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Essays on Mortgage Debt Payment

Meagan Nicole McCollum
Louisiana State University and Agricultural and Mechanical College

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by
Meagan Nicole McCollum
B.A., Samford University, 2008
M.B.A., Samford University, 2011
M.S., The University of Alabama, 2012
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Abstract

In this dissertation, I offer three independent studies that each contribute to the literature on mortgage debt payments. In the first paper, I examine the recent phenomenon of mortgage curtailment (borrowers making voluntary partial prepayments) and link this behavior to consumer deleveraging trends. In the second paper, I use the curtailment measures developed in the first essay to examine heterogeneity in sensitivity to current mortgage leverage in default decisions. Considering the group of borrowers who have previously curtailed mortgage debt, I posit such borrowers should be less sensitive to current leverage than borrowers without past curtailments because previous curtailers have revealed a lower value on the embedded option to default on their loan because to do so would forfeit the full amount of past partial prepayments. Indeed, I show that for borrowers estimated to have negative equity positions, borrowers with past curtailments have approximately 30-50% less sensitivity to current leverage than borrowers who have never made extra payments.

Finally, in the third essay I examine the role of income stability in mortgage default decisions. I study default decisions in a sample of borrowers (governmental employees from Clark County NV, FY2009–2010) whose current employment and income is known with certainty and future prospects for continued employment are above average. I find that while the group with known employment has a lower default rate than the remainder of homeowners (whose employment status is unknown), but both groups have the same sensitivity to mortgage leverage. Both the second and third studies provide evidence of strategic default behavior in the residential mortgage market and suggest that when faced with a wave of mortgage defaults, investors and policymakers cannot provide solutions targeted towards ability to pay without addressing declines in asset values.

Chapter 1. Introduction

In 2015 the average American is certainly more aware of the potential perils present in the housing market than he was ten years ago. Although today there is a consensus that the worst of the mortgage market crisis has passed, few households emerged entirely unscathed by the experience. As aggregate house prices continue to stabilize and reestablish a pattern of steady growth, it remains an open question if the problems of the crisis have been solved or merely survived. More specifically, what can be done by lenders and policymakers to improve assessment of default risk in individual mortgages? The essays in this dissertation aim to exploit underutilized information about individual borrowers to improve understanding of mortgage payment patterns and outcomes.

1.1 Evolution of mortgage lending in the US

A basic familiarity with the history of the American mortgage is essential to understanding what challenges exist in evaluating mortgage risk post-origination. Modern mortgage lending has arisen primarily as a reaction to past crises and regulatory actions. Prior to the Great Depression mortgages the typical mortgage would be virtually unrecognizable today. In the early US mortgage market, loans almost exclusively had a floating interest rate, were relatively short term (between 5 to 10 years), were typically non-amortizing (payments covered only the interest), and had high down payment requirements often only allowing the borrower to finance half of the purchase price. Additionally, mortgages were primarily issued by insurance companies or savings and loans associations as opposed to commercial banks or mortgage brokers (Green and Watcher, 2005). When a crisis hit, borrowers were faced not only with the problems of reduced collateral value and reduced ability to make mortgage payments, but also the additional problem of lenders frequently refusing to renew the loans,

which led to loss of the property if the borrower was unable to come up with a large lump sum to repay the remainder of the balance due on the property. While much has been made about the role of teaser rates[1] in the recent crisis (Mayer, Pence, and Sherlund, 2009), the potential non-renewal of the typical early 20th century loan put the borrower entirely at the lenders' mercy.

As a response to the widespread foreclosures during the Great Depression, the federal government undertook several reforms and initiatives aimed at promoting long term growth and stability in the residential mortgage market. In 1932, the lending landscape was completely overhauled as savings and loan associations (S&Ls) were provided liquidity to make mortgage loans, while simultaneously being restricted to lending within a 50-mile radius. This forced localization of a large portion of mortgage lending incentivized relationship lending and careful screening of potential mortgagors by the S&Ls. This basic framework stayed in place for decades and residential mortgage lending remained largely local until the widespread financial deregulation that occurred in the late 1980s that changed the rules governing the S&Ls.

Also, as a result of the Great Depression, various institutions were formed to help provide stability and liquidity to the mortgage market. The first of the these, the Federal Housing Administration (FHA), provided a mechanism in which a borrower paid insurance enables FHA to guarantee mortgage payments to the lender, which served the purpose of easing the fears and loosening the purse strings of otherwise reluctant lenders. Similarly, the Federal National Mortgage Association (FNMA or Fannie Mae)[2] was begun a few years later to help develop a secondary market for mortgages (von Hoffman, 2000).

As guarantees made by such entities, both implicit and explicit, became more valuable to lenders and investors, the groundwork began to be laid for the securitization of residential

[1] A teaser rate is a below market interest rate charged to a borrower for a short period of time (typically 1-2 years) after which is interest rate resets according to a predetermined method or rate for the remainder of the life of the loan.

[2] Other important institutions that emerged later the served similar, but distinct purposes include Freddie Mac and Ginnie Mae.

mortgages. From the first simple pass-through mortgage backed security (MBS) issued by Ginnie Mae in 1970 [3] to the complex MBS that emerged in the late 20th and early 21st century, securitization provided a vehicle for participation in the market by investors as well as an additional channel for lenders to move mortgages of their balance sheets, freeing up capital for other purposes.

While securitization, both among players like Fannie Mae and Freddie Mac as well as private label securities issued directly by lenders, grew rapidly, another technology helped to change the landscape of mortgage lending– the automated underwriting system (AUS). An AUS is a computer program in which an applicant inputs information about herself and the program makes a decision to grant the loan or refer the loan to additional screening. The automation of a large portion of the lending process cut down on the time spent and expense incurred in making a loan. A study Fannie Mae in the early 2000s showed that the use of an AUS cut the cost of making a loan by $916 (von Hoffman, 2000).

Both securitization and the rising of automated lending have had profound impacts in the residential mortgage marketplace; for the purposes of this dissertation I draw attention to how the changes in the lending landscape created distance between the mortgagor and the ultimate mortgagee. The rise in volume and scale of mortgage backed securities and market-wide reliance on automated underwriting lead to loss of some individual information, such as soft information that lenders of yesteryear were able to develop on individual borrowers through relationship lending over time and product categories. While this information may not be as important when times are good, much as the short term balloon mortgages worked fine until the Great Depression hit, differences in individual borrowers that can emerge after loan origination can be essential in predicting and developing appropriate responses to adverse market conditions.

[3] A pass-through security simply entails varies investors, each owning claim to a fractional share of the cash flows generated by a pool of mortgages, receiving a payment proportional to their ownership interests each month, less fees collected by the securitizer.

1.2 Information problems in mortgage lending

Residential mortgages are by far the largest component of outstanding household debt in the United States. Additionally, mortgage debt is the single largest component of non-financial sector debt, dwarfing even corporate debt (see Figure 1.1). However, from the perspective of the lender (or the ultimate investor), mortgage contracts have some important distinctions from other forms of debt. Most pertinent to my analysis is the fact that although mortgages are long term debt[4], information on the borrower's financial position may only be collected at the point of loan origination.

