" securitizations containing loans that had at one time been severely delinquent, but these deals are not included in my sample.

consistent with the issuer maintaining or increasing his reputation of quality.

Because I am only able to observe loans that were placed into a securitization, I am not able to test the effect that early payment behavior has on the issuer's decision whether or not to securitize the loan in the first place. Hence, all of my analysis is conditional on the loans being securitized. The result found in Downing, Jaffee, and Wallace (2009) would suggest that loans exhibiting early payment behavior (which are then more likely to prepay) are more likely to be securitized in the first place. However, their analysis was conducted within agency RMBS transactions where an (in their case) implicit guarantee by the federal government largely removes the credit risk concerns on the loans. As such the expected effect of early payment behavior on the securitization decision is indeterminate.[40] It should be noted, however, that while the ability of early payment behavior to distinguish delinquency and default rates is powerful from the beginning of the life of the loan (see Figures 2.3 and 2.4), the same can not be said of prepayment. Figure 2.6 shows a different pattern when it comes to prepayment behavior. While in the long run the pattern exhibited is consistent (although oppositely signed) with that of delinquency and default, early in the life of the loan, early payment behavior is a poor indicator of likelihood of prepayment. This suggests that an influence on securitization timing on the order of weeks is not likely to be driven by borrower behavior that will manifest itself years later (remembering that all of these loans were ultimately securitized).[41]

[40]While the issuer did retain an equity interest in the loans, it was largely a leveraged exposure to credit risk and (initially) no exposure to prepayment risk. For most deals all prepayments for the first few years were directed exclusively to the senior certificates (and often to tranches specifically designed to have an increased exposure to extension and contraction risk). Prepayment cashflows were held back from the mezzanine and junior classes in order to not compromise the default protection these classes provided the senior certificates. This is itself further evidence that default played a more important role in the overall security design of these deals than did prepayment risk. See, for example, the definition and usage of the term "Senior Accelerated Distribution Percentage" in RALI Series 2007-QS6 (2007a).

[41]The results found in Table 2.8 are largely the same when restricting to only ARM loans where the effect of prepayment risk is expected to be non-existent.

2.4.4 Credit Rating Agency Involvement

Prior to the closing of the securitization the credit rating agencies, in principle, had access to all the information available to the issuer. This section demonstrates that the credit rating agencies either missed the signal, didn't understand it, or chose to ignore it.

Table 2.9 reports results from regressing various pool rating proportions on measures of private information and selected observable covariates at the deal level. All tranches in a deal received ratings of either prime, investment, or junk, or were not rated. The dependent variables in Columns 1 through 4 address all of these proportions, and together these variables are mutually exclusive and collectively exhaustive (they sum to 1). The reported coefficients on the proxy for the average early payments observed by the issuer during warehouse seasoning are all insignificant. Additionally, coefficients are reported for the average level of warehouse seasoning in the deal. These are also all insignificant with the exception of the proportion not rated. The proportion not offered is highly correlated with the proportion not rated (correlation of 0.7383) and as such this result is not surprising given column 4 of Table 2.6. The covariates included in Table 2.9 are parsimonious, showing that only conditioning on the average FICO and fixed effects for the month of securitization closing and the broad securitization structure type is enough to remove any significant correlation between the early payment information and the ratings.

While Table 2.9 demonstrates that the early payment behavior observed in the warehouse did not impact the ratings proportions provided by the credit rating agencies, Table 2.10 demonstrates that it should have. Column 1 regresses the proportion of the pool that had defaulted[42] as of December 2014 on the early payment information observed by the issuer as well as the proportion of the pool that was retained and the proportion of the pool that received either a prime or investment grade rating.[43] All coefficients are negative and

[42]Entered foreclosure, became real estate owned, or was liquidated in a manner other than a borrower prepayment in full.

[43]All results in Table 2.10 are robust to specifications involving either the proportion of the pool that ever went delinquent or the net loss percentage at the pool level as dependent variables.

significant at the 1% level, suggesting that the more the issuer retained, the higher the average rating of the deal, and the more early payments observed in the warehousing stage, the better the deal performed from a default perspective. Column 2 of Table 2.10 reports results when all observable deal level controls are included. The coefficients for ratings and retention level are no longer significantly different from zero, implying that their explanatory ability as it related to the proportion of the pool that would ultimately default was simply a summary of the observables. The coefficient relating to the early payment behavior remains large, -0.111, and significant, t-statistic of -3.84, suggesting that the early payment behavior contains information relevant to the ex-post default performance of the deals that are not contained in the observables.[44]

All of these results together suggest that while the credit rating agencies should have (and, in principle, could have) accounted for the early payment information in their ratings, they either missed it, didn't understand it, or chose to ignore it.

[44]These inferences also carry through by looking at the incremental R^2 of successive specifications. A regression of only the observables has an R^2 of 97.48%. Including the proportion retained does not change that value, whilst including the proportion that received a prime or investment rating adds 1bp. Adding the early payment information however increases the R^2 by 23bp over the specifications both with and without the rating and retention level covariates included.

2.5 Conclusion

The contributions of this chapter are two-fold. First, a new borrower risk characteristic is described empirically and is motivated behaviorally. Borrowers that make their payments prior to the day on which they are actually due exhibited a borrower characteristic called diligence that is associated with lower likelihood of delinquency and default. This behavior, observed on a handful of payments at the beginning of the life of the loan, remains a powerful predictor of these outcomes for years into the life of the loan. The characteristic is unobservable at origination, and is first observed privately by the issuer prior to securitization.

Second, the behavior of an issuer of residential mortgage backed securities is examined in relation to his receipt of the previously described signal. The issuer does not signal the content of this powerful private information through equity retention. Nor does he take advantage of the information to increase the price charged to investors. Surprisingly, he takes this signal of reduced credit risk and uses it to securitize better loans faster. This is in direct conflict with the conventional wisdom regarding his motivations, holding loans that are at a greater risk of delinquency for longer increases the likelihood he will be unable to securitize the loan. This behavior was not enforced by the credit rating agencies who in fact seemed to have missed the importance of this signal entirely. Instead, it appears that reputational concerns motivated the issuer to securitize quality loans more quickly.

The ability for the exact timing of a borrower payment to signal ex-post loan outcomes is not limited to mortgages. Application can be made to all forms of debt and should be considered when evaluating a borrower's overall creditworthiness. Increased understanding of this signal will lead to better lending decisions, improving borrower outcomes and possibly extending credit to consumers otherwise shut out of the market. The findings in this chapter oppose the conventional image of a pre-crisis RMBS issuer taking maximal advantage of its asymmetric information at the expense of the investor. We are now forced to think differently about the role that reputation can play in mitigating asymmetric information problems and have come to a better understanding of the empirical behavior of key financial intermediaries.

Table 2.1

Summary Statistics

Summary statistics provided for the 109,818 loans for which the early pay behavior for the initial six payments is observable. Loan Amount is the principal balance of the mortgage loan at origination as stated in the Note. Credit Score is the primary borrower's FICO score. LTV is the loan-to-value ratio, excluding any other liens. Debt-To-Income is the ratio of the borrower's total monthly debt payment to their monthly income (Back-end DTI) and summary statistics are provided only for the 65,253 loans for which that data is available. The First Payment Due Date is the due date of the borrower's first payment, generally occurring one to three months after the note date on the loan. The Note Rate is gross of all servicing fees and is the initial rate provided for in the Note. P&I Payment is the initial principal and interest payment and does not include taxes and insurance. Property Value is the appraised value of the underlying property for the purposes of loan closing. Fixed Rate loans have a fixed interest rate throughout the life of the loan, as opposed to an adjusting rate that resets at some margin over an index on a periodic basis. Owner Occupied is an indicator that the loan was originated as the primary residence of the mortgagee. In Cash-Out Refinances the borrower withdraws equity from the property, whilst for Rate/Term Refinances the borrower is seeking a different interest rate or maturity date. Full Documentation means that assets and income were both fully documented by the originator, the remainder were stated documentation loans. Ever Delinquent is an indicator for whether a borrower payment had not been received by the end of the business day immediately preceding the date of the next due payments for the intersection of dates of when the loan was owned by a securitization and between 1/1/2004 and 12/31/2014. Ever Defaulted is an indicator as to whether the loan ever entered foreclosure, was foreclosed on, or liquidated (excluding borrower prepayments in full) for the same time frame as Ever Delinquent. Ever Prepay In Full is an indicator as to whether the borrower prepaid the loan in full in the same time frame as Ever Delinquent.

	Mean	Median	Standard Deviation	1^{st}%	99^{th}%
Loan Amount	208,472.50	151,000.00	168,613.10	44,250.00	800,000.00
Credit Score	687.58	691.00	63.35	533.00	803.00
LTV	79.63	80.00	14.22	28.00	103.00
Debt-To-Income	38.96	40.00	8.91	13.00	55.00
First Payment Due Date	10/21/2005	11/1/2005	12 mos., 4 days	1/1/2004	9/1/2007
Note Rate	7.11	7.00	1.01	5.00	9.99
P&I Payment	1,315.05	994.97	985.75	317.91	4,791.67
Property Value	283,989.50	188,716.00	278,272.10	55,000.00	1,315,000.00
Fixed Rate	0.63				
Owner Occupied	0.77				
Cash-Out Refinance	0.34				
Rate/Term Refinance	0.20				
Full Documentation	0.56				
Ever Delinquent	0.49				
Ever Defaulted	0.27				
Ever Prepay In Full	0.49				

Table 2.2

Early Pay Behavior, Delinquency, and Default

This table divides the 109,818 loans with observable early payment information for the initial six borrower payments into categories based on the number of early payments observed. The delinquency rate and default rate, as well as overall frequency of behavior in each cross-section is reported. The delinquency rate and default rates are monotonically decreasing as the borrower is observed to have had made early payments at increasing levels. The frequency of early payment behavior is bimodal, with a majority of borrowers exhibiting no early payments in their initial six payments.

	DQ Rate	Default Rate	Frequency
No Early Pays	53.5%	29.1%	54.0%
1 Early Pay	49.1%	26.4%	15.9%
2 Early Pays	48.1%	25.9%	8.1%
3 Early Pays	44.8%	24.1%	5.8%
4 Early Pays	40.8%	22.4%	4.9%
5 Early Pays	38.0%	20.0%	5.0%
6 Early Pays	31.7%	17.5%	6.3%
Total	49.0%	26.5%	100%

Table 2.3

The Impact of Borrower Diligence

This table presents results from regressions of binary indicators of ex-post loan outcomes on early payment behavior and a vector of covariates. The regressands are binary indicators of delinquency (columns 1 and 2), default (column 3), and prepayment in full (column 4). The regressor #Early Pays, Mos 1-6 is a discrete variable with support between 0 and 6 (inclusive), accumulating the number of early payments observed over the initial six borrower payments. Coefficients are reported for borrower FICO score. Monthly Fixed Effects include an indicator for the month a borrower's first payment was due. Loan Characteristics include borrower (back-end) Debt-To-Income ratio (missing values are coded to zero and an indicator of this is included as a separate covariate) at origination, Note Rate at origination, Principal and Interest Payment at origination, Original Loan Balance, Loan-To-Value at origination, Mortgage Insurance Percentage at origination as well as indicators for Adjustable Rate, Balloon Payment, Rate/Term Refinance, Equity Refinance, Full Doc, and the broad collateral classification (the designation of the securitization the loan was ultimately placed into). Property Characteristics include whether the loan was originated as Owner Occupied and factors for various Property Type classifications (single family, condo, etc.). Pool Fixed Effects include indicators for each pool the loans resided in (559 pools in the 284 securitizations). Zip Fixed Effects include indicators for each zip code that contains a loan in the sample (15,092 zip codes). Reported t-statistics in parentheses are clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Delinquent		Default	Prepay In Full
	(1)	(2)	(3)	(4)
#Early Pays, Mos 1-6	-0.0339***	-0.0236***	-0.0117***	0.0109***
	(-35.50)	(-23.32)	(-14.37)	(11.97)
FICO		-0.00163***	-0.000831***	0.000787***
		(-34.85)	(-20.44)	(15.19)
LTV		0.00392***	0.00468***	-0.00474***
		(15.50)	(20.90)	(-16.85)
Monthly FE		Yes	Yes	Yes
Loan Characteristics		Yes	Yes	Yes
Prop Characteristics		Yes	Yes	Yes
Pool FE		Yes	Yes	Yes
Zip FE		Yes	Yes	Yes
Clustered SE	Pool	Pool	Pool	Pool
N	109,818	109,818	109,818	109,818
adj. R^2	0.016	0.165	0.146	0.199

Table 2.4

Borrower Diligence is Unobservable at Origination

This table presents results from regressions of various loan characteristics on early payment behavior and a vector of covariates. The regression in Column 1 is run on the full sample of loans, while columns 2 and 3 are for ARM loans only. Column 1 shows a regression of the Note Rate at origination on early payments. If a borrower's diligence characteristic (which is measured herein through early payment behavior) was observable at origination, it would likely be priced into the note rate at origination. Column 2 restricts attention only to ARM loans to remove concerns that diligent borrowers are more likely to prepay in full. The reported coefficient is expressed as percentage points per early payment (-0.0107 means that each early payment is associated with a 1 bp reduction in ARM Margin). Column 3 demonstrates that the correlation between early payments and delinquency outcomes is similar in the ARM only sample as it is in the full sample. Covariate categories are the same as Figure 2.3. Additionally included here is the Property Value. Some covariates in the Loan Characteristics category are excluded as they are co-determined with the Note Rate. Those included are borrower (back-end) Debt-To-Income ratio (missing values are coded to zero and an indicator of this is included as a separate covariate) at origination, and indicators for Rate/Term Refinance, Equity Refinance, and Full Doc. Reported t-statistics in parentheses are clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full Sample	ARM Loans Only	
	Note Rate	ARM Margin	Delinquent
	(1)	(2)	(3)
#Early Pays, Mos 1-6	-0.000421	-0.0107**	-0.0277***
	(-0.31)	(-2.44)	(-13.76)
FICO	-0.00748***	-0.0171***	-0.00131***
	(-31.70)	(-36.59)	(-18.18)
Property Value	Yes	Yes	Yes
ARM Margin	No	No	Yes
Monthly FE	Yes	Yes	Yes
Loan Characteristics	Some	Some	Yes
Prop Characteristics	Yes	Yes	Yes
Pool FE	No	No	Yes
Zip FE	Yes	Yes	Yes
Clustered SE	Pool	Pool	Pool
N	109,818	40,942	40,942
adj. R^2	0.504	0.739	0.140

Table 2.5

Information Measure Summary Statistics

This table reports descriptive statistics for two measures of private information at both the loan and deal level. Warehouse Seasoning is defined as the number of payments due prior to the loan being securitized. Early Payments Observed in Private Information, Proxy is defined only on loans that made at least one payment into the warehouse and aggregates the number of early payments observed for the first three loan payments made into the securitization. Given the high level of correlation between early payment observation windows this serves as a proxy for the private information available to the issuer at the time of securitization. In Panel A loan level statistics are presented for all observations where a calculated value is valid. Panel B restricts attention to the loan set for which the issuer could have reasonably made a warehouse length decision based on this proxy information. In Panel C principal balance weighted averages of the underlying loan level values are taken at the deal level and summary statistics are reported. Panel C also reports summary statistics for the proportion of the pool that was designated as non-offered at securitization.

