Agency conflicts in securitization: Evidence from Ginnie Mae early buyouts

Arka P. Bandyopadhyay *   Dongshin Kim †   Patrick S. Smith ‡

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Abstract

This paper provides new evidence of agency conflicts in securitization by documenting adverse selection in Ginnie Mae issuers' early buyout activity. Conditioning on delinquency, we find issuers buy out less risky loans with higher interest rate spreads. We illustrate not only how information asymmetries arise during the loan servicing process but also how issuers exploit them in their early buyout decisions. Unlike prior studies examining information asymmetries introduced by the securitization process, we employ unique data on a subset of early buyout loans that *directly* observes the soft information collected by issuers.

Key Words: Adverse Selection, Agency Conflict, Early Buyouts, Ginnie Mae, Securitization

*Leeds School of Business, University of Colorado Boulder

†Graziadio Business School, Pepperdine University

‡Fowler College of Business, San Diego State University; Contact Author: patrick.smith@sdsu.edu

1 Introduction

Most mortgages originated in the United States are not held in lenders' portfolios. Instead, the mortgages are pooled into mortgage-backed securities (MBS) and sold to investors.[1] Securitization creates value for lenders, investors, and borrowers. Lenders and investors benefit through improved liquidity, capital management, and asset diversification (Loutskina 2011); while borrowers benefit through expanded credit availability (Loutskina and Strahan 2009; Nadauld and Weisbach 2012). However, the benefits of securitization are not costless. Securitization introduces agency conflicts that propagate through information asymmetry and incentive incompatibility.

This paper provides new evidence of agency conflicts in securitization by examining early buyout activity in GNMA MBS.[2] GNMA issuers have the right to buy delinquent loans out of a pool at par value if the borrower misses three or more consecutive payments. The early buyout option exists for several reasons. Early buyouts provide issuers some control over their exposure to required principal and interest pass-through payments on delinquent loans. Early buyouts also facilitate loss mitigation because GNMA prohibits loan modifications that affect the amount or duration of loan payments. Furthermore, early buyouts allow issuers to keep delinquency rates below GNMA's specified threshold levels (e.g., less than 5% of loans can be 90 days delinquent), thereby avoiding penalties and maintaining good standing.

Although early buyouts are sometimes necessary, we provide evidence of adverse selection in issuers' buyout decisions. We find GNMA issuers buy out delinquent loans with high interest rate spreads regardless of their portfolio's overall delinquency rate.[3,4] When the loans cure, either naturally or due to a loan modification, issuers re-securitize the reperforming

[1] Since 2000, the annual share of securitized first lien mortgage originations has ranged between 62% and 88% (Urban Institute 2020).

[2] The Government National Mortgage Association (GNMA), or Ginnie Mae, is a government agency within the United States Department of Housing and Urban Development. Section 2 describes GNMA's business model and their role in the secondary mortgage market.

[3] We focus on the loan's current interest rate spread, not its interest rate spread at origination. The current interest rate spread, hereafter interest rate spread, is a time-varying measure of the loan's contract interest rate at origination minus the 10-year Treasury Constant Maturity Rate at the time of delinquency. The interest rate spread at origination, hereafter origination rate spread, is a time-invariant measure of the loan's contract interest rate at origination minus the 10-year Treasury Constant Maturity Rate at origination.

[4] Early buyouts stemming from GNMA's delinquency thresholds do not preclude adverse selection. When issuers must buy out delinquent loans to maintain good standing with GNMA, they still have an incentive to buy out less risky loans with higher interest rate spreads.

loans into new GNMA MBS pools with the loans' original coupon rate. In a declining interest-rate environment, the re-securitized loans sell for a premium, creating additional earnings for the issuer. The issuers' economic gains come at the expense of the original security holders, who must reinvest their funds at a lower rate.

Conditional on a loan becoming seriously delinquent, we find a one standard deviation (or 1.1 percentage point) increase in interest rate spread, increases the probability of an early buyout by 9 - 11%. The effect persists, albeit at a slightly lower rate, when we examine early buyouts by the same issuer, within the same MBS pool, during the same month of delinquency. The adverse selection we document is the product of misaligned incentives between GNMA issuers and the MBS investors they represent. The idea that misaligned incentives create principal-agent conflicts is not new. However, providing conclusive evidence has proven difficult. We overcome the limitations of previous studies by testing for adverse selection among relatively homogeneous pools of federally insured loans. In doing so, we avoid endogeneity issues stemming from the comparison of portfolio loans to securitized loans (Keys, Mukherjee, Seru, and Vig 2010; Agarwal, Chang, and Yavas 2012; Elul 2016).

In addition to our main results documenting adverse selection in GNMA issuers' early buyout activity, we make several further contributions to the literature. There is a dearth of research on GNMA MBS, even though its outstanding first lien debt has more than doubled over the past decade to approximately the same size as Freddie Mac and two-thirds the size of Fannie Mae. Accordingly, we undertake the first systematic examination of GNMA MBS. Our analysis highlights the growth and changing composition of GNMA MBS across its program, issue, pool, and loan types.

GNMA's growth coincides with the rise of non-depository shadow banks in residential mortgage markets (Pozsar, Adrian, Ashcraft, and Boesky 2010; Buchak, Matvos, Piskorski, and Seru 2018). We document shadow bank issuers' substantial increase in GNMA loan issuances, from 40% at the end of 2013 to over 80% in 2020, and examine its effect on GNMA MBS pool dynamics. Similar to Buchak et al. (2018), we find shadow bank loans have significantly higher prepayment risk relative to traditional bank loans. However, we also find shadow bank loans have significantly lower early buyout risk - which represents an alternative type of prepayment risk unique to GNMA MBS. Taken together, shadow bank loans' lower early buyout risk offsets a portion of their higher prepayment risk relative to traditional banks, but increases their overall absolute risk to GNMA MBS investors.

We also illustrate how information asymmetries develop between GNMA issuers and investors during the mortgage servicing process. When a borrower misses a mortgage payment, issuers contact the delinquent borrower to determine the reason for delinquency, their intent, and whether they are occupying the property. Issuers are required to document all communication efforts and discussions with delinquent borrowers. Although the information is collected on behalf of the MBS investors, we show GNMA issuers can exploit the soft information in their early buyout decisions. The notion that soft information influences lending and securitization decisions is well established in the literature. However, this is one of the first studies to use direct and precise data to illustrate how GNMA issuers can exploit soft information to the detriment of MBS investors.[5]

Using proprietary data on a subset of over 3,000 early buyout loans, we find soft information collected during the delinquent loan servicing process provides critical insight into whether a loan will reperform and be re-securitized in a new GNMA MBS pool. Specifically, we find including soft information from loan servicing logs in a regression increases its explanatory power by as much as 68% relative to a baseline regression that includes only hard information. The improved performance does not provide causal evidence that GNMA issuers exploit the soft information in their early buyout decisions. However, taken together with the adverse selection in our main results, the improved performance illustrates how information asymmetries that develop during the delinquent loan servicing process can create agency conflicts if issuers' and MBS investors' incentives are not properly aligned.

The early buyout option has served as a potential source of profit for GNMA issuers for some time as evidenced by a 2003 PricewaterhouseCoopers report touting "improved earnings associated with the buyout of loans from GNMA (PWC, 2003)." Despite being a long-established program, there is a paucity of research on the topic. This paper provides the first systematic review of early buyout activity in GNMA MBS pools. We identify the key determinants of early buyout activity and document principal-agent conflicts associated

[5]See Berger, Miller, Petersen, Rajan, and Stein (2005), Hauswald and Marquez (2006), Agarwal and Hauswald (2010), and An, Deng, and Gabriel (2011) for examples of studies that use indirect proxies of soft information. See Aiello (2016) for a rare example using direct private information.

with the practice.

Our findings have important implications from policy, investment, and societal perspectives. Regarding policy, GNMA early buyouts recently came under scrutiny when issuers purchased large quantities of GNMA loans in COVID-related forbearance programs (Maloney, 2020).[6] In response, GNMA imposed a temporary restriction on the re-securitization of early buyout loans to "ensure that transactional activity related to these options does not impair market confidence in Ginnie Mae securities." Our findings provide evidence of adverse selection that support GNMA's COVID-related early buyout restriction. Moreover, our findings document adverse selection in early buyout activity well before COVID-19.

From an investment perspective, we find 48.8% of delinquent loans, which constitute approximately 5.7% of all GNMA loans, are bought out early by GNMA issuers. Taken together with the adverse selection in our main results, the substantial volume indicates early buyouts represent a significant form of prepayment risk unique to GNMA MBS. From a societal perspective, the early buyout process introduces an additional source of servicing friction. The friction stems from the resale or transfer of the early buyout loan to a different servicer. Instead of dealing with one single party, borrowers have to deal with several different parties to resolve issues with their loans. The friction is a concern because it creates additional obstacles for borrowers - many of whom belong to underserved communities - who are already in financial distress.

2 Data

2.1 GNMA loan-level data

The primary data set is publicly available GNMA single-class MBS loan-level data. GNMA is a government-owned agency housed within the U.S. Department of Housing and Urban Development (HUD). In contrast to the government-sponsored enterprises (i.e., Fannie Mae and Freddie Mac), GNMA does not issue the mortgage pools it guarantees and does not use its own balance sheet to manage delinquencies. Instead, GNMA guarantees timely payment

[6]For example, Wells Fargo bought out $19 billion of GNMA loans in July and August of 2020 alone. Analysts estimate the loans were purchased for $1.5 billion less than their market value (Light, 2020).

for pass-through securities sold by approved issuers.[7] GNMA's business model minimizes its exposure to credit risk by guaranteeing the issuer's servicing performance - not the underlying collateral. Over the past decade, GNMA's outstanding first lien mortgage debt has more than doubled from just under 1 trillion dollars in 2010 to 2.1 trillion dollars in 2020 (Urban Institute 2020).

GNMA offers two distinct single-family MBS programs: GNMA I and GNMA II. GNMA I MBS (issue type X) are single-issuer securities whose underlying mortgages have the same or similar maturities and the same interest rate. GNMA II MBS includes "custom" single-issuer securities (issue type C) and multi-issuer securities (issue type M).[8] GNMA II pools differ from GNMA I pools in that they allow interest rates to vary by as much as one percentage point. When testing for adverse selection in GNMA issuers' early buyout activity, we exploit the variation in interest rates in GNMA II pools by including issuer-by-pool-by-month-by-year fixed effects. Including the fixed effects allows us to isolate the effect of interest rate spreads on early buyout decisions by the same issuer within the same MBS pool during the same month and year of delinquency.

The GNMA loan-level data includes over 23.8 million unique loans in 320,928 distinct mortgage pools from December 2013 through December 2020.[9] Panel A of Figure 1 plots the number of active loans and pools each month during the study period. The plot indicates the GNMA I and GNMA II MBS programs did not contribute equally to GNMA's growth over the past decade. The number of GNMA I MBS loans decreased by ∼50% over the seven year study period. The decrease in GNMA I MBS loans was more than offset by the ∼66% growth in GNMA II MBS loans. Panel A also highlights the relatively smaller size of single-issuer GNMA I pools compared to multi-issuer GNMA II pools.

Panel B of Figure 1 plots the relative share of GNMA loans by issue type over time. The

[7]GNMA issuers are fully responsible for the administration of the securities and the servicing of the pooled mortgages. The issuer is permitted to arrange for a subservicer to perform some, though not all, of the required servicing functions on their behalf. The subservicer must be a GNMA approved issuer. The internet appendix provides a detailed list of the functions the subservicer can perform.

[8]The multi-issuer GNMA II pools allow small issuers who do not meet the dollar requirements of the GNMA I MBS program to participate in the secondary mortgage market. Each participating issuer in the multi-issuer pools is responsible for administering the loans they submit.

[9]We downloaded the loan-level data directly from www.ginniemae.gov. The totals reported do not include non-standard mortgage pool types. For example, we filter out pools with buydown and graduated payment mortgages. A complete list of filters is available in the appendix.

plot indicates both GNMA II issue types, C and M, increased their relative shares during the study period. Issue type M had the largest share throughout the entire study period, increasing from 59.7% in December 2013 to 71.5% in December 2020. Issue type C initially had the lowest share (5.9% in December 2013), but increased to the second largest share by the end of the study period (19.0% in December 2020). In contrast, issue type X's share decreased from 34.4% in December 2013 to 9.5% in December 2020.

GNMA securities are backed by mortgages from one of four federally insured or guaranteed loan programs: Federal Housing Administration (FHA), Department of Veterans Affairs (VA), Department of Agriculture's Rural Development (RD), and Public and Indian Housing (PIH). The summary statistics displayed in Table 1 show FHA loans (64%) are the most prevalent mortgage type in GNMA MBS followed by VA loans (29%), RD loans (7%), and PIH loans (less than 1%). Panel C of Figure 1 provides insight into the changing composition of GNMA MBS by plotting the relative share of new loans entering MBS pools by loan type. The plot highlights the decreasing relative share of new FHA loans and increasing relative share of new VA loans entering GNMA MBS between December 2013 and December 2020.

The GNMA loan-level data provides detailed information about the loan at the time of origination, such as the principal balance (i.e., loan amount), loan term, contract interest rate, loan-to-value (LTV) ratio, and the borrower's credit score. Panel A of Table 1 presents summary statistics for the full GNMA loan-level data set. The average loan amount is just under $194,000, the average credit score is 690.55, and the average loan-to-value ratio at origination (ltv_orig) is 84.35%. The summary statistics in Panel A of Table 1 highlight a relatively low level of dispersion in loan characteristics compared to previous studies that examine adverse selection in mortgage securitization (Ambrose, LaCour-Little, and Sanders 2005; Keys et al. 2010; Agarwal et al. 2012; Elul 2016). We attribute the lower level of dispersion in our data to the fact that we do not compare portfolio loans to securitized loans. Instead, we test for adverse selection using a relatively homogeneous sample of federally insured or guaranteed loans in a single security type.

For our regressions, we use a subsample of delinquent loans, focusing on the first instance of delinquency during the study period. We consider a loan delinquent when the borrower misses three consecutive monthly mortgage payments.[10] We restrict the delinquent loan subsample to only include loans whose first instance of delinquency occurred between February 2014 and September 2020. The leading and trailing three month windows are necessary to identify delinquent loans and examine post-delinquency loan outcomes. In subsequent analysis, we use twelve month windows to demonstrate the robustness of our results.

Additional filters are applied to remove delinquent loans with incomplete information. After applying the filters, there are approximately 2.7 million delinquent loans remaining. The internet appendix provides a detailed list of the filters and their associated effect on the sample size across the GNMA I and GNMA II programs. Panel B of Table 1 displays summary statistics for the filtered delinquent loan subsample. Relative to the full sample, delinquent loans have a lower average principal balance (opb) and credit score, and a higher average LTV and interest rate at origination.

Panels B, C, and D of Table 1 include five fields that are not populated in Panel A. The fields include unpaid principal balance (upb), LTV at the time of delinquency (ltv_dlq), interest rate spread (rate_spread), delinquency history (dlq_history), and a forbearance indicator. Each loan's interest rate spread, which is our primary variable of interest, is calculated as the difference between its contract interest rate at origination minus the 10-year Treasury Constant Maturity Rate when the loan first becomes delinquent. We focus on interest rate spreads because they capture the potential economic gain associated with an early buyout. The dlq_history field equals 1 if the borrower missed at least one other payment in the 12 months leading up to the loan's delinquency, and 0 otherwise. The forbearance field equals 1 if the delinquent loan is part of a forbearance program, and 0 otherwise. The forbearance field equals 0 prior to May 2020 when it was first made available.[11]

Panel C of Table 1 presents summary statistics for 1,356,705 delinquent loans that were not bought out by GNMA issuers during the 3-month post-delinquency window. Similar summary statistics are displayed in Panel D for 1,346,401 early buyouts that occurred during

[10] Our definition of delinquency aligns with the early buyout guidelines provided in Section B.1(c) of Part 3 in Chapter 18 of the GNMA MBS Guide. Specifically, Section B.1(c) states, "For loans backing a Ginnie Mae security with an issue date on or after January 1, 2003, Issuers may buy out any pooled loan without written permission from Ginnie Mae if the loan is due, but unpaid, for three consecutive months."

[11] GNMA started tracking forbearance to ensure delinquent loans in forbearance did not negatively affect an issuer's status, as would normally occur when delinquency levels exceed GNMA's predetermined threshold.

the 3-month window. The internet appendix presents similar summary statistics for early buyouts that occurred during the 12-month window. Relative to the non-early buyout loan sample in Panel C, the early buyout subsample has a lower average principal balance both at origination (opb) and the time of delinquency (upb). The average credit score (credit_score) and LTV at origination (ltv_orig) are fairly similar. However, the early buyout subsample has a lower average LTV at delinquency (ltv_dlq), higher average interest rate (interest_rate), and a higher average interest rate spread (rate_spread).

The GNMA loan-level data provides information about the "removal reason", if any, for each delinquent loan. There are six possible outcomes captured in the "removal reason" classifications. We infer two additional outcomes for loans that are not removed during the specified post-delinquency window. The first outcome we infer identifies delinquent loans that self-cure and reperform (reason = 7). The second outcome we infer identifies delinquent loans that are not removed and do not cure during the specified post-delinquency window (reason = 8). Table 2 tabulates the "removal reasons" for the delinquent loan subsample using a 3-month (Panel A) and 12-month (Panel B) trailing post-delinquency window. Almost half of the delinquent loans are bought out by the servicer during the 3-month trailing window.[12] Extending the trailing window to 12 months increases the fraction of early buyouts to just over 54%, thereby indicating that most early buyouts occur within three months of delinquency. Table 2 also highlights the large fraction of loans that remain delinquent but are not bought out within 3 months (40.81%) or 12 months (27.12%). The relatively high fraction indicates GNMA issuers do not buy out every delinquent loan - thereby suggesting issuers may systematically buy out loans with favorable characteristics.