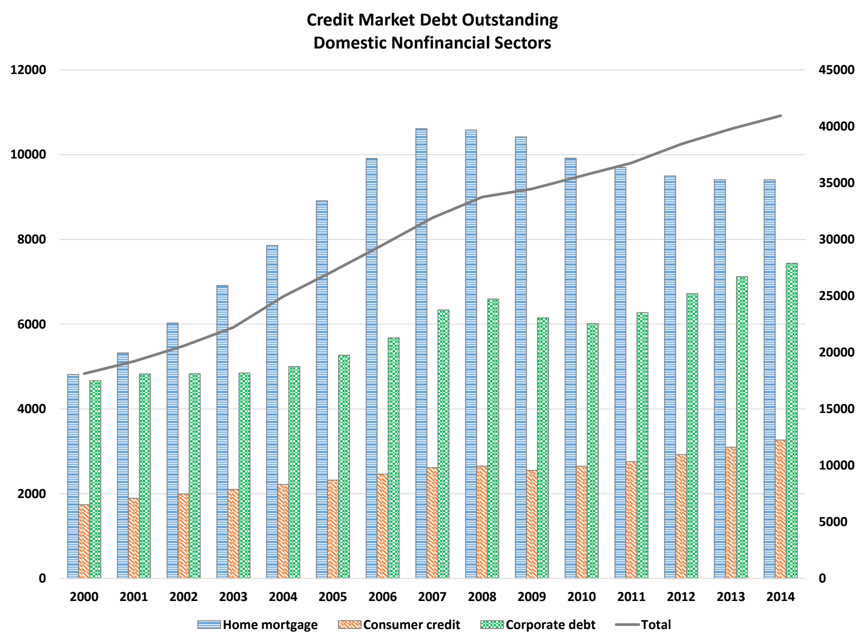

Figure 1.1: Credit Market Debt Outstanding: Domestic Nonfinancial Sectors

Data from Federal Reserve Statistical Release Z1, 2014. Figures for 2014 are through 3Q. Amounts are presented in billions of dollars. Total debt plotted on right axis, all other categories presented on left.

As time passes, borrower characteristics known at origination become less predictive of future payments as borrowers may change or lose jobs, take on or repay debt outside of

[4]Most mortgage debt has a 30 year term, although approximately 15% has a shorter term, the majority of which are 15 year mortgages.

the original mortgage, or otherwise experience changes in their creditworthiness. This is contrast to other forms of debt, such as corporate bonds where investors have access to updated financial statements quarterly and are able to observe new debt or equity issued by the firm.

Additionally, many theoretically important measures of borrower financial distress measured at the aggregate level (e.g. county level unemployment or average changes in per-capita income) have low informational content in predicting individual mortgage defaults. Although much of this evolution in household balance sheets is unobservable, at least directly, to investors, progress to resolving this information problem can be valuable to market participants, even if the loan will likely not be renegotiated as the result of such an update.

1.3 Household Financial Decisions

Since homeownership rates have historical been high in the US, housing assets have long been an important component of household balance sheets. However, as household savings rates have declined, housing wealth has become relatively more important. According to the Bureau of Economic Analysis, household personal savings rates as a percentage of disposable personal income (which excludes money paid towards housing expenses) declined from over 9 percent in the early 1990s to about 2 percent in late 2005. Accounting for inflation, in real terms, the average saving rate was negative during the height of the real estate bubble. However, the repayment of a mortgage plays an important part in wealth acquisition for many households, given stable or rising housing values. Building equity in a home can be thought of as a regular enforceable savings mechanism for households with a mortgage.

Given the high levels of leverage in many mortgages originated in the mid-2000s combined with lower personal savings rates, it follows for the average homeowner that housing became an increasingly large and risky portion of personal wealth. Given that even before the run up in housing values, housing accounted for approximately 70% of personal wealth (Amromin,

Huang, and Sialm, 2007), increasing the lack of diversification placed many households in a precarious financial position. Therefore, a household with highly levered home and a low personal savings rates (or few assets outside of housing) was susceptible to even small changes in the value of the collateral for their loan, their house.

In fact, zipcodes with the largest share of subprime loans closely correlate with the zipcodes with the smallest relative income growth in the early 2000s, when mortgage credit availability greatly expanded (Mian and Sufi, 2009). Indeed, most of the growth in wealth during this period, especially for the subprime households was concentrated in rising house prices, which offset stagnant or even declining wages.

In the midst of the crisis, the role of mortgage in household portfolio and spending decisions has become more evident; highly levered households had larger declines in spending than other homeowners, despite having smaller changes in their net worth. This suggests that mortgage leverage drove consumption during the house price run-up and weighed it down more heavily during the decline above levels that would have predicted by changes in wealth alone (Dynan, 2012). The declines in household spending and consumption were closely linked to households that had relatively high marginal propensities to consume out of housing wealth, namely households in zipcodes that had higher concentrations of poor and highly levered households (Mian, Rao, and Sufi, 2013).

Clearly, since the wealth of the median homeowner is concentrated in his home, changes in the housing market can have a larger impact on net worth. To the extent that such changes can drive ability and desire for other forms of consumer spending, a better understanding of how individuals make mortgage payment decisions is useful. Although some of this heterogeneity across borrowers is captured by geography (e.g. average characteristics at the zipcode or Census tract level), utilizing more individual level information can help lenders, investors, and policymakers in both predicting and reacting to changes in local housing markets.

1.4 Overview

In the remainder of this dissertation, I present three essays that explore different facets of borrower payment decisions in the US residential mortgage market.

The second chapter is entitled *Deleveraging and Mortgage Curtailment*. Using monthly loan-level data, I observe individual curtailment payments from January 2001 to June 2011 for mortgages in twenty metropolitan statistical areas. Contrary to some earlier assertions, American homeowners now frequently commit funds towards their mortgage payments in excess of the amount due; over 30% of loans outstanding have made at least one curtailment payment. After controlling for borrower and loan-level variables, I show that the latent propensity to curtail has steadily risen from 2003 to 2006 and remains at elevated levels. Therefore, curtailment provides an example of consumer deleveraging behavior that began prior to the Great Recession.

The third chapter is entitled *Curtailment and Strategic Mortgage Default*. In this essay, I consider borrowers, who have a strategic default (put) option on their mortgage that rises in value with mortgage leverage. When mortgagors choose to curtail their loans by making voluntary payments in excess of the amount due, mortgage leverage decreases and their incentives to default strategically diminish. I examine the sensitivity of default to mortgage leverage. I show that when households who curtail (good borrowers) default (go bad), such defaults are only half as sensitive to current mortgage leverage as compared to borrowers who do not curtail.

When house prices decline and mortgage leverage increases, default can occur for liquidity reasons as well as for strategic ones when the borrower exercises his put option. My findings show that in such environments, payment histories are useful in identifying borrowers who are less likely to strategically default. By doing so, it contributes to a better understanding of default decisions during the recent mortgage crisis.

The fourth chapter is entitled *Income Stability and Mortgage Default.* Debate exists on the relative importance of employment status and house price declines in accounting for the large number of mortgage defaults during the Great Recession. To avoid the complexities posed by potential interactions among house prices, employment status, and income, I propose the natural experiment of examining the default decisions of homeowners with job security and income stability.

Specifically, I observe governmental workers employed in Clark County Nevada in FY2009-2010, during the Great Recession, and compare the sensitivity of their default decisions to changes in house values to the general population. Relative to the overall population, those homeowners with known income stability exhibit a somewhat lower rate of default than the general public, but both groups are equally sensitive to price in their default decisions.

The findings of these three studies are summarized in Chapter 5. Additionally, in this chapter I suggest directions for future research.

Chapter 2. Deleveraging and Mortgage Curtailment

2.1 Introduction

Consumer debt levels fell during the Great Recession. Various reasons have been posited for this change, including increased lending standards and a reduction in the demand for debt. During the crisis, households responded to adverse economic conditions by increasing savings. One of the ways that households engaged in savings behaviors was through the reduction of outstanding consumer debt, including paying down mortgage debt (Charkrabarti et al. 2011).

Advantages of examining changes in existing mortgage loans include: (1) Unlike new debt, existing debt is not directly affected by changing lending standards[1]; (2) Aggregation bias is avoided because detailed observations are available on individual behavior; (3) Deleveraging due to charge-offs or foreclosures can be separated from deleveraging due to acceleration of debt repayments. Mortgage curtailment (voluntary partial prepayment) is a setting in which consumer deleveraging choices for individuals can be observed.

I cannot observe borrowers non-mortgage consumer debts. However, mortgage debt represents 70% of all household liabilities (Justiniano et al. 2013). Often mortgage debt is less expensive than other forms of debt such as credit card debt or personal loans; in this case rational deleveraging should appear in those higher cost debts prior to reduction of mortgage debt. If mortgage debt is relatively expensive, it would be difficult for borrowers to replace large amounts of mortgage debt with other forms of consumer debt. Nonetheless, not having information on individual borrowers' non-mortgage debts represents a possible omitted variable issue.