Panel A - Full Loan Level	Obs.	Mean	Median	Std. Dev.	1^{st}%	99^{th}%
Warehouse Seasoning	878,385	0.71	0.00	2.24	0.00	6.00
Early Payments Observed in Private Information, Proxy	319,103	0.54	0.00	0.97	0.00	3.00

Panel B - Partial Loan Level	Obs.	Mean	Median	Std. Dev.	1^{st}%	99^{th}%
Warehouse Seasoning	251,205	1.73	1.00	1.32	1.00	7.00
Early Payments Observed in Private Information, Proxy	251,205	0.58	0.00	1.00	0.00	3.00

Panel C - Deal Level	Obs.	Mean	Median	Std. Dev.	1^{st}%	99^{th}%
Average Warehouse Seasoning	284	0.76	0.63	0.50	0.16	2.85
Average Early Payments Observed in Private Information, Proxy	284	0.59	0.59	0.17	0.31	1.00
Proportion, Not Offered	284	1.81%	1.30%	1.26%	0.25%	5.65%

Table 2.6

Issuer Signaling of Private Information

In this table the proportion of the pool that was considered non-offered at the time of securitization is regressed on various measures of both public and private information at the deal level. In column 1 retention is regressed on the proxy for the early payment information that would have been observable to the issuer prior to securitization. Column 2 repeats that specification, adding in only the average FICO score at the deal level to demonstrate that the issuer was not signaling based on the observed private information content. Column 3 suggests that retention increases with the support of the private information available to the issuer, measured by the number of payments he was able to observe in the warehouse. Column 4 includes a vector of observable deal characteristics to show that signaling in relation to warehouse seasoning is not explained by observables. All loan level averages are issuance principal balance weighted unless otherwise specified. Covariates include Average FICO, Average Interest Rate, Average Loan-To-Value ratio, Average Principal and Interest Payment at loan origination, and origination Debt-To-Income ratio of the loans in the deal. Simple average issuance loan balance as well as total loan balance and loan count are also included. Proportions of the pool (issuance balance weighted) are included for Fixed Rate, Owner Occupied, Full Documentation, Cash Out Refinance, Rate/Term Refinance, and located in California, Texas, and Florida (each separately) are also included. Fixed effects for the quarter of deal closing and the deal designation (broad collateral category and deal structure type) are also included. The proportion of the pool that was sold to the securitization by an affiliate of GMAC-RFC (largely either GMAC Mortgage, Homecomings Financial, or Ditech) is included. Finally, the largest proportion of the pool that was sold to the securitization by a single seller that was not affiliated with GMAC-RFC is included. Reported t-statistics in parentheses are clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Proportion, Not Offered			
	(1)	(2)	(3)	(4)
Average Early Payments Observed in	-0.0486***	-0.00604		-0.00209
Private Information, Proxy	(-14.44)	(-1.20)		(-0.54)
Average Warehouse Seasoning			0.00364**	0.00377**
			(2.46)	(2.59)
Average FICO		-0.000190***		-0.0000542
		(-10.31)		(-0.61)
Interest Rate, LTV, Loan Balance, P&I, DTI				Yes
Quarter and Des FE, Deal Size				Yes
Proportions: Fixed, OO, Full Doc				Yes
Cash Out Refi, RT Refi				
Proportions: CA, TX, and FL				Yes
Proportion, Affiliated Seller				Yes
Proportion, Largest Non-Affiliated Seller				Yes
Clustered SE				Closing Month
N	284	284	284	284
adj. R^2	0.423	0.580	0.018	0.771

Table 2.7

Investors Do Not Price Early Pay Behavior

In this table the tranche balance weighted average of the margin over LIBOR for each prime rated adjustable rate class within a particular deal is regressed on various measures of public and private information at the deal level. Observations for 82 of the 284 deals are missing because they lack any adjustable rate classes. With inclusion of all public observables, the margin over LIBOR is not varying with the proxy for the early payments that would have been observable to the issuer nor to the number of warehouse payments observed prior to securitization. This implies that the "price" of these tranches is not correlated with the early payment private information of the issuer. The coefficient on the proportion of the pool retained by the issuer is also not significantly different from zero, suggesting that the price of the securitization was not sensitive to the retention level of the issuer. Included controls are the same as listed in Table 2.6. Reported t-statistics in parentheses are clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Weighted Average Margin, AAA Tranches (1)
Early Payments Observed in	0.0313
Private Information, Proxy	(0.35)
Average Warehouse Seasoning	-0.0185
	(-0.78)
Proportion, Not Offered	-0.9161
	(-1.25)
All Controls	Yes
Clustered SE	Closing Month
N	202
adj. R^2	0.823

Table 2.8

Warehouse Seasoning and Early Pay Behavior

This table regresses warehouse seasoning on the proxy for early payments observed by the issuer prior to securitization at the loan level. The loan set is restricted to that for which the loan's first payment was made into the warehouse and where a valid proxy for early payment information is observable. The standard set of loan level controls are included with the exception of fixed effects for the month of first payment due and the pool the loan was securitized into. These two fixed effects perfectly pin down the warehouse seasoning. Column 1 leaves them both out while column 2 and column 3 exclude first payment month and pool fixed effects respectively. Reported t-statistics in parentheses are clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Warehouse Seasoning		
	(1)	(2)	(3)
Early Payments Observed in	-0.0364***	-0.0316***	-0.0327***
Private Information, Proxy	(-11.24)	(-10.71)	(-11.05)
FICO	0.000180	-0.0000636	0.0000542
	(1.04)	(-0.44)	(0.34)
First Payment		Warehouse	
Monthly FE	No	No	Yes
Loan Characteristics	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes
Pool FE	No	Yes	No
Zip FE	Yes	Yes	Yes
Clustered SE	Pool	Pool	Pool
N	251,205	251,205	251,205
adj. R^2	0.054	0.177	0.131

Table 2.9

Early Pay Behavior Does Not Impact Ratings

This table reports regression results for various pool rating proportions on measures of private information and selected observable covariates at the deal level. Tranches are either rated prime, investment, junk, or not rated. The dependent variable in all cases is the principal balance of the tranches in the securitization receiving the specified rating divided by the total loan balance of the deal. These four proportions are mutually exclusive and collectively exhaustive (they sum to one at the deal level). The proxy for the early payment behavior observed by the issuer (and theoretically observable by the credit rating agency) does not vary with any measure of ratings placed onto the securitization. The average warehouse seasoning varies only with the proportion of the pool that was not rated, which is highly correlated with the proportion not offered and is thus a very similar regression specification as column 3 in Table 2.6. The only covariates included are the Average FICO score of the loans in the pool and fixed effects for the month the securitization closed and for the deal designation (broad collateral category and deal structure type). Without these covariates the coefficient on the early payment information proxy is significant for some specifications but the parsimonious specification is intended to demonstrate the weakness of that result. Reported t-statistics in parentheses. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Proportion, Prime (1)	Proportion, Investment (2)	Proportion, Junk (3)	Proportion, Not Rated (4)
Average Early Payments Observed in Private Information, Proxy	0.0214	-0.0154	0.00140	-0.00738
	(0.74)	(-0.57)	(0.36)	(-1.32)
Average Warehouse Seasoning	-0.00000379	-0.00527	-0.000701	0.00597***
	(-0.00)	(-1.01)	(-0.94)	(5.52)
Average FICO	0.00138***	-0.00134***	-0.0000267	-0.00000869
	(3.81)	(-3.97)	(-0.55)	(-0.12)
Month FE	Yes	Yes	Yes	Yes
Des FE	Yes	Yes	Yes	Yes
N	284	284	284	284
adj. R^2	0.775	0.754	0.302	0.711

Table 2.10

Ratings Are Insufficient

This table reports regression results for the ex-post proportion of loans (issuance balance weighted) in a deal that ultimately defaulted (through the end of 2014) on various measures of public and private information. Column 1 demonstrates that in the absence of controls the proportion of the pool that receives a prime or investment quality rating, as well as the proportion of the pool that was retained by the issuer at securitization are negatively correlated with the ultimate ex-post default outcomes of the pool. However, column 2 includes a vector of observable covariates (see Table 2.6) and demonstrates that the ratings and retention levels appear to largely be summaries of observable deal characteristics and carry no additional information about the default likelihood of the pool. The early payment information content however conveys information not contained in the observables. Incremental R^2 improvements with the inclusion of early payment information are an order of magnitude larger than when just the rating or retention information is included. Additionally, similar results hold for the proportion of the pool that ultimately went delinquent as well as for the actual net losses experienced on the loans. Reported t-statistics in parentheses are clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Proportion, Default	
	(1)	(2)
Average Early Payments Observed in Private Information, Proxy	-0.424***	-0.111***
	(-7.24)	(-3.84)
Proportion, Prime and Investment	-7.397***	0.393
	(-8.78)	(0.92)
Proportion, Not Offered	-2.716***	0.0481
	(-2.71)	(0.15)
Deal Level Controls		Yes
Clustered SE		Closing Month
N	284	284
adj. R^2	0.468	0.973

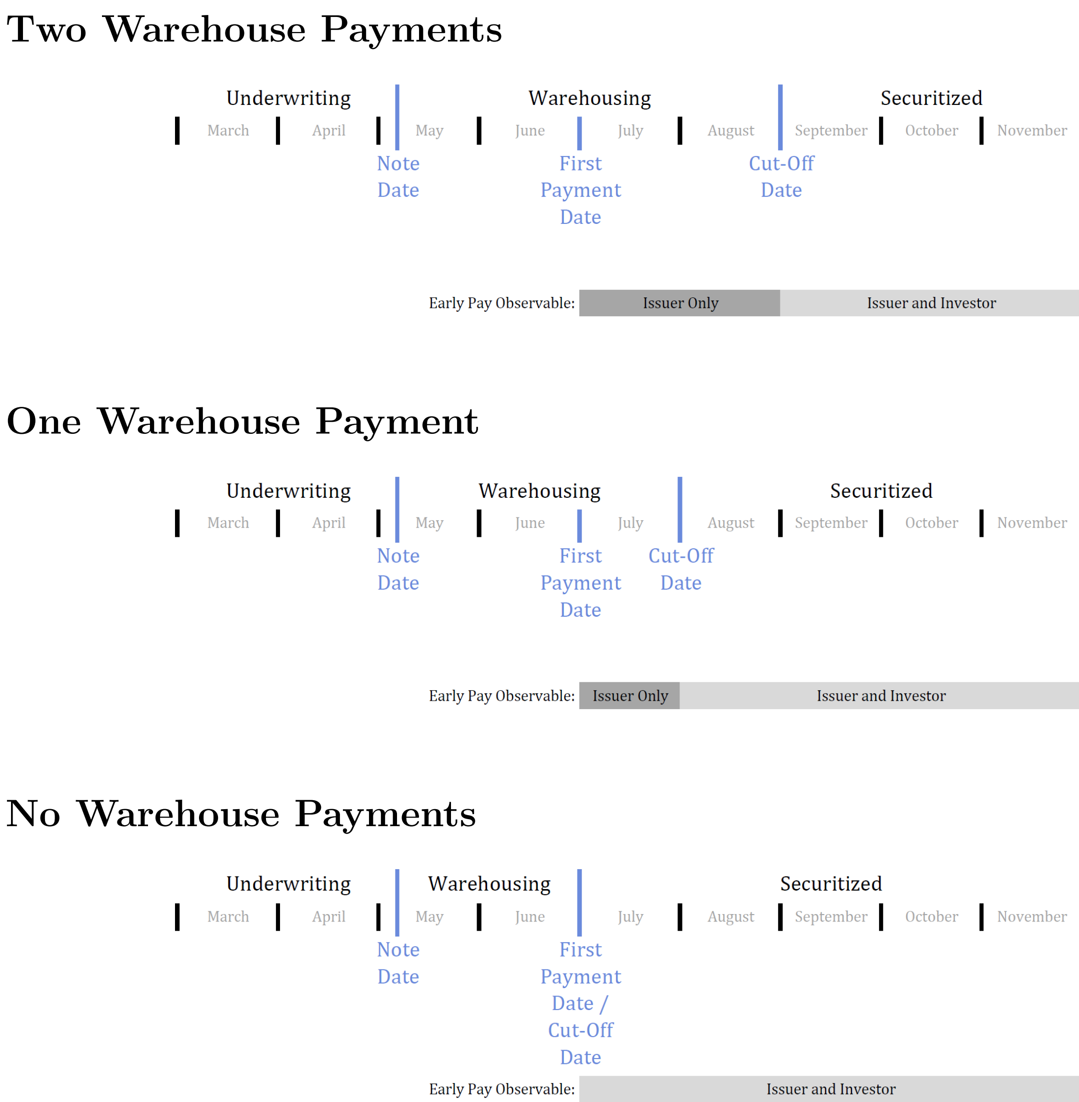

Figure 2.1. Securitization Timing.

This figure depicts a hypothetical timeline of the securitization process from the perspective of an individual loan. During the underwriting process the originator works closely with the prospective borrower to determine the correct mortgage instrument fit and pricing to meet the borrower's needs. Once the underwriting is complete the mortgage enters into effect on the note date. The borrowers first payment, due on the first payment date, usually occurs on the first of the month immediately following a full calendar month after the note date. Prior to the first payment date, as well as until the securitization that the loan is placed into closes, the loan is warehoused by the issuer. Payments made by the borrower during this warehousing stage are owned by the issuer. Each securitization has a defined date, the cut-off date, whereat any borrower payments due on or after this date are then owned by the securitization. The issuer gains private information relating to the early pay behavior of the borrower during the warehousing stage. Early pay behavior once the loan is securitized is observable to the investors. The issuer, in determining which security the loan is placed into, determines how long the warehousing stage will last and how many warehouse payments they observe.

Class	Pass-Through Rate	Initial Certificate Principal Balance	Initial Rating (S&P/Fitch)
Offered Certificates			
Class A Certificates:			
A-1	6.000%	$250,000,000	AAA/AAA
A-2	6.000%	$100,000,000	AAA/AAA
A-3	6.000%	$52,527,000	AAA/AAA
A-P	0.000%	$3,733,389	AAA/AAA
A-V	Variable	Notional	AAA/AAA
Class M Certificates:			
M-1	6.000%	$12,596,700	NA/AA
M-2	6.000%	$3,149,000	NA/A
M-3	6.000%	$2,099,400	NA/BBB
Non-Offered Certificates			
Class B Certificates:			
B-1	6.000%	$1,049,700	NA/BB
B-2	6.000%	$1,049,700	NA/B
B-3	6.000%	$1,049,736	NA/NA

Figure 2.2. Sample Deal Structure - Senior-Subordinated.

This figure presents a stylized example of the class listing of a broad classification of securitizations with senior-subordinated (senior-sub) structures, representative of a common table at the front of a securitization's prospectus supplement, which is the offering document provided to potential investors. A securitization is divided into individual tranches each with differing payment priorities, interest rates, sizes, and ratings. These characteristics are listed in the table. Generally, classes at the top of the table have higher payment priority than those at the bottom. Senior (class A) interest has highest priority and is paid pro-rata based on accrued interest. Next senior classes receive their principal payment per a complicated principal cash waterfall delineated in the governing documents. After the senior certificates had received both their principal and interest payments the subordinate certificates (Mezzanine and Junior, or class M and class B respectively) were paid in the following order: M-1 Interest, M-1 Principal, M-2 Interest, M-2 Principal... B-3 Interest, B-3 Principal. Losses were allocated to write down the outstanding principal balance of the most junior outstanding class, known as the "first loss piece." This makes the B-3 the class whose value is the most sensitive to the credit risk information of the issuer. The classes listed as offered were a part of the public offering under the prospectus supplement, whereas those that were non-offered were initially retained by the issuer, to either be held for investment or sold later in a much less informationally sensitive market. The division between offered and non-offered does not always coincide with the mezzanine-junior line. Ratings are provided by credit rating agencies (generally some or all of Standard and Poor's, Fitch, and Moody's) and, for the purposes of this study, will be classified as Prime (AAA/Aaa), Investment Grade (AA+/Aa1 through BBB-/Baa3), Junk (BB+/Ba1 and below), or Not Rated. All offered certificates were rated by at least one credit rating agency, some not offered certificates received a rating. When the rating agencies disagreed, the majority (or, in the case of a tie, the more moderate) rating was used.