2.2 Issuer type classifications

The residential mortgage market has undergone a drastic shift in the 21st century. Pozsar et al. (2010) and Buchak et al. (2018) provide exhaustive reviews of the shifting landscape showing that lending has shifted away from traditional banks to shadow banks - which

[12]The trailing windows include the month of delinquency as well as the 3 (12) months after. For example, if a loan is flagged as delinquent on 01/01/2017, the 3-month trailing window includes February, March, and April.

they define as non-depository institutions falling outside the scope of traditional banking regulation. The shifting landscape is of particular interest to this study because Buchak et al. (2018) find (i) shadow banks securitize almost all of the loans they originate and (ii) a large fraction of shadow banks more recent growth occurred in the FHA market - where shadow banks held a 75% market share in 2015. Implicit in these findings is shadow banks have become a major issuer of GNMA MBS. However, Buchak et al. (2018) do not include GNMA loan-level data in their empirical analysis.[13] Nor do they examine adverse selection in GNMA issuers' early buyout decisions - which is the primary focus of this study.

Before discussing our issuer type classification process, we first highlight its importance by documenting the continual rise of shadow banking in GNMA MBS. Panel A of Figure 2 plots the relative share of new loans entering GNMA MBS pools by issuer type. In December 2013, traditional banks originated just under 60% of the loans entering GNMA MBS pools. Although shadow banks originated a substantial fraction of GNMA loans, they clearly lagged traditional banks with approximately 40% of new loans entering GNMA MBS pools. However, by 2020, shadow banks were the clear market leader, originating over 80% of the new loans entering GNMA MBS pools. Panel B shows shadow banks' share of delinquent loans increased in tandem with their share of new issuances, albeit at a slower rate. The same cannot be said for early buyouts. Panel C of Figure 2 shows shadow banks' relative share of early buyouts lagged its new issuances and delinquencies - both of which surpassed traditional banks in July 2014 and September 2017, respectively.

Shadow banks' unique organizational structure (i.e., no deposits) and prominent role in GNMA MBS motivate our exploration of their early buyout activity relative to traditional banks. Central to our exploration is the classification of GNMA issuers by bank type. At the highest level, we classify an issuer as either a traditional bank, shadow bank, or state financing authority. We further segment the issuer classifications by separating credit unions from traditional banks and fintech lenders from shadow banks.

We begin the classification process by cross referencing the "Issuer Name" field in the GNMA issuer files to the lender classifications in Buchak et al. (2018) and Fuster, Plosser,

[13]The most likely explanation for the exclusion is that historical GNMA loan-level data was unavailable. Currently, only historical data dating back to October 2013 is publicly available. We reached out to GNMA several times to obtain historical data prior to October 2013. Our attempts were unsuccessful.

Schnabl, and Vickery (2019). During the classification process, we flagged fifteen issuers that are state-sponsored lenders. We classify these lenders separately as state financing authorities. For the subset of issuer names without a match, we classify the issuer as a traditional bank if they are included in the Federal Deposit Insurance Corporation (FDIC) or National Credit Union Administration (NCUA) institution lists. Then, we manually searched the internet for the remaining unmatched issuers to ensure they are not subsidiaries of traditional banks. In sixteen cases, we found evidence that an unmatched issuer was a subsidiary of a traditional bank. The sixteen subsidiaries are included in the traditional bank classification. The remaining unmatched banks were classified as shadow banks. The internet appendix provides a list of the largest GNMA issuers for each of the three high-level classifications: traditional bank, shadow bank, and state financing authorities.

2.3 Loan servicing data

We examine whether GNMA issuers' can exploit their informational advantage to buy out less risky loans using proprietary data obtained from a large private equity firm that specializes in distressed mortgage workouts. The unique data set includes 3,084 early buyout loans that the private equity firm purchased from five different GNMA issuers between January 2016 and April 2019.[14] The data includes much of the standard hard information available in the GNMA loan-level data as well as soft information (i.e., call logs) collected during the delinquent loan servicing process.

Panel A of Table 3 displays select summary statistics for the 3,084 early buyout loan subsample. The principal balance at origination (opb) and unpaid balance at delinquency (upb) are both considerably lower than the full early buyout sample in Panel D of Table 1. The subsample in Table 3 also has a lower average LTV (ltv_dlq) and interest rate spread (rate_spread) at delinquency. However, the average LTV at origination (ltv_orig) and contract interest rate (interest_rate) at origination are comparable. The lower average interest rate spread is not surprising for two reasons. First, GNMA issuers likely keep and re-

[14]The proprietary data includes over 20,000 additional early buyout loans that were purchased in 2020. However, we restrict the data to pre-COVID purchases because many of the 2020 loans are in forbearance and do not provide a sufficient trailing window to track loan outcomes.

securitize loans with higher interest rate spreads themselves. Second, the private equity firm specializes in difficult loan workouts. Accordingly, the firm is less concerned with interest rate spreads because they purchase the difficult loans for a discount from the GNMA issuer.

The loan status variables in Table 3 identify whether the loan is still active in the private equity portfolio (prefix *act*) or the loan has been liquidated (prefix *liq*) as of December 2020. The active loans are further demarcated to identify if the borrower is working through a bankruptcy (act_bk), making payments and current (act_cur), or still delinquent (act_dlq). The liquidated loans are further demarcated as paid in full (liq_pif), re-securitized in a GNMA MBS Pool without a modification (liq_rp), re-securitized in a GNMA MBS Pool with a modification (liq_rpm), or liquidated via a short sale or real estate owned (REO) transaction (liq_ss_reo). Issuers have a strong financial incentive to only buy out delinquent loans with relatively high interest rate spreads that they expect to reperform.[15] The summary statistics in Panel A indicate over 64% of the loans either reperformed and were re-securitized or were in the process of reperforming (act_cur); whereas only 17% of the loans were liquidated via a short sale or REO.[16]

Table 3 also provides insight into the soft information collected during the delinquent loan servicing process. The soft information identifies the borrower's intent and reason for default. We extract the two pieces of information from text-based servicing logs. There are over 1.16 million unique servicing logs for the 3,084 loans. The logs document the servicers' actions (i.e., title search ordered, property inspection completed) as well as communications with the borrower (i.e., call logs). For the purposes of this study, we are primarily interested in the call logs that summarize the servicers' discussions with delinquent borrowers.

We populate the borrower intent and reason for default variables in Table 3 using data from the first successful contact with the delinquent borrower. We focus on the first contact

[15]Issuers also have a strong incentive to buy out loans to keep their delinquency rate below GNMA's specified threshold. However, issuers forced to buy out loans to maintain good standing - of which there are relatively few - still have discretion over which loans they buy out. In other words, even if a fraction of the early buyouts are caused by the delinquency threshold, adverse selection can still exist. Furthermore, we provide evidence the delinquency rate thresholds are not driving our results in Section 3.2.

[16]Early buyout loans liquidated via short sales and REOs do not necessarily have a negative financial impact on issuers because the loans are federally insured. However, issuers can maximize their earnings by leaving delinquent loans they do not expect to reperform in GNMA pools and using their limited financial resources to buy out loans they expect to reperform.

because it provides the best proxy for the soft information available to issuers when they perform early buyouts. Table 4 presents a truncated servicing log sequence for one of the early buyout loans in the data. The servicing log sequence displays 4 of the initial 107 servicing logs for the loan over a five month period. All loan, location, servicer, and personally identifiable information has been [redacted].

The example in Table 4 highlights the soft information available in the servicing logs. Sample Log 1 is the first entry in the sequence. It provides information about the loan and borrower that has been redacted. However, much of the information in the log is already codified and available in the hard information. Sample Log 2 is the second entry in the servicing log sequence. It captures the first successful contact between the borrower and the special servicer. In contrast to the previous log, Sample Log 2 contains soft information that has not already been captured in the hard information. For example, Sample Log 2 indicates the borrower is intent on keeping the property and their income has been curtailed. Similar information is available in a fairly structured format for most of the 3,084 loans. Sample Log 2 also contains a wealth of soft information in unstructured text. For example, the text in Sample Log 2 indicates the borrower is living in the property and working two part-time jobs. Sample Log 2 also indicates the borrower is in the process of getting a full-time job with better pay. This soft information highlights the borrower's (i) conviction to reperform, (ii) ability to reperform, and (iii) improving prospects of reperforming. Sample Log 2 also indicates the servicer offered the borrower a loan modification.

Sample Logs 3 and 4 document the borrower's navigation of the loan modification process. Approximately one month after the loan modification was offered, Sample Log 3 displays an email received by the servicer stating the borrower will fax their loan modification request the next day. Approximately one week later, the servicer enters a note indicating they received the loan modification request. However, the servicing log also notes the modification package was missing both proof of income and tax returns. This truncated sequence of servicing logs provides a glance into the detailed soft information collected by mortgage servicers.

We use the structured text in Sample Log 2 to populate the borrower intent and reason for default fields. The borrower intent fields in Table 4 identify whether the borrower wants to keep the property (intent_keep), liquidate the property (intent_liq), or their intent is unknown (intent_na). As noted earlier, issuers have little financial incentive to buy out delinquent loans if the borrower is not intent on keeping the property because a short sale or REO liquidation is inevitable. Thus, it is not surprising that 93% of the borrowers in the early buyout loan subsample (Panel A of Table 3) state that they want to keep their home.

The bottom section of Table 3 identifies the borrower's reason for default. The two most common reasons for default are income curtailment (rfd_income: 29%) and excess financial obligations (rfd_excess: 19%). Other common reasons suggest the borrower had a temporary setback and is no longer delinquent (rfd_not_dlq: 13%) or blamed their default on a servicing issue (rfd_servicing: 8%). The internet appendix provides a detailed description of the remaining reason for default variables. Taken together, the borrower intent and reason for default variables represent soft information issuers can exploit to inform their early buyout decisions. Information asymmetry concerns arise because MBS investors do not have access to this soft information, even though it is collected on their behalf as part of the delinquent loan servicing process.

3 Methodology and Results

3.1 Early buyout decisions

This section examines the determinants of early buyouts, with a particular focus on interest rate spreads. We focus on interest rate spreads because they provide a direct measure of the potential profits GNMA issuers can earn by buying out, curing, and re-securitizing delinquent loans. We begin our analysis by estimating a simple OLS specification that takes the following form:

$$Pr(EBO_n = 1|Delinquency) = \beta rate\_spread_{nt} + X_n\alpha + Z_{nt}\gamma + S\delta_s + Y\Psi_t + I\Phi_i + \varepsilon \quad (1)$$

The dependent variable, EBO_n, is an indicator variable for a delinquent loan n that takes the value of 1 if the issuer chooses to buy the loan out early, and 0 otherwise. Conditioning on delinquency is natural because issuers can only buy out delinquent loans. The primary variable of interest, $rate\_spread_{nt}$, measures the difference between the delinquent loan's contract rate and the 10-year treasury rate at the time of delinquency. In this specification, β measures the impact of the interest rate spread on an issuer's decision to either buy out the delinquent loan or leave it in the GNMA MBS pool.

X_n is a vector of time-invariant loan and borrower characteristics, such as credit score and issue type, that are collected and reported at issuance. Z_{nt} is a vector of time-varying loan characteristics that include the log unpaid principal balance (log_upb) and current loan-to-value (LTV) at the time of delinquency.[17] Our baseline specification includes fixed effects for the state in which the house is located (S), the calendar year in which the loan is first delinquent (Y), and the issuer of loan (I). In subsequent regressions, we include issuer-by-pool-by-month-by-year fixed effects to demonstrate the robustness of our results.

Our main results are presented in Table 5. The results highlight the effect of interest rate spreads at the time of delinquency on issuers' early buyout decisions. We estimate the selected coefficients displayed in Table 5 using Equation (1) and a 3-month post-delinquency window. The internet appendix reports the full set of coefficient estimates for both a 3-month and 12-month post-delinquency window in Tables C1 and C2, respectively. The results are similar regardless of the post-delinquency window employed.

The interest rate spread (rate_spread) coefficient estimates in columns 1 to 3 of Table 5 are consistently positive and statistically significant. This suggests that, conditional on being delinquent, a loan with a higher interest rate spread is more likely to be bought out. A one standard deviation (or 1.1 percentage point) increase in interest rate spread, increases the probability of an early buyout by 6-7%. This effect is very significant, both statistically and economically. The effect is even stronger in our preferred specifications (columns 4-6) where we restrict the sample to remove the potential confounding impact of COVID-19.

Column 4 of Table 5 includes loans whose first instance of delinquency occurred before 2020, so the 3-month post-delinquency window only includes early buyouts through March 2020. Columns 5 and 6 further restrict the sample to include loans whose first instance of delinquency occurred between January 2015 and December 2019. Restricting both the

[17] We estimate the current LTV of the mortgage by amortizing the loan and using a state-level FHFA house price index to adjust its value.

front-end and back-end of the sample allows us to address the potential impact of COVID-19 and include a control that identifies whether borrowers missed more than three payments in the twelve months leading up to their first instance of delinquency.

Column 6 only differs from Column 5 in that it includes one additional control variable: origination rate spread. We include the variable to address concerns that the loan and borrower characteristics included in columns 1 to 5 do not adequately capture the riskiness of the loan at origination. In other words, a higher origination rate spread may reflect the increased riskiness of the borrower. Similar to columns 1 to 3, the interest rate spread coefficient estimates in our preferred specifications are consistently positive and statistically significant. The results in columns 4 to 6 indicate that a one standard deviation increase in interest rate spread, increases the probability of an early buyout by 9-11%.

Columns 7 and 8 of Table 5 further highlight the importance of interest rate spreads in issuers' early buyout decisions. Both columns include issuer-by-pool-by-month-by-year (IxPxM) fixed effects in place of the standard issuer, state, and year (I+S+Y) fixed effects in columns 1 to 6. Furthermore, columns 7 and 8 only use loan-level data from GNMA II MBS pools because they permit interest rates to vary by as much as one percentage point. Thus, the IxPxM fixed effects allow us to isolate the effect of interest rate spreads on early buyout decisions by the same issuer within the same pool at exactly the same time.

The interest rate spread coefficients in columns 7 and 8 remain positive and statistically significant. This finding suggests that when two or more loans become delinquent at the same time within the same pool, issuers are more likely to buy out loans with higher interest rate spreads. A one standard deviation increase in within pool interest rate spread, increases the probability of an early buyout by the same issuer within the same pool by approximately 3-4%. Although the magnitude of the coefficient estimate decreased relative to our preferred specifications, it is important to note that the specifications in columns 7 and 8 artificially restrict the variation in interest rate spreads and issuers' early buyout options. In reality, issuers do not face monthly within pool early buyout decisions. Instead, they make early buyout decisions on a continuous basis across their entire portfolio.

Up to this point, our primary focus has been on the effect of interest rate spreads on early buyout activity. The remainder of this subsection briefly discusses the additional determinants reported in Table 5. The determinants indicate issuers are more likely to buy out less risky loans, thereby providing further evidence of adverse selection. For example, we find delinquent loans with higher LTVs at the time of delinquency (ltv_dlq) are less likely to be bought out. A higher LTV increases the likelihood the property will need to be liquidated via a short sale or REO (Alexander, Grimshaw, McQueen, and Slade 2002; Holden et al. 2012; Scharlemann and Shore 2016). In which case, there is very little benefit associated with an early buyout from the issuer's perspective. Our results also indicate delinquent adjustable rate mortgages (ARMs) are less likely to be bought out. This finding supports our claim of adverse selection because ARMs are typically considered riskier than fixed rate mortgages (FRMs) due to their higher default probability (e.g., Demyanyk and Van Hemert 2011). Moreover, the interest rate on ARMs adjusts with market conditions, thereby limiting its interest rate spread and attractiveness from an early buyout perspective.

We also find delinquent loans in which the borrower missed at least one additional payment in the twelve months leading up to their first instance of delinquency (prev_dlq_history) are less likely to be bought out.[18] Similar to Aiello (2016), this finding suggests issuers can use borrowers' payment history to inform their decisions. However, Aiello (2016) finds issuers do not exploit payment information in their securitization decisions. In contrast, we find - in an admittedly much different setting - issuers use payment history information to buy out less risky loans.

Finally, we find loans originated by third-party originators (TPOs), such as mortgage brokers and mortgage banks, are less likely to be bought. There are several plausible explanations why issuers buy out fewer loans originated by TPOs. Similar to the explanations above, TPO loans are considered riskier because they are more likely to default (Alexander et al., 2002). TPO loans are also considered riskier due to agency issues introduced by TPOs' compensation structure. TPOs are compensated based on origination volume (i.e., fee-based compensation) and have no stake in the loan's subsequent performance. Moreover, issuers have less soft information about TPO loans because they do not oversee the origination pro-

[18] Issuers can only buy out delinquent loans with three consecutive missed payments. If a borrower makes payments every other month for a year, the loan is more than three months delinquent but cannot be bought out. However, if the borrower misses three consecutive payments in the following year, the loan is eligible to be bought out. The previous year of payment history (prev_dlq_history) provides a credible signal that the issuer can use to inform their early buyout decision.

cess. Issuers' incomplete information makes an early buyout riskier and less likely. Unless, of course, issuers are able to acquire "missing" soft information during the delinquent loan servicing process. We explore this dynamic in more detail in Section 3.4.