[1] Although there is no direct effect, individuals could still modify their future borrowing behavior due to changes in opportunities.

The institutional setting of mortgage payments provides a relatively controlled setting to examine borrowers' leverage choices and motivations for reducing debt. Initially, it must be determined if borrowers are rate sensitive in their deleveraging decisions. If so, curtailment is primarily an investment strategy wherein individuals choose to minimize (maximize) their leverage when rates are high (low) by making excess (only minimum scheduled) principal payments. If individuals are not rate sensitive, this suggests that other factors may drive curtailment behavior. In general, household attitudes towards debt (and by extension, the desire to reduce household debt levels) are also related to non-pecuniary social psychological factors in consumer debt and savings behaviors (Lunt and Livingstone 1991, Lea et al. 1993, 1995, Brown et al. 2005).

Much of the deleveraging literature examines household behavior in response to the Great Recession, which is associated with subsequently lower levels of leverage (Bricker et al. 2011). In fact, aggregate consumer debt did not begin to decline until mid-2008 (Brown et al. 2011). In contrast to these results, we find that the latent propensity to engage in curtailment payments (after controlling for many economic factors) began to increase as early as 2003 during a time period (2002-2007) where, in aggregate, consumers demanded higher levels of debt (Weller 2007). This is important because it shows that within the controlled setting of curtailment, household deleveraging (all else equal) began prior to the Great Recession.

Curtailment payments are applied directly to the mortgage principal balance. A borrower who elects to make a partial prepayment reduces his outstanding debt, the life of the mortgage, and future interest costs. Making a curtailment payment is a voluntary action on the part of the borrower and may be done at any point in time[2] and in any amount less than the total balance outstanding.[3]

[2]Theoretically, curtailments can even be made even when the mortgage is delinquent, but in this case any excess payment will first be applied to past balance due and late fees before being considered a curtailment.

[3]Many mortgages have a prepayment penalty in effect for the first 12-60 months of the life of the loan that prevents a borrower from repaying greater than 20% of the mortgage outstanding in excess of the regular payment schedule in a single year without facing a substantial penalty.

Mortgage curtailment has historically been a relatively rare choice for American homeowners, but I observe a dramatic increase in the popularity of this behavior in recent years (see Figure 2.1). In January 2004, only 0.23% of borrowers in my sample made a curtailment payment of at least \$100 that month; the same time in 2005 1.41% chose curtailment. In January 2006, 6.63% of borrowers chose to curtail their mortgages that month.

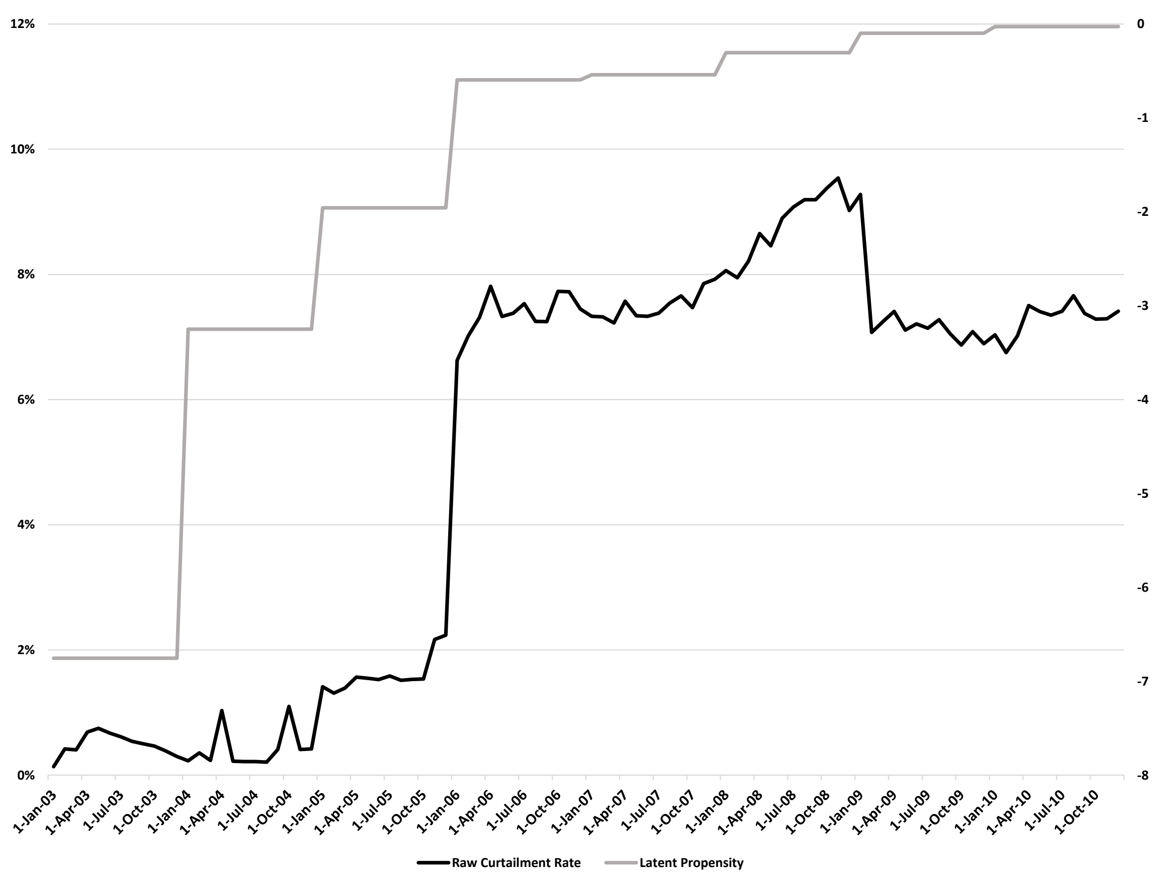

Figure 2.1: Curtailment Rates

The curtailment rate is calculated using data from private securitized mortgage market. This graph uses the \$100 minimum value of curtailment. The left axis graphs the monthly raw curtailment rate, the right axis illustrates the yearly propensity to curtail as compared to the base case of 2011.

Additionally, the monthly curtailment rate remains high through June 2011, the end of our sample period. Note that there is a dramatic jump between 4Q 2005 and 1Q 2006, but after accounting for borrower and loan-level variables the latent propensity to engage in cur-

tailment behavior begins three years earlier and shows a much smoother rise. Curtailment behavior continues to increase in popularity through the end of our sample period, June 2011.

The goal of this chapter is to better understand the motivations for mortgage curtailment behavior, and by extension household deleveraging behavior, among US homeowners. After allowing for variation in loan, borrower, locational, vintage, and servicer characteristics, I show that the choice to make additional payments has become more attractive to borrowers in recent years. This documents the increasing importance of mortgage curtailment in the US mortgage market.

Mortgage curtailment is often omitted from mortgage pricing and payment models, but I suggest that this event reveals additional information about and insights into borrower behavior. I show that as the spread between current mortgage interest rate and the short term risk-free rate increases, the probability of making a curtailment payment increases, particularly for borrowers estimated to have positive equity in the property at the time of observation.

A certain subset of homeowners who have (unobservable) discretionary income available and do not currently value the default option on their mortgage[4] may be motivated to commit those funds to accelerate paying down their relatively high interest rate mortgage as return on safe investments, such as savings accounts, becomes less unattractive. After accounting for variation in a host of borrower and loan characteristics, the pattern of curtailment from 2001-2011 is smoothed, and shows a secular increase over the sample period (See Figure 2.1).[5]

The remainder of this chapter is organized as follows: Section 2.2 briefly outlines previous curtailment literature, discusses borrower behavior, and presents the choice to curtail in an options framework, Section 2.3 discusses the empirical models employed, Section 2.4 discusses the different data sources used in this study, defines key variables, and provides summary

[4]That is, they view the timely repayment of their outstanding mortgage debt as certain, at least in the short term.