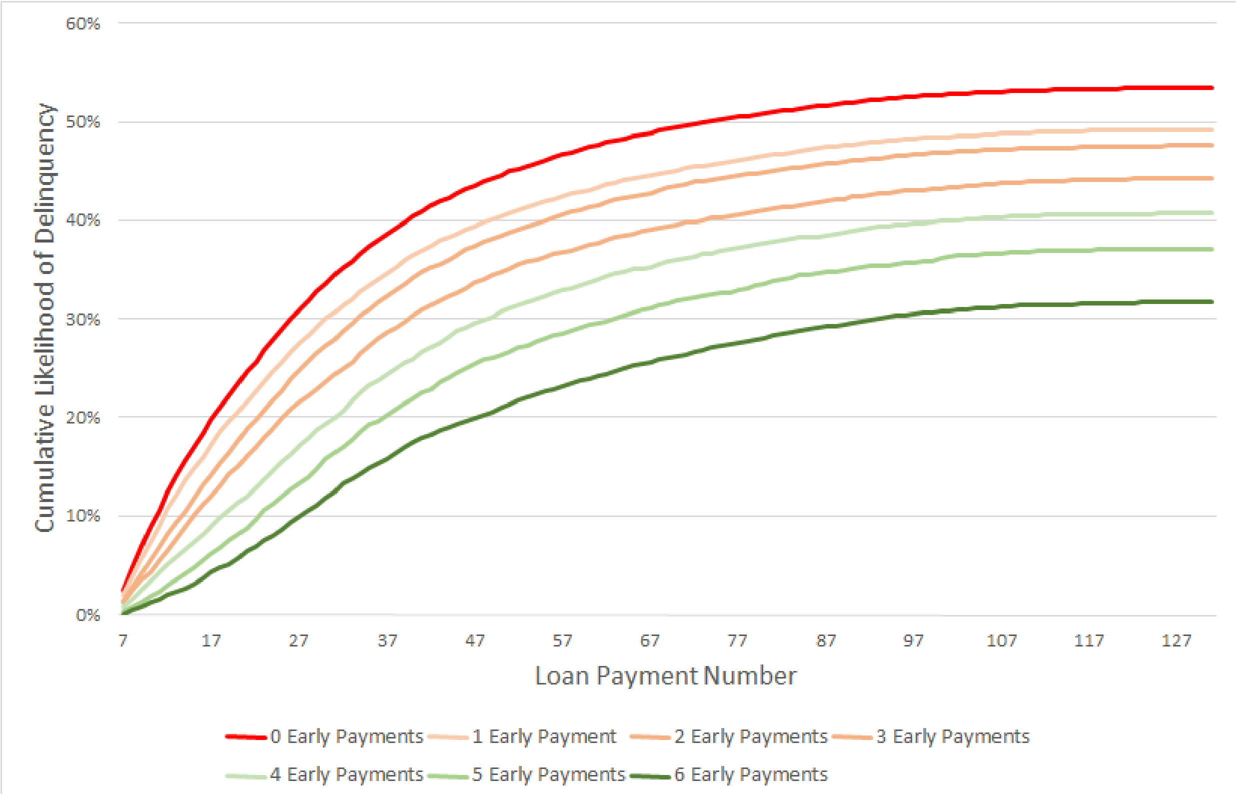

Figure 2.3. Cumulative Delinquency - Early Pay Cross Section.

This figure presents, for the cross section of early payment behaviors, cumulative rates of delinquency. The number of early payments in the borrower's first six payments are counted to determine the subpopulation they are placed into. Beginning with the borrower's seventh payment the cumulative delinquency in each subpopulation is graphed. The red line represents those borrowers that made none of their first six payments early. Their delinquency rate rises faster and earlier than the other groups. The cumulative performance of the loans is monotonically increasing in the number of early payments made in the first six months. Delinquency here is defined as the first time a borrower has not made a payment by the time the due date for his next payment has arrived.

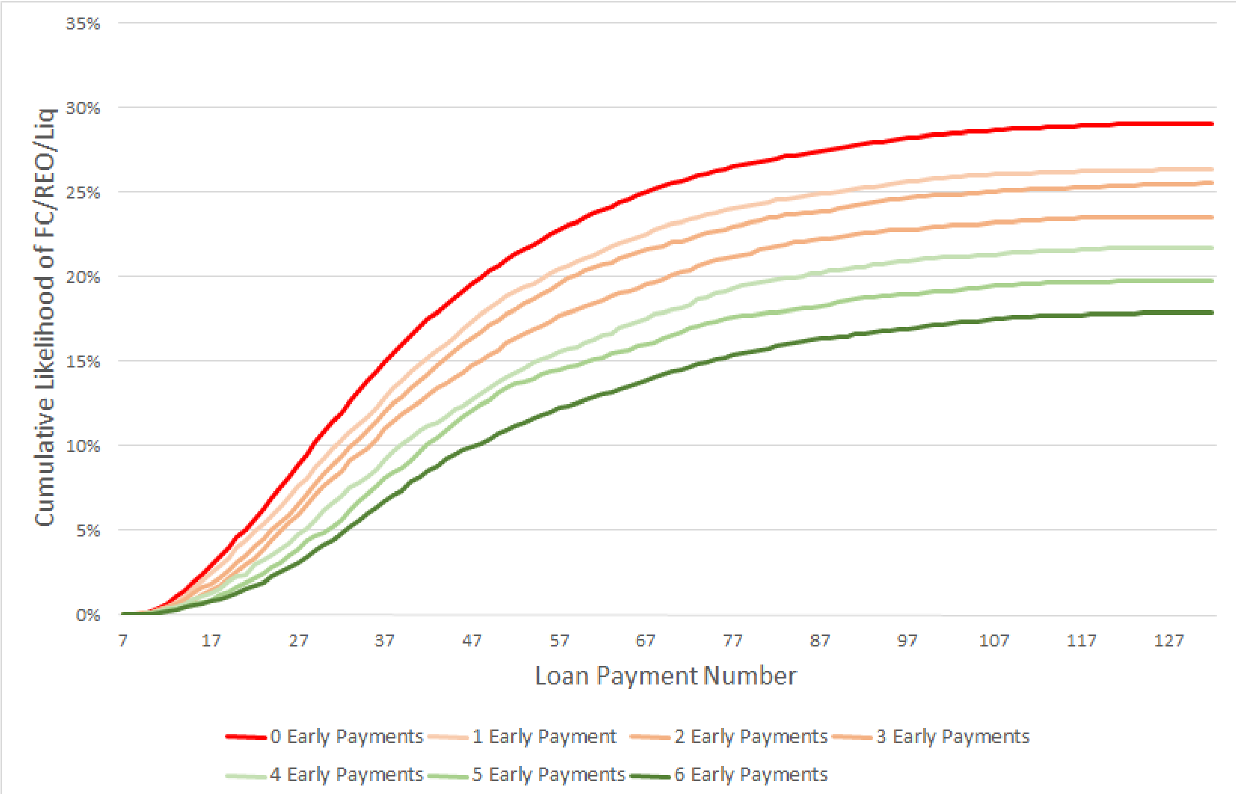

Figure 2.4. Cumulative Default - Early Pay Cross Section.

This figure presents, for the cross section of early payment behaviors, cumulative rates of default. The number of early payments in the borrower's first six payments are counted to determine the subpopulation they are placed into. Beginning with the borrower's seventh payment the cumulative default in each subpopulation is graphed. The red line represents those borrowers that made none of their first six payments early. Their default rate rises faster and earlier than the other groups. The cumulative performance of the loans is monotonically increasing in the number of early payments made in the first six months. Default here is defined as the first monthly reporting period where the servicer has entered foreclosure proceedings against the borrower, has acquired the REO property, or the loan has liquidated (either as an REO disposition, third party sale, short sale, or charge-off).

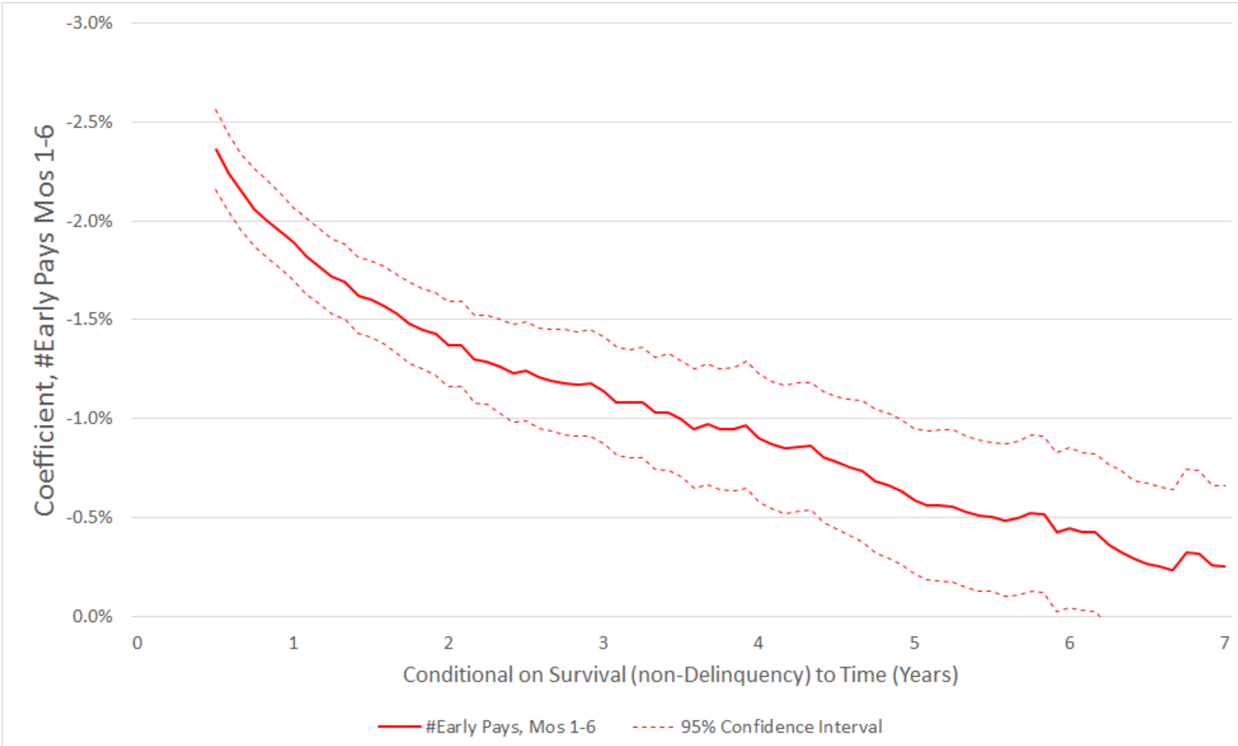

Figure 2.5. Effect Persistence.

This figure presents the estimated coefficient for the regression of an indicator of delinquency on early payment behavior for various conditioning sets. Early payment behavior is observed for the initial six payments of the life of the loan. Moving to the right along the horizontal axis restricts the regression sample to greater levels of consecutive current payments after the six month observation period. The vertical axis then reports the coefficient on the early payment variable for the loans so conditioned. The regression is specified (except for the additional conditioning) identically to column 2 in Table 2.3. 95% confidence bands are also reported. The coefficient is significantly different than zero at the 95% level conditioning through 6 years and 2 months of consecutive current payments starting with the borrower's initial payment.

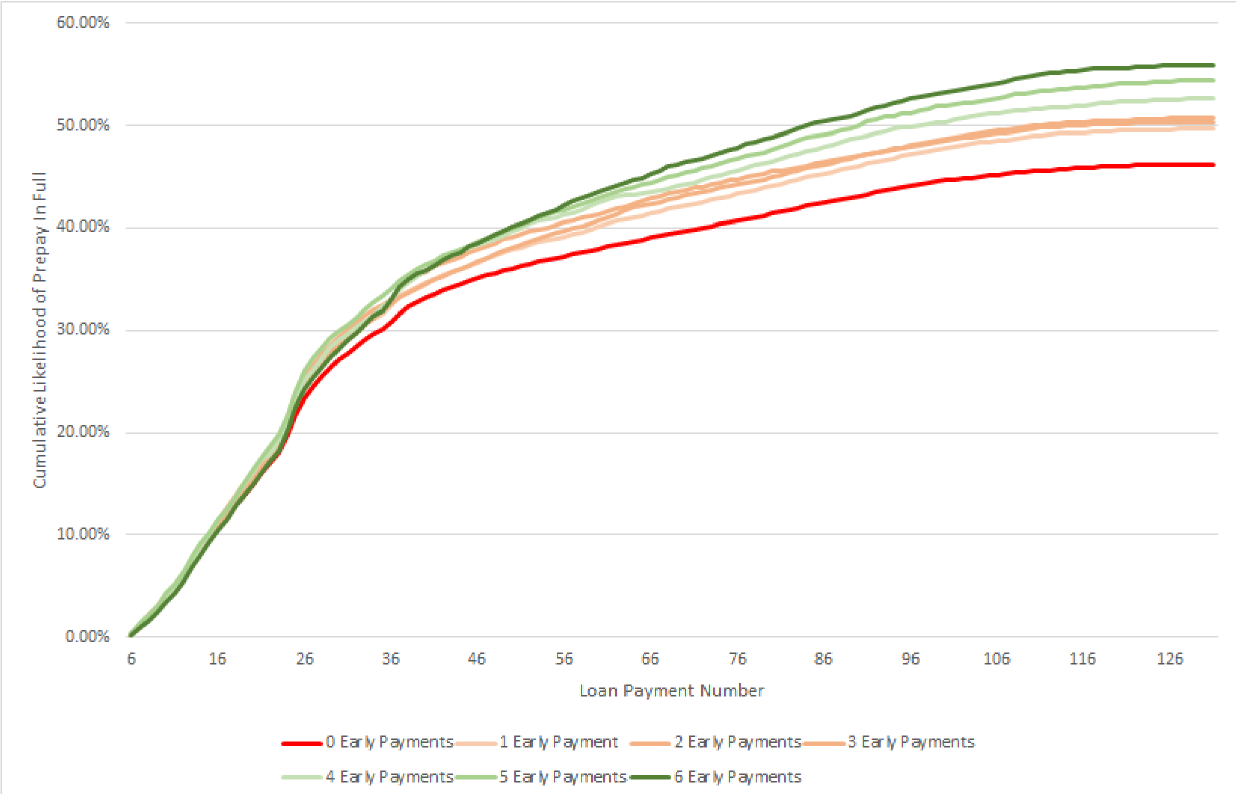

Figure 2.6. Cumulative Prepayment In Full - Early Pay Cross Section.

This figure presents, for the cross section of early payment behaviors, cumulative rates of borrower prepayment in full. The number of early payments in the borrower's first six payments are counted to determine the subpopulation they are placed into. Beginning with the borrower's seventh payment the cumulative number of borrowers who have paid off their loan early in each subpopulation is graphed. The red line represents those borrowers that made none of their first six payments early. Early payment behavior is a poor indicator of prepayment behavior early in the life of the loan. Later in the life of the loan the cumulative prepayment rate is weakly monotonically decreasing in the number of early payments made in the first six months.

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CHAPTER 3

Competing for Deal Flow in Mortgage Markets
(with Mark J. Garmaise and Gabriel Natividad)

The competitiveness of banking markets is important both for its direct impact on the quantity and pricing of financing made available to borrowers and for the potential spillover effects of lending terms on broad sectors of the economy. As a result, banking competition has been the subject of sustained interest both in academic and policy circles.[1] In this chapter, we show that across local mortgage markets in the U.S. lenders engage in tournament-like competition for applicant deal flow. We begin by showing that plausibly exogenous increases in a lender's current period originations in a local area lead to increased applications and lending in the following year. Applicants are attracted to growing lenders. We then analyze the competitive dynamics of mortgage markets and show that only the quickest-growing lenders in a market have an impact on others. This feature of the market is consistent with a tournament model in which the fastest growing lenders receive disproportionate applicant attention. In support of this interpretation, we show that future lending is convex in current year originations. We also find, somewhat unexpectedly, that increased lending by their quickest-growing competitor leads banks to increase the interest rates they charge locally. Together these findings have implications for the strategies of banks striving for market share and for investors, regulators and depositors seeking to understand the evolution of banking markets and to assess which lenders are most vulnerable.

Two central ideas from the theoretical literature motivate our analysis. The first is the argument that market share serves as a signal of quality to consumers (Caminal and Vives

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[1] See Berger, Demsetz, and Strahan (1999) and Degryse and Ongena (2008) for literature reviews and https://www.federalreserve.gov/bankinforeg/competitive-effects-mergers-acquisitions-faqs.htm (accessed Feb. 27, 2017) and DOJ-FTC (2010) for regulatory guidelines.