3.2 Delinquency Thresholds

The baseline results in Table 5 provide strong evidence of adverse selection in GNMA issuers' early buyout activity. However, the results do not control for the fact that GNMA issuers must maintain delinquency rates below set threshold levels. This section discusses the delinquency threshold levels and examines the degree to which the thresholds drive the early buyout activity documented in the previous subsection. As noted earlier in the paper, although the delinquency thresholds may play a role in issuers' early buyout decisions, they do not preclude adverse selection.

Issuers must maintain delinquency rates on outstanding pools and loan packages below the threshold levels described in the GNMA servicing guide. The delinquency rate thresholds differ based on the size of the issuers' loan portfolio. Issuers with more than 1,000 active loans (hereafter large issuers) have a lower delinquency threshold than issuers with 1,000 or fewer active loans (hereafter small issuers) in their GNMA portfolio. Figure 3 plots the fraction of loans that are 2 months delinquent, 3 or more months delinquent, or in a forbearance program over time by issuer size. Figure 3 shows small issuers (Panel A) had higher delinquency rates than large issuers (Panel B).

GNMA evaluates delinquency rates using three delinquency ratios: DLQ2+, DLQ3+, and DQP. GNMA calculates the DLQ2+ (DLQ3+) delinquency ratio as the number of loans that are either in the foreclosure process or are two (three) months or more delinquent divided by the total number of loans in the issuer's portfolio. The DQP ratio is calculated as the accumulated amount of delinquent principal and interest payments divided by the total monthly fixed principal and interest payments due to the issuer. Our analysis focuses on the DLQ2+ and DLQ3+ ratios because we do not have a precise measure of the accumulated amount of outstanding delinquent principal and interest payments owed to each issuer.

Panel A of Table 6 summarizes the acceptable delinquency rates detailed in Chapter 18 of the GNMA servicing guide. We examine the effect of the delinquency thresholds on early buyout activity by grouping issuers based on their size and the level of their DLQ3+ ratio over time. For example, GNMA requires small issuers to maintain a DLQ3+ ratio below 9% and large issuers to maintain a DLQ3+ ratio below 5% to avoid penalties and maintain good standing. Using the DLQ3+ cutoffs in Panel B of Table 6, we further identify issuers as either having a low DLQ3+ ratio, high DLQ3+ ratio, or being above the threshold specified by GNMA. We calculate and assign the issuers' DLQ3+ ratio and grouping each month.

Table 7 tabulates several key measures of issuer performance over time using data from the month of June each year. Panel A displays the key measures for small issuers and Panel B displays the key measures for large issuers. The first row of Table 7 shows the number of small and large issuers was relatively stable over time. Rows 2 to 4 provide insight into the number of issuers in each of the DLQ3+ groupings listed in Panel B of Table 6. Rows 3 and 4 show the number of issuers at risk of exceeding (row 3) or currently exceeding (row 4) GNMA's DLQ3+ ratio thresholds was relatively low. However, there was a noticeable uptick towards the end of the study period.

The bottom half of Table 7 tracks delinquency rates at the loan-level. Row 5 tracks the total number of loans (in thousands) over time. By definition, the small issuers in Panel A had fewer loans. In 2014, small issuers averaged approximately 272 active loans versus 54,696 active loans for large issuers.[19] Row 6 tracks the percent of active loans that are two or more months delinquent and row 7 tracks the percent of active loans that are three or more months delinquent. The percent of loans that are exactly two months delinquent can be inferred by taking the difference between rows 6 and 7. Finally, row 8 tracks the percent of loans in forbearance. The forbearance data is only available from May 2020 onward, so row 8 equals zero up until 2020. Loans in forbearance are not considered delinquent in the loan-level or issuer delinquency ratio calculations.

We examine the impact of the delinquency thresholds on issuers' early buyout activity by modifying Equation 1 to include the delinquency threshold variables. Table 8 displays select coefficient estimates using a 3-month post-delinquency window. Tables C3 and C4 in the internet appendix provide the full set of coefficient estimates using a 3-month and

[19] We calculate the average number of active loans by dividing the number of loans in row 5 by the number of issuers in row 1. For example, we calculate 272 active loans in 2014 for small issuers by dividing 31,000 loans by 114 issuers.

12-month post-delinquency window, respectively. Column 1 of Table 8 displays a baseline interest rate spread coefficient estimate similar to column 4 of Table 5, which uses the same pre-2020 loan subsample.

Columns 2 to 7 of Table 8 introduce several different versions of the delinquency thresholds as additional controls. The delinquency threshold controls in Column 2 identify GNMA issuers that are currently above or approaching GNMA's DLQ3+ threshold. The inclusion of the controls has little impact on the interest rate spread coefficient estimate, thereby suggesting the delinquency thresholds do not drive GNMA issuers' early buyout decisions. That said, the inclusion of the current month indicator variables introduces endogeneity and reverse causality concerns.

We address these concerns using two distinct approaches. First, we lag the indicator variables. Column 3 includes the delinquency threshold indicator variables lagged one month. Column 4 includes a count of the indicator variables lagged three months prior to delinquency. The Above DLQ3+ and High DLQ3+ variables in column 4 range from 0 to 3, where Above DLQ3+ = 3 and High DLQ3+ = 0 when a GNMA issuer exceeds their delinquency threshold in the three months leading up to the loan's delinquency. The inclusion of the lagged variables has little impact on the interest rate spread coefficient estimates. Moreover, the coefficient estimates for the DLQ3+ threshold indicator variables are negative indicating issuers with higher levels of delinquency in their loan portfolio are less likely to buy out loans. This likely occurs because issuers with high levels of delinquency have to advance principal and interest payments on delinquent loans, thereby depleting their balance sheet liquidity (i.e., depository funds) and limiting their ability to perform early buyouts.

Second, we create a continuous DLQ3+ buffer variable that measures how close the issuer is to their delinquency threshold over time. We scale the DLQ3+ buffer variable to the size of the issuer by subtracting each issuers' DLQ3+ ratio from its delinquency threshold on a monthly basis. A high (low) DLQ3+ buffer indicates low (high) levels of delinquency in the issuer's loan portfolio. Column 5 of Table 8 includes the DLQ3+ buffer variable for the current month, column 6 includes the DLQ3+ buffer variable lagged one month, and column 7 includes an average of the DLQ3+ buffer variable lagged over three months. The inclusion of the DLQ3+ buffer variables has no impact on the interest rate spread coefficient estimates. Moreover, the coefficient estimates on the DLQ3+ buffer variables indicate that an decrease in buffer size (i.e., reduced levels of delinquency) increases the probability of an early buyout. Once again, the results indicate interest rate spreads, not delinquency thresholds, are the primary determinant of GNMA early buyout activity, thereby confirming our finding of adverse selection.[20]

3.3 Traditional vs. Shadow Banks

Table 9 extends the analysis in the preceding subsection by comparing delinquency (DLQ3+) and early buyout rates by issuer size and issuer type, focusing on the difference between traditional banks and shadow banks. The results in Table 9 indicate traditional banks have significantly lower average monthly delinquency rates relative to shadow banks. However, traditional banks buy out delinquent loans at a much higher average rate than shadow banks. This finding provides additional evidence that the delinquency thresholds explored in Section 3.2 are not the primary driver of early buyout activity. Table 9 also highlights the role of issuer size. Larger traditional banks, who presumably have more financial resources at their disposal, buy out delinquent loans at a higher average rate than shadow banks - regardless of their size - and smaller traditional banks.

Figure 4 plots the fraction of loans that are 2 months delinquent, 3 or more months delinquent, or in a forbearance program over time by issuer type. Figure 4 shows traditional banks (Panel A) have lower delinquency rates than shadow banks (Panel B) and state financing authorities (Panel C). Figure 4 also indicates traditional banks are the only issuer type whose DLQ2 rate is almost always greater than their DLQ3+ rate. Traditional banks' higher DLQ2 rate can be attributed to the fact that they are more likely to buy out loans that are three or more months delinquent. Figure 4 also highlights the large drop in the fraction of loans in forbearance for traditional banks relative to shadow banks and state financing authorities.

The large decline in the fraction of loans in forbearance in Panel A of Figure 4 was driven

[20]In unreported results, we also interact the delinquency threshold and buffer variables with the size of the issuer. The inclusion of the interaction variables has no effect on the interest rate spread coefficient estimates.

by early buyout activity. Table 10 tabulates the removal reason, if any, by issuer type for every loan in forbearance in the GNMA loan-level data. Loans that were not removed are classified as still in forbearance (removal reason = 9). Table 10 highlights several key stylized facts. Shadow banks had almost two times as many loans in forbearance than traditional banks. However, shadow banks bought out less than 13% of their loans in forbearance. In contrast, traditional banks bought out over 83% of their loans in forbearance. Thus, despite having half as many loans in forbearance, traditional banks bought out over three times as many loans as shadow banks. In response to the rapid increase in early buyout activity, GNMA imposed a temporary restriction on the re-securitization of early buyout loans to disincentivize forbearance-driven adverse selection.

Next, we investigate loan performance in GNMA MBS pools by issuer type. We begin by providing complementary default and prepayment analysis à la Buchak et al. (2018) *and* then advance the literature by examining early buyout activity. Following Buchak et al. (2018), we examine default (i.e., delinquency) and prepayment of new loans within two years of origination.[21] To allow for the two year trailing window and avoid confounding issues associated with COVID-19, we restrict the default and prepayment analysis to loans originated between December 2013 and December 2017. We include controls for the mortgage interest rate and borrower and loan characteristics in the regressions. We compare mortgage performance within a state and calendar year, using additively separable state and year of origination fixed effects. The results are similar when multiplicatively separable fixed effects are included.

The results in column 1 of Table 11 indicate shadow bank loans in GNMA MBS pools are more likely to default than traditional bank loans. However, the magnitudes are small. Shadow bank borrowers default at rates about 0.3% higher than traditional bank borrowers. Moreover, we find non-fintech shadow bank borrowers drive the effect (column 2 of Table 11). Our results closely align with Buchak et al. (2018), who find shadow bank borrowers default at a 0.02% higher rate and the effect is mostly driven by non-fintech shadow banks. We also find state financing authority (credit union) borrowers are more (less) likely to default than

[21] Buchak et al. (2018) define default as a mortgage that is at least 60 days delinquent within two years of origination. For consistency purposes, we define default as a mortgage that is at least three months delinquent within two years of origination.

traditional bank borrowers.

Similar to Buchak et al. (2018), we also find larger absolute differences in loan prepayment rates. However, the magnitude of the prepayment rates are considerably higher in our study. We find shadow bank borrowers prepay at rates about 6.2 - 6.9% higher than traditional bank borrowers. The base rate of prepayment within two years of origination is just under 19.5%, meaning shadow bank loans are between 32% and 35% more likely to be prepaid than comparable traditional bank loans. Relative to traditional banks, fintech loans exhibit an even larger probability of prepayment. The coefficient estimates in column 4 of Table 11 indicate fintech loans are 12.2% more likely to be prepaid. In contrast, credit union loans are 2.6% less likely to be prepaid. These results support Buchak et al. (2018) finding that shadow bank loans are riskier to investors ex-post from a prepayment perspective.

Columns 5-8 of Table 11 examine early buyout risk in GNMA MBS by issuer type. The results displayed in columns 5 to 8 reaffirm our earlier finding that issuers buy out loans with higher interest rate spreads. The results also highlight significant differences in early buyout activity across issuer types. The baseline estimates in columns 5 and 6 indicate shadow bank issuers buy out delinquent loans at a 50% lower rate than traditional banks. It is unclear why shadow bank issuers buy out delinquent loans at a significantly lower rate. On one hand, shadow bank issuers may not buy out delinquent loans because they are looking out for the best interests of MBS investors (or some other plausible reason such as reputational concerns). On the other hand, early buyouts are capital intensive and shadow banks may not have the balance sheet liquidity necessary to buy out as many loans as traditional banks.

We explore whether the effect is driven by financial constraints by interacting the issuer type and interest rate spread variables. We suspect that if shadow banks are financially constrained, they will be more selective in terms of the delinquent loans they buy out. The interaction variables (shadowXspread and fintechXspread) in columns 7 and 8 support our conjecture. We find shadow banks and fintech lenders are significantly less likely to buy out delinquent loans relative to traditional banks. However, when they buy out delinquent loans, shadow banks and fintech lenders buy out loans with significantly higher interest rate spreads.

The results in Table 11 indicate a portion of shadow banks' relatively higher prepayment risk is offset by their significantly lower early buyout risk. That said, early buyout risk is an additive form of prepayment risk. Although shadow banks' lower early buyout risk offsets a portion their *relative* prepayment risk, it increases their *absolute* prepayment risk. Similarly, traditional bank issuers' higher early buyout rates indicate traditional bank GNMA MBS loans carry a higher *relative* and *absolute* prepayment risk than previously documented. Taking the fairly high frequency of early buyouts (48.8% of delinquencies and 5.7% of all GNMA loans) together with the adverse selection we document, our findings highlight an economically significant form of prepayment risk unique to GNMA MBS investors.

3.4 Soft information

Issuers' ability to identify and buy out less risky loans is predicated on the assumption that the soft information they collect during the loan servicing process has explanatory power. Accordingly, we examine how much variation in the probability that an early buyout loan is re-securitized is explained by standard borrower and loan characteristics (i.e., hard information) relative to regressions that also include soft information. The baseline regression that includes only the hard information takes the following form:

$$Pr(RS_n = 1|EBO) = H_{nt}\alpha + S\delta_s + Y\Psi_t + \varepsilon \tag{2}$$

The dependent variable, RS_n, is an indicator variable for early buyout loan n that takes the value of 1 if the loan is cured and re-securitized into a new GNMA MBS pool, and 0 otherwise. Conditioning on an early buyout is natural because only early buyout loans can be re-securitized. H_{nt} includes both time-invariant and time-varying loan and borrower characteristics that represent the hard information in our regressions. We estimate the regressions using the subsample of 3,084 early buyout loans in Table 3. The R^2 from the regressions measures the object of interest: how much variation in the probability of re-securitization is explained by soft information relative to regressions that include only hard information?

Column 1 of Table 12 displays the R^2 for the baseline regression that includes only hard information. The hard information, which explains 6.8% of the variation in the probability of re-securitization, includes most of the same variables as the earlier GNMA loan-level regressions. One key difference is the private equity data includes the borrowers' current credit score at the time of delinquency, which we include in place of the borrowers' credit score at origination. Thus, our regressions examine whether the soft information collected during the servicing process provide explanatory power above and beyond the information captured in borrowers' current credit score.

Columns 2 to 4 in Table 12 incorporate the two pieces of soft information (borrower intent and reason for default) discussed in Section 2.3. The regression results displayed in Column 2 includes the delinquent borrowers' intent to keep their house, Column 3 includes the borrowers' reason for default, and Column 4 includes both pieces of soft information. The combined regression in Column 4 explains 11.4% of the variation in the probability of re-securitization. The 4.6 percentage point increase in explanatory power represents a 68% increase relative to the baseline estimation in Column 1 that only includes hard information.

Table C6 in the internet appendix reports the full set of coefficient estimates. A quick glance at the soft information variables indicates loans with borrowers' who are intent on keeping their house have a significantly higher probability of being re-securitized. In contrast, several of the reason for default variables indicate loans with borrowers who are ill, experiencing marital problems, or have excessive financial obligations have a significantly lower probability of being re-securitized.

Not all early buyout opportunities are equally attractive to GNMA issuers. When considering an early buyout, issuers need to determine whether a loan modification will be necessary to cure and re-securitize the loan. Loan modifications are a concern because they frequently affect the terms of the loan, which ultimately affects the profitability of the early buyout. Accordingly, we examine if the soft information provides insight into the probability that an early buyout loan is modified prior to being re-securitized.

Columns 5 and 6 of Table 12 examine the probability of re-securitization without a loan modification. The dependent variable in columns 5 and 6 equals 1 if the early buyout loan was re-securitized without a modification, and 0 otherwise. Column 5 includes only hard information and Column 6 includes both the hard and soft information. The inclusion of the soft information in column 6 increases the relative explanatory power of the model by

96% compared to the baseline estimation in Column 5 that only includes hard information.

Columns 7 and 8 examine the probability of re-securitization with a loan modification. The dependent variable in columns 7 and 8 equals 1 if the early buyout loan was modified prior to being re-securitized, and 0 otherwise. Column 7 includes only hard information and Column 8 includes both the hard and soft information. Once again, the inclusion of the soft information increases the relative explanatory power of the model by 79%. Moreover, the coefficient estimates for several of the reason for default variables reported in the internet appendix provide additional insight. The coefficient estimates indicate loans whose borrowers' have excessive financial obligations, are ill, have had their income curtailed, or are unemployed are more likely to require a loan modification in order to cure and re-securitize the loan. These results are straightforward and intuitive. Yet, the soft information used to produce the results is typically only available to the GNMA issuer servicing the loan. Thus, the results indicate GNMA issuers have a considerable informational advantage they can exploit to inform their early buyout decisions.

4 Conclusion

We investigate the determinants of GNMA issuers' early buyout decisions, focusing on the characteristics of the delinquent loans bought out of GNMA pools relative to those not bought out. We show issuers buy out less risky loans with higher interest rate spreads. In our preferred specifications, we find a one standard deviation increase in interest rate spread increases the probability of an early buyout by 9-11%. We also illustrate how issuers can exploit soft information collected during the loss mitigation process to inform their early buyout decisions. Our findings provide strong evidence of a "lemons" problem (Akerlof, 1970) in GNMA securitizations, whereby issuers buy out higher quality delinquent loans and pass over the lower quality "lemon" loans. The adverse selection we document represents a principal-agent problem between GNMA issuers (agent) and investors (principal). Issuers buy out delinquent loans that have a higher probability of reperforming and being re-securitized, thereby generating an economic gain at the expense of the investors they represent.