[5]The latent propensity is derived from the coefficients of the observation year fixed effects from the main empirical specification, presented in Section 2.5.

statistics, Section 2.5 presents the results, and Section 2.6 summarizes as well as proposes directions for future research.

2.2 Literature Review and Discussion

First, I summarize the previous research related to mortgage curtailment in Section 2.2.1. Second, I discuss some interesting patterns of curtailment behavior and present several potential economic and behavioral motivations for engaging in curtailment behavior in Section 2.2.2. Finally, I discuss the choice to curtail within an options framework in Section 2.2.3.

2.2.1 Previous Research

Mortgage curtailment has not received much attention in the real estate literature. Relative to the extensive academic literature on prepayments in full, the literature on curtailment is limited. Also, a large portion of research related to mortgage payment decisions is targeted towards the importance of payment events for the pricing of mortgage backed securities. Campbell (2006) notes that despite the importance of housing and mortgage debt for households, there is a limited amount of research on mortgage decisions from the perspective of individual households. By exploring determinants of mortgage curtailment decisions for individual borrowers, I contribute to the literature on personal mortgage payment choices.

The first study to investigate mortgage curtailment is Hayre and Lauterbach (1991). They highlight the importance of accounting for partial prepayments in calculating the weighted average maturities (WAM) of mortgage pools in the context of securitization. Also, they observe that failing to account for curtailment will upwardly bias the average age of the mortgage pool.

Budinger and Fan (1995) examine curtailments in the context of pools of jumbo loans. They find that curtailments seldom occur early in the life of the mortgage and that curtail-

ment rates significantly increase in the later years of a mortgage. Budinger and Fan also observe a trend of seasonality with curtailment at the pool level being least likely in the fall months and increasing curtailment frequency beginning in December until reaching a peak in April.

A borrower who makes a curtailment payment may choose to repeat this behavior several times over the course of the life of the loan. Fu (1997) finds that records of previous curtailment for a given mortgage greatly enhance the chance that the borrower will make a curtailment payment in the future. Although they do not specifically study curtailment, Amromin, Huang, and Sialm (2007) document the reluctance of households to participate in financial markets and how paying down existing debt can be viewed as an alternate method of personal savings.

Budinger and Fan (1995) identify three variables: the mortgage interest rate, loan size, and loan to value (LTV) ratio, that help forecast future curtailments.[6] A borrower's liquidity, value of retiring debt, loan age, and available alternative uses of discretionary funds help predict the likelihood of engaging in curtailment behavior (Abrahams 1997).

Additionally, some previous studies have focused largely on the impact of curtailments in Asian markets since curtailment behavior has been linked to populations with high household savings rates (Lin et al. 2005). In another study of curtailment behavior in Asian markets, Ling and Yang (2005) find individuals who curtail their mortgages exhibit different behaviors than those who do not; curtailment is associated with a 85% reduction in default risk and a 23% higher probability of future prepayment. These behaviors have implications for both the pricing of and investment in mortgage backed securities.

In the most recent study of this behavior by American homeowners using survey data to infer curtailment behavior, a household's propensity to save is found to be highly positively correlated with the probability of mortgage curtailment (as measured by being ahead on mortgage payments) and that liquidity risk also factors into the decision to make a curtail-

[6]The authors utilize LTV at origination, not an estimate of current leverage at the time each observed payment.

ment payment (Adleman, Cross, and Shrider 2010). In contrast, this is the first study to specifically examine loan-level time-varying curtailment behavior in the American mortgage market.

2.2.2 Curtailment Motivation and Descriptive Statistics

Curtailment is an individual expression of a borrower's desired level of mortgage leverage. Conditional on borrowers having funds available to make a curtailment payment, the choice to do so or not will be a reflection of their preferences among available alternatives.[7] A household that engages in this behavior has the choice to spend discretionary income in any manner they see fit, but has elected to apply funds towards the principal outstanding on their mortgage. Household investment and leverage preferences vary across time and may be impacted by changes in variables that are closely connected to housing and mortgage decisions such as interest rate levels and changes in housing price levels.

A borrower who desires to decrease their overall financial leverage may have other outstanding debts that may have higher interest rates (such as credit card debt) or shorter amortization periods (such as automobile loans or student loans) that I do not observe in my dataset. Rationally, a borrower may choose to prioritize to accelerate repayment of these forms of debt instead of reducing mortgage debt, therefore the study of mortgage curtailment cannot provide an exhaustive analysis of a borrower's deleveraging actions, but it can characterize the borrower's appetite for reducing debt in for what a majority of households is their largest financial liability, their home mortgage.

Additionally, a curtailment payment is a reaffirmation of the borrower's commitment to repay the mortgage debt. By putting more funds towards the loan than the mortgage contract requires, the borrower who engages in mortgage curtailment reveals they place a low

[7]Mortgage curtailment is always the choice of a borrower, not an obligation. Since borrowers are never obligated to curtail their mortgage, the amount of money observed to be used as a curtailment payment is some unknown portion of a given borrower's discretionary income.

value on the option to default. Observing curtailment behavior gives insight into borrower choices beyond what is revealed by prepayment or default decisions, such as appetite for leverage.

When a borrower prepays or defaults they are no longer observable, but when a borrower makes a curtailment payment I can continue to monitor their behavior. When the curtailment option is optimally exercised by a rational household, the full menu of mortgage options is available in the next payment period ranging from default to prepayment, but if a borrower prepays in full or loses the home in foreclosure, the mortgage is terminated and no mortgage options may be exercised in the future. Curtailment payments are part of an intertemporal household utility maximization exercise; rational borrowers engaging in this behavior must be of the belief that curtailment payments provide the most utility for a given amount of discretionary income at a given point in time (Chinloy 1993).

Therefore, curtailment behavior decisions hinges on both the desire and ability of the borrower to make curtailment payments. For many borrowers, mortgage curtailment appears to be a regular planned behavior. For example, I observe many borrowers who curtail in the same amount at regular intervals (i.e. a curtailment equal to an extra month's payment once every year or an extra $100 each month). For other borrowers, they may choose to curtail infrequently or perhaps only once over the life of their loan, often in a large dollar amount.[8] Examination of the dollar amount curtailment payments amounts reveals that for all observations with curtailment payment of at least $100, 25.69% make a curtailment payment of exactly $100, 14.04% curtail $200, 10.69% curtail $500, and 9.34% curtail $1,000. Additionally, 36.24% (1,692,475 monthly remittance reports) of all observations with curtailment observations are in the amount of $500 or more and 18.97% of borrowers that engage in this behavior (890,359 monthly remittance reports) curtail $1,000 or more.[9] The distribution of all curtailment dollar amounts for all monthly observations is presented in Figure 2.2.

[8] A complete description of the curtailment criteria and measurement is presented in Section 2.4.2.

[9] Individual curtailments in the amount in excess of $10,000 were not considered in calculating these distributions.