(1996)). Increased lending by a bank will therefore attract other potential borrowers. A similar concept arises in network models of social learning (e.g., Young (2009)): as more local borrowers engage with a given lender, others in the same area become more likely to adopt the same practice and approach the bank. This reasoning also suggests that increased lending by a lender's competitors will reduce its future opportunities. The second theory is that firms compete in tournaments in which the actions of market leaders are particularly important.[2] Under this analysis, it is the lenders with the most positive signals (increases in mortgage originations, in our setting) who will have the greatest effect on market outcomes. We apply these two theories to the mortgage market and find that both are highly effective in describing how it operates.

Assessing bank strategies is challenging, as these strategies are fundamentally endogenous. Our empirical design is centered on identifying shocks to the probability that a bank extends a mortgage to a given applicant. We analyze the 251 million mortgage applications in the Home Mortgage Disclosure Act (HMDA) database between 2003 and 2014. We use half of the data, which we label the training sample, to estimate each bank's mortgage approval model (each year) as a function of applicants' debt-to-income (DTI) ratios. DTI ratios are a typical input to bank acceptance models (e.g., Mian and Sufi (2009) and Dell'Ariccia, Igan, and Laeven (2012)), and it is standard for different banks to use varying DTI cutoffs in assessing applications (Tempkin, Levy, and D. Levine, 1999; Listokin et al., 2001; Rose, 2011), with loans above the cutoffs significantly less likely to be approved. We use the data from the training sample to identify these bank-specific cutoffs for each lender's national loan approval model.

Our empirical strategy contrasts different applications received by a given bank in various areas. Applications just above a bank's national DTI threshold are deemed to be relatively unattractive, and applications just below a cutoff should be relatively attractive. If a bank happens to receive many relatively attractive applications in one local area and many rela-

[2]The mutual fund tournament literature explores this idea in an examination of fund flows (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; J. Huang, Wei, and Yan, 2007; Barber, X. Huang, and Odean, 2016).

tively unattractive applications in a second area, then we should expect to observe a local lending surge in the first region but not in the second.

We test this hypothesis by discarding the training sample and examining the second half of the data, labeled the test sample. Our first result is that applicants from the test sample with DTIs in narrow bins shown to be relatively attractive for a given bank in the training sample are indeed discontinuously more likely to be offered a loan. These discontinuities generate loan attractiveness shocks, and we show that they are unrelated to a number of contemporaneous covariates across narrow DTI bins, suggesting that favored applications are otherwise quite similar to unfavored applications. Further, we document that there is not an inordinate number of applications in the attractive bins, thus offering evidence that loan officers (or applicants) are not systematically manipulating them into the favored narrow bins.

We define local lending shocks by aggregating each bank's application attractiveness shocks jointly at the census tract and application amount decile level, and consider their impact on the future (next year) lending of the bank. To be sure, as described above, exogenously attractive applications are more likely to be offered a loan, but how does the aggregate shock influence the bank's expansion next year in that local market? We find a positive and statistically strong effect of the current year's lending supply shocks on next year's local applicant flow, controlling for bank, local market, and year fixed effects. The elasticity of future applications with respect to current originations is approximately 37%. We also find that current period shocks generate more future originations and a higher dollar volume of future originations. This is clear evidence in favor of the Caminal and Vives (1996) theory that increased market share attracts future consumers. The magnitudes of the impacts on applications and originations are similar, suggesting that the main driver of increased future lending is greater borrower interest, rather than a change in bank local lending policy.

These local lending shocks are defined for each bank, which allows us to study the impact on a bank of shocks to its competitors. Do future originations for one bank come at the cost of future originations to its competitors? We show that a bank's future applicant flow and lending are both unaffected by the total shocks of its competitors, the shocks of its three largest competitors or the shock to the local Herfindahl-Hirschman Index (HHI). We do find, however, that the quickest-growing competitor (i.e., the competitor with the largest current origination shock) significantly hurts the focal bank's future applications and originations. The elasticity of a bank's future applications with respect to the largest current origination increase of its competitors is roughly -19%. The fact that only the quickest-growing competitor's lending matters, not that of all competitors nor that of the largest, indicates that the mortgage market has features of a tournament. The mutual fund tournament model of J. Huang, Wei, and Yan (2007) describes a setting in which information-constrained investors are only willing to pay a cost to learn more about the funds with the highest signals, so the sensitivity of future flows to the current signal is greatest for those funds with the best signals. We find that a similar dynamic applies in the mortgage market: increased current originations (higher signals) lead to more future lending particularly for those lenders that are already making many loans.

We show that the relevant market for the competitive shocks we analyze is highly localized; the negative impact of the quickest-growing tract-level competitor is more than twice that of the quickest-growing zip code-level competitor. This is consistent with work showing that competitive effects diminish considerably with distance for firms in a variety of industries (Davis, 2006; Pinkse, Slade, and Brett, 2002; Seim, 2006) including banking (Degryse and Ongena, 2005). Our spatial findings suggest that lenders are competing in local tournaments.

It is a standard characteristic of tournament markets that future outcomes are convex in the current period signal, as signal improvements matter most for the best performers. We show that the mortgage market displays this feature: future lending and applications are both convex in current origination shocks, and current origination shocks have a greater impact on future outcomes for lenders whose shock is in the top quartile locally.

The results described above focus on quantity effects. What is the price response of a bank to increased competition? We merge the HMDA loan-level data with interest rate and performance information from BlackBox, Fannie Mae and Freddie Mac. Somewhat surprisingly, we find that banks increase the rates they charge in the face of greater competition. This may be explained by the fact that when faced with increased shocks to its quickest-growing competitor, a bank originates mortgages with higher loan-to-value ratios. Competition leads banks to retreat to a riskier subset of the overall market.

Do all these competition considerations matter for loan performance? We find that a bank's current origination shocks have no significant effects on future loans' probability of delinquency. However, we find that delinquency is increasing in the origination shock of the quickest-growing competitor of the focal bank. This suggests that banks underestimated the powerful negative effects of competition on the quality of their local borrowing pools. Competition appears to have increased both observable and unobservable risks.

From a methodological perspective, we make two points. First, our approach simultaneously identifying plausibly exogenous shocks to the financing supplied by both a lender and its competitors provides a new technique for analyzing banking competition and allows us to supply direct evidence on competitive dynamics in mortgage markets. Second, our method of analyzing shocks in the training sample and verifying their importance in the test sample enables us to avoid endogeneity issues that arise when the entire sample is used to both identify shocks and test their impact. Specifically, it is clear that assessing the effect of current local lending on future local lending simply by regressing the latter on the former is subject to the concern that both are influenced by unobserved variables. If one sample is used to both identify relatively attractive DTI bins and to test their impact on future lending, there is a possibility that a bin may be identified as relatively attractive simply because it contains a specific local loan that was approved. Regressing future lending on the relative attractiveness of current period loan applications would thus be quite similar to regressing future local lending on current local lending. In our approach, we separately identify relatively attractive DTI bins in the national training sample and then relate future lending only to the attributed relatively attractive loans from the test sample, where the attribution of attractiveness arises from test sample applications submitted across the country. We thus sidestep this endogenity problem, as we do not specifically condition on the approval of any current local applications.

Our emphasis is on the functioning of micro banking markets and the identities of the key competitive players, in contrast to most prior studies of banking competition that have focused on either broad market regulatory constraints (e.g., Jayaratne and Strahan (1996) and Caprio, Barth, and R. Levine (2001)) or bank-specific evaluations of competitive behavior (e.g., Schaeck, Cihak, and Wolfe (2009) and Bikker, Shaffer, and Spierdijk (2012)). The same bank can play very different competitive roles in varying local areas. The local competitive actions of lenders along dimensions such as advertising (Gurun, Matvos, and Seru, 2016), information acquisition (Stroebel, 2016), and their potential exertion of market power (Scharfstein and Sunderam, 2014) have attracted recent attention.

Our results establish that the mortgage market is susceptible to competitive fragility. Specifically, our central findings are that current growth fuels future growth and that this effect is convex. This suggests that new lenders can quickly achieve substantial market presence and even dominance. As a result, lenders without a long-established history and, perhaps, without a mature system of loan risk evaluation can become the most important mortgage suppliers in the market. The consequences of this competitive upheaval can be very negative, as has become clear after the 2008 crisis.

3.1 Data

The data in this chapter consist primarily of residential mortgage loan applications reported to the Federal Financial Institutions Examination Council under the Home Mortgage Disclosure Act (HMDA) for the years 2003 through 2014. The HMDA requires that all financial institutions ("lenders") subject to the regulation[3] report into the Loan Application Registrar information about all applications for a residential mortgage loan that it receives within a particular calendar year. The data covers about 80 percent of all residential mortgage loans nationwide (e.g., Bhutta, Popper, and Ringo (2015)).

There are 219,612,982 application observations in the full data set. We split into the

[3]Institutions subject to the HMDA are those that have a branch or office within a defined Metropolitan Statistics Area.

training and test samples all applications with a DTI less than five[4], leaving 104,933,664 and 104,944,092 in each sample respectively. Observations are dropped from the test sample if the corresponding DTI bin in the training sample is an empty set. Our final test sample then consists of 103,068,422 loan applications. All of the following statistics, unless otherwise noted, are in regards to this population.

As described in Table 3.1, the data include detailed demographic and geographic characteristics as well as the borrower's income and the requested loan amount (each rounded to the nearest thousand). The DTI reported is the ratio of the requested loan amount to the income of the prospective borrower. Demographic information primarily consists of race and ethnicity. General loan type characteristics are also reported, including whether or not the loan will be occupied by the borrower, whether it is a conventional loan (any loan other than FHA, VA, FSA, or RHS loans), the property type, and whether the loan was for the purchase of a home or to refinance. We also observe whether or not the loan application was accepted by the lender and whether or not it was ultimately originated.

The HMDA data set includes a geographic indicator at the census tract level. We associate a corresponding zip code by utilizing the United States Postal Service Zip Code Crosswalk files from the U.S. Department of Housing and Urban Development. These files provide the percentage of residential addresses for a census tract that lay within a particular zip code. We assign the zip code that is most prevalent within a census tract as the zip code for that loan application.

Our data contain 12,557 unique lenders (87,252 lender-years) and 87,424 census tracts[5] (807,952 tract-years). Local markets are likely different for loans of different sizes. We calculate requested loan amount deciles across the entire data set and define a local market of applications to be the set of all applicants in a given year that are located in the same

[4]Our empirical method requires that DTIs lie in a fairly dense range, so we exclude outlier DTIs from the analysis

[5]This is 13,290 more census tracts than were defined in the 2010 census because our sample crosses census regimes. Census tract boundaries were redefined after the 2010 census and some tract designations were eliminated while others were created.

census tract and belong to the same requested loan size decile. Tracts are then divided into 821,768 markets (6,594,937 market-years), providing a total of 38,526,152 lender-market (65,375,784 lender-market-year) observations.

We define lenders by their federal tax identification numbers. This allows our lenders to be invariant to reorganizations of the HMDA reporting structure. Entire classes of mortgage lenders were moved between reporting agencies during the sample period and agencies often reorganized respondent identification numbers between years. Additionally, the use of tax identification numbers mitigates the impact of merger activity within mortgage lenders as it allows for the separateness of pre-merged entities while maintaining at least some portion of an appropriate lending history across time for the post-merger entity.

Additionally we append interest rate and performance data (the latter is observed for the life of the loan within a securitization, through December 2015) and a broader set of borrower characteristics using loan-level data provided from BlackBox Logic for a subset of 13,061,184 originated loans (6,234,543 in the test sample), from the Fannie Mae Single-Family Loan Performance Data for a subset of 14,982,509 originated loans (7,075,341 in the test sample) and from the Freddie Mac Single Family Loan-Level Dataset for a subset of 13,287,303 originated loans (6,313,509 in the test sample). Summary Statistics for performance outcomes in the test sample are presented in Table I.

3.2 Empirical Specification

The focus of this study is to assess the effectiveness and implications of bank expansion strategies in the mortgage market. Strategies, however, are deeply endogenous and may be influenced by a variety of unobserved factors. Our empirical specification therefore aims to identify plausibly exogenous shocks to bank lending activity in local markets. From a general perspective, the first step is to use half the data (the training sample) to estimate national bank origination models each year relating a loan's DTI to its probability of acceptance. Different banks use heterogenous DTI cutoffs in assessing applications (Tempkin, Levy, and D. Levine, 1999; Listokin et al., 2001; Rose, 2011); applications with DTIs above the cutoffs are substantially less likely to be approved.[6] In the second step, we use the training sample origination models to identify these bank-specific DTI cutoffs.[7] We discard the training sample, and use the estimated DTI cutoffs to attribute to each application in the test sample an estimated measure of its attractiveness to a given bank. We regard test sample applications in narrow bins just below DTI cutoffs to be relatively attractive, while those in bins just above cutoffs are relatively unattractive.

For the third step, we test whether relatively attractive test sample applications are indeed more likely to be originated. In the fourth step, we aggregate all the test sample applications in a local market. We view the frequency of relatively attractive local applications as a shock to a bank's lending activity in that market. Although DTI thresholds are determined endogenously, the arrival of applications from one market just above or just below the thresholds creates quasi-random variation in the number of mortgages granted locally by the bank. We thus use our measure of relatively attractive applications as an instrument for the bank's local lending volume this period, and trace its impact on future lending.

3.2.1 Estimating Bank Acceptance Models Using the Training Sample

We begin by assigning each application, with equal probability, to either the training or test samples. The training sample is used to estimate bank acceptance models while the test sample is set aside for later analysis. The key variable in our estimated acceptance models is the applicant's debt-to-income ratio (DTI). The DTI is standard input to bank decision models (Dell'Ariccia, Igan, and Laeven, 2012). We do not observe loan interest rates (or the rate for which the applicant applied) so we calculate the DTI as the ratio of the loan amount requested to the applicant's income. We group applications into bins of DTI of width 0.1, and we define separate bins for each bank b every year t for each defined set of applicant

[6] For a recent application, see Consumer Financial Protection Consumer Financial Protection Bureau (2016). Agarwal et al. (2017) study the use of credit score cutoffs.

[7] Porter and Yu (2015) discuss the issue of unknown regression discontinuity points.

characteristics c. We center the bin boundaries at the DTI sample mean $\hat{\mu} = 2.08$. Formally, we define DTI bin i for bank b in year t for applicants with characteristics c as

$$bin_{i,b,t,c} = \big\{applications : applicant\,applied\,to\,bank\,b\,in\,year\,t, \tag{3.1}$$

$$has\,characteristics\,c\,and\,has\,DTI \in \big[0.1 * i + \hat{\mu}, 0.1 * (i+1) + \hat{\mu}\big)\big\},$$

where the set of characteristics c is a 2-tuple describing the applicant's ethnicity (white or non-white) and owner-occupancy status and i may take positive, zero or negative values as the bins range over the full set of sample DTIs.

The first step in our analysis is to calculate an average acceptance rate $ar(bin_{i,b,t,c})$ for each bin. That is, we use the training sample to estimate each bank's national acceptance model every year as a function of applicant DTIs (we allow the model to vary across some applicant characteristics).

3.2.2 Uncovering Discontinuities in Estimated Acceptance Rates

The training sample thus supplies us with an estimated acceptance rate for every observation that is a function of the observation's bin. We now discard the training sample but use the model we estimated from it to assign to each observation k in the test sample an estimated acceptance rate that depends on its bin.