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Table 1: GNMA Loan-level Summary Statistics

	Panel A: Full		Panel B: Delinquent		Panel C: Non-EBO		Panel D: EBO	
	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
orig_year	2014.38	4.64	2013.83	4.12	2015.26	3.57	2012.39	4.12
opb (000s)	193.99	108.61	173.24	95.37	191.67	101.24	154.67	85.13
upb (000s)	-	-	162.27	93.25	182.65	99.50	141.74	81.50
credit_score	690.55	59.58	653.94	55.03	654.70	51.51	652.96	59.22
ltv_orig	84.35	29.61	95.06	6.95	95.11	6.99	95.00	6.92
ltv_dlq	-	-	78.05	15.12	80.72	13.66	75.36	16.02
interest_rate	4.19	0.95	4.44	0.86	4.28	0.75	4.60	0.93
rate_spread	-	-	2.68	1.12	2.65	1.12	2.72	1.11
upfront_mip	0.95	0.87	1.04	0.84	1.11	0.84	0.96	0.84
annual_mip	0.51	0.63	0.61	0.78	0.62	0.55	0.61	0.95
arm	0.02	-	0.01	-	0.01	-	0.01	-
issue_type_x	0.14	-	0.13	-	0.08	-	0.18	-
issue_type_c	0.13	-	0.13	-	0.15	-	0.11	-
issue_type_m	0.73	-	0.74	-	0.77	-	0.70	-
fha	0.64	-	0.79	-	0.77	-	0.82	-
va	0.29	-	0.13	-	0.16	-	0.10	-
rd	0.07	-	0.08	-	0.07	-	0.08	-
pih	0.00	-	0.00	-	0.00	-	0.00	-
purchase	0.57	-	0.61	-	0.66	-	0.55	-
refinance	0.32	-	0.19	-	0.22	-	0.17	-
mod_hamp	0.02	-	0.10	-	0.06	-	0.13	-
non_hamp	0.06	-	0.09	-	0.05	-	0.12	-
purpose_na	0.02	-	0.02	-	0.01	-	0.03	-
term15	0.04	-	0.01	-	0.01	-	0.01	-
term20	0.01	-	0.00	-	0.00	-	0.00	-
term25	0.01	-	0.01	-	0.01	-	0.01	-
term30	0.95	-	0.98	-	0.98	-	0.98	-
first_time	0.37	-	0.43	-	0.49	-	0.38	-
multi_borrow	0.38	-	0.29	-	0.30	-	0.28	-
multi_units	0.02	-	0.02	-	0.02	-	0.02	-
ot_broker	0.08	-	0.08	-	0.12	-	0.03	-
ot_correspond	0.28	-	0.28	-	0.32	-	0.24	-
ot_retail	0.34	-	0.35	-	0.38	-	0.33	-
ot_unknown	0.31	-	0.29	-	0.18	-	0.40	-
prev_dlq_history	-	-	0.47	-	0.45	-	0.49	-
forbearance	-	-	0.30	-	0.41	-	0.19	-
Observations	23,805,281		2,703,106		1,356,705		1,346,401	

Note: Table 1 reports the summary statistics for the key variables in our analysis. Panel A displays summary statistics for the full GNMA loan-level sample. Panel B displays summary statistics for a subsample of delinquent loans. We consider a loan delinquent when the borrower missed three consecutive monthly payments. Panel C displays summary statistics for a subsample of loans that were not bought out by the issuer within three months of becoming delinquent. Panel D displays summary statistics for a subsample of loans that were bought out by the issuer within three months of becoming delinquent. A detailed description of each variable is provided in the appendix.

Table 2: GNMA Removal Reasons

	Panel A: 3-month Window		Panel B: 12-month Window	
	Frequency	Fraction	Frequency	Fraction
1: Mortgagor Payoff	83,097	3.07%	113,557	4.20%
2: Early Buyout	1,346,401	49.81%	1,463,559	54.14%
3: FC with Claim Payment	1,567	0.06%	22,183	0.82%
4: Loss Mitigation	67,710	2.50%	183,629	6.79%
5: Substitution	288	0.01%	371	0.01%
6: Other	745	0.03%	1,099	0.04%
7: Reperforming	100,148	3.70%	185,746	6.87%
8: Delinquent	1,103,150	40.81%	732,962	27.12%
Total	2,703,106		2,703,106	

Note: Table 2 reports the "removal reason" provided in the GNMA loan-level data for each delinquent loan. Panel A reports the frequency and fraction of loan outcomes using a 3-month window. Panel B reports the frequency and fraction of loan outcomes using a 12-month window. If a "removal reason" is not reported and the loan remains securitized, we identify whether the loan has self-cured and is reperforming (reason = 7) or remains delinquent (reason = 8) during the specified post-delinquency time frame.

Table 3: Servicer Loan-level Summary Statistics

	Panel A: All Loans		Panel B: Not Re-securitized		Panel C: No Modification		Panel D: Modification	
	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
remain_term	286.66	53.53	283.69	53.61	288.68	54.50	295.58	49.48
opb (000s)	128.53	74.83	129.39	78.09	116.86	62.41	153.05	80.77
upb (000s)	112.11	76.45	113.35	80.38	97.94	62.60	140.94	79.82
curr_credit_score	559.45	65.68	562.50	68.45	564.18	65.00	533.62	45.19
ltv_orig	95.32	8.75	95.73	8.67	94.81	8.72	94.68	9.09
ltv_dlq	58.81	24.50	58.06	25.63	55.00	21.91	71.64	20.70
interest_rate	4.39	0.88	4.34	0.87	4.46	0.91	4.48	0.85
rate_spread	1.74	0.92	1.71	0.93	1.76	0.92	1.85	0.87
Loan Status								
act_bk	0.04	-	0.08	-	0.00	-	0.00	-
act_cur	0.22	-	0.38	-	0.00	-	0.00	-
act_dlq	0.09	-	0.15	-	0.00	-	0.00	-
liq_pif	0.05	-	0.09	-	0.00	-	0.00	-
liq_rp	0.30	-	0.00	-	1.00	-	0.00	-
liq_rpm	0.12	-	0.00	-	0.00	-	1.00	-
liq_ss_reo	0.17	-	0.29	-	0.00	-	0.00	-
Borrower Intent								
intent_keep	0.93	-	0.89	-	0.98	-	0.98	-
intent_liq	0.06	-	0.09	-	0.01	-	0.02	-
Reason for Default								
rfd_bk	0.04	-	0.04	-	0.05	-	0.00	-
rfd_casualty	0.01	-	0.01	-	0.00	-	0.01	-
rfd_death	0.01	-	0.01	-	0.00	-	0.01	-
rfd_excess	0.19	-	0.20	-	0.18	-	0.20	-
rfd_family	0.02	-	0.02	-	0.02	-	0.03	-
rfd_illness	0.03	-	0.03	-	0.02	-	0.04	-
rfd_income	0.29	-	0.28	-	0.21	-	0.53	-
rfd_marital	0.02	-	0.03	-	0.02	-	0.02	-
rfd_emergency	0.02	-	0.03	-	0.00	-	0.00	-
rfd_not_dlq	0.13	-	0.12	-	0.22	-	0.00	-
rfd_own_xfer	0.04	-	0.05	-	0.06	-	0.01	-
rfd_pmt_adj	0.01	-	0.01	-	0.02	-	0.00	-
rfd_pmt_disp	0.02	-	0.02	-	0.02	-	0.01	-
rfd_property	0.01	-	0.01	-	0.00	-	0.00	-
rfd_servicing	0.08	-	0.07	-	0.10	-	0.06	-
rfd_unable_sell	0.01	-	0.01	-	0.00	-	0.00	-
rfd_unemployment	0.03	-	0.03	-	0.02	-	0.08	-
rfd_other	0.05	-	0.05	-	0.07	-	0.00	-
Observations	3,084		1,775		929		380	

Note: Table 3 reports the summary statistics for select hard and soft information variables for a subsample of early buyout loans. Panel A displays summary statistics for the full loan-level sample. Panel B displays summary statistics for the subsample of loans that were not re-securitized. Panel C displays summary statistics for the subsample of loans that were re-securitized into a new GNMA pool without a modification. Panel D displays summary statistics for the subsample of loans that were re-securitized into a new GNMA pool with a modification. The appendix provides a detailed description of each variable.

Table 4: Servicing Log Sequence Example

Sample Log 1			
Loan ID	Date	Time	Type
123456789	09/30/2016	3:03:19 PM	Servicer Note
Loan information package received. [Buyer and loan information redacted]			
Sample Log 2			
Loan ID	Date	Time	Type
123456789	10/03/2016	6:23:42 PM	Inbound
HUD Loss Mitigation Options Offered. Borrower Intent - Keep Property rfd006 - Curtailment of Income - [Property Information Redacted] ib warm trnsf from [servicer name redacted], spoke with [servicer name redacted], borrower states they want to keep property, offered mod, adv of docs needed, updated email info. living in the property, working 2 part time job, in process of getting a better full time paying job adv to send docs asap.			
Sample Log 3			
Loan ID	Date	Time	Type
123456789	11/02/2016	10:11:15 AM	Inbound
(mailfrom:[emailredacted]@gmail.com) Sent: Tuesday, November 01, 2016 4:39 (mailto: [servicer name redacted]) Subject: Re: [Loan info redacted] Hi [servicer name redacted], I apologize for not getting back to you previously. I will fax over my request for modification papers in the morning. If there is any information I'm missing please let me know and I'll get it to you right away. Thank you again for your help.			
Sample Log 4			
Loan ID	Date	Time	Type
123456789	11/08/2016	4:07:21 PM	Servicer Note
Rcvd incomplete mod pkg; still need:. Proof of income; one mon of pay stubs. Signed/dated or e-filed fed tax returns.			

Note: Table 4 displays a partial servicing log sequence in which all loan, location, and personally identifiable information has been redacted. We indicate where the information has been [redacted] in each log. There are a total of 107 unique call log entries for this loan ranging from September 30, 2016 to February 15, 2017. This example displays four entries for informational purposes.

Table 5: Early Buyout Probability Given Delinquency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rate_spread	0.054***	0.066***	0.065***	0.089***	0.097***	0.093***	0.025***	0.033***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
ltv_dlq	−0.0004***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	0.0004***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
arm	−0.162***	−0.156***	−0.158***	−0.190***	−0.187***	−0.179***		
	(0.009)	(0.009)	(0.009)	(0.011)	(0.012)	(0.012)		
prev_dlq	−0.018***	−0.015***	−0.016***	−0.019***	−0.020***	−0.020***	−0.012***	−0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
ot_broker	−0.027***	−0.024***	−0.024***	−0.036***	−0.035***	−0.035***	−0.003**	−0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
ot_correspond	−0.006***	−0.012***	−0.010***	−0.015***	−0.016***	−0.016***	−0.006***	−0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ot_unknown	−0.006***	−0.018***	−0.016***	−0.014***	−0.018***	−0.021***	0.015	−0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.011)	(0.018)
Observations	2,703,106	2,157,478	2,157,478	1,315,894	1,149,170	1,149,170	1,467,983	709,573
Adjusted R^2	0.581	0.574	0.574	0.541	0.534	0.535	0.744	0.677
Fixed Effects	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	IxPxM	IxPxM
Sample	Full	Full	Full	Pre2020	15thru19	15thru19	Full	15thru19

*p<0.1; **p<0.05; ***p<0.01

Note: Table 5 displays select coefficient estimates from a series of regressions examining the primary determinants of GNMA Issuers' early buyout activity. The dependent variable, EBO, equals 1 if the delinquent loan was bought out by its issuer within 3 months of its first instance of delinquency, and 0 otherwise. Every column includes a full set of borrower and loan characteristics in the regressions as controls. One of the control variables, *credit_score*, is not included in columns 1 and 2. The sample size decreases in columns 2 and 3 when loans that are missing *credit_score* information are dropped. The *credit_score* variable is included in the regression in columns 3 to 8. Column 4 includes loans whose first instance of delinquency occurred before 2020. Columns 5, 6 and 8 further reduce the sample size to include loans whose first instance of delinquency occurred between January 2015 and December 2019. Columns 1 to 6 include additively separable issuer, state, and delinquent year fixed effects. Column 6 differs from column 5 only in that it includes the origination rate spread variable as a robustness check. Columns 7 and 8 include multiplicatively separable issuer, pool, and delinquent month-by-year fixed effects. The internet appendix provides coefficient estimates for the full set of borrower and loan characteristics included in the regressions.

Table 6: GNMA Delinquency Thresholds

	Issuer Size	
	Large	Small
Panel A: GNMA Thresholds		
DLQ3+ Ratio	5.0%	9.0%
DLQ2+ Ratio	7.5%	10.0%
DQP Ratio	60.0%	90.0%
Panel B: DLQ3+ Groupings		
Low DLQ3+	$\leq$ 2.5%	$\leq$ 4.5%
High DLQ3+	$\leq$ 5.0%	$\leq$ 9.0%
Above DLQ3+	$>$ 5.0%	$>$ 9.0%

Note: Panel A of Table 6 displays the three delinquency threshold measures employed by GNMA. The thresholds vary by issuer size. Following the guidelines described in the GNMA servicing guide, we label an issuer as "large" if they have more than 1,000 active portfolio loans. We label an issuer as "small" if they have 1,000 or less active portfolio loans. Panel B splits issuers into three separate groups based on their DLQ3+ ratio and portfolio size.

Table 7: GNMA Delinquency Rates

	Panel A: Small Issuers							Panel B: Large Issuers						
	2014	2015	2016	2017	2018	2019	2020	2014	2015	2016	2017	2018	2019	2020
Number of Issuers	114	120	117	122	123	124	109	168	183	192	201	193	188	203
Issuers Low DLQ3+	105	108	112	115	116	107	96	123	138	143	144	121	113	129
Issuers High DLQ3+	7	9	5	4	7	14	8	36	40	44	51	63	65	57
Issuers Above DLQ3+	2	3	0	3	0	3	5	9	5	5	6	9	10	17
Number of Loans (000s)	31	28	34	38	43	36	40	9,189	9,600	10,116	10,628	10,998	11,352	11,242
Percent Loans DLQ2+	1.80	2.34	2.24	2.44	2.86	3.48	2.63	2.34	2.18	2.04	2.24	2.49	2.59	2.26
Percent Loans DLQ3+	0.94	1.45	1.33	1.48	1.88	2.20	1.99	1.20	1.13	1.06	1.14	1.41	1.42	1.74
Percent Loans Forbearance	0.00	0.00	0.00	0.00	0.00	0.00	5.50	0.00	0.00	0.00	0.00	0.00	0.00	8.42

Note: Table 7 displays summary statistics for delinquency rates at both the issuer and loan level. Panel A provides an annual snapshot of delinquency rates for small issuers with 1,000 or fewer active portfolio loans. Panel B provides an annual snapshot of delinquency rates for large issuers with more than 1,000 active portfolio loans. The annual snapshots are tabulated using data from June each year.

Table 8: Early Buyout Probability With Threshold Controls

	Baseline	Indicator			DLQ3+ Buffer		
		Current	Lag1	Lag3	Current	Lag1	Lag3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
rate_spread	0.089***	0.089***	0.090***	0.090***	0.089***	0.089***	0.089***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Above DLQ3+		−0.106***	−0.083***	−0.024***			
		(0.008)	(0.007)	(0.002)			
High DLQ3+		−0.022*	−0.003	0.001			
		(0.012)	(0.004)	(0.002)			
DLQ3+ Buffer					5.243***	4.250***	3.455***
					(0.341)	(0.292)	(0.285)
Observations	1,315,894	1,315,894	1,287,051	1,287,051	1,287,051	1,287,051	1,287,051
Adjusted R^2	0.541	0.542	0.543	0.543	0.545	0.544	0.544
Fixed Effects	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y
Sample	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020

*p<0.1; **p<0.05; ***p<0.01

Note: Table 8 reports select coefficient estimates using a 3-month post-delinquency window. The dependent variable, EBO, equals 1 if the delinquent loan was bought out by its issuer within the specified post-delinquency time window, and 0 otherwise. Every column includes a full set of borrower and loan characteristics as well as additively separable delinquent year, issuer, and state fixed effects. Columns 1 displays baseline estimates prior to including the delinquency threshold controls. Column 2 includes indicator variables identifying issuers that are approaching or are above GNMA's delinquency thresholds in the current month. Column 3 includes similar indicator variables that are lagged one month. Column 4 includes the count of the indicator variables lagged over the previous three months. Columns 5 to 7 include a continuous delinquency threshold buffer variable that measures how close the issuer is to their delinquency threshold (threshold minus DLQ3+ ratio). A negative DLQ3+ buffer indicates the issuer is above the delinquency threshold. Column 5 includes the current month DLQ3+ buffer, column 6 includes the DLQ3+ buffer lagged one month, and column 7 includes an average of the DLQ3+ buffer lagged over the previous three months. The internet appendix provides coefficient estimates for the full set of borrower and loan characteristics included in the regressions.