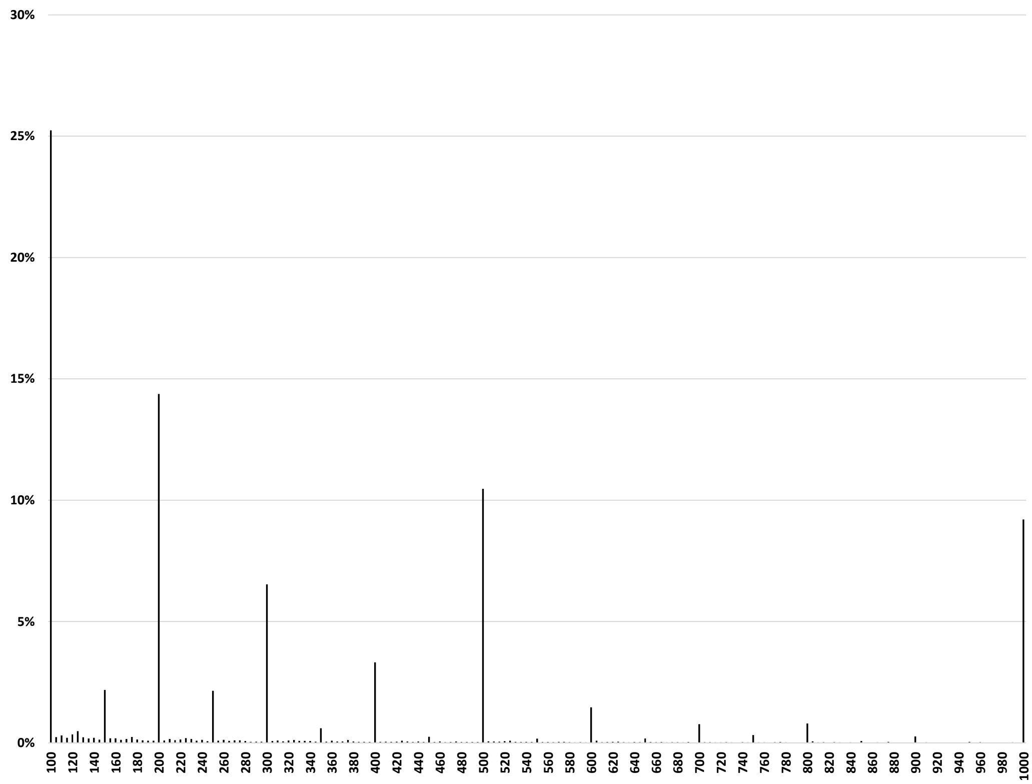

Figure 2.2: Curtailments by Dollar Amount

Curtailments under $100 or greater than 90% of loan balance outstanding are counted as 0 and omitted from this graph.

Considering all loans active as of June 2011, 30.26% had at least one observation of a curtailment at least $100 in their payment history and 11.38% had at least one record of a curtailment of $1,000 or more. Of all borrowers making curtailments over the sample period, about 65% made two or more curtailment payments in our observation period (see Figure 2.3). This contrasts with the earlier findings of Adleman, Cross, and Shrider (2010), who observed that among borrowers in the 1992, 1995, 1998, 2001, 2004 iterations of the Federal Reserve's Survey of Consumer Finances, 22.20% of borrowers made an curtailment payment of any amount sometime in the life their mortgage.

Note that I am only observing loans that were originated in 1998 or later and our observation period ends in mid-2011; there are very few observations of loans over 10 years old in

my sample[10] and as noted by Budinger and Fan (1995) and Abrahams (1997) higher levels of curtailment are associated with older loans, particularly loans nearing the end of their amortization schedule. What I am primarily observing is curtailments of loans fairly early in their amortization schedules.

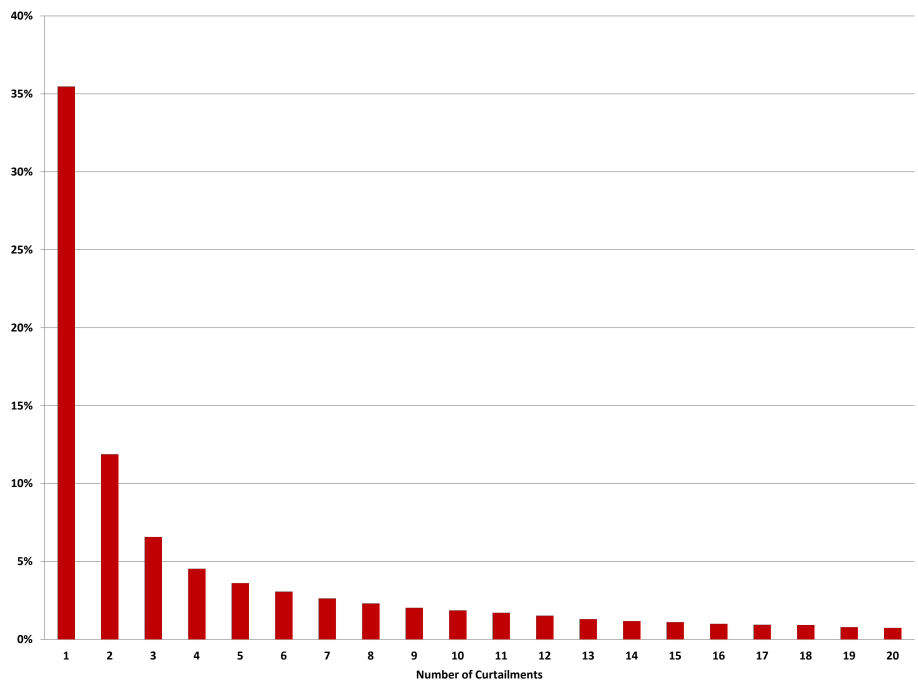

Figure 2.3: Number of Curtailments Per Loan

Only loans containing at least one curtailment are graphed. 14.75% of curtailing borrowers had more than 20 curtailment observations.

As additional evidence that curtailment is an economically significant behavior, I compare average curtailment amounts (using $100 as a minimum value an individual observation being recorded as curtailment) to average principal and total payment due across all observations in the sample. On average across the sample period for every dollar of principal due, there are an additional 8 cents paid as curtailment and on average for every dollar of total payment (principal plus interest) due, I observe an additional 12 cents paid as curtailment.

[10]The average loan of a loan in my sample is 32 months and approximately 95% of the loans within the sample were originated post-2002.

2.2.3 Option aspects of curtailment

Option pricing provides a canonical way to model mortgage choices (Kau and Keenan 1995, Kau et al. 1992, 1995 and Quigley and Van Order 1995). Another way to characterize the choice to curtail a mortgage is within an option pricing framework in which the decision to make an extra payment is a non-terminal choice (Chinloy 1993). However, due to a lack of popularity of curtailment as a payment option to American borrowers in the past, previous empirical studies using US data omit the curtailment choice from the menu of options considered by the borrower (Fei 2010).

A borrower must make a decision each period of whether to pay, not pay, prepay in full, or to partially prepay (curtailment). In a myopic world, where P is the property price, B is the mortgage balance, r is the current rate of interest, and c is the existing rate on the mortgage contract, the borrower would pay in the state of the world where the price $P > B$ and $c < r$, would refinance (prepay) in the state of the world where $P > B$ and $c > r$, and would not pay in the state of the world where $P < B$. Note, a pecuniary motivation for curtailment does not emerge in such a myopic world. However, in the option pricing view of mortgages where the borrower makes decisions today based on various states of the world over the future periods, all possible states have some potential influence on decisions made today. For example, borrowers could decide to pay today even if $P < B$ because of possible states of the world such that $P_t > B_t$, where t is a future time period.

Are there any states of the world or situations where curtailment has pecuniary value? Consider the situation where the borrower needs to have sufficient equity to fall below the maximum permitted loan-to-value ratio (LTV_{max}) to be eligible refinance the mortgage.[11] Now suppose the borrower does not meet the loan-to-value restriction and also pays an above market rate ($c > r$ and $P < B/LTV_{max}$). Furthermore, suppose the borrower does not anticipate or intend to default, and wishes to refinance. In this case, to refinance the

[11] Daglish (2009) discusses the potentially diminished value of the default option for subprime borrowers within a declining interest rate environment.

borrower must reduce the balance B (assuming constant P).

There are two ways to do undertake this strategy. The first way would be to invest money at prevailing short-term risk-free interest rates s until acquiring enough funds to reduce B sufficiently. The second method would be to partially prepay B over time until B has reached the desired level. This curtailment strategy could be undertaken by making several extra payments over time, or if the borrower has sufficient cash on hand, make one large curtailment payment.[12] In environments where $r < c$ and with positive sloping yield curves, $s < r < c$. In this case, curtailment will have a pecuniary advantage over investing funds and deferred prepayment (with the important proviso that the borrower does not anticipate or intend to default). Since curtailment has value in some states of the world, it has a non-zero probability of occurrence. Given that the probabilities associated with the various choices (default, current, curtailment, and prepayment) sum to one, the introduction of the curtailment choice affects the probability of the other choices.[13] To assess the factors that influence the curtailment choice, the curtailment option must be considered alongside the options to default, make the contractually obligated payment, or fully prepay the loan.