We are interested in identifying applications that are relatively attractive to specific banks. In particular, we seek applications that are substantially more likely to be accepted by a bank than other, quite similar, applications. Our analysis therefore contrasts the estimated average acceptance rates of neighboring bins. For example, if one bin has a much higher estimated acceptance rate than its neighbor with a higher DTI, then applications in the first bin are apparently much more attractive to a bank than those in the second. This would be indicative of a DTI cutoff in the bank's acceptance model. We make use of the estimated bank acceptance models to identify these acceptance ratio jumps. We define comparison bins that straddle two bins and contrast the estimated average acceptance rates across the two bins that are straddled. Formally, we define comparison bin i for bank b in year t for applicants with characteristics c as

$$compbin_{i,b,t,c} = \Big\{ applications : applicant\ applied\ to\ bank\ b\ in\ year\ t, \tag{3.2}$$

$$has\ characteristics\ c\ and\ has\ DTI \in \big[0.1 * i + \hat{\mu} + 0.05, 0.1 * (i+1) + \hat{\mu} + 0.05\big)\Big\}.$$

Comparison bin $compbin_{i,b,t,c}$ thus straddles half of $bin_{i,b,t,c}$ and half of $bin_{i+1,b,t,c}$. Every observation j in the test sample is a member of a bin denoted by $bin(j)$ and a comparison bin denoted by $compbin(j)$. We estimate the regression

$$ar(bin(j)) = \alpha_{compbin(j)} + u_j, \tag{3.3}$$

where $ar(bin(j))$ is the average acceptance rate of $bin(j)$, $\alpha_{compbin(j)}$ is a fixed effect for all the elements of $compbin(j)$ and u_j is an error term. The residuals $\hat{u}_j$ from regression (3.3) provide information about the differences in estimated acceptance rates between observation j's bin and the neighboring bin that is included in the comparison bin. Observations with a positive residual are in relatively high estimated acceptance ratio bins: they appear to be attractive to the bank. Observations with a negative residual are in apparently less attractive bins. An illustrative example of our approach for one lender is provided in Figure 3.1.

To identify *bank-specific* origination shocks, for each bank and set of characteristics we demean $\hat{u}_k$ by the corresponding shocks for the relevant DTI bin for all banks in the sample that year. We label these bank-specific shocks $\hat{v}_k$, and we use them as our primary measure of discontinuities in bank acceptance models. Industry-wide DTI cutoffs are thus not reflected in these shocks- they identify loans that are particularly attractive or unattractive to a given bank.

3.2.3 Acceptance Rate Jumps and Mortgage Origination in the Test Sample

Does the estimated acceptance model from the training sample actually predict the origination of mortgages from the test sample applications? To answer this question, we regress for every observation k in the test sample

$$originate_k = \xi \hat{v}_k + \epsilon_k, \tag{3.4}$$

where ϵ_k is an error term. The $\hat{v}_k$ terms describe bank-specific origination shocks generated from jumps in estimated loan acceptance models. A positive and significant estimate of ξ indicates that the acceptance model estimated from the training sample does indeed predict jumps in originations in the test sample over small ranges of DTI.

3.2.4 Local Lending Shocks in the Test Sample

We define market-bank shocks $\hat{v}_{M,b,t}$ to be the sum of all the $\hat{v}_k$ for applications in a given market M made to bank b in year t. We examine the impact of these shocks on total current originations by the bank in this market:

$$originations_{M,b,t} = \phi \hat{v}_{M,b,t} + \beta_M + \zeta_b + \delta_t + controls + \eta_{M,b,t} \tag{3.5}$$

where β_M is a market fixed effect, ζ_b is a bank fixed effect, δ_t is a year fixed effect and $\eta_{M,b,t}$ is an error term. We also consider the impact of the origination shocks on future market-bank characteristics in regressions of the form

$$future\,outcome_{M,b,t+1} = \psi \hat{v}_{M,b,t} + \beta_M + \zeta_b + \delta_t + controls + \theta_{M,b,t} \tag{3.6}$$

where future outcomes include application and origination volumes and loan performance measures in the following year and $\theta_{M,b,t}$ is an error term. A positive and significant estimate of ψ is evidence that plausibly exogenous shocks to a bank's local originations this year generate an increase in the bank's local originations in the following year. We typically cluster the standard errors in these regressions at the bank and market levels.

3.3 Results

3.3.1 Relatively Attractive Loans and Origination

As described in Section 3.2, we use the training sample to estimate acceptance models and to identify loans that have DTIs that appear to make them attractive to a given bank. Our first test examines whether the loans in the test sample that are predicted to be attractive are actually accepted and originated by banks. We estimate equation (3.4) with mortgage acceptance by the bank as the dependent variable. The result is displayed in the first column of Table 3.2. We find a coefficient on the bank-specific shock of 0.02 and a t-statistic of 19.78. This is clear evidence that the estimated acceptance model from the training sample does identify jumps in the bank's probability of granting a loan. Test sample applicants with DTIs in narrow bins shown to be favored in the training sample are significantly more likely to be offered a loan.

Including DTI as a control has little impact on the estimated effect of the bank-specific shock, nor does including a third-degree polynomial in DTI, as shown in the second and third columns of Table 3.2. The DTI bins and comparison bins are quite narrow, and the bank-specific shock is capturing discontinuities in acceptance rates for applications with very similar DTIs. As expected, we do find in the regression described in the second column that higher DTI loans are less likely to be accepted, but including this variable has very little impact on our the bank-specific shock coefficient estimate. In the fourth column of Table 3.2, we show that our main result is also robust to the inclusion of bank and year fixed effects and to clustering at the bank level. Including third degree polynomials in the distance of an application's DTI from the closest bin boundary also has little effect, as shown in the fifth column of Table 3.2.

The results in the sixth through tenth columns of Table 3.2 show that bank-specific jumps are highly effective in predicting loan origination, as well as loan acceptance. The estimated coefficient on the bank-specific shock is robust to including DTI, a third-degree polynomial in DTI, bank and year fixed effects and a third-degree polynomial in distance to the bin boundary.

3.3.2 Exogeneity of Shocks

3.3.2.1 Covariate Balance

The results in Table 3.2 show that the estimated bank-specific acceptance rate jumps do identify applications that a particular bank is likely to originate. Do these loans differ in other ways from loans with similar DTIs that the bank is less likely to originate? The basic acceptance rate jumps are estimated from models that condition on ethnicity and owner-occupancy status so we expect little systematic variation between high and low jump applications across these variables. The bank-specific acceptance rate jumps, though, reflect an additional adjustment for jumps from other banks and might in theory weight more heavily on one of these characteristics. Do other characteristics such as loan type (conventional or non-conventional), property type (single or multi-family) and loan purpose (purchase or refinance) covary with the bank-specific shocks? To examine this question, we regress indicators for all these characteristics on the bank-specific acceptance rate jump and display the results in Table 3.3. As shown in the first five columns of the table, there is no significant relationship between the bank-specific jumps and any of these characteristics. In the sixth column of Table 3.3 we show that there is also no systematic relationship between the bank-specific jumps and a loan's DTI: the bank-specific jumps identify loans that are attractive to a bank relative to other loans with quite comparable DTIs. The result displayed in the seventh column of Table 3.3 shows that the bank-specific shocks are not correlated with the jumbo status of the loan application.

3.3.2.2 Loan Officer DTI Manipulation

Might it be the case that the bank wants to make certain loans and therefore manipulates the income or loan amount to ensure origination? There is well-documented evidence of misrepresentation in retail mortgage applications (Jiang, Nelson, and Vytlacil, 2014; Garmaise, 2015; Griffin and Maturana, 2016). It is important to note, however, that we are focusing on bank-specific jumps in the acceptance rate. Any industry-wide factors such as minimum DTIs for securitization have been removed. If the bank as an organization wanted to originate a specific loan in a given area, it could presumably choose to do so, making an exception to its own rules if that is what it desired. A more difficult question is whether particular loan officers may be manipulating the DTI to ensure origination of their loans. There is evidence for this practice as well (Keys et al., 2010). Are the loans with positive acceptance rate jumps chosen quasi-randomly or are they the specific loans manipulated by loan officers to boost origination volume?

We explore this issue by calculating application counts for each bin and comparison bin pair. For each pair, we also have a bank-specific acceptance rate jump. If loan officers are manipulating applications so that they enter the narrow DTI ranges that are relatively attractive, then we should expect to see more applications in those ranges and fewer in the less attractive ranges. We test this hypothesis by regressing the log of the number of applications on the bank-specific acceptance rate jump. Results are displayed in the eighth column of Table 3.3. The t-statistic on the bank-specific acceptance rate jump is 1.10. In other words, there is no systematic evidence that loan officers are pushing applications into the most attractive bins. While this manipulation was likely present to some degree during the sample period, it does not appear to have been prevalent enough to affect our results.

3.3.2.3 Why Discard the Training Sample?

The results in Section 3.3.1 make clear that the DTI cutoffs identified in the training sample do indeed provide useful predictions for which test sample loan applications will be approved. One may ask, however, what is the purpose in discarding the training sample? Why not make use of the full sample to estimate DTI cutoffs?

Our ultimate goal is to study the effects of a current period local lending surge on a bank's own future lending and on the future lending of its competitors. It is clear that regressing a bank's future lending on its current lending would not supply a clean estimate of the causal impact of the latter on the former, as both these variables may be influenced by unobserved factors. If the entire sample is used to estimate the DTI cutoffs, a similar problem arises. Consider a specific loan application that is approved in one local area. A full-sample estimate of the lender's DTI cutoffs would quite likely regard this application's narrow DTI bin as relatively attractive. After all, this application was approved. If we were to regress future local lending on the attractiveness of current applications, it would be quite similar to regressing local lending on current application approvals, with the same attendant endogeneity issue.

Under our approach of separately identifying the DTI cutoffs from the training sample and estimating the impact of current lending on future lending using the attractiveness of the test sample, this difficulty does not arise. The bank origination model generates estimates of DTI cutoffs using application approvals from the national training sample. These cutoffs are then applied to attribute the relative attractiveness of applications from the test sample. The actual approval of test sample applications plays no role in estimating the attractiveness of an application- we do not condition on test sample loan approval. We instead assess the attractiveness of a test sample application by considering the approval rates of loans from the training sample from across the country with which its shares a narrow DTI bin. In other words, we ask to what degree applications with very similar DTIs were approved nationally, in a manner that is specific to this bank. This is presumably unrelated to any unobserved local variable. Our subsequent analysis will consider the relationship between the concentration of these bank-specific attractive applications and future lending.

3.3.3 Local Origination Shocks and Future Lending Activity

We now analyze the impact of a bank's expansion of its current market presence on its future local lending activity in the same market. When we observe banks lending more in a given area this is often driven by strategic considerations and other unknown determinants. Any observed correlations over time in local lending could be due to medium-term bank decisions to concentrate on certain markets. It is difficult to assess the future causal impact on a bank of more lending today in a given region. We propose to use the presence of bank-specific relatively attractive applications as a plausibly exogenous shock to the bank's current local lending. Consider a bank that receives applications in two different areas. Suppose the average DTIs of applicants in both areas are quite similar, but that, due to chance, most of the applicants in the first area fall just short of the bank's institution-specific DTI cutoffs while most of the applicants in the second area have DTIs that slightly exceed these thresholds. It is likely that the bank will make relatively more loans in the first area, as the applications from that area will be regarded as relatively attractive in the bank's acceptance model. We argue that the first area receives a local origination supply shock. In essence, we are using the discontinuities in the bank's estimated acceptance model to generate an instrument for local bank lending strategy- we are identifying shocks to the amount of lending that banks do in different markets.

Caminal and Vives (1996) argue that consumers (potential mortgage applicants, in our setting) gauge the quality of a firm (i.e., lender) in part though an analysis of its volume of transactions. A lender who experiences a surge in originations is attracting many new customers, who apparently think highly of the lender. As a result, an increase in origination is a positive signal about a lender, and lenders who originate more loans should attract greater future customer flow. The lending shocks we study are exogenous, but that is not observable to potential applicants; they simply see an increase in lending by a bank and raise their assessment of the lender's quality.

In order to generate a measure of local origination shocks, we must define the local market. The HMDA data provide census tract locations for all applicants. Local markets depend on both the location of applicants and the loan size. As described in Section 3.1, we define a local market of applications to be the set of all applicants in a given year that are located in the same census tract and belong to the same requested loan size decile. The local market for loans is defined in an analogous manner. We define the local origination shock by aggregating all the bank-specific acceptance rate jumps across the local market. As shown in Table 3.2, these jumps do indeed predict origination at the loan level. We limit attention to banks that exist in the following year and consider whether shocks to current local lending increase future lending as well.

First we consider whether loan-level acceptance rate shocks aggregate. Do banks with higher local origination shocks experience more overall lending this year? We regress the log of one plus the current originations on the current local origination shock and the following set of controls: the log of one plus the number of local applications in the previous year, the log of one plus the current number of applications, bank fixed effects, market fixed effects and year fixed effects. We cluster the standard errors at both the bank and market levels. For market-level regressions like this one, the unit of observation is a bank-market-year. The result, displayed in the first column of Table 3.4, is that the coefficient on the local origination shock is 0.0165 and the t-statistic is 8.59. This is strong evidence of aggregation: markets with more positive shocks experience significantly more originations that year. This result also makes clear that banks do not adjust or correct for the presence of many relatively-attractive local applications by reducing originations to other applicants to maintain a fixed level of local originations. We are identifying shocks to the supply of local mortgage financing by banks.

To examine the impact of expanded market presence on future applicant flow, we regress the log of one plus the number of local applications next year on the current local origination shock and the previously described controls. We cluster these regressions as well at both the bank and market levels. As detailed in the second column of Table 3.4, the coefficient on the local origination shock is 0.0061 and the t-statistic is 4.28. A shock to local originations in the current year has a follow-on effect in generating more applications in the next year as well. This is consistent with the intuition from Caminal and Vives (1996) that increased lending this year leads to greater customer flow next year, as applicants view lenders who experience origination surges in a more positive light.

In the third column of Table 3.4 we report results from an instrumental variables regression of the log of one plus future applications on the log of one plus current originations, using the local origination shock as an instrument (the first stage from this regression is described in the first column of Table 3.4). The coefficient on instrumented log of one plus current originations is 0.37 and the t-statistic is 4.28. We use one plus the number of applications/originations in the arguments of the log functions to include markets with zero applications/originations, but this causes the estimated elasticity to depend on the number of current originations and future applications. As long as these are of similar magnitude, however, the elasticity of future applications with respect to current originations is approximately 0.37, as described by the coefficient in column three. This gives a sense of the meaningful economic magnitude of the impact of current originations on future applicant flow.

The current period origination shock also generates more originations in the following year (coefficient of 0.0065 and t-statistic of 4.77) and a higher total dollar volume of originations in a year (coefficient of 0.016 and t-statistic of 2.41), as shown in the fourth and fifth columns of Table 3.4. The coefficients on the origination shock are similar for both future applications and future originations, which suggests that the increased originations are driven by increased applications (i.e., heightened applicant interest, as suggested by Caminal and Vives (1996)) rather than by a systematic change in future bank local lending standards.

3.3.4 Competition

What is the impact of a bank's increased lending on other banks in the local market? The most natural hypothesis is that the pool of potential applicants is relatively fixed, in which case increased future originations for one bank must come at the cost of future originations to its competitors. Alternatively, it is possible that more originations in the current year may actually expand the overall market (for example, by raising information levels or general awareness of mortgages) which may lead to a neutral impact or even a potentially positive spillover effect on other banks. We examine this question by regressing a bank's future applications on its own current local origination shock, the sum of all the local origination shocks of its competitors, a fixed effect for the number of local competitors and the standard controls. The result, described in the first column of Table 3.5, is that the total current origination shock for all competitors has an insignificant effect (coefficient=0.0005 and t-statistic=0.64) on a bank's future applications. This somewhat surprising finding implies that banks may simply ignore the competitive effects of expanded market presence on the part of all their competitors taken as a whole.

It may be suggested that only the actions of a bank's largest competitors will matter. We regress a bank's future applications on its current origination shock, the origination shock of its three competitors with the largest local market shares and the usual controls. We find an insignificant impact (coefficient=0.0009 and t-statistic=0.71) of the shock of the three largest competitors, as detailed in the second column of Table 3.5. A bank's future applications are unaffected by the extent to which its largest local competitors expand their current lending.

We also examine the impact of the origination shocks on the Herfindahl-Hirschman Index (HHI) of all local competitors. The analysis precedes in three steps. First, we calculate the HHI of all local competitors employing the count of current originations as the measure of market share. Second, using the origination shocks of each lender and the regression model for current deal count described in the first column of Table 3.4, we calculate the estimated deal count for each lender if the shocks did not occur. Third, we calculate the HHI of all local competitors using the estimated deal counts in the absence of shocks and subtract this from the actual HHI. This difference we describe as the HHI origination shock. We show, in the third column of Table 3.5, that the HHI origination shock has an insignificant impact (coefficient=1.176 and t-statistic=1.33) on a bank's future applicant flow.