Table 9: Delinquency and Early Buyout Ratios by Issuer Type

Panel A: DLQ3+ Ratio					
		Traditional	Shadow	Diff.	t-stat
Large Issuer	mean	1.575	2.503	**-0.928**	-31.318
	std dev	1.375	1.565		
	obs	3,683	6,722		
Small Issuer	mean	1.352	2.077	**-0.724**	-7.664
	std dev	3.531	4.803		
	obs	2,507	5,833		
Diff.		**0.222**	**0.426**		
t-stat		3.004	6.482		
Panel B: Early Buyout Ratio					
		Traditional	Shadow	Diff.	t-stat
Large Issuer	mean	14.910	1.807	**13.103**	15.713
	std dev	50.087	7.062		
	obs	3,647	6,697		
Small Issuer	mean	6.094	1.655	**4.439**	8.471
	std dev	19.612	10.753		
	obs	1,575	3,807		
Diff.		**8.816**	0.152		
t-stat		9.132	0.784		

Note: Table 9 compares the DLQ3+ (Panel A) and early buyout (Panel B) ratios by issuer size (large vs. small) and issuer type (traditional vs. shadow). Each observation in Panel A captures the percent of loans that are delinquent by issuer on a monthly basis. Each observation in Panel B captures the percent of delinquent loans that are bought out early by issuer on a monthly basis.

Table 10: Forbearance Removal Reasons

	Panel A: Shadow Bank		Panel B: State Authority		Panel C: Traditional Bank		Panel D: Full Sample	
	Frequency	Fraction	Frequency	Fraction	Frequency	Fraction	Frequency	Fraction
1: Mortgagor Payoff	24,679	4.76%	561	3.57%	2,660	0.99%	27,900	3.48%
2: Early Buyout	66,774	12.88%	100	0.64%	224,663	83.62%	291,537	36.31%
3: FC with Claim Payment	11	0.00%	0	0.00%	0	0.00%	11	0.00%
4: Loss Mitigation	26,086	5.03%	109	0.69%	3,232	1.20%	29,427	3.67%
5: Substitution	0	0.00%	0	0.00%	0	0.00%	0	0.00%
6: Other	79	0.02%	3	0.02%	9	0.00%	91	0.01%
9: Forbearance	400,862	77.31%	14,933	95.08%	38,109	14.18%	453,904	56.54%
Total	518,491		15,706		268,673		802,870	

Note: Table 10 tracks the "removal reason", if any, provided in the GNMA loan-level data for each loan placed in forbearance in 2020. If a "removal reason" is not reported, we classify the loan as remaining in forbearance (reason = 9). Panel A reports the frequency and fraction of removal reasons for shadow bank loans. Panel B reports the frequency and fraction of removal reasons for state financing authority loans. Panel C reports the frequency and fraction of removal reasons for traditional banks loans. Panel D reports the frequency and fraction of removal reasons for all loans placed in forbearance in 2020.

Table 11: Default, Prepayment, and Early Buyout by Issuer Type

	Default		Prepayment		Early Buyout			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
shadow	0.003***	0.003***	0.069***	0.062***	−0.504***	−0.500***	−0.746***	−0.748***
	(0.001)	(0.0005)	(0.003)	(0.002)	(0.008)	(0.008)	(0.010)	(0.010)
state_fin	0.008**	0.008**	0.002	−0.002	−0.678***	−0.677***	−0.637***	−0.636***
	(0.003)	(0.003)	(0.010)	(0.010)	(0.026)	(0.026)	(0.043)	(0.044)
fintech		0.002		0.122***		−0.613***		−0.695***
		(0.003)		(0.006)		(0.012)		(0.014)
credit_union		−0.008*		−0.026**		−0.549***		−0.521***
		(0.004)		(0.010)		(0.109)		(0.141)
rate_spread					0.086***	0.086***	0.026***	0.026***
					(0.003)	(0.003)	(0.003)	(0.003)
shadowXspread							0.121***	0.123***
							(0.003)	(0.002)
state_finXspread							−0.020	−0.020
							(0.015)	(0.015)
fintechXspread								0.039***
								(0.008)
cuXspread								−0.036
								(0.023)
Observations	6,788,890	6,788,890	6,788,890	6,788,890	1,315,894	1,315,894	1,315,894	1,315,894
Adjusted R^2	0.073	0.073	0.100	0.101	0.370	0.373	0.380	0.384
Fixed Effects	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y
Sample	14thru17	14thru17	14thru17	14thru17	Pre2020	Pre2020	Pre2020	Pre2020

*p<0.1; **p<0.05; ***p<0.01

Note: Table 11 displays loan performance and early buyouts by issuer type relative to traditional banks. The issuer types include shadow banks (*shadow*), state financing authorities (*state_fin*), fintech lenders (*fintech*), and credit unions (*credit_union*). Odd numbered columns include the high-level issuer type classifications where traditional banks are grouped together with credit unions and shadow banks are grouped together with fintech lenders. Even numbered columns group the aforementioned issuer types separately. Columns 1 to 4 use a subset of loans that were originated between December 2013 and December 2017. Similar to Table 8, columns 5 to 8 examine early buyouts using a subset of loans that were delinquent before 2020 regardless of when they were originated. Columns 1 and 2 display the results for default within two years of origination where default equals three missed monthly mortgage payments. Columns 3 and 4 display the results for prepayment within two years of origination. Columns 5 to 8 display results for early buyouts conditional on delinquency.

Table 12: Probability of Re-securitization

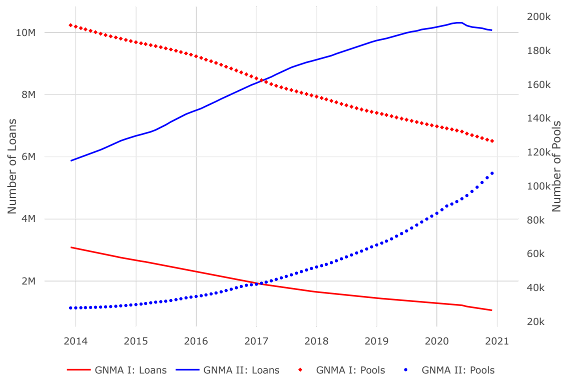
	Re-securitized				No Modification		Modification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hard Information	Y	Y	Y	Y	Y	Y	Y	Y
Borrower Intent	N	Y	N	Y	N	Y	N	Y
Reason for Default	N	N	Y	Y	N	Y	N	Y
Observations	3,084	3,084	3,084	3,084	3,084	3,084	3,084	3,084
Adjusted R^2	0.068	0.102	0.086	0.114	0.053	0.104	0.075	0.134
Fixed Effects	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y

*p<0.1; **p<0.05; ***p<0.01

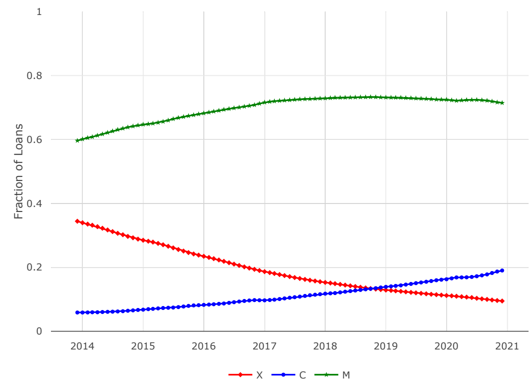
Note: Table 12 reports the Adjusted R^2 of observables for several regressions examining the probability that an early buyout loan is re-securitized. The dependent variable in columns 1 to 4 equals 1 if the early buyout loan was re-securitized, and 0 otherwise. The dependent variable in columns 5 and 6 equals 1 if the early buyout loan was re-securitized without a modification, and 0 otherwise. The dependent variable in columns 7 and 8 equals 1 if the early buyout loan was re-securitized with a modification, and 0 otherwise. Columns 1, 5, and 7 only include the hard information variables. Columns 2, 3, 4, 6, and 8 include both the hard and soft information variables. Column 2 includes soft information related to the borrowers' intent to keep the house. Column 3 includes soft information identifying the borrowers' reason for default. Columns 4, 6, and 8 include both the borrowers' intent to keep the house and reason for default. Every column includes additively separable state and year of delinquency fixed effects. The internet appendix provides coefficient estimates for the full set of borrower and loan characteristics included in the regressions.

Figure 1: GNMA Loan and Pool Characteristics

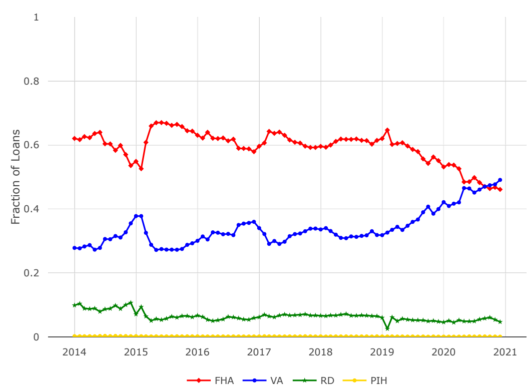
(a) Loan and Pool Counts by Program



(b) Share by Issue Type



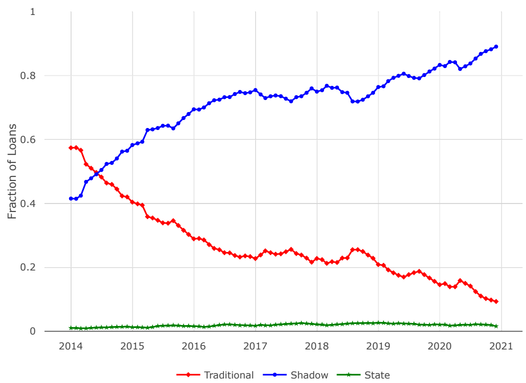
(c) New Loans by Agency



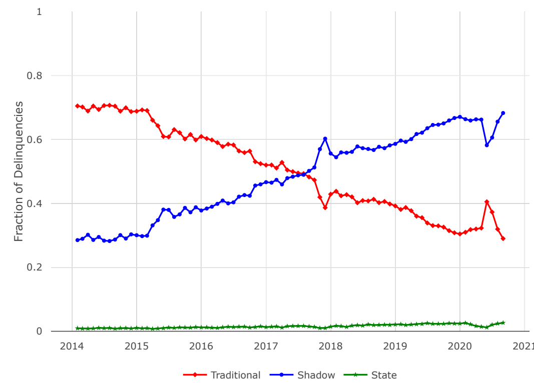
Note: Panel A of Figure 1 plots the number of GNMA MBS I and II pools and loans on a monthly basis. The number of loans (solid lines) are tied to the y-axis on the left and the number of pools (dashed lines) are tied to the y-axis on the right. Panel B plots the relative share of GNMA loans by issue type over time. Loans are classified as either single-issuer GNMA I MBS (issue type X), "custom" single-issuer GNMA II MBS (issue type C), or multi-issuer GNMA II MBS (issue type M). Panel C plots the relative share of *new* loans entering GNMA MBS pools by government agency over time. The agencies include the Federal Housing Administration (FHA), Department of Veterans Affairs (VA), Department of Agriculture's Rural Development (RD), and Public and Indian Housing (PIH).

Figure 2: GNMA Issuer Types

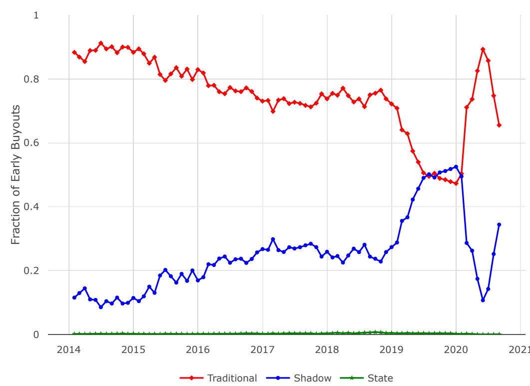
(a) New Loans by Issuer Type



(b) Delinquency by Issuer Type



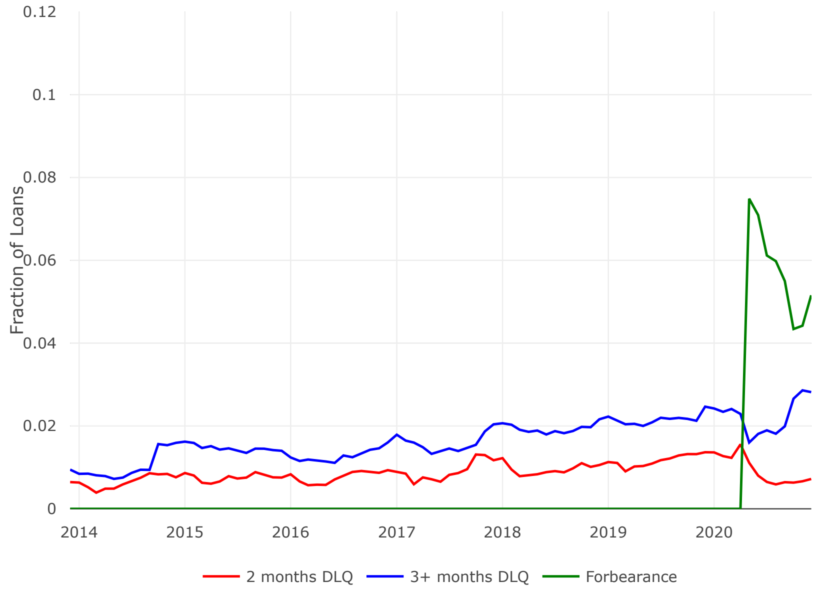
(c) Early Buyout by Issuer Type



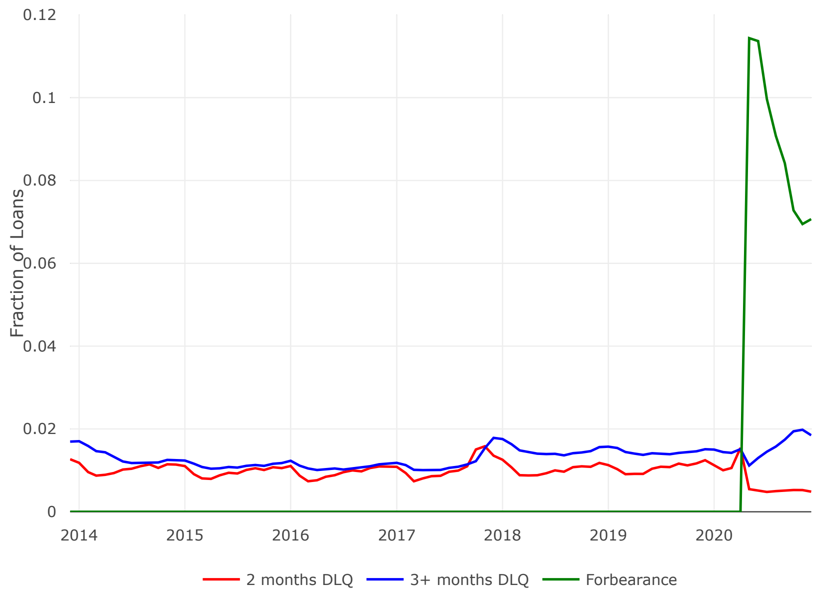
Note: Panel A of Figure 2 plots the relative share of *new* loans entering GNMA MBS pools by issuer type. Panel B plots the relative share of delinquent loans by issuer type. Panel C plots the relative share of early buyouts by issuer type. The issuer types in each panel include traditional banks, shadow banks, and state financing authorities.

Figure 3: Delinquency Rates Over Time by Issuer Size

(a) Small Issuers <= 1,000 Loans



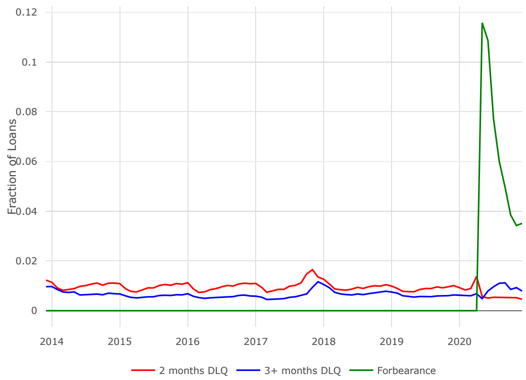
(b) Large Issuers > 1,000 Loans



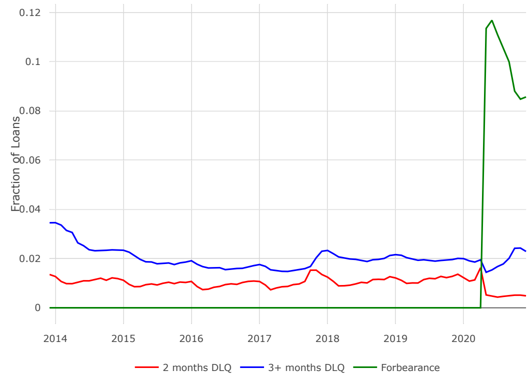
Note: Figure 3 plots the fraction of loans that are 2 months delinquent, 3 or more months delinquent, or in a forbearance program. Panel A plots the monthly delinquency rates for small issuers and Panel B plots the monthly delinquency rates for large issuers.

Figure 4: Delinquency Rates Over Time by Issuer Type

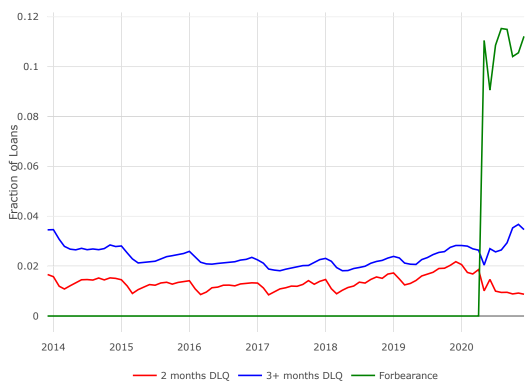
(a) Traditional Banks



(b) Shadow Banks



(c) State Financing Authorities



Note: Figure 4 plots the fraction of loans that are 2 months delinquent, 3 or more months delinquent, or in a forbearance program. Panel A plots the monthly delinquency rates for loans issued by traditional banks. Panel B plots the monthly delinquency rates for loans issued by shadow banks. Panel C plots the monthly delinquency rates for loans issued by state financing authorities.