2.3 Empirical Strategy

The simplest way of estimating multiple probabilities is by multinomial logistic regression which has been employed in several other mortgage studies (Archer et al 1996, Clapp et al 2001, Clapp et al 2006).[14] Multinomial logit estimates a separate equation for each identified choice as shown in (2.1) where l is the identified choice which runs from 1 to J as shown in (2.2), i is the ith individual observation, x_{it} is a 1 by k vector containing the ith individual's

[12] Theoretically, the borrower could finance the curtailment by taking on new debt, but it unlikely that such a strategy would be financially optimal or even feasible.

[13] Moreover, curtailment in a given period could be followed by states of the world in which continuing curtailment, reverting to regular payment, or choosing a full prepayment could be optimal. In this sense, curtailment can be viewed in a compound options context.

[14] Multinomial logit was chosen over multinomial probit because of computational difficulties and chosen over a competing hazards model due to the potentially repetitive nature of the curtailment choice, unlike the terminal choices of default or prepayment.

explanatory variable data in the tth time period, and y_{it} is the ith individual's choice in the tth time period. However, the mortgage data contains information about individuals without differentiating information specific to each choice. Accordingly, one choice is not identified and becomes the base case. The other estimated equations are in terms of the differences between the respective choice and the base case. Let $\gamma^{(l)}$ represent the difference between the k by 1 parameter vector associated with the lth choice $\beta^{(l)}$ and the base case choice parameter values $\beta^{(0)}$.

$$\Pr(y_{it} = l) = \frac{\exp(x_{it}\gamma^{(l)})}{1 + \sum_{j=1}^{J} \exp(x_{it}\gamma^{(j)})} \tag{2.1}$$

$$\gamma^{(l)} = \beta^{(l)} - \beta^{(0)}, \; l = 1, \cdots, J \tag{2.2}$$

In this context, the base case is that the mortgage is current; the other cases are late, curtailment, or fully prepaid.

Additionally, I employ a two-limit tobit regression model to investigate the effects of the variables of interest on the amount of curtailment a mortgagee, i, chooses to make in a given time period, t. I estimate a model where y^*_{it} is the unobserved latent variable of interest, the amount of curtailment a borrower makes of the form:

$$y^*_{it} = x_{it}\beta + \varepsilon_{it} \tag{2.3}$$

where x_{it} is a vector of borrower characteristics. These borrower characteristics are largely known and fixed at origination, although some individual time varying characteristics are included. Additionally, the vector of borrower characteristics may include fixed effects for loan vintage, location, observation year and time, and servicer that are identified at the individual loan level.

The observed curtailment amount, y_{it}, is related to the latent variable y^*_{it} as follows[15]:

$$y_{it} = \begin{cases} \$0 & \text{if } y^*_{it} \leq \$0 \\ y^*_{it} & \text{if } \$0 < y^*_{it} < \$13,215 \\ \$13,215 & \text{if } y^*_{it} \geq \$13,215 \end{cases}$$

2.4 Data, Variable Definitions and Summary Statistics

I describe data sources and detail our sample section procedure in Section 2.4.1. Next, I define my measurements of curtailment in Section 2.4.2. I define variables and present hypothesis in Section 2.4.3. Last, I provide summary statistics and a correlation matrix for key variables in Section 2.4.4.

2.4.1 Data

Loan-level data comes from Blackbox Logic, LLC (BBx).[16] BBx covers over 90% of non-agency residential securitized mortgages including prime, alt-a, and subprime loans.[17] BBx has detailed mortgage contract information at loan origination and monthly records of mortgage payment information. BBx contains information on 21,409,761 loans, and 708,373,906 remittance records (497,925,228 of which are for single family properties) as of June 2011. The composition of loans in the sample changes over time. New loans enter the sample as they are originated and securitized. Loans exit the sample when they are prepaid in full, the loan term period is finished, or when a property is repossessed by the lender due to

[15] The number of left censored observations depends on the threshold for curtailment used in a given model (e.g. \$100, or \$1,000)The right-censoring value, \$13,215, is the 99th percentile value for positive curtailment observations.

[16] Detailed BBx data information is available at http://www.bbxlogic.com/data.htm.

[17] Agarwal, Chang and Yavas (2012) find evidence of adverse selection in the prime securitzed market, but no clear evidence of adverse selection in the subprime market using similar large mortgage datasets.

non-payment on the part of the borrower. For details of the time-varying market coverage of the BBx database, see Table 2.1.[18]

Table 2.1: BBx Market Coverage 2001-2010, trillions of dollars

Year	BBx	Total Securitized	Total Single Family	Securitized Market	Total Market
2001	$0.11	$3.54	$5.66	3%	2%
2002	$0.25	$3.96	$6.41	6%	4%
2003	$0.34	$7.24	$4.46	8%	5%
2004	$0.59	$4.97	$8.27	12%	7%
2005	$1.10	$5.67	$9.39	19%	12%
2006	$1.77	$6.60	$10.46	27%	17%
2007	$2.25	$7.40	$11.17	30%	20%
2008	$2.19	$7.55	$11.07	29%	20%
2009	$1.84	$7.60	$10.87	24%	17%
2010	$1.53	$3.05	$10.52	50%	15%

Securitized market includes total securitized market, public and private. BBx covers over 90% of the total private securitized market.

Monthly home price index levels for twenty major metropolitan areas comes from the S&P Case-Shiller Composite 20 (CS-20) index. I limit this study to the metropolitan statistical areas represented in the CS-20 index.[19] The Case-Shiller index methodology provides a list of counties included in each of the CS-20 areas; loans in the BBx database are also identified by county as one of the list of variables recorded about the loan at origination. Included in our sample are loans in these geographic areas for which loan characteristics at origination and monthly payment information is available. New observations enter our sample as additional loans are securitized. Mortgages may be seasoned before they appear as observations in our sample since they only enter the database at the point of securitization.[20] Since the CS-

[18] Market coverage was calculated using the methodology from Pafenberg (2005).

[19] Detailed information about Case-Shiller geographic coverage and methodology is available at http://www.standardandpoors.com/indices/sp-case-shiller-home-price-indices/en/us/?indexId=spusa-cashpidff–p-us—-. The CS-20 areas differ slighlt from the Metropolitans Statistical Areas (MSAs) that contain these cities.

[20] For example, in 2001 there could be observations from a 30 year loan originated as early as 1971. However, over 99% of the mortgages in this database are originated in 1998 or later. For simplicity we exclude loans originated before 1998 from our sample.

20 index is based on single family residential transactions (1-4 home properties), I exclude large investment properties (such as apartment complexes). Additionally, for simplicity, we exclude junior mortgages and interest-only loans from our sample.

The key information utilized from BBx is the series of monthly payment data for the over 4 million loans that are located in a county that is included in a CS-20 area. From these remittance records, excess principal payments (curtailments) can be identified on the individual level by date and amount. Additional information utilized from BBx includes loan origination date, securitization date, loan to value (LTV) ratio at origination, FICO score at origination, original loan balance, payment records for each month, prepayment penalty indicator, loan term (15 or 30 year)[21], loan interest type (adjustable rate or fixed rate mortgage), loan documentation level, and loan interest rate both at origination and observation dates.

Prevailing monthly market mortgage rates are from the Federal Reserve, 12 month London Interbank Offered Rate (LIBOR) based on the U.S. dollar are from the British Bankers' Association, and historical loan conforming limits by county are from Fannie Mae.

2.4.2 Identification and Measurement of Curtailment Payments

I identify curtailments at the loan level by the following criteria. First, in the base specifications the curtailment payment in a given month must be at least \$100 and the sum of all curtailments must be greater than \$100 for a loan to be identified as a mortgage that exhibits curtailment behavior.[22] The purpose for setting this minimum value is that in the raw data there are many observations that had very small payments that likely resulted from the borrower rounding the payment amount to the nearest dollar, or even forgetting

[21] Loans of other maturities, such as 20 year or 40 year make up less than 1% of all observations and are excluded from this analysis.