These results show that neither the overall lending of its competitors, nor the lending of its largest competitors nor the change in its competitors' HHI appears to be important to a lender, but are there some competitors whose actions are strategically relevant? It seems unlikely that banks may completely disregard the origination strategies of their competitors.

The mutual fund tournament literature provides a useful insight. This research shows that fund inflows respond in a convex manner to the fund's previous year returns (Chevalier and Ellison (1997), Sirri and Tufano (1998), J. Huang, Wei, and Yan (2007), and Barber, X. Huang, and Odean (2016), though see Spiegel and Zhang (2013) for a contrary view), which is consistent with the argument that funds are engaged in a tournament to attract investors' attention. J. Huang, Wei, and Yan (2007) provide a theoretical model that argues that investors must pay an information cost to investigate a fund for potential investment. To minimize these costs, investors limit their research to funds that had high returns last year, as these funds are the likeliest to be worthy of investment.

In our setting, we showed in Table 3.4 that high local originations this year lead a lender to receive more applications and make more loans in the following year. This suggests that increased local lending volume is viewed by mortgage applicants as a positive signal. Applying the reasoning of J. Huang, Wei, and Yan (2007) to the mortgage market, we should expect applicants to be most interested in paying information costs to investigate lenders who experienced large lending surges in the previous year; these are the lenders that are likeliest to be of high quality. An increase in current year originations will not have much impact on the future applicant flow of a lender that is not experiencing a surge, for even with this increase the lender's apparent quality will be too low to attract the attention of applicants. An increase in current originations will, however, have a meaningful effect on future applicant flow for a lender that is already making a large number of loans, for its current level of lending activity places it in the region in which applicants are considering investigating it further, and higher current lending will make this lender even more attractive. If this tournament-like description of the competition of local lenders for applicant attention is correct, then the lenders with the biggest impact on the market will be those who increased their originations most quickly this year, rather than the largest lenders.

We test this hypothesis by examining the impact of the lending of a bank's quickest-growing competitor, which we define to be the competitor with the largest current local origination shock. We regress a bank's future applications on its current origination shock, the origination shock of its quickest-growing competitor and the standard controls, and we display the results in the fourth column of Table 3.5. We find that the origination shock of the quickest-growing competitor has a strong negative impact (coefficient=-0.0149 and t-statistic=-5.37) on the bank's future lending. The most important competitors for a bank are those who are growing most quickly, consistent with the intuition of J. Huang, Wei, and Yan (2007). In columns five through eight of Table 3.5 we display results showing a similar pattern for future originations: a bank's future originations are unaffected by the total origination shock of its competitors, the shocks to its three largest competitors or the HHI origination of its competitors, but future originations decrease strongly in the origination shock of a bank's quickest-growing competitor.

These results highlight some interesting features of local banking market competition. Competitive analyses often focus on the market shares or overall quantities produced by a firm's competitors, but these do not appear to have much of an impact on a bank's future applications or lending. It also common for competitive studies to focus on HHI measures of market concentration that are most sensitive to expansion by the largest market players, but we find that an increase in current lending by a firm's largest competitors does not have a significant effect, nor does the HHI itself. It is instead the actions of a bank's quickest-growing competitors that have the most deleterious effects. Essentially, what is most important for a bank are the dynamics of local competitive tournaments, in which the lenders who are most quickly increasing their originations play the central roles.

3.3.5 Quickest-Growing Competitor

To get a sense of the mechanism underlying the impact of the quickest-growing competitor, we regress the log of one plus the largest increase in deal count for any competitor on the origination shock of the quickest-growing competitor. The result, reported in the first column of Table 3.6, shows that the quickest-growing competitor origination shock does indeed have a positive and significant impact on the largest deal count increase experienced by any of the bank's competitors. This regression is restricted to the sample in which the largest increase is at least zero so that the log is well-defined. In this restricted sample, the shock of the quickest-growing competitor is again strongly negatively associated with a bank's future applications, as shown in the second column of Table 3.6. The causal impact of increased loans by the bank's quickest-growing competitor is negative, as displayed in the instrumented regression displayed in third column of Table 3.6. The elasticity of a bank's future applications with respect to the largest increase in originations for its competitors is approximately -19% (t-statistic=-6.38).

We also find that the elasticity of a bank's future originations with respect to the largest increase in originations for its competitors is negative and significant (coefficient=-0.17 and t-statistic=-5.99), as shown in the fourth column of Table 3.6. These results describe the effects of exogenous increases in originations by the quickest-growing competitor. In the fifth column of Table 3.6, by contrast, we detail the results from an endogenous, descriptive regression in which we regress a bank's future deal count on the largest deal count increase experienced by a competitor. We find a *positive* and significant result (coefficient=0.03 and t-statistic=9.68). On a naive interpretation this would seem to suggest that banks benefit when their competitors make more loans. This is likely driven, of course, by the fact that positive local shocks lead to more originations both for a bank and its competitors. The causal impact of increasing lending by a bank's quickest-growing competitor, however, as demonstrated in the previous regressions, is clearly negative. When aggregating the origination shocks of the bank's two quickest-growing local competitors, we find a similar very negative causal effect, as shown in the sixth column of Table 3.6.

How local are the negative competitive effects? We calculate the quickest-growing competitor shock at the zip code-level and contrast its impact with our main tract-level competitor shock. We regress a bank's future originations on its own tract-level origination shock, the tract-level shock of its quickest-growing competitor, the zip-level shock of its quickest-growing competitor and the previous controls. (The zip and tract level competitors are defined at their respective geographies and may thus differ.) We find, as shown in the seventh column of Table 3.6 that the coefficient on the tract-level competitor shock of -0.017 (t-statistic=-7.55) is significantly larger, at the 1% level, than the -0.006 coefficient (t-statistic=-3.39) on the zip-level competitor shock. We find that competition between mortgage lenders is a highly localized phenomenon. The tournaments for applicant deal flow are occurring largely at the census-tract level.

3.3.6 Convexity

The results in Tables 3.5 and 3.6 show that the competitiveness of the local lending market is mainly determined by the actions of the quickest-growing lenders; other lenders appear not to have much impact. This is consistent with a tournament style of competition. The mutual fund tournament literature has also emphasized that in this form of competition the payoff from sending a better signal is convex. When firms are far behind in the tournament, an increase in their signal will not attract much additional interest from consumers. For firms that are leading the tournament, by contrast, an improved signal will influence additional prospective customers to pay information costs to investigate their products (J. Huang, Wei, and Yan, 2007). In our setting, increased current period originations is the positive signal. This suggests the prediction that a bank's future lending will be convex in its current period origination shock.

We test this hypothesis by regressing a bank's future applications on its current origination shock, the square of its current origination shock and the standard controls. As shown in the results displayed in the first column of Table VII, the coefficient on both origination shock and the squared origination shock are positive and significant (with t-statistics of 4.35 and 3.86, respectively). This demonstrates that a lender's future applications are increasing and convex in its current origination shock. This result holds true for future originations as well, as shown in the second column of Table VII. These results provide strong evidence consistent with the tournament hypothesis. Lenders are competing for applicant attention and those experiencing the largest surge in current deals receive disproportionate future customer flows.

We further explore the differential effects of increased current lending for banks with varying positions in the local tournament by regressing a bank's future applications on its current origination shock, an indicator for lenders with origination shocks in the top quartile of their local market, the interaction between these two variables and the standard controls. Do increases in current originations matter more for top quartile lenders? In the third and fourth columns of Table VII we show that they do. The interaction between the top quartile indicator and the current origination shock has a positive and significant effect on both future applications (t-statistic=2.02) and originations (t-statistic=2.66). Overall, there is robust evidence that a bank's current originations have a convex impact on future deal flow and that increases in current lending matter more for those who are already lending more than their competitors. These results emphasizing the crucial roles played by the local market leaders are precisely what tournament theories predict.

3.3.7 Lender Risk Taking and Competition

How do lenders respond to increased competition? Tables 3.5 and 3.6 show that greater current period lending by the quickest-growing competitor leads to reduced future lending by the other local banks. What is the price impact of increased lending by the quickest-growing competitor? We analyze this question by regressing the interest charged on a mortgage on the previous origination shock of the lender, the previous origination shock of the quickest-growing competitor and the standard HMDA application and market controls. We find, as described in the first column of Table 3.8, that a lender's own previous shock has an insignificant (t-statistic=-0.01) effect on the rate charged, but the prior origination shock of the quickest-growing competitor has a positive and significant impact (coefficient=0.02 and t-statistic=2.55). That is, lenders charge higher rates in the presence of increased competition. This a surprising and counter-intuitive finding. To provide additional insight, we regress applicant FICO scores on the origination shocks of the lender and its quickest-growing competitor and find, as displayed in the second column of Table 3.8, that the quickest-growing competitor shock has an insignificant impact (coefficient=-0.07 and t-statisic=-0.26). The lender's own shock also has an insignificant impact. Lender LTV values increase with the quickest-growing competitor shock, but loan terms are unaffected, as shown in the fourth and fifth columns of Table 3.8. An explanation consistent with these results is that greater competition from its quickest-growing competitor leads a lender to provide riskier mortgages-some of this risk is observable to us (in higher LTV values) and other aspects may not be, but the higher risk is reflected in higher rates. Lenders with little growth in origination activity who fall behind in the tournament competition for applicant attention, appear to receive both fewer and riskier future applications. As before, changes in the HHI index appear uninformative about loan terms, as shown in columns six through ten of Table 3.8.

3.3.8 Performance

In Table 3.8 we showed that tougher competition leads lenders to lend to make riskier loans at higher interest rates. What is the impact of competition on future loan delinquency? To address this question, we regress an indicator for whether a loan ever experiences a 60-day delinquency on the previous year local origination shock, HMDA controls, FICO, interest rate, LTV, loan term, bank fixed effects, market fixed effects and year fixed effects. We cluster standard errors at the market and bank levels. The result, displayed in the first column of Table 3.9, is that the previous year local origination shock has an insignificant effect (coefficient=0.002 and t-statistic=1.12) on a loan's probability of delinquency.

We examine the impact of competition on performance by regressing the 60-day delinquency indicator on the bank's origination shock, the shock of its quickest-growing competitor and the previously outlined controls other than loan characteristics. The result, shown in the second column of Table 3.9, is that delinquency is increasing (coefficient=0.003 and t-statistic=2.03) in the origination shock of the quickest-growing competitor. When a bank's quickest-growing competitor makes more loans, the performance of the bank's future loans degrades significantly. When including controls for interest rate and other loan characteristics, the result continues to hold at the 10%-level, as shown in the third column of Table 3.9, so it appears that competition has an even more negative impact on lenders than they expected during our sample period. The result in column four of Table 3.9 shows that this finding holds at the 10%-level as well in the specification in which we instrument for the largest deal increase of a competitor with the quickest-growing competitor shock. As shown in the fifth column, the shock to HHI has no impact on delinquency. Results described in the sixth through tenth columns of Table 3.9 confirm the same pattern of results (with slightly stronger statistical significance) for loan default.

Why does the increased lending of the quickest-growing competitor have a negative impact on the bank's loan performance? The results in Tables 3.6 and Table 3.8 show that in the face of strong competition, lenders supply fewer mortgages and make riskier loans. During our sample period, lenders whose loan growth was weak and who did not win their local competition tournaments may have underestimated the changing unobservable risk characteristics of the pool of applicants they subsequently faced. This suggests that the greatest competitive threat to a bank may be a silent danger: quickly expanding competitors seize not just more potential applicants but especially those whose positive characteristics are hard to uncover.

3.4 Conclusion

In this chapter we analyze the dynamics of competition in the U.S. mortgage market. Using discontinuities in the acceptance rates of applications with very similar debt-to-income ratios, we provide evidence that a plausibly exogenous shock to a bank's local lending this year leads to more applications and originations in the following year. Applicants are attracted to growing lenders. We show that local mortgage markets resembles tournaments in which the lending of a bank's quickest-growing competitors has the strongest negative impact on its future lending; neither the overall lending of all competitors, nor the lending of the largest competitors has much effect. We confirm the disproportionate influence of the quickest-growing lenders by showing that future applications and originations are convex in the current period shock to lending. Greater lending shocks to a bank's quickest-growing competitor lead it to charge higher interest rates; this may be partly driven by the fact that competition leads lenders to make riskier (higher LTV) loans. We further find that a bank's mortgage performance is harmed by intense competition; the higher rates it charges are insufficient to compensate for the unobservable risk of the borrowers it receives in the face of greater lending by its quickest-growing competitor.

The tournament-like features we describe are reminiscent of the common intuition that it is important for firms to play a dominant role in the markets in which they compete. We provide evidence for a dynamic variation on this static argument: we show that it is the quickest-growing, rather than the largest, lenders who are the toughest competitors. Our results also show that in certain essential respects banking markets are highly local. More generally, our approach of exploiting bank-specific shocks to analyze mortgage market dynamics may be applied to a broader set of questions about competition and firm interactions in other settings.

3.5 Appendix 1

Table 3.10 reports comparative statics between the training and test samples described in Section 1.A. Applications in both samples are statistically indistinguishable from each other across all observable dimensions (The loan amounts applied for in the test sample are slightly higher than those in the training sample at the 10% level).

In order to further test the quality of our sample split procedure, columns 1 and 2 in Table 3.11 replicate columns 4 and 9 in Table 3.2 respectively, with 100 different random sample splits. In these columns the bin centering is held fixed at the test sample mean DTI utilized in Section 1.A. Additionally, the choice of centering the bin boundaries at the test sample mean DTI is investigated in columns 3 and 4 in Table 3.11. These columns replicate columns 4 and 9 in Table 3.2 respectively, with 100 different randomly chosen bin centers (the centers are varied within a window of width 0.1 around the test sample mean DTI), holding fixed the sample split.

Average coefficients and t-statistics on all covariates, as well as the standard deviation of the t-statistics, are reported. Neither the choice of sample split nor the choice of bin center has any meaningful impact on the ability of our instrument to determine whether the loans in the test sample that are predicted to be attractive are actually accepted and originated by lenders.

3.6 Appendix 2

Our primary data source, the Home Mortgage Disclosure Act (HMDA), consists of information relating to the vast majority of mortgage applications in the United States. However, it lacks some important classes of information important to our study. We attach mortgage performance data and certain underwriting characteristics for originated mortgages in the HMDA dataset from three additional sources. BlackBox Logic provides information relating to loans securitized into a non-agency security, and both Fannie Mae and Freddie Mac provide similar information for a large portion of their portfolios.

There does not exist a single unique identifier between any of these data sets. Consequently, we utilize a matching procedure (largely following An, Deng, and Gabriel (2015)) that relies on loan characteristic indicators held in common between the datasets. All datasets have type indicators for if the loan was owner occupied and for the loan purpose (purchase, refi, etc.). Additionally, the performance datasets (BBx, FNMA, and FHLMC) contain the exact original dollar amount of the mortgage loan, which is then rounded to the nearest $1,000 in a manner consistent with the rounding of the HMDA loan amount field. The year of origination is also utilized as a matching field. All datasets contain a state indicator and both BBx and HMDA contain a county field. These relationships lead to five "exact match" fields: owner occupancy, loan purpose, loan balance, origination year, and geography (state only for FNMA-HMDA and FHLMC-HMDA, county-state for BBx-HMDA). The final two pieces of the match process are the loan's geography and, within the HMDA dataset, the securitization population.

HMDA has geographic detail at the census tract level, while BBx has a 5-digit zip code and FNMA and FHLMC have 3-digit zip codes. There is no one-to-one relationship between census tracts and zip codes. Zip codes are maintained by the United States Postal Service (USPS) in order to allocate and deliver mail efficiently, while the census tracts are developed by the United States Census Bureau as a grouping of households of approximately equal population. Zip codes contain many census tracts and census tracts often cross into multiple zip codes. In order to rationalize this geographic structure, we utilize crosswalk files from the USPS which measure the percentage of residential addresses within a census tract that lie within a particular zip code (or vice-versa). For any potential geographic match between a census tract and a zip code (either 5-digit or 3-digit) this residential address overlap is used to rank order the likely geographic match-ups between loans.