Appendices

Contents

A Data Overview

A.1 Data preparation

The GNMA loan-level data is publicly available on www.ginniemae.gov. After downloading the raw data files, we apply several filters to remove non-standard mortgage pool types. The filters remove the following pool types:

Table A1: Non-standard Pool Types

Code	Pool Type	Description
BD	Buydown	Designation for a pool of single-family, level payment mortgages that contains one or more buydown mortgages.
GA	Graduated Payment	The designation for a pool of single-family mortgages on which the monthly payments increase at a rate of 4 percent annually over the life of each loan.
GD	Graduated Payment	The designation for a pool of single-family mortgages on which the monthly payments increase annually at a rate and for the number of years acceptable to FHA or VA.
GP	Graduated Payment	The designation for a pool of single-family mortgages on which monthly payments increase annually for the first five (5) years.
GT	Graduated Payment	The designation for a pool of single-family mortgages on which the monthly payments increase annually for the first ten (10) years.
JM	Jumbo	Economic Stimulus Act of 2008 fixed rate loans originated with a note date before October 1, 2008, pursuant to FHA Mortgagee Letter 2008-06 that exceed GNMA's loan balance limitations (see Chapter 33 of Ginnie Mae MBS Guide for more information).
MH	Manufactured Home	The designation for a pool type consisting of manufactured home (mobile home) loans.
SN	Serial Note	The designation for a pool of single-family, level payment mortgages that backs an issue of serial note securities, each unit of which is subject to sequential retirement by a single payment, subject to the amount of principal available each month for that purpose.

The focal point of the empirical analysis is the first instance of delinquency. We define delinquency as three consecutive missed monthly payments. There are 3,349,158 delinquent loans in the GNMA loan-level data during the study period. We clean the delinquent data by applying several filters. This section describes each individual filter. Table A2 reports the number of observations remaining after each filter is applied.

The first filter removes loans in Puerto Rico and the Virgin Islands. The next set of filters removes loans whose first delinquency occurs after September 2020 (2) and before February 2014 (3). We drop delinquent loans that have a high likelihood of misclassification by removing loans whose "number of months delinquent" field does not equal 1 and then 2 prior to its first instance of being 3 months delinquent. The fifth filter removes delinquent loans whose LTV or loan amount at origination are not available.

The sixth filter reports the number of delinquent loans remaining after merging the data with the monthly 10-year Treasury Constant Maturity Rate using both the month of origination and delinquency. The seventh filter mirrors the sixth except for it merges the monthly 2-year Treasury Constant Maturity Rate. The next set of filters reports the number of delinquent loans after merging the data with state-level quarterly FHFA house price indexes (HPIs) using both the quarter of origination (8) and delinquency (9). The HPIs are used to approximate the loans LTV at delinquency. The tenth filter removes delinquent loans whose LTV at delinquency is not available.

The next filter (11) reports the number of delinquent loans after merging the data with a cross reference file that indicates whether the loan is located in a judicial or non-judicial foreclosure state. The twelfth filter drops delinquent loans whose loan age is unavailable the month of, before, and after the loan is first delinquent. The thirteenth filter drops delinquent loans with an unpaid principal balance less than $10,000 or not available at the time of delinquency. Finally, the next set of filters drops delinquent loans whose LTV ratio was less than 50% (14) or greater than 120% (15) at the time of origination.

After applying the filters, 2,703,106 delinquent loans or 80.7% of the original delinquent subsample remains. Table A2 reports the number of loans that are dropped in the GNMA I, GNMA II, and combined sample for each filter. The inclusion of the filtered data, where possible, does not materially impact the results reported in this paper.

Table A2: Delinquent Loan Filters

	GNMA I	GNMA II	Total
0. Unfiltered delinquent loans	508,529	2,840,629	3,349,158
1. require state or DC	470,137	2,829,340	3,299,477
2. require three months lag	397,934	2,717,304	3,115,238
3. require three months lead	385,686	2,509,016	2,894,702
4. drop misclassifications	384,863	2,503,379	2,888,242
5. drop ltv_orig or opb is NA	362,196	2,357,511	2,719,707
6. merge with 10yr CMR	362,196	2,357,511	2,719,707
7. merge with 2yr CMR	362,196	2,357,511	2,719,707
8. merge with hpi - contract date	362,196	2,357,447	2,719,643
9. merge with hpi - dlq date	362,196	2,357,447	2,719,643
10. ltv_dlq is NA	362,196	2,357,440	2,719,636
11. merge with judicial state	362,196	2,357,440	2,719,636
12. drop loan-age is NA	361,550	2,355,332	2,716,882
13. drop upb $\leq$ 10K or NA	359,176	2,354,073	2,713,249
14. drop ltv_orig $<$ 50	357,857	2,346,508	2,704,365
15. drop ltv_orig $>$ 120	357,817	2,345,289	2,703,106

A.2 Variable descriptions: Main results

This section provides a detailed description of the key variables included in the regression analysis. All of the variables are provided in the GNMA loan-level data unless otherwise stated. We describe the variables in the order they appear in the summary statistics table.

- **orig_year**: the year in which the loan was originated.
- **opb**: an abbreviation for the original principal balance, which represents the loan amount at pool issuance.
- **upb**: an abbreviation for unpaid principal balance, which represents the remaining mortgage balance at the time of delinquency.
- **credit_score**: a numerical representation of the borrower's creditworthiness ranging from 300 (bad) to 850 (good).
- **ltv_orig**: the loan-to-value ratio at the time of origination. LTVs of less than 10% and LTVs greater than 125% are disclosed as blank in the GNMA file. These records are dropped.
- **ltv_dlq**: the loan-to-value ratio at the time of delinquency. We calculate this variable by estimating the value of the house at the time of delinquency using state-level FHFA house price indexes.
- **interest_rate**: the interest rate of the loan at the time of origination.
- **rate_spread**: we calculate this variable by taking the contract interest rate (interest_rate) minus the 10-year Treasury yield at the time of delinquency. This is the primary variable of interest throughout the study.
- **upfront_mip**: an abbreviation for the upfront mortgage insurance premium percentage rate charged by the lender to insure an FHA loan. Data collection began in September 2012. When unavailable we code the upfront_mip as 0.

- **annual_mip**: an abbreviation for the annual mortgage insurance premium percentage rate charged by the lender to insure an FHA loan. Data collection began in September 2012. When unavailable we code the annual_mip as 0.
- **arm**: an abbreviation for an adjustable rate mortgage which equals 1 if the loan is an arm, and 0 otherwise.
- **issue_type_x**: equals 1 if the loan is part of a single-issuer GNMA MBS I pool, and 0 otherwise.
- **issue_type_c**: equals 1 if the loan is part of a "custom" single-issuer GNMA MBS II pool, and 0 otherwise.
- **issue_type_m**: equals 1 if the loan is part of a multi-issuer GNMA MBS II pool, and 0 otherwise.
- **fha**: populated using the agency field in the loan-level data (agency=F). Equals 1 if the loan is insured by the Federal Housing Administration (FHA), and 0 otherwise.
- **va**: populated using the agency field in the loan-level data (agency=V). Equals 1 if the loan is guaranteed by the Department of Veterans Affairs (VA), and 0 otherwise.
- **rd**: populated using the agency field in the loan-level data (agency=R). Equals 1 if the loan is insured by the Department of Agriculture's Rural Development (RD), and 0 otherwise.
- **pih**: populated using the agency field in the loan-level data (agency=N). Equals 1 if the loan is insured by the Department of Public and Indian Housing (PIH), and 0 otherwise.
- **purchase**: populated using the loan purpose field in the loan-level data (purpose=1). Equals 1 if the loan purpose was to purchase a house, and 0 otherwise.

- **refinance**: populated using the loan purpose field in the loan-level data (purpose=2). Equals 1 if the loan purpose was to refinance an existing mortgage, and 0 otherwise.

- **mod_hamp**: populated using the loan purpose field in the loan-level data (purpose=3). Equals 1 if the loan purpose was a modification under the Home Affordable Modification Program (HAMP), and 0 otherwise.

- **non_hamp**: populated using the loan purpose field in the loan-level data (purpose=4). Equals 1 if the loan purpose was a modification outside of HAMP, and 0 otherwise.

- **purpose_na**: populated using the loan purpose field in the loan-level data (purpose=NA). Equals 1 if the loan purpose is unavailable because data collection began in February 2010, and 0 otherwise.

- **term15**: populated using the original loan term field in the loan-level data. Equals 1 if the the loan term is less than or equal to 180 months, and 0 otherwise.

- **term20**: populated using the original loan term field in the loan-level data. Equals 1 if the the loan term is greater than 180 months and less than or equal to 240 months, and 0 otherwise.

- **term25**: populated using the original loan term field in the loan-level data. Equals 1 if the the loan term is greater than 240 months and less than or equal to 300 months, and 0 otherwise.

- **term30**: populated using the original loan term field in the loan-level data. Equals 1 if the the loan term is greater than 300 months and less than or equal to 360 months, and 0 otherwise.

- **first_time**: an indicator for purchase loans that identifies whether the borrower qualifies as a first-time home buyer. Equals 1 if the field equals "Y", and 0 otherwise.

- **multi_borrow**: an indicator identifying if there are multiple borrowers associated with the loan. Equals 1 if the number of borrowers field is greater than 1, and 0 otherwise.
- **multi_unit**: populated using the number of living units field in the loan-level data. Equals 1 if the the number of units is greater than 1, and 0 otherwise.
- **ot_broker**: populated using the third-party origination type field in the loan-level data (ot=1). Equals 1 if the loan is originated by a broker, and 0 otherwise.
- **ot_correspond**: populated using the third-party origination type field in the loan-level data (ot=2). Equals 1 if the loan is originated by a correspondent lender, and 0 otherwise.
- **ot_retail**: populated using the third-party origination type field in the loan-level data (ot=3). Equals 1 if the loan is originated by a retail lender, and 0 otherwise.
- **ot_unknown**: populated using the third-party origination type field in the loan-level data (ot=NA). Equals 1 if the loan is originator is unknown, and 0 otherwise.
- **dlq_history**: we calculate the delinquency history field based on the twelve months preceeding the first instance of delinquency in the loan-level data. Equals 1 if the borrower missed at least one other payment in the 12 months leading up to the loan's delinquency, and 0 otherwise.
- **forbearance**: populated using the monthly loan-level forbearance files available from May 2020 onward. Equals 1 if the delinquent loan is included in the forbearance file, and 0 otherwise.

A.3 Variable descriptions: Soft information

This subsection provides a detailed description of the soft information variables included in the regression analysis. The *Loan Status* variables capture the loan outcome as of December

2020 as reported by the private equity firm that provided the data. We populate the *Borrower Intent* and *Reason for Default* variables using the structured and unstructured text in the loan servicing logs. We describe the variables in the order they appear in the summary statistics table.

Loan Status

- **act_bk**: equals 1 if the loan is active in the private equity firm's portfolio and the borrower is working through the bankruptcy process, and 0 otherwise.
- **act_cur**: equals 1 if the loan is active in the private equity firm's portfolio and the borrower has made payments to become current, and 0 otherwise.
- **act_dlq**: equals 1 if the loan is active in the private equity firm's portfolio and the loan is still delinquent, and 0 otherwise.
- **liq_pif**: equals 1 if the loan is no longer part of the private equity firm's portfolio because the borrower made a payment in full, and 0 otherwise.
- **liq_rp**: equals 1 if the loan is no longer part of the private equity firm's portfolio because it reperformed without modification and was re-securitized, and 0 otherwise.
- **liq_rpm**: equals 1 if the loan is no longer part of the private equity firm's portfolio because it reperformed with a modification and was re-securitized, and 0 otherwise.
- **liq_ss_reo**: equals 1 if the loan is no longer part of the private equity firm's portfolio because it was liquidated via a short sale or real estate owned (REO) transaction, and 0 otherwise.

Borrower Intent

- **intent_keep**: equals 1 if the borrower indicated they wanted to keep the house during a discussion with the loan servicer, and 0 otherwise.

- **intent_liq**: equals 1 if the borrower indicated they did not want to keep the house during a discussion with the loan servicer, and 0 otherwise.

- **intent_na**: equals 1 if the borrower's intent is unknown, and 0 otherwise.

Reason for Default

- **rfd_bk**: equals 1 if the borrower indicated bankruptcy was the reason for default, and 0 otherwise.

- **rfd_casualty**: equals 1 if the borrower indicated a casualty loss was the reason for default, and 0 otherwise.

- **rfd_death**: equals 1 if the borrower's death was the reason for default, and 0 otherwise.

- **rfd_excess**: equals 1 if the borrower indicated excess financial obligations or expenses were the reason for default, and 0 otherwise.

- **rfd_family**: equals 1 if the borrower indicated a death or illness in their family was the reason for default, and 0 otherwise.

- **rfd_illness**: equals 1 if the illness of the mortgagor or sickness of the principal borrower was the reason for default, and 0 otherwise.

- **rfd_income**: equals 1 if the borrower indicated curtailment of income was the reason for default, and 0 otherwise.

- **rfd_marital**: equals 1 if the borrower indicated marital difficulties or a divorce was the reason for default, and 0 otherwise.

- **rfd_emergency**: equals 1 if the borrower indicated a national emergency or natural disaster was the reason for default, and 0 otherwise.

- **rfd_not_dlq**: equals 1 if the borrower indicated they are no longer delinquent, and 0 otherwise.

- **rfd_own_xfer**: equals 1 if the borrower indicated ownership of the house had been transferred, and 0 otherwise.
- **rfd_pmt_adj**: equals 1 if the borrower indicated a change in payments was the reason for default, and 0 otherwise.
- **rfd_pmt_disp**: equals 1 if the borrower indicated a payment dispute was the reason for default, and 0 otherwise.
- **rfd_property**: equals 1 if the borrower indicated issues with the property itself were the reason for default, and 0 otherwise.
- **rfd_servicing**: equals 1 if the borrower indicated servicing issues were the reason for default, and 0 otherwise.
- **rfd_unable_sell**: equals 1 if the borrower indicated the reason for default was their inability to sell the house, and 0 otherwise.
- **rfd_unemployment**: equals 1 if the borrower indicated unemployment or lack of work was the reason for default, and 0 otherwise.
- **rfd_other**: equals 1 if the borrower indicated something other than the reasons above as the reason for default, and 0 otherwise.

B Data Overview (Internet Appendix)

B.1 Extended summary statistics

This section reports detailed summary statistics for the key variables in our analysis. Table B1 displays summary statistics for the full sample. Table B2 displays summary statistics for the delinquent loan subsample. Table B3 displays summary statistics for the subsample of loans that were *not* bought out by the issuer within three months of the loan becoming delinquent. Table B4 displays summary statistics for the subsample of loans that were bought out by the issuer within three months of the loan becoming delinquent. Table B5 displays summary statistics for the subsample of loans that were bought out by the issuer within twelve months of the loan becoming delinquent. A detailed description of each variable is provided in Sections A.2 and A.3 of the appendix.