[22] I also set the minimum at \$10 and \$1,000 and the results do not materially change. However, it is worth noting with that with the \$10 minimum, the percentage of loans exhibiting curtailment increases, particularly in the early years of the sample to as high as 3.5% of all observations exhibiting in some months prior to 2006.

the exact amount due; these small amounts likely do not reflect a conscious effort on the part of the borrower to make additional principal payment and increase home equity.

Secondly, I filter the curtailment observations to ensure that the curtailment amount observed does not have a negative offset later (implying the original observation had a recording error). Additionally, I insure that the payment I observe beyond the balance due is for a borrower who is current on mortgage payments and that it results in a corresponding reduction in total balance outstanding in the following period, ensuring that the extra payment is not part of an unobservable late penalty. All observations a mortgage while delinquent in payments are classified as having zero curtailment. However, these observations are still included in our sample, and if they exhibited curtailment behavior before becoming delinquent, those extra payments would still be classified as curtailments and if the borrower later becomes current, any extra payments made after the loan is reclassified as current would be considered curtailments.

Lastly, the partial prepayment must be for less than 90% of the outstanding balance to be considered a curtailment in the sample. The rationale for this criterion is that a large partial prepayment of 90% or more of the balance outstanding is effectively a prepayment in full and therefore not representative of curtailment behavior as we have defined it. This is a reasonable restriction because the vast majority of loans in our sample are early in their amortization schedules, therefore any partial prepayment of greater than 90% is akin to full prepayment; indeed most loans where such a large partial prepayment is observed are paid in full the next month.

Once these restrictions are applied, there are 20,669,757 curtailment events for single family loans identified in the database in the time period January 2001 to June 2011. BBx contains nearly 95 million single family remittance records that are located in a CS-20 city; curtailment behavior is observed in approximately 4.15% of all available monthly observations across all years covered by the database. Although curtailment amounts have a wide

range of values,[23] in the main specification I treat the dependent variable, curtailment, as a dummy variable taking the value 1 if the borrower makes a curtailment payment for a given monthly remittance report, 0 otherwise. I use a binary variable to represent curtailment, because I contrast curtailment with other binary payment choices the borrower may make, being delinquent, remaining current, or full prepayment.

2.4.3 Independent Variables

Previous studies identified several borrower and loan characteristics associated with borrower curtailment choices. In this section, I propose new variables potentially related to a borrower's likelihood of curtailment. Also, I provide additional insight to previously identified curtailment factors.

2.4.3.1 Borrower Leverage

The first key independent variable uses an estimate of current loan to value ratio at each monthly observation, $t{=}m$. This variable is constructed with five key data points, the loan to value ratio (LTV) at origination, which includes the mortgage balance at origination, ($MB_{t=0}$), and value of the home at time of origination ($V_{t=0}$), mortgage balance outstanding at time of observation, ($MB_{t=m}$), the Case-Shiller index level for a given city, i, at origination ($CS^{i}{}_{t=0}$), and the Case-Shiller index level for that city, i, at the time of the observation ($CS^{i}{}_{t=m}$).

A precise updated monthly measure of LTV is not possible, since property appraisals are conducted infrequently, and even when they are conducted, that information is not part of our data set.[24] Since LTV is not updated continuously, this measure provides a reasonable proxy for the changing home price environment the borrower encounters.

[23]Curtailment amounts are allowed to range from \$10, \$100 or \$1,000 (depending on the specification) to 90% of current loan balance outstanding.

[24]As Andersson and Mayock (2014) point out, it is important to use the most accurate measure of CLTV as possible to avoid noisy equity estimates creating biases in estimates.

The current loan to value estimate (CLTV) is given by:

$$current\_ltv_{it} = \left(\frac{(MB_{t=0} + \Delta MB)}{(V_{t=0} \cdot (1 + \Delta CS^{i}))} \right) \tag{2.4}$$

where ΔMB equals the change in mortgage balance from $t=0$ to $t=m$ and ΔCS^{i} is the proportional change in the Case-Shiller index for city i from $t=0$ to $t=m$.

Examining how CLTV influences the propensity to make curtailment payments can offer insight to the borrowers reacting to not only the change in value of their properties over time, but the amount of equity they have in their properties. Level of borrower equity impacts many household decisions, including ability to get home equity loans or refinance their mortgage.

For example, a borrower who originated a loan at the peak of the housing market with a LTV of 1 (the home purchase is 100% financed) and has been making regular payments since origination would have had no trouble obtaining a refinance loan in a growing or stable housing price environment, all else equal. However, if that borrower's property is in an area which has suffered a substantial decline in housing value since origination, the LTV may now exceed 1. If market rates have also declined since origination to the extent that refinance would be favorable for the borrower, without positive equity, refinancing may not be available.[25] This gives the borrower that has sufficient disposable income or other relatively liquid and low-yield savings an incentive to adjust LTV through curtailment, and this incentive is intensified the greater the future savings refinance offers to that individual.

Alternatively, a borrower with very high CLTV may be underwater on their mortgage, that is they owe more on their mortgage obligation than their home is currently worth. Such borrowers may be at higher risk of delinquency or foreclosure and may be financially constrained, making them less likely to make curtailment payments.

Using the CLTV estimate, I construct an indicator variable *neg_ eq* that takes the value

[25] Of course, exact refinance requirements for a given loan are unobservable and may vary by lender and time. However, at the extreme, a reasonable assumption is that having a non-negative equity position would be a necessary condition for finance for most borrowers.

of 1 if a given observation has a CLTV>=1, and 0 otherwise, as well as a complementary indicator variable for positive equity, where *pos_ eq* takes the value of 1 if a given observation has a CLTV<1, and 0 otherwise.

Additionally, borrower leverage at origination is measured by *LTV_ origination*. Although the relationship at origination between choice of leverage and credit spreads is likely endogenous (Titman et al 2005), I am interested in the effects of the initial choice of leverage on future payment decisions. For instance, we would expect high initial leverage to be positively associated with default probabilities, but negatively associated with curtailment or prepayment. Post-origination changes in leverage cannot affect the rate charged on the mortgage or other mortgage features that were contracted at origination of the loan, therefore there is no simultaneous feedback loop between current leverage and mortgage characteristics determined at origination.

2.4.3.2 Savings Premium

The premium over the risk free rate proxy, 12 month LIBOR, is used to measure the relative attractiveness of curtailment as an alternate investment opportunity and is expressed as:

$$savings\_premium_{it} = currentrate_{it} - libor12_t \tag{2.5}$$

As the premium between a mortgage's current interest rate and the prevailing short term risk-free rate grows, investment in reducing the relatively high interest rate mortgage debt may be an attractive alternative investment to some borrowers who view the timely repayment of their mortgage as certain. For accelerated repayment of mortgage debt, borrowers may choose between curtailments and full prepayment depending on household financial situations and preferences as well as refinance eligibility and desirability.

I then consider the possibility that borrowers with current positive equity positions may behave differently than those that currently have negative equity positions. I interact the

savings premium with the positive and negative equity indicator variables (*pos_ eq savings premium* and *neg_ eq savings premium*) to examine the savings premium on borrowers estimated to have positive and negative equity, respectively. The savings premium for negative equity borrowers is expressed as:

$$neg\_eq\_savings\_premium_{it} = savings\_premium_{it} \cdot neg\_eq_{it} \tag{2.6}$$

The savings premium for positive equity borrowers is expressed as:

$$pos\_eq\_savings\_premium_{it} = savings\_premium_{it} \cdot pos\_eq_{it} \tag{2.7}$$

For mortgagors with sufficient levels of home equity to be eligible for refinance, a sizable positive premium over LIBOR should increase the relative probability of prepayment over curtailment. However, observed refinance behavior tends to lag optimal timing for refinance by an average of a year (Stanton 1995), even in periods when excess leverage does not constrain refinance ability. I would anticipate the savings premium to be positively associated with both prepayment and curtailment. However, those borrowers with negative equity may be less able to take advantage of potential savings than those with positive equity. I would expect that savings premium effects may not be significant to other borrowers who may be financially constrained and have no free cash to make a curtailment payment, even as it becomes more financially attractive. Although this hypothesis is not directly testable, a negative equity position is likely correlated with overall financial constraint for the borrower.