We began the match process by sequentially examining a HMDA loan's potential as a match for BBx, FNMA, and then FHLMC. We kept HMDA application records that were ultimately originated, and were not Farm Service Agency or Rural Housing Service loans. Potential BBx matches were drawn from HMDA originations that were purchased by either a private securitization, a commercial bank, savings bank or savings association, a life insurance company, credit union, mortgage bank, or finance company, an affiliate of the originator, an "other" classification, or was not sold in the same calendar year it was originated. Potential FNMA matches were drawn from HMDA when they were either purchased by FNMA or were not sold in the same calendar year as originated (and was also not matched to a BBx loan). Potential FHLMC matches were either purchased by FHLMC or were not sold in the same calendar year as originated (and was also not matched to a either a BBx or FNMA loan).

We began the iterative match process by generating all possible matches based on the five "exact match" fields detailed above as well as restricting to the correct HMDA population. Each possible match was then assigned a Zip to Census Tract residential address overlap "probability."[8] A specific match was then formed if the residential address probability for the match was the highest amongst all possible performance record matches for that HMDA origination as well as if it was the highest amongst all possible HMDA originations for that performance record. Ties were broken randomly. These matches were then flagged as final and both the HMDA origination record and the performance record was removed from possible consideration for future matches and the process iterated until no more matches

[8]Only matches with a non-zero residential address overlap were considered. The residential overlap percentage used was the percentage of the census tract that existed within a particular zip code. Because zip codes vary in size more than census tracts, this direction for the match percentage was chosen in order to give all census tracts that proportionally lay the same amount in the same zip code an approximately even probability of being selected as a match.

were possible.

There were 161,733,217 HMDA originations that were in populations eligible to be matched to either BBx (80,258,392), FNMA (47,878,118), or FHLMC (33,596,707). 41,330,996 total were matched (13,061,184 for BBx, 14,982,509 for FNMA, 13,287,303 for FHLMC) for an average HMDA match rate of 25.56%. Performance record match rates were much higher. 83.59% of the 15,625,925 valid BBx records, 90.18% of the 16,614,548 valid FNMA records, and 82.04% of the valid 16,196,065 FHLMC records were matched for an average performance record match rate of 85.33%.

Table 3.1

Summary Statistics

For the first two panels below, observations are at the loan application level. Summary Statistics for all of these items are related to the 103,068,422 applications in the test sample. For the third panel below, observations are at the level indicated. Lender Specific Origination Shock ($\hat{v}_k$) is our primary measure of discontinuities in lender acceptance models. Debt-To-Income is the ratio of the requested loan amount to the applicant's income. Income ('000s) is the applicant's gross annual income in thousands of dollars. Loan Amount ('000s) is the amount, in thousands of dollars, requested for the loan. Loan Accepted is an indicator of whether or not the loan request was approved. Loan Originated is an indicator of whether or not the loan was ultimately originated (and is a subset of Loan Accepted). White is an indicator of whether or not the applicant disclosed their race as white. Owner Occupied is an indicator as to whether or not the proposed loan is intended to be occupied by the applicant. Conventional is an indicator for any loan other than FHA, VA, FSA, or RHS loans. Single Family is an indicator for whether the property type is a one to four family (other than manufactured housing) structure. Purchase is an indicator as to whether the loans is intended for the purchase of a new home (as opposed to for refinancing or home improvement). Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t}$) is the sum at the market level of all Lender Specific Origination Shocks ($\hat{v}_k$). Deals in Lender-Market-Year is the number of loans a lender originated in a market for the year. Applications in Lender-Market-Year is the number of applications a lender received in a market for the year. Volume ('000s) in Lender-Market-Year is, in thousands of dollars, the total loan amount a lender originated in a market for the year. Lender Count in Market-Year is the count of unique lenders that received a loan application in a market for the year. Lender Deal Share in Market-Year is the number of loans originated by an individual lender divided by the total loans originated by all lenders in a market for the year. For the final panel, the Delinquency and Default Rates are calculated for the loans in the relevant subsamples of the test sample for which performance data was matched. Delinquent is an indicator of whether or not the loan ever went 60 days or more delinquent at any point in the observed performance of the loan. Default is an indicator of whether or not the loan ever entered Foreclosure, became a Real Estate Owned property, or was liquidated (in a manner other than a borrower payoff in full) at any point in the observed performance of the loan. Observed performance of the loan begins at the first month the loan was placed into a securitization and ends at the earlier of loan liquidation, borrower payoff in full, or December 2015.

	Mean	Median	St Dev	10^{th}%	90^{th}%
Lender Specific Origination Shock ($\hat{v}_k$)	0.00	0.00	0.05	-0.03	0.03
Debt-To-Income	2.08	2.02	1.19	0.50	3.76
Income ('000s)	99.09	72.00	149.95	33.00	172.00
Loan Amount ('000s)	175.15	135.00	172.57	35.00	350.00
Loan Accepted	0.64				
Loan Originated	0.57				
White	0.63				
Owner Occupied	0.91				
Conventional	0.90				
Single Family	0.97				
Purchase	0.34				
Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t}$)	0.00	0.00	0.06	-0.03	0.03
Deals in Lender-Market-Year	1.48	1.00	2.59	0.00	3.00
Applications in Lender-Market-Year	2.60	1.00	3.70	1.00	5.00
Volume ('000s) in Lender-Market-Year	280.52	112.00	1,006.95	0.00	600.00
Lender Count in Market-Year	9.36	6.00	9.41	1.00	21.00
Lender Deal Share in Market-Year	0.10	0.04	0.17	0.00	0.25

	Full Sample	BBx	FNMA	FHLMC
Delinquency Rate	0.17	0.40	0.07	0.07
Default Rate	0.12	0.33	0.02	0.03

Table 3.2

Instrument Tests

This table reports results related to tests of the validity of our methodology for identifying discontinuities in lender acceptance models. An indicator for loan application acceptance (columns 1-6) or loan originated (columns 7-12) within the test sample are regressed on our Lender Specific Origination Shock ($\hat{v}_k$) calculated from the training sample. The regressions also include as controls the Debt-To-Income Ration of the application (columns 2-3, 5, 8-9 and 11) as well as a third-degree polynomial in DTI (columns 3, 5, 9, and 11). Bin Fixed Effects are included (columns 4 and 10). Lender and Year Fixed Effects are included (columns 5-6 and 11-12). A measure of DTI proximity to the nearest bin boundary is included (columns 6 and 12). 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.

	Application Accepted						Loan Originated					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lender Specific	0.0200***	0.0200***	0.0200***	0.0200***	0.0218***	0.0219***	0.0172***	0.0172***	0.0172***	0.0172***	0.0188***	0.0189***
Origination Shock ($\hat{v}_k$)	(19.78)	(19.79)	(19.79)	(19.78)	(8.83)	(8.75)	(16.41)	(16.42)	(16.41)	(16.41)	(8.83)	(8.74)
DTI		-0.00479***	0.0946***		0.0720***			-0.000887***	0.117***		0.0858***	
		(-118.77)	(245.89)		(2.59)			(-21.44)	(296.08)		(3.18)	
DTI^2			-0.0315***		-0.0251**				-0.0376***		-0.0295***	
			(-173.00)		(-2.54)				(-202.10)		(-3.13)	
DTI^3			0.00241***		0.00211**				0.00295***		0.00259***	
			(97.13)		(2.00)				(116.45)		(2.61)	
Distance From						-0.150***						-0.155***
Bin Boundary						(-11.44)						(-12.10)
Squared Distance From						0.286***						0.294***
Bin Boundary						(2.64)						(2.63)
Cubed Distance From						136.7***						141.7***
Bin Boundary						(17.85)						(19.71)
Lender FE					Yes	Yes					Yes	Yes
Year FE					Yes	Yes					Yes	Yes
Bin FE				Yes						Yes		
Lender Clustered SE					Yes	Yes					Yes	Yes
N	103,068,422	103,068,422	103,068,422	103,068,422	103,068,164	103,068,164	103,068,422	103,068,422	103,068,422	103,068,422	103,068,164	103,068,164
adj. R^2	0.000	0.000	0.002	0.003	0.199	0.198	0.000	0.000	0.003	0.003	0.190	0.189

Table 3.3

Covariate Balance

This table reports results demonstrating that characteristics observed in the data do not vary systematically with our lender-specific acceptance rate jumps. Indicators for all available characteristics are regressed on our Lender Specific Origination Shock ($\hat{v}_k$) (columns 1-7). Column 8 tests the quasi-random nature of loans with positive acceptance rate jumps, distinguishing them from loans that may have been specifically manipulated by loan officers to boost origination volume, by regressing the log of one plus the application counts on the lender-specific acceptance rate jump. Reported t-statistics in parentheses are heteroskedasticity-robust. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	White	Owner Occ	Conventional	Single Fam	Purchase	DTI	jumbo	log(1+Applications)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lender Specific	-1.15e-10	1.18e-10	0.000841	0.000112	0.000481	0.0000549	-0.000144	0.00279
Origination Shock ($\hat{v}_k$)	(-0.00)	(0.00)	(1.25)	(0.30)	(0.45)	(0.02)	(-0.28)	(1.10)
N	103,068,422	103,068,422	103,068,422	103,068,422	103,068,422	103,068,422	103,068,422	5,967,599
adj. R^2	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000

Table 3.4

Impact of Shock on Future Activity

This table reports regressions demonstrating that a lender's current expansion of its market presence increases its future local lending activity in the same market. Column 1 regresses a lender's current year originations in a market for the year on our instrument, the Market Level Lender Specific Origination Shock, representing the first stage in our instrumental variable approach. Column 2 regresses a lender's applications received one year in the future in a market on our same instrument, representing the reduced form representation of our instrumental variable approach. Column 3 reports a 2SLS coefficient of future applications on current originations (instrumented with the Market Level Lender Specific Origination Shock). Columns 4 and 5 report reduced form results (similar to Column 2) for future origination count and loan amount volume respectively. The regressions also include as controls the previous period's origination count (column 4), the current period's application count (columns 1-4), the previous period's application count (columns 1-3) and the previous period's originated dollar volume (column 5). Lender, Market, and Year fixed effects are also included. 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.

	log(1+Curr Deal Count)	log(1+Fut App Count)		log(1+Fut Deal Count)	log(1+Fut Vol Total)
	(1)	(2)	(3)	(4)	(5)
Market Level Lender Specific	0.0165***	0.00612***		0.00651***	0.0157**
Origination Shock ($\hat{v}_{M,b,t}$)	(8.59)	(4.28)		(4.77)	(2.41)
log(1+Curr Deal Count)			0.370		
(Instrumented with $\hat{v}_{M,b,t}$)			(4.28)		
log(1+Prev Deal Count)				Yes	
log(1+Curr App Count)	Yes	Yes	Yes	Yes	
log(1+Prev App Count)	Yes	Yes	Yes		
log(1+Prev Vol Total)					Yes
Lender FE	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes
N	56,017,529	56,017,529	56,017,529	56,017,529	56,017,529
adj. R^2	0.659	0.434	0.418	0.402	0.276

Table 3.5

Comparing Measures of Competition

This table reports comparative results related to the interaction between a lender's lending activity and that of it's competitors for various measures of the level of competition within a market. The number of applications received by a lender in a market for the following year (columns 1-4) and the number of loans originated by a lender in a market for the following year (columns 5-8) is regressed on that lender's market level origination shock and a set of covariates of interest. The covariates of interest include the sum of all the origination shocks of a lender's competitors in a market for that year (columns 1 and 5), the shock of the largest three (by origination volume in a market for that year) competitors in a market for that year (columns 2 and 6), the shock to the Herfindahl-Hirschman Index of a particular market for that year (columns 3 and 7), and the largest shock of a competitor in a market for that year (columns 4 and 8). The regressions also include as controls the count of competitors in a market for that year, the previous period's origination count (columns 5-8), the current period's application count (columns 1-8), and the previous period's application count (columns 1-4). Lender, Market, and Year fixed effects are also included. 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.

	log(1+Fut App Count)				log(1+Fut Deal Count)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Level Lender Specific	0.00619***	0.00619***	0.00531***	0.00544***	0.00657***	0.00645***	0.00620***	0.00589***
Origination Shock ($\hat{v}_{M,b,t}$)	(4.27)	(4.12)	(3.22)	(3.73)	(4.77)	(4.62)	(3.95)	(4.20)
Total Competitor	0.000531				0.000443			
Origination Shock	(0.64)				(0.63)			
Largest Three Competitors		0.000946				0.000140		
Origination Shock		(0.71)				(0.12)		
Herfindahl-Hirschman Index			1.176				0.436	
Origination Shock			(1.33)				(0.59)	
Quickest-Growing Competitor				-0.0149***				-0.0147***
Origination Shock				(-5.37)				(-5.26)
log(1+Prev Deal Count)					Yes	Yes	Yes	Yes
log(1+Curr App Count)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log(1+Prev App Count)	Yes	Yes	Yes	Yes				
Competitor Count FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	56,017,529	53,047,248	37,777,357	55,404,549	56,017,529	53,047,248	37,777,357	55,404,549
adj. R^2	0.434	0.434	0.460	0.434	0.402	0.404	0.405	0.402

Table 3.6

Competition Impact of Quickest-Growing Competitor

This table reports results detailing the competitive impact the quickest-growing competitor has on a market. Column 1 regresses the largest increase in originations for any one competitor within a market and year over the prior year on the largest shock of a competitor in a market for that year (our instrument for this table) and the Market Level Lender Specific Origination Shock, representing the first stage in our instrumental variable approach. Column 2 regresses the number of applications received by a lender in a market for the following year on our same instrument, representing the reduced form representation in our instrumental variable approach. Column 3 reports a 2SLS coefficient of the largest increase in originations for any one competitor within a market and year over the prior year (instrumented with the largest shock of a competitor in a market for that year). Column 4 repeats the 2SLS specification, with the number of loans originated by a lender in a market for the subsequent year as the dependent variable. Column 5 reports the results of the naive OLS version of column 4. Column 6 is similar to column 2, but instead uses the sum of the two largest competitor shocks within the market. Column 7 regresses a lender's originations one year in the future in a market on the largest shock received by a competitor at two different geographic-market levels. The F-Statistic for the difference in these coefficients are also reported. The regressions also include as controls the count of competitors in a market for that year (columns 1-6 at the tract-market level, column 7 at the zip-market level), the previous period's origination count (columns 4-7), the current period's application count (columns 1-7), and the previous period's application count (columns 1-3). Lender, Market, and Year fixed effects are also included. 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.

	log(1+Largest Competitor Deal Increase)	log(1+Fut App Count)		log(1+Fut Deal Count)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t}$)	0.00459***	0.00516***	0.00603***	0.00659***	0.00644***	0.00566***	0.00553***
	(4.51)	(3.40)	(3.98)	(4.55)	(4.50)	(3.99)	(3.77)
Quickest-Growing Competitor Origination Shock	0.0991***	-0.0187***					-0.0168***
	(26.97)	(-6.69)					(-7.55)
log(1+Largest Competitor Deal Increase)					0.0272***		
					(9.68)		
log(1+Largest Competitor Deal Increase) (Instrumented with Quickest-Growing Competitor Origination Shock)			-0.189***	-0.172***			
			(-6.38)	(-5.99)			
Two Quickest-Growing Competitors Origination Shocks						-0.0147***	
						(-5.30)	
Quickest-Growing Zip-Market Competitor Origination Shock							-0.00642***
							(-3.39)
log(1+Prev Deal Count)				Yes	Yes	Yes	Yes
log(1+Curr App Count)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log(1+Prev App Count)	Yes	Yes	Yes				
Tract Competitor Count FE	Yes	Yes	Yes	Yes	Yes	Yes	
Zip Competitor Count FE							Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	48,020,874	48,020,874	48,020,874	48,020,874	48,020,874	54,386,746	49,208,873
adj. R^2	0.660	0.436	0.422	0.391	0.407	0.403	0.405
Tract=Zip Comp Shock F:							14.58
p-value							0.0001