Table B1: Full Sample Summary Statistics

	N	Mean	StDev	p25	p50	p75
orig_year	23,805,281	2,014.38	4.64	2,012	2,015	2,018
opb (000s)	23,805,281	193.99	108.61	118	170	245
upb (000s)	23,805,281	0.00	0.00	0	0	0
credit_score	19,561,871	690.55	59.58	650.00	685.00	732.00
ltv_orig	23,805,281	84.35	29.61	87.21	96.50	98.19
interest_rate	23,805,281	4.19	0.95	3.62	4.00	4.62
upfront_mip	23,805,281	0.95	0.87	0.00	1.50	1.75
annual_mip	23,805,281	0.51	0.63	0.00	0.55	0.85
arm	23,805,281	0.02	0.13	0	0	0
issue_type_x	23,805,281	0.14	0.35	0	0	0
issue_type_c	23,805,281	0.13	0.34	0	0	0
issue_type_m	23,805,281	0.73	0.45	0	1	1
fha	23,805,281	0.64	0.48	0	1	1
va	23,805,281	0.29	0.46	0	0	1
rd	23,805,281	0.07	0.25	0	0	0
pih	23,805,281	0.002	0.04	0	0	0
purchase	23,805,281	0.57	0.49	0	1	1
refinance	23,805,281	0.32	0.47	0	0	1
mod_hamp	23,805,281	0.02	0.16	0	0	0
non_hamp	23,805,281	0.06	0.23	0	0	0
purpose_na	23,805,281	0.02	0.16	0	0	0
term15	23,805,281	0.04	0.19	0	0	0
term20	23,805,281	0.01	0.09	0	0	0
term25	23,805,281	0.01	0.11	0	0	0
term30	23,805,281	0.95	0.23	1	1	1
first_time	23,805,281	0.37	0.48	0	0	1
multi_borrow	23,805,281	0.38	0.48	0	0	1
multi_units	23,805,281	0.02	0.12	0	0	0
ot_broker	23,805,281	0.08	0.27	0	0	0
ot_correspond	23,805,281	0.28	0.45	0	0	1
ot_retail	23,805,281	0.34	0.47	0	0	1
ot_unknown	23,805,281	0.31	0.46	0	0	1

Table B2: Delinquent Summary Statistics

	N	Mean	StDev	p25	p50	p75
orig_year	2,703,106	2,013.83	4.12	2,011	2,014	2,017
opb (000s)	2,703,106	173.24	95.37	107	152	218
upb (000s)	2,703,106	162.27	93.25	96.97	141.68	206.60
credit_score	2,157,478	653.94	55.03	629.00	653.00	683.00
ltv_orig	2,703,106	95.06	6.95	95.00	96.50	98.19
ltv_dlq	2,703,106	78.05	15.12	69.29	81.03	89.70
interest_rate	2,703,106	4.44	0.86	3.88	4.25	4.88
rate_spread	2,703,106	2.68	1.12	1.81	2.68	3.45
upfront_mip	2,703,106	1.04	0.84	0.00	1.50	1.75
annual_mip	2,703,106	0.61	0.78	0.35	0.55	0.85
arm	2,703,106	0.01	0.10	0	0	0
issue_type_x	2,703,106	0.13	0.34	0	0	0
issue_type_c	2,703,106	0.13	0.34	0	0	0
issue_type_m	2,703,106	0.74	0.44	0	1	1
fha	2,703,106	0.79	0.40	1	1	1
va	2,703,106	0.13	0.33	0	0	0
rd	2,703,106	0.08	0.27	0	0	0
pih	2,703,106	0.001	0.03	0	0	0
purchase	2,703,106	0.61	0.49	0	1	1
refinance	2,703,106	0.19	0.40	0	0	0
mod_hamp	2,703,106	0.10	0.29	0	0	0
non_hamp	2,703,106	0.09	0.28	0	0	0
purpose_na	2,703,106	0.02	0.13	0	0	0
term15	2,703,106	0.01	0.11	0	0	0
term20	2,703,106	0.004	0.06	0	0	0
term25	2,703,106	0.01	0.08	0	0	0
term30	2,703,106	0.98	0.15	1	1	1
first_time	2,703,106	0.43	0.50	0	0	1
multi_borrow	2,703,106	0.29	0.45	0	0	1
multi_units	2,703,106	0.02	0.13	0	0	0
ot_broker	2,703,106	0.08	0.26	0	0	0
ot_correspond	2,703,106	0.28	0.45	0	0	1
ot_retail	2,703,106	0.35	0.48	0	0	1
ot_unknown	2,703,106	0.29	0.45	0	0	1
prev_dlq_history	2,703,106	0.47	0.50	0	0	1
forbearance	2,703,106	0.30	0.46	0	0	1

Table B3: Non-Early Buyout 3-month Window Summary Statistics

	N	Mean	StDev	p25	p50	p75
orig_year	1,356,705	2,015.26	3.57	2,013	2,016	2,018
opb (000s)	1,356,705	191.67	101.24	121	170	242
upb (000s)	1,356,705	182.65	99.50	112.82	162.00	232.19
credit_score	1,212,713	654.70	51.51	629.00	652.00	682.00
ltv_orig	1,356,705	95.11	6.99	95.07	96.50	98.19
ltv_dlq	1,356,705	80.72	13.66	73.20	83.44	91.12
interest_rate	1,356,705	4.28	0.75	3.75	4.12	4.62
rate_spread	1,356,705	2.65	1.12	1.73	2.74	3.45
upfront_mip	1,356,705	1.11	0.84	0.00	1.75	1.75
annual_mip	1,356,705	0.62	0.55	0.00	0.80	0.85
arm	1,356,705	0.01	0.12	0	0	0
issue_type_x	1,356,705	0.08	0.27	0	0	0
issue_type_c	1,356,705	0.15	0.35	0	0	0
issue_type_m	1,356,705	0.77	0.42	1	1	1
fha	1,356,705	0.77	0.42	1	1	1
va	1,356,705	0.16	0.37	0	0	0
rd	1,356,705	0.07	0.26	0	0	0
pih	1,356,705	0.002	0.04	0	0	0
purchase	1,356,705	0.66	0.47	0	1	1
refinance	1,356,705	0.22	0.42	0	0	0
mod_hamp	1,356,705	0.06	0.23	0	0	0
non_hamp	1,356,705	0.05	0.22	0	0	0
purpose_na	1,356,705	0.01	0.09	0	0	0
term15	1,356,705	0.01	0.11	0	0	0
term20	1,356,705	0.003	0.06	0	0	0
term25	1,356,705	0.01	0.08	0	0	0
term30	1,356,705	0.98	0.15	1	1	1
first_time	1,356,705	0.49	0.50	0	0	1
multi_borrow	1,356,705	0.30	0.46	0	0	1
multi_units	1,356,705	0.02	0.14	0	0	0
ot_broker	1,356,705	0.12	0.32	0	0	0
ot_correspond	1,356,705	0.32	0.47	0	0	1
ot_retail	1,356,705	0.38	0.49	0	0	1
ot_unknown	1,356,705	0.18	0.38	0	0	0
prev_dlq_history	1,356,705	0.45	0.50	0	0	1
forbearance	1,356,705	0.41	0.49	0	0	1

Table B4: Early Buyout 3-month Window Summary Statistics

	N	Mean	StDev	p25	p50	p75
orig_year	1,346,401	2,012.39	4.12	2,010	2,013	2,015
opb (000s)	1,346,401	154.67	85.13	95	136	191
upb (000s)	1,346,401	141.74	81.50	85.06	124.12	177.29
credit_score	944,765	652.96	59.22	629.00	654.00	684.00
ltv_orig	1,346,401	95.00	6.92	95.00	96.50	98.00
ltv_dlq	1,346,401	75.36	16.02	65.43	78.17	87.90
interest_rate	1,346,401	4.60	0.93	3.9	4.4	5
rate_spread	1,346,401	2.72	1.11	1.89	2.65	3.44
upfront_mip	1,346,401	0.96	0.84	0.00	1.50	1.75
annual_mip	1,346,401	0.61	0.95	0.50	0.55	0.85
arm	1,346,401	0.01	0.09	0	0	0
issue_type_x	1,346,401	0.18	0.39	0	0	0
issue_type_c	1,346,401	0.11	0.32	0	0	0
issue_type_m	1,346,401	0.70	0.46	0	1	1
fha	1,346,401	0.82	0.38	1	1	1
va	1,346,401	0.10	0.29	0	0	0
rd	1,346,401	0.08	0.27	0	0	0
pih	1,346,401	0.001	0.02	0	0	0
purchase	1,346,401	0.55	0.50	0	1	1
refinance	1,346,401	0.17	0.37	0	0	0
mod_hamp	1,346,401	0.13	0.34	0	0	0
non_hamp	1,346,401	0.12	0.32	0	0	0
purpose_na	1,346,401	0.03	0.16	0	0	0
term15	1,346,401	0.01	0.11	0	0	0
term20	1,346,401	0.004	0.06	0	0	0
term25	1,346,401	0.01	0.09	0	0	0
term30	1,346,401	0.98	0.15	1	1	1
first_time	1,346,401	0.38	0.48	0	0	1
multi_borrow	1,346,401	0.28	0.45	0	0	1
multi_units	1,346,401	0.02	0.13	0	0	0
ot_broker	1,346,401	0.03	0.17	0	0	0
ot_correspond	1,346,401	0.24	0.43	0	0	0
ot_retail	1,346,401	0.33	0.47	0	0	1
ot_unknown	1,346,401	0.40	0.49	0	0	1
prev_dlq_history	1,346,401	0.49	0.50	0	0	1
forbearance	1,346,401	0.19	0.39	0	0	0

Table B5: Early Buyout 12-month Window Summary Statistics

	N	Mean	StDev	p25	p50	p75
orig_year	1,463,559	2,012.54	4.14	2,010	2,013	2,015
opb (000s)	1,463,559	156.68	86.32	96	137	194
upb (000s)	1,463,559	144.06	82.96	86.23	125.99	180.57
credit_score	1,044,371	652.94	58.61	629.00	654.00	684.00
ltv_orig	1,463,559	95.01	6.88	95.00	96.50	98.17
ltv_dlq	1,463,559	75.84	15.91	66.06	78.76	88.29
interest_rate	1,463,559	4.59	0.92	3.9	4.4	5
rate_spread	1,463,559	2.72	1.12	1.87	2.65	3.45
upfront_mip	1,463,559	0.98	0.84	0.00	1.50	1.75
annual_mip	1,463,559	0.62	0.93	0.50	0.55	0.85
arm	1,463,559	0.01	0.09	0	0	0
issue_type_x	1,463,559	0.18	0.38	0	0	0
issue_type_c	1,463,559	0.12	0.32	0	0	0
issue_type_m	1,463,559	0.70	0.46	0	1	1
fha	1,463,559	0.83	0.38	1	1	1
va	1,463,559	0.09	0.29	0	0	0
rd	1,463,559	0.08	0.27	0	0	0
pih	1,463,559	0.001	0.03	0	0	0
purchase	1,463,559	0.56	0.50	0	1	1
refinance	1,463,559	0.17	0.37	0	0	0
mod_hamp	1,463,559	0.13	0.34	0	0	0
non_hamp	1,463,559	0.11	0.32	0	0	0
purpose_na	1,463,559	0.03	0.16	0	0	0
term15	1,463,559	0.01	0.10	0	0	0
term20	1,463,559	0.004	0.06	0	0	0
term25	1,463,559	0.01	0.09	0	0	0
term30	1,463,559	0.98	0.15	1	1	1
first_time	1,463,559	0.39	0.49	0	0	1
multi_units	1,463,559	0.02	0.13	0	0	0
ot_broker	1,463,559	0.04	0.19	0	0	0
ot_correspond	1,463,559	0.24	0.43	0	0	0
ot_retail	1,463,559	0.33	0.47	0	0	1
ot_unknown	1,463,559	0.39	0.49	0	0	1
prev_dlq_history	1,463,559	0.49	0.50	0	0	1
forbearance	1,463,559	0.20	0.40	0	0	0

B.2 Classification of GNMA Issuers

This section provides a list of the top ten early buyout issuers by bank type (traditional banks vs. shadow banks) as well as an exhaustive list of the state financing authorities. The list is compiled based on the number of early buyouts, not the rate of early buyouts.

Traditional banks

- WELLS FARGO BANK, NA
- JP MORGAN CHASE BANK N.A.
- U. S. BANK, NA
- MIDFIRST BANK
- BANK OF AMERICA, N.A.
- PNC BANK, NA
- TRUIST BANK
- CITIMORTGAGE, INC.
- M&T BANK
- FIFTH THIRD MORTGAGE COMPANY

Shadow banks

- LAKEVIEW LOAN SERVICING, LLC
- PENNYMAC LOAN SERVICES, LLC
- CARRINGTON MORTGAGE SERVICES, LLC

- NATIONSTAR MORTGAGE, LLC
- CALIBER HOME LOANS, INC.
- SUNTRUST MORTGAGE, INC.
- PHH MORTGAGE CORPORATION
- AMERIHOME MORTGAGE COMPANY,LLC
- THE MONEY SOURCE INC.
- PLANET HOME LENDING, LLC

State financing authorities

- ALABAMA HOUSING FINANCE AUTHORITY
- COLORADO HOUSING AND FINANCE AUTHORITY
- IDAHO HOUSING AND FINANCE ASSOCIATION
- KENTUCKY HOUSING CORP.
- MASSACHUSETTS HOUSING FINANCE AGENCY
- NEW HAMPSHIRE HOUSING FINANCE AUTHORITY
- NEW JERSEY HOUSING AND MORTGAGE FINANCE AGENCY
- NEW MEXICO MORTGAGE FINANCE AUTHORITY
- NORTH DAKOTA HOUSING FINANCE AGENCY
- PENNSYLVANIA HOUSING FINANCE AGENCY
- RHODE ISLAND HOUSING AND MORTGAGE FINANCE CORP.

- UTAH HOUSING CORPORATION
- VIRGINIA HOUSING DEVELOPMENT AUTHORITY
- WISCONSIN HOUSING AND ECONOMIC DEVELOPMENT AUTHORITY
- WYOMING COMMUNITY DEVELOPMENT AUTHORITY

B.3 Issuers and Third Party Originators

Table B6 tabulates the number of early buyouts by issuer (columns) and third party originator (rows) type. The issuer classifications include fintech shadow banks, non-fintech shadow banks, and traditional banks. The traditional bank classification includes credit unions. The third party originators (TPOs) are identified in the GNMA loan-level data.

Table B6: Issuer Type and Third Party Originator Breakdown

	Issuer Type		
TPO	fintech	shadow	traditional
broker	10,452	92,759	13,737
correspondent	924	272,188	238,838
retail	76,458	230,845	333,423
unknown	7,027	159,442	463,014

C Full Table Regression Results (Internet Appendix)

This section reports the coefficient estimates for the full set of variables included in the regression analysis. Table C1 presents the coefficient estimates that align with Panel A of Table 5. Table C2 presents the coefficient estimates that align with Panel B of Table 5. Table C3 presents the coefficient estimates that align with Panel A of Table 8. Table C4 presents the coefficient estimates that align with Panel B of Table 8. Table C5 presents the coefficient estimates that align with Table 11. Finally, Table C6 presents the coefficient estimates that align with Table 12.

C.1 Early buyout probability: 3-month window

Table C1: Early Buyout Probability Given Delinquency: 3-month window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rate_spread	0.054***	0.066***	0.065***	0.089***	0.097***	0.093***	0.025***	0.033***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
log_upb	0.002***	0.003***	0.003***	−0.004***	−0.001	−0.001	0.001	−0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
credit_score			−0.0001***	−0.0002***	−0.0002***	−0.0001***	−0.0001***	−0.0001***
			(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
ltv_dlq	−0.0004***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	0.0004***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
loan_age	−0.0001***	−0.0001***	−0.0001***	−0.001***	−0.001***	−0.001***	0.0005***	0.001***
	(0.00004)	(0.00004)	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
forbearance	−0.172***	−0.187***	−0.187***				−0.126***	
	(0.005)	(0.005)	(0.005)				(0.005)	
first_time	0.014***	0.007***	0.007***	0.008***	0.010***	0.010***	−0.002**	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
fha	0.050***	0.052***	0.052***	0.055***	0.059***	0.059***	0.063***	0.078***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)	(0.002)	(0.005)
purchase	−0.004***	0.007***	0.008***	0.001	0.001	0.0002	−0.001	−0.005*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
modified	0.023***	0.030***	0.025***	0.016***	0.014***	0.014***	−0.015***	−0.017***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
multi_borrow	−0.008***	−0.003***	−0.004***	−0.005***	−0.006***	−0.006***	−0.003***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
arm	−0.162***	−0.156***	−0.158***	−0.190***	−0.187***	−0.179***		
	(0.009)	(0.009)	(0.009)	(0.011)	(0.012)	(0.012)		
multi_unit	−0.003	−0.003	−0.001	0.002	0.002	0.002	−0.0004	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
ot_broker	−0.027***	−0.024***	−0.024***	−0.036***	−0.035***	−0.035***	−0.003**	−0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
ot_correspond	−0.006***	−0.012***	−0.010***	−0.015***	−0.016***	−0.016***	−0.006***	−0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
prev_dlq	−0.018***	−0.015***	−0.016***	−0.019***	−0.020***	−0.020***	−0.012***	−0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
ot_unknown	−0.006***	−0.018***	−0.016***	−0.014***	−0.018***	−0.021***	0.015	−0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.011)	(0.018)
issue_type_x	−0.019***	−0.032***	−0.032***	−0.035***	−0.022***	−0.021***		
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)		
issue_type_c	0.006***	0.007***	0.007***	0.020***	0.020***	0.019***		
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)		
contract_spread						0.009***		
						(0.001)		
Observations	2,703,106	2,157,478	2,157,478	1,315,894	1,149,170	1,149,170	1,467,983	709,573
Adjusted R^2	0.581	0.574	0.574	0.541	0.534	0.535	0.744	0.677
Fixed Effects	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	IxPxM	IxPxM
Sample	Full	Full	Full	Pre2020	15thru19	15thru19	Full	15thru19

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

C.2 Early buyout probability: 12-month window

Table C2: Early Buyout Probability Given Delinquency: 12-month window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rate_spread	0.053***	0.066***	0.065***	0.082***	0.090***	0.085***	0.034***	0.036***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
log_upb	0.001	0.002*	0.002*	−0.006***	−0.004**	−0.003**	0.002	−0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
credit_score			−0.0001***	−0.0002***	−0.0002***	−0.0001***	−0.0001***	−0.0001***
			(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00001)
ltv_current	−0.0001	−0.0003***	−0.0003***	−0.0004**	−0.0004*	−0.0003	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
loan_age	−0.0001**	−0.0002***	−0.0002***	−0.001***	−0.001***	−0.0005***	0.0003***	0.001***
	(0.00005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
forbearance	−0.138***	−0.153***	−0.152***				−0.092***	
	(0.004)	(0.004)	(0.004)				(0.005)	
first_time	0.013***	0.006***	0.006***	0.007***	0.010***	0.010***	−0.002*	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
fha	0.070***	0.075***	0.075***	0.059***	0.062***	0.062***	0.088***	0.079***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
purchase	−0.001	0.009***	0.009***	−0.002	−0.001	−0.002	−0.001	−0.007***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
modified	0.022***	0.026***	0.020***	0.012***	0.010***	0.009***	−0.021***	−0.013***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
multi_borrow	−0.008***	−0.003***	−0.004***	−0.007***	−0.007***	−0.008***	−0.003***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
arm	−0.144***	−0.147***	−0.148***	−0.174***	−0.174***	−0.163***		
	(0.009)	(0.008)	(0.008)	(0.009)	(0.011)	(0.010)		
multi_unit	−0.0001	0.0003	0.002	0.005**	0.004*	0.004*	0.001	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ot_broker	−0.026***	−0.023***	−0.023***	−0.036***	−0.036***	−0.035***	−0.003*	−0.009***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
ot_correspond	−0.005***	−0.009***	−0.008***	−0.013***	−0.014***	−0.014***	−0.004***	−0.007***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
prev_dlq	−0.023***	−0.020***	−0.021***	−0.022***	−0.022***	−0.022***	−0.019***	−0.019***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
ot_unknown	−0.007***	−0.020***	−0.018***	−0.016***	−0.020***	−0.023***	0.033*	0.024
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.017)	(0.017)
issue_type_x	−0.017***	−0.027***	−0.027***	−0.026***	−0.015***	−0.014***		
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)		
issue_type_c	0.005***	0.006***	0.006***	0.020***	0.020***	0.018***		
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)		
contract_spread						0.013***		
						(0.001)		
Observations	2,703,106	2,157,478	2,157,478	1,315,894	1,149,170	1,149,170	1,467,983	709,573
Adjusted R^2	0.535	0.522	0.522	0.496	0.492	0.492	0.665	0.619
Fixed Effects	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	IxPxM	IxPxM
Sample	Full	Full	Full	Pre2020	15thru19	15thru19	Full	15thru19