Table 3.7

Convexity

This table reports results detailing the convexity of the payoff received from sending a better signal. Columns 1 and 2 regress a lender's applications received one year in the future in a market and a lender's current year originations in a market for the year, respectively, on its current origination shock and the square of its current origination shock. Columns 3 and 4 regress a lender's applications received one year in the future in a market and a lender's current year originations in a market for the year, respectively, on its current origination shock, an indicator for lenders with origination shocks in the top quartile of their local market, and the interaction between these two variables. The regressions also include as controls the previous period's origination count (columns 2 and 4), the current period's application count (columns 1-4), the previous period's application count (columns 1 and 3). Lender, Market, and Year fixed effects are also included. 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.

	log(1+Fut App Count) (1)	log(1+Fut Deal Count) (2)	log(1+Fut App Count) (3)	log(1+Fut Deal Count) (4)
Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t}$)	0.00622***	0.00672***	-0.00747	-0.0357
	(4.35)	(4.94)	(-0.51)	(-1.45)
Squared Market Level Lender Specific Origination Shock	0.0581***	0.120***		
	(3.86)	(4.43)		
Top Quartile of Market Level Lender Specific Origination Shock			-0.00244	-0.00269*
			(-1.56)	(-1.65)
Market Level Lender Shock * Top Quartile			0.0457**	0.105***
			(2.02)	(2.66)
log(1+Prev Deal Count)		Yes		Yes
log(1+Curr App Count)	Yes	Yes	Yes	Yes
log(1+Prev App Count)	Yes		Yes	
Lender FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes
N	56,017,529	56,017,529	56,017,529	56,017,529
adj. R^2	0.434	0.402	0.434	0.402

Table 3.8

Portfolio Risk Taking in Response to Competition

This table reports results investigating the impact increased competition has on the portfolio of loans originated by lenders. Columns 1 and 5 investigate the impact on the Original Interest Rate of a loan. Columns 2 and 6 look at the change in the FICO composition, while columns 3 and 7 as well as 4 and 8 look at the LTV and Amortization Terms at origination, respectively. Columns 1-4 measure increased competition through the Quickest-Growing Competitor Origination Shock, while columns 5-8 utilize the shock to the market Herfindahl-Hirschman Index. Applicant/Loan Characteristic Controls include indicators for White, Owner Occupied, Conventional, Single Family, and Purchase. Tract-Market Competitor Count, Lender, Market, and Year fixed effects are also included. 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.

	Int Rate (1)	FICO (2)	LTV (3)	Term (4)	Int Rate (5)	FICO (6)	LTV (7)	Term (8)
Previous Market Level Lender Specific	-0.0000576	-0.00912	0.109	-0.263	0.00186	0.0760	0.102	-0.362
Origination Shock ($\hat{v}_{M,b,t-1}$)	(-0.01)	(-0.03)	(1.12)	(-0.71)	(0.23)	(0.21)	(1.03)	(-0.95)
Previous Quickest-Growing Competitor	0.0187**	-0.0683	0.250**	0.234				
Origination Shock	(2.55)	(-0.26)	(2.16)	(0.85)				
Previous Herfindahl-Hirschman Index					5.120	272.5	-11.73	134.3
Origination Shock					(1.49)	(1.39)	(-0.22)	(0.63)
Applicant/Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competitor Count FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,423,376	7,060,182	7,510,336	7,405,496	6,760,202	6,446,421	6,837,189	6,746,798
adj. R^2	0.568	0.351	0.347	0.174	0.565	0.341	0.343	0.175

Table 3.9

Portfolio Performance in Response to Competition

This table reports the results from regressions of ex-post performance outcomes on the Market Level Bank Specific Origination Shock and the Quickest-Growing Competitor Origination Shock in the year preceding the loan application. The performance outcomes investigated are Delinquent (columns 1-5) and Default (columns 6-10). Delinquent is an indicator of whether or not the loan ever went 60 days or more delinquent at any point in the observed performance of the loan. Default is an indicator of whether or not the loan ever entered Foreclosure, became a Real Estate Owned property, or was liquidated (in a manner other than a borrower payoff in full) at any point in the observed performance of the loan. Observed performance of the loan begins at the first month the loan was placed into a securitization and ends at the earlier of loan liquidation, borrower payoff in full, or December 2015. Columns 1 and 6 include only the Lender Specific Origination Shock. Columns 2, 3, 7 and 8 include the Quickest-Growing Competitor Origination Shock in addition to the Lender Specific one, representing the reduced form representation in our instrumental variable approach. Columns 4 and 9 report 2SLS coefficients of the largest increase in originations for any one competitor within a market and year over the prior year (instrumented with the largest shock of a competitor in a market for that year). Columns 5 and 10 compare to columns 3 and 8 respectively, instead utilizing the shock to the Herfindahl-Hirschman Index. Controls for FICO, Interest Rate, LTV and Amortization Term at origination are also included (in all columns except 2 and 7). Applicant/Loan Characteristic Controls include indicators for White, Owner Occupied, Conventional, Single Family, and Purchase. Lender, Market, and Year fixed effects are also included. 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.

			Delinquent					Default		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Previous Market Level Lender Specific	0.00220	0.00288	0.00302	0.00281	0.00226	0.00100	0.00186	0.00133	0.00110	0.000632
Origination Shock ($\hat{v}_{M,b,t-1}$)	(1.12)	(1.38)	(1.55)	(1.46)	(1.13)	(0.66)	(1.06)	(0.85)	(0.71)	(0.41)
Previous Quickest-Growing Competitor		0.00336**	0.00290*				0.00343**	0.00324**		
Origination Shock		(2.03)	(1.80)				(2.15)	(2.16)		
log(1+Previous Largest Competitor				0.0278*					0.0310**	
Deal Increase) Instrumented with				(1.84)					(2.22)	
Previous Quickest-Growing										
Competitor Origination Shock										
Previous Herfindahl-Hirschman Index					1.165					0.467
Origination Shock					(1.28)					(0.66)
FICO	-0.00131***		-0.00133***	-0.00133***	-0.00131***	-0.000750***		-0.000775***	-0.000774***	-0.000747***
	(-19.89)		(-17.11)	(-17.09)	(-19.04)	(-11.60)		(-10.11)	(-10.09)	(-11.12)
Int Rate	0.00957***		0.0100***	0.0101***	0.00851**	0.0132***		0.0137***	0.0138***	0.0119***
	(3.02)		(3.26)	(3.29)	(2.56)	(3.97)		(4.23)	(4.26)	(3.41)
LTV	0.00168***		0.00175***	0.00174***	0.00171***	0.00134***		0.00140***	0.00139***	0.00136***
	(9.99)		(9.06)	(9.04)	(9.61)	(8.32)		(7.62)	(7.60)	(7.98)
Term	0.000220***		0.000198***	0.000198***	0.000215***	0.000155***		0.000134***	0.000134***	0.000151***
	(5.53)		(5.52)	(5.52)	(5.36)	(3.88)		(3.69)	(3.69)	(3.77)
Applicant/Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competitor Count FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,823,231	6,517,056	6,040,782	6,040,782	6,229,038	6,823,231	6,517,056	6,040,782	6,040,782	6,229,038
adj. R^2	0.320	0.306	0.348	0.347	0.320	0.296	0.294	0.318	0.317	0.296

Table 3.10

Test vs Training Comparative Statics

Mean estimates and standard deviations are reported for both the 104,944,092 and 104,933,664 application observations in the test and training samples, respectively, for various application characteristics. Debt-To-Income is the ratio of the requested loan amount to the applicant's income. Income ('000s) is the applicant's gross annual income in thousands of dollars. Loan Amount ('000s) is the amount, in thousands of dollars, requested for the loan. Loan Accepted is an indicator of whether or not the loan request was approved. Loan Originated is an indicator of whether or not the loan was ultimately originated (and is a subset of Loan Accepted). White is an indicator of whether or not the applicant disclosed their race as white. Owner Occupied is an indicator as to whether or not the proposed loan is intended to be occupied by the applicant. Conventional is an indicator for any loan other than FHA, VA, FSA, or RHS loans. Single Family is an indicator for whether the property type is a one to four family (other than manufactured housing) structure. Purchase is an indicator as to whether the loans is intended for the purchase of a new home (as opposed to for refinancing or home improvement). The Delinquency and Default Rates are calculated for the loans in the relevant subsamples of the test and training sample for which performance data was matched. Delinquent is an indicator of whether or not the loan ever went 60 days or more delinquent at any point in the observed performance of the loan. Default is an indicator of whether or not the loan ever entered Foreclosure, became a Real Estate Owned property, or was liquidated (in a manner other than a borrower payoff in full) at any point in the observed performance of the loan. Observed performance of the loan begins at the first month the loan was placed into a securitization and ends at the earlier of loan liquidation, borrower payoff in full, or December 2015.

	Test Sample	Training Sample	p-value
Debt-To-Income	2.0829	2.0829	0.935
	(0.00012)	(0.00012)	
Income ('000s)	99.3630	99.3415	0.307
	(0.0149)	(0.0149)	
Loan Amount ('000s)	175.0131	174.9695	0.069*
	(0.0170)	(0.0169)	
Loan Accepted	0.6422	0.6422	0.935
	(0.00005)	(0.00005)	
Loan Originated	0.5690	0.5690	0.818
	(0.00005)	(0.00005)	
White	0.6337	0.6337	0.734
	(0.00005)	(0.00005)	
Owner Occupied	0.9041	0.9041	0.910
	(0.00003)	(0.00003)	
Conventional	0.8993	0.8993	0.783
	(0.00003)	(0.00003)	
Single Family	0.9733	0.9733	0.826
	(0.00002)	(0.00002)	
Purchase	0.3451	0.3451	0.885
	(0.00005)	(0.00005)	
Delinquency Rate	0.1737	0.1737	0.773
	(0.00008)	(0.00008)	
Default Rate	0.1219	0.1219	0.902
	(0.00007)	(0.00007)	

Table 3.11

Random Sample Splits and Threshold Centers

This table reports results from regression specifications identical to those found in columns 4 and 9 in Table II. Columns 1 and 2 average results obtained by varying the training vs test sample split randomly 100 times. Columns 3 and 4 average results obtained by varying the bin centers 100 times. t-statistics are heteroskedasticity-robust and clustered at the level indicated.

	Application Accepted	Loan Originated	Application Accepted	Loan Originated
	(1)	(2)	(3)	(4)
	Random Sample Splits		Random Threshold Centers	
Lender Specific Origination Shock ($\hat{v}_k$)				
Average Coefficient	0.02233	0.01882	0.02162	0.01881
Average t-statistic	(9.20)	(9.02)	(8.94)	(8.84)
St. Dev.	(0.3422)	(0.4379)	(0.2431)	(0.3214)
DTI				
Average Coefficient	0.07193	0.08552	0.07101	0.08459
Average t-statistic	(2.58)	(3.15)	(2.59)	(3.17)
St. Dev.	(0.0110)	(0.0111)	(0.0015)	(0.0014)
DTI^2				
Average Coefficient	-0.02501	-0.02936	-0.02492	-0.02931
Average t-statistic	(-2.53)	(-3.10)	(-2.55)	(-3.13)
St. Dev.	(0.0143)	(0.0148)	(0.0047)	(0.0043)
DTI^3				
Average Coefficient	0.00210	0.00258	0.00211	0.00259
Average t-statistic	(1.99)	(2.58)	(2.00)	(2.61)
St. Dev.	(0.0169)	(0.0178)	(0.0017)	(0.0018)
Lender FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes
Average N	103,062,624	103,062,624	103,071,264	103,071,264
Average R^2	0.199	0.190	0.199	0.190
Number of Draws	100	100	100	100

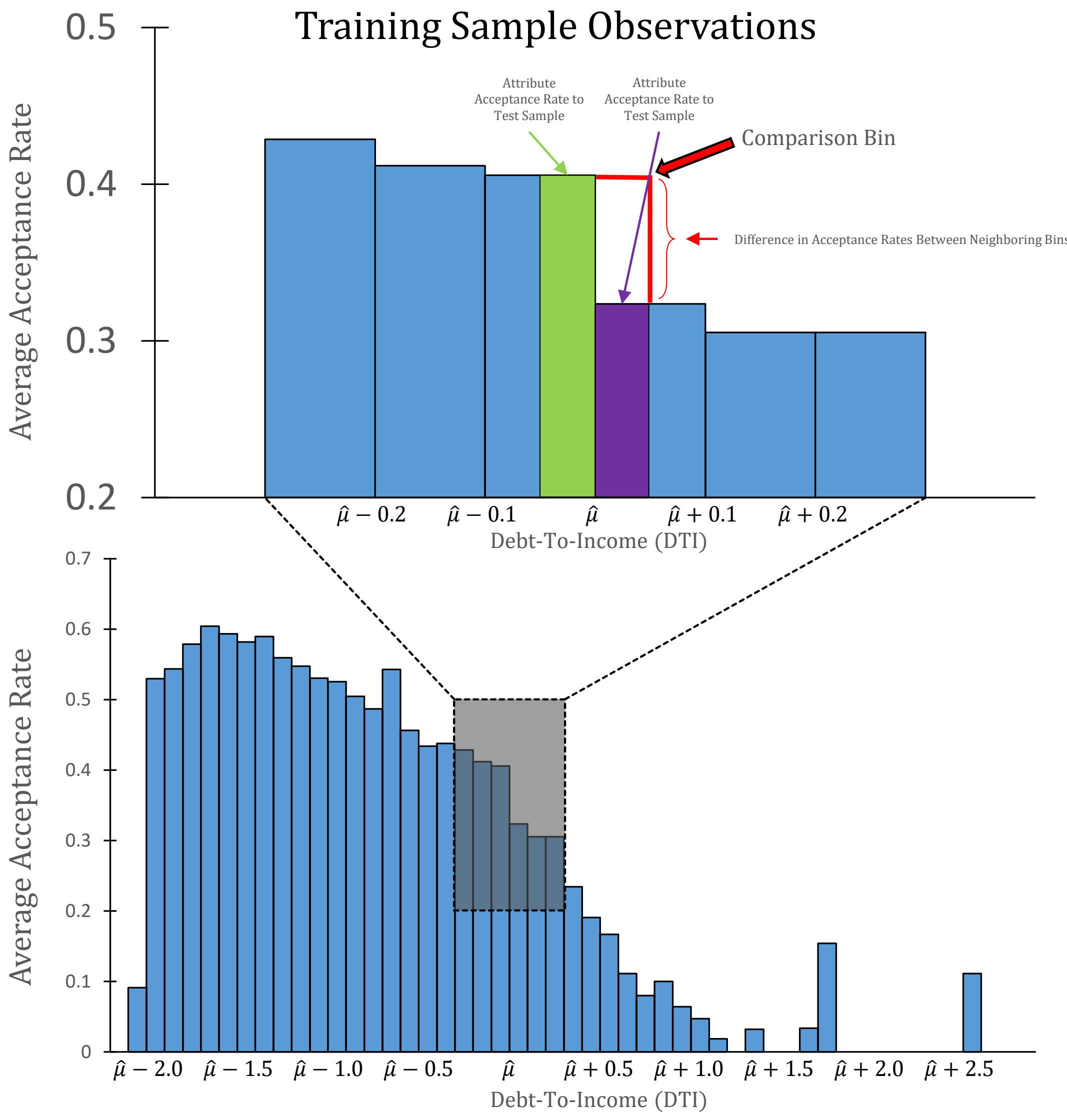

Figure 3.1. Example of Estimated Lender Origination Model

This graph displays the estimated origination model of the lender 21st Mortgage Corporation for white owner-occupied applicants in 2011. Data from the training sample is used to estimate the average acceptance rate as a function of applicant DTI. The upper portion of the figure highlights the differences in acceptance rates for two neighboring DTI bins sharing a comparison bin. The average acceptance rates depicted for each DTI bin are attributed to the test sample in order to estimate the acceptance ratio jumps and generate lender-specific shocks for applicants with varying DTIs.

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