*p<0.1; **p<0.05; ***p<0.01

C.3 Early buyout with DLQ ratios: 3-month window

Table C3: Early Buyout Probability With Threshold Controls: 3-month Window

	Baseline	Indicator			DLQ3+ Buffer		
		Current	Lag1	Lag3	Current	Lag1	Lag3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
rate_spread	0.089***	0.089***	0.090***	0.090***	0.089***	0.089***	0.089***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Above DLQ3+		−0.106***	−0.083***	−0.024***			
		(0.008)	(0.007)	(0.002)			
High DLQ3+		−0.022*	−0.003	0.001			
		(0.012)	(0.004)	(0.002)			
DLQ3+ Buffer					5.243***	4.250***	3.455***
					(0.341)	(0.292)	(0.285)
log_upb	−0.004***	−0.003**	−0.003**	−0.003**	−0.003*	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
credit_score	−0.0002***	−0.0001***	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
ltv_current	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
loan_age	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
first_time	0.008***	0.008***	0.008***	0.008***	0.009***	0.009***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
fha	0.055***	0.055***	0.055***	0.055***	0.056***	0.056***	0.056***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
purchase	0.001	0.001	0.002	0.002	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
modified	0.016***	0.017***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
multi_borrow	−0.005***	−0.004***	−0.005***	−0.005***	−0.005***	−0.005***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
arm	−0.190***	−0.189***	−0.191***	−0.191***	−0.192***	−0.191***	−0.191***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
multi_unit	0.002	0.002	0.002	0.002	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ot_broker	−0.036***	−0.035***	−0.035***	−0.035***	−0.035***	−0.035***	−0.035***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ot_correspond	−0.015***	−0.015***	−0.014***	−0.014***	−0.014***	−0.014***	−0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
prev_dlq	−0.019***	−0.019***	−0.021***	−0.021***	−0.022***	−0.021***	−0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ot_unknown	−0.014***	−0.013***	−0.013***	−0.013***	−0.010***	−0.010***	−0.010***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
issue_type_x	−0.035***	−0.034***	−0.032***	−0.032***	−0.031***	−0.032***	−0.032***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
issue_type_c	0.020***	0.020***	0.020***	0.020***	0.021***	0.021***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
small_issuer	−0.009*	−0.015**	−0.011**	−0.009*	−0.185***	−0.159***	−0.124***
	(0.005)	(0.007)	(0.005)	(0.005)	(0.016)	(0.010)	(0.009)
Observations	1,315,894	1,315,894	1,287,051	1,287,051	1,287,051	1,287,051	1,287,051
Adjusted R^2	0.541	0.542	0.543	0.543	0.545	0.544	0.544
Fixed Effects	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y
Sample	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020

*p<0.1; **p<0.05; ***p<0.01

C.4 Early buyout with DLQ ratios: 12-month window

Table C4: Early Buyout Probability With Threshold Controls: 12-month Window

	Baseline	Indicator			DLQ3+ Buffer		
		Current	Lag1	Lag3	Current	Lag1	Lag3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
rate_spread	0.082***	0.082***	0.083***	0.083***	0.082***	0.082***	0.083***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Above DLQ3+		−0.076***	−0.052***	−0.013***			
		(0.013)	(0.008)	(0.003)			
High DLQ3+		−0.021	−0.001	0.003			
		(0.015)	(0.006)	(0.002)			
DLQ3+ Buffer					4.275***	3.127***	2.210***
					(0.373)	(0.294)	(0.254)
log_upb	−0.006***	−0.006***	−0.006***	−0.006***	−0.005***	−0.005***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
credit_score	−0.0002***	−0.0001***	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00002)	(0.00002)
ltv_current	−0.0004**	−0.0004**	−0.0004*	−0.0004*	−0.0003	−0.0003	−0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
loan_age	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
first_time	0.007***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
fha	0.059***	0.059***	0.059***	0.059***	0.060***	0.060***	0.059***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
purchase	−0.002	−0.002	−0.002	−0.001	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
modified	0.012***	0.013***	0.011***	0.011***	0.011***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
multi_borrow	−0.007***	−0.006***	−0.007***	−0.007***	−0.007***	−0.007***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
arm	−0.174***	−0.174***	−0.176***	−0.176***	−0.176***	−0.176***	−0.176***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
multi_unit	0.005**	0.005**	0.005**	0.005**	0.004*	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ot_broker	−0.036***	−0.035***	−0.035***	−0.035***	−0.036***	−0.036***	−0.036***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ot_correspond	−0.013***	−0.012***	−0.013***	−0.013***	−0.012***	−0.012***	−0.012***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
prev_dlq	−0.022***	−0.022***	−0.023***	−0.023***	−0.024***	−0.023***	−0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ot_unknown	−0.016***	−0.015***	−0.016***	−0.016***	−0.013***	−0.013***	−0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
issue_type_x	−0.026***	−0.026***	−0.024***	−0.024***	−0.024***	−0.024***	−0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
issue_type_c	0.020***	0.021***	0.020***	0.020***	0.021***	0.021***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
small_issuer	−0.008	−0.014	−0.009	−0.007	−0.151***	−0.118***	−0.081***
	(0.010)	(0.012)	(0.010)	(0.010)	(0.017)	(0.013)	(0.011)
Observations	1,315,894	1,315,894	1,287,051	1,287,051	1,287,051	1,287,051	1,287,051
Adjusted R^2	0.496	0.496	0.497	0.497	0.499	0.498	0.497
Fixed Effects	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y	I+S+Y
Sample	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020	Pre2020

*p<0.1; **p<0.05; ***p<0.01

C.5 Default, Prepayment, and Early Buyout by Issuer Type

Table C5: Default, Prepayment, and Early Buyout by Issuer Type

	Default		Prepayment		Early Buyout			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
shadow	0.003***	0.003***	0.069***	0.062***	−0.504***	−0.500***	−0.746***	−0.748***
	(0.001)	(0.0005)	(0.003)	(0.002)	(0.008)	(0.008)	(0.010)	(0.010)
state_fin	0.008**	0.008**	0.002	−0.002	−0.678***	−0.677***	−0.637***	−0.636***
	(0.003)	(0.003)	(0.010)	(0.010)	(0.026)	(0.026)	(0.043)	(0.044)
fintech		0.002		0.122***		−0.613***		−0.695***
		(0.003)		(0.006)		(0.012)		(0.014)
credit_union		−0.008*		−0.026**		−0.549***		−0.521***
		(0.004)		(0.010)		(0.109)		(0.141)
rate_spread					0.086***	0.086***	0.026***	0.026***
					(0.003)	(0.003)	(0.003)	(0.003)
shadowXspread							0.121***	0.123***
							(0.003)	(0.002)
state_finXspread							−0.020	−0.020
							(0.015)	(0.015)
fintechXspread								0.039***
								(0.008)
cuXspread								−0.036
								(0.023)
credit_score	−0.0005***	−0.0005***	−0.0003***	−0.0003***	−0.0001***	−0.0001***	−0.0001***	−0.0001***
	(0.00002)	(0.00002)	(0.00003)	(0.00003)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
first_time	0.010***	0.010***	−0.049***	−0.050***	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
fha	0.002	0.002	−0.020***	−0.021***	0.030***	0.031***	0.034***	0.034***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
purchase	0.008***	0.008***	−0.061***	−0.054***	0.010***	0.004	−0.001	−0.005*
	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
modified	0.225***	0.225***	−0.196***	−0.184***	0.158***	0.144***	0.156***	0.145***
	(0.005)	(0.005)	(0.011)	(0.011)	(0.006)	(0.006)	(0.005)	(0.006)
multi_borrow	−0.025***	−0.025***	−0.008***	−0.009***	−0.012***	−0.012***	−0.013***	−0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
arm	0.001	0.002	0.078***	0.063***	−0.183***	−0.176***	−0.194***	−0.194***
	(0.001)	(0.001)	(0.005)	(0.005)	(0.009)	(0.009)	(0.010)	(0.009)
multi_unit	−0.009***	−0.009***	−0.017**	−0.016**	0.002	0.002	0.003	0.003
	(0.002)	(0.002)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)
ot_broker	0.007***	0.007***	−0.013***	−0.004	0.005	−0.004	0.020***	0.012*
	(0.001)	(0.001)	(0.004)	(0.004)	(0.006)	(0.007)	(0.006)	(0.007)
ot_correspond	0.005***	0.005***	0.006**	0.015***	0.075***	0.063***	0.079***	0.068***
	(0.001)	(0.0004)	(0.002)	(0.003)	(0.006)	(0.007)	(0.006)	(0.007)
ot_unknown	0.130	0.130	−0.109	−0.110	0.045***	0.037***	0.041***	0.035***
	(0.110)	(0.110)	(0.099)	(0.099)	(0.004)	(0.004)	(0.004)	(0.004)
issue_type_x	0.010***	0.010***	0.029***	0.029***	−0.021***	−0.022***	−0.025***	−0.026***
	(0.001)	(0.001)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
issue_type_c	0.005***	0.005***	0.005	0.004	0.068***	0.069***	0.065***	0.066***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
log_upb					−0.002	−0.004**	−0.002	−0.004**
					(0.002)	(0.002)	(0.002)	(0.002)
ltv_current					−0.0005*	−0.001**	−0.0001	−0.0002
					(0.0003)	(0.0002)	(0.0002)	(0.0002)
loan_age					0.001***	0.001***	0.002***	0.001***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	6,788,890	6,788,890	6,788,890	6,788,890	1,315,894	1,315,894	1,315,894	1,315,894
Adjusted R^2	0.073	0.073	0.100	0.101	0.370	0.373	0.380	0.384
Fixed Effects	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y
Sample	14thru17	14thru17	14thru17	14thru17	Pre2020	Pre2020	Pre2020	Pre2020

*p<0.1; **p<0.05; ***p<0.01

C.6 Probability of Re-securitization with Soft Information

Table C6: Probability of Re-securitization

	Re-securitized				No Modification		Modification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rate_spread	−0.005	0.005	−0.003	0.006	0.010	0.016	−0.015**	−0.010
	(0.016)	(0.015)	(0.015)	(0.014)	(0.013)	(0.012)	(0.007)	(0.007)
log_upb	−0.018	−0.015	−0.014	−0.012	−0.023	−0.017	0.006	0.005
	(0.024)	(0.023)	(0.023)	(0.022)	(0.018)	(0.016)	(0.012)	(0.012)
curr_credit_score	−0.0002	−0.0001	−0.0002	−0.0002	0.0002	−0.0001	−0.0003***	−0.0002*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
ltv_dlq	−0.004***	−0.004***	−0.004***	−0.003***	−0.004***	−0.003***	0.0001	−0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.001)
loan_age	−0.001**	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.0001	−0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
sf	0.020	0.003	0.004	−0.009	−0.019	−0.047	0.039*	0.038*
	(0.035)	(0.032)	(0.036)	(0.033)	(0.029)	(0.029)	(0.022)	(0.019)
owner_occupied	0.014	0.007	0.012	0.008	−0.039	−0.041	0.053***	0.050***
	(0.040)	(0.040)	(0.038)	(0.039)	(0.041)	(0.038)	(0.009)	(0.009)
fha	−0.141***	−0.147***	−0.131***	−0.136***	−0.079***	−0.065***	−0.063***	−0.072***
	(0.029)	(0.029)	(0.027)	(0.028)	(0.020)	(0.020)	(0.019)	(0.019)
intent_keep		0.422***		0.396***		0.221***		0.175***
		(0.030)		(0.032)		(0.030)		(0.021)
intent_na		0.291***		0.268***		0.180***		0.087***
		(0.064)		(0.065)		(0.064)		(0.031)
rfd_bk			−0.061	−0.036		−0.027		−0.009
			(0.055)	(0.051)		(0.053)		(0.013)
rfd_casualty			−0.108	−0.061		−0.256***		0.195**
			(0.084)	(0.084)		(0.082)		(0.085)
rfd_death			−0.266***	−0.198***		−0.290***		0.092*
			(0.075)	(0.072)		(0.060)		(0.053)
rfd_excess			−0.086**	−0.081**		−0.189***		0.107***
			(0.032)	(0.032)		(0.039)		(0.018)
rfd_family			−0.081	−0.076		−0.218***		0.142**
			(0.055)	(0.055)		(0.056)		(0.057)
rfd_illness			−0.150***	−0.150***		−0.301***		0.151***
			(0.045)	(0.049)		(0.060)		(0.045)
rfd_income			−0.071*	−0.071*		−0.244***		0.173***
			(0.039)	(0.040)		(0.044)		(0.018)
rfd_marital			−0.202***	−0.184***		−0.248***		0.064*
			(0.059)	(0.057)		(0.047)		(0.035)
rfd_emergency			−0.391***	−0.386***		−0.415***		0.029**
			(0.056)	(0.055)		(0.052)		(0.012)
rfd_own_xfer			−0.058	−0.046		−0.088		0.042***
			(0.061)	(0.059)		(0.067)		(0.015)
rfd_pmt_adj			0.026	0.017		0.030		−0.013
			(0.071)	(0.067)		(0.085)		(0.043)
rfd_pmt_disp			−0.056	−0.059		−0.134*		0.075**
			(0.071)	(0.072)		(0.075)		(0.030)
rfd_property			−0.374***	−0.316***		−0.322***		0.006
			(0.098)	(0.093)		(0.089)		(0.049)
rfd_servicing			−0.029	−0.027		−0.103		0.076***
			(0.058)	(0.057)		(0.063)		(0.017)
rfd_unable_sell			−0.489***	−0.300***		−0.321***		0.021
			(0.039)	(0.060)		(0.045)		(0.032)
rfd_other			−0.134***	−0.136***		−0.092**		−0.044**
			(0.045)	(0.045)		(0.046)		(0.017)
rfd_unemployment			−0.056	−0.044		−0.276***		0.232***
			(0.054)	(0.055)		(0.068)		(0.045)
Observations	3,084	3,084	3,084	3,084	3,084	3,084	3,084	3,084
Adjusted R^2	0.068	0.102	0.086	0.114	0.053	0.104	0.075	0.134
Fixed Effects	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y	S+Y

*p<0.1; **p<0.05; ***p<0.01

D Miscellaneous (Internet Appendix)

D.1 GNMA Subservicers

Servicing of all GNMA program types, except manufactured housing (MH) pools, can be performed on behalf of the issuer by a subservicer. The subservicer must be a GNMA approved issuer and the subservicing arrangement must be approved in writing by GNMA. There can only be one subservicer assigned to each pool or loan package. This section provides an overview of the permitted subservicing functions. See Chapter 4 of the GNMA MBS servicing guide for additional information.

Functions Performed by Issuer Only

- Withdraw funds from principal and interest custodial account
- Access documents at document custodian
- Sign any certifications to GNMA required by the MBS servicing guide, the guaranty agreement, or requested by GNMA, other than the monthly reporting certification
- Sign checks to security holders that are paid by check
- Authorize withdrawal of funds from central principal and interest custodial account for payment of all book-entry securities and GNMA guaranty fee
- Sign remittance advice to security holders
- Fund the guaranty fee in the principal and interest custodial account for ACH debit
- Maintain register of security holders
- Authorize withdrawal of funds from central principal and interest custodial account for payment to security holders and payment of GNMA guaranty fee

Permitted Subservicing Functions

- Collect principal and interest and escrow amounts
- Deposit funds into principal and interest and escrow custodial accounts
- Withdraw funds from escrow custodial accounts
- Supply funds for advances to security holders
- Absorb losses on foreclosures not covered by FHA, VA, RD, or PIH settlements
- Prepare and transmit to GNMA the issuer's monthly report of pool and loan data
- Complete the monthly reporting certification required by the GNMA servicing guide
- Prepare and send checks to security holders that are paid by check
- Prepare and send remittance advice to security holders
- Report monthly guaranty fees via GinnieNET
- Perform accounting and monitoring functions of participations related to HECM loans

D.2 Early Buyout Curative Process

Re-performing early buyout loans can be re-securitized if they satisfy the mortgage eligibility requirements in Chapter 9 of the GNMA MBS servicing guide. The eligibility requirements include a delinquency status stipulation (Section 2.E in Chapter 9) stating that as of the pooling date, no more than one monthly payment can be due or unpaid. Furthermore, if the terms of the loan were modified, the loan must be current as of the issuance date of the related security.

There are several other items that must be resolved before the early buyout loans can be re-securitized into GNMA securities. The items include title, property, legal, document, and other compliance related defects that must be resolved before the reperforming loan can be re-securitized. Given that this study focuses on the issuers' early buyout decision we leave further exploration of the curative process to future research on this topic.