2.4.3.3 Measurement of Credit Risk

A borrower's credit quality at origination is largely captured by his FICO score. FICO scores provide a method of ranking potential borrowers by the probability of having a negative credit event in the next two years, typically on a scale from 400 to 850. (Most scores are between 550 and 800.) A negative credit event can be as small as a single missed payment, or can

be a large scale event like foreclosure. Borrowers with lower scores have a greater chance of all types and magnitudes of negative credit events than borrowers with higher scores. Previous studies (e.g., LaCour-Little 1999, Pennington-Cross 2003, and Ghent and Kudlyak 2011) have shown that FICO score at origination is positively associated with prepayments and negatively associated with defaults in both the prime and subprime mortgage markets. Since the curtailment option is more closely associated with prepayment than default, I would anticipate high credit quality to be associated with a higher probability of curtailment, all else equal. Similarly we would expect the relationship between *fico* and prepayment to also be positive.

Additionally, another dimension of borrower's riskiness is captured by the initial interest rate premium. To construct this variable, the initial interest rate on a mortgage is compared with the market rate for a similar type of mortgage at the time of loan origination. For example, the interest rate on a 15 year fixed rate first lien mortgage is compared with the prevailing 15 year fixed mortgage rate for the month that mortgage was originated.

$$rate\_premium_i = initialrate_i - marketrate_{t=0} \tag{2.8}$$

The initial premium attempts to capture a element of borrower risk that is not encompassed by FICO. For example, a cash out refinance mortgage typically has a higher initial interest rate than a traditional refinance. Even if the borrower has an excellent credit score, they may still have an interest rate premium on such a loan. Additionally, the rate premium may be negative for a borrower who has a below market “teaser rate" for some initial portion of the loan's life. I would expect higher values rate premium to increase the likelihood of both default for borrowers with negative equity and increased likelihood of prepayment for borrowers with positive equity, conditional on the loan not being in a period of prepayment penalty.[26]

[26] Although the presence of a positive or negative deviation from market interest rate at origination may not necessarily be a measure of credit risk, because the borrower may or may not have qualified for other mortgages products, it is informative in identifying deviations from a standard contract, a choice on the part

2.4.3.4 Adjustable and Fixed Rate Mortgages

Mortgage type is denoted with an indicator variable that equals one if a loan is an adjustable rate mortgage (ARM), and zero if it is a fixed rate mortgage (FRM). Campbell and Cocco (2003) show that using a life-cycle model with borrowing constraints and income risk that an ARM is generally an attractive choice relative to a fixed-rate mortgage, but this relative attractiveness is diminished for risk-averse households with characteristics such as large mortgages and low moving probabilities.

Since ARMs typically have lower interest rates at origination than FRMs and there is a general declining interest rate regime over our sample period, ARMs may be associated with a higher rate of curtailment if the borrowers are financially non-constrained and respond to lower than anticipated monthly payments associated with declining interest rates. Additionally, making curtailment payments on ARM loans will lead to a reduction in monthly balance due at the next interest reset period, but will not change the overall length of the amortization schedule.[27] This ability to lower future required monthly payments may make curtailment attractive to financially non-constrained ARM borrowers.[28]

2.4.3.5 Term of Loan

In addition to the payment amount and interest rate difference between loans of different lengths, the choice of a 15 or 30 year loan reveals some information about borrowers' debt preferences.[29] Borrowers who choose a 15 year loan show their preference for a shorter term loan, which in and of itself is a form of curtailment (Adelman, Cross, and Shrider 2010). Given this, I might expect borrowers with shorter term loans to have a higher propensity to

of the borrower.

[27] Of course, if interest rates risen, the monthly payment will also rise, but less than it would have if curtailment payments had not been made.

[28] Additionally, ARM borrowers with teaser rates may choose to make curtailment payments near interest rate reset dates to protect against payment shock. Although we do not explicitly test this hypothesis due to data reporting limitations for some servicers, we acknowledge this may be a motivation for borrowers with initial teaser rates.

[29] Although loans for terms other than 15 or 30 years exist in our dataset, I limit this analysis to these two most popular loan terms.

make curtailments than those that have 30 year loans. Alternatively, the future savings in reduced interest payments may offer greater pecuniary benefits for borrowers with 30 year terms than borrowers with 15 year amortization schedules, which could lead to borrowers with 30 year loans having a higher likelihood of curtailment.

2.4.3.6 Loan Size

I classify loans by size according to whether they fit the Fannie Mae conforming loan limits. For a given loan, the original balance is compared to the historic conforming limit for a loan originated in that county for that year.[30] If the original loan balance is higher than the conforming limit, I classify that mortgage as a jumbo loan. All else equal, I would expect large loans to have a higher probability of curtailment as has been found in previous studies.[31]

2.4.3.7 Prepayment Penalty

A prepayment penalty indicates that the borrower may not repay the loan in full or prepay more than 20% of the loan in a single year for some specified period of time after origination without facing a substantial financial penalty. Prepayment penalties have been shown to increase the value of delaying mortgage prepayment in the commercial mortgage sector where such penalties are common (Kelly and Slawson 2001). Prepayment penalties for single-family loans largely fell out of favor in the 1980s, but by the beginning of the sample period, such penalties began to increase in popularity again.

I construct an indicator variable for prepayment penalty that equals one if a loan has a prepayment penalty at the time of a given remittance report, and zero if there is no prepayment penalty currently present for that loan. In my sample the length of the prepayment penalty ranges from 0 months to the full term of the loan. However, 61.89% of the loans

[30] https://www.fanniemae.com/content/fact_sheet/historical-loan-limits.pdf.

[31] Budinger and Fan (1995) and Lin and Yang (2005) both find a positive relationship between loan size and curtailment probability.

contain no prepayment penalty, 5.53% have a prepayment penalty in place for one year, 11.75% for two years, 17.38% for three years, and 2.95% for five years.[32] Since borrowers with prepayment penalties are only severely penalized from repaying their loans in full, all else equal, it is likely that such borrowers are more likely to engage in partial prepayment, or curtailment behavior.[33] Additionally, the presence of a prepayment penalty should lower the likelihood of a full prepayment, due to the large financial penalties that would result from such a decision.

2.4.3.8 Documentation Level

Another variable of interest is the level of documentation a loan is reported to have at time of origination. I create indicator variables for low documentation loans (*documentation_low*) and loans with unknown levels of documentation (*documentation_unknown*), which I compare to the base case of a full documentation loan. I would expect low documentation loans to have lower probability of curtailment and prepayment and higher chance of default relative to loans that are fully documented. Since I do not know the documentation level of the unknown documentation category, I do make predictions of this status on payment outcomes, but simply use it as a means through which I can compare loans known to have full or low documentation.

2.4.3.9 Observation Year Fixed Effects

I use a series of indicator variables to control for the year that each remittance report is observed. As suggested by the raw data, I would expect the coefficients on these variables would be increasing over time. However, unlike the raw data, I would expect the pattern of curtailment to show a smoother increasing trend after accounting for all of the loan level variable and fixed effects.

[32] Cross-sectionally this translates into 77.19% of remittance reports having no prepayment penalty present.

[33] Most curtailment amount are far below the 20% repayment penalty threshold; therefore borrowers with a prepayment penalty will not penalized for engaging in curtailment behavior.

2.4.3.10 Servicer Fixed Effects

Mortgagors' curtailment patterns may vary significantly depending on which institution services the loan. Although borrowers may curtail at anytime, many borrowers may be uneducated about this option unless informed about it by their servicer. Differences in servicer experience and competency may lead to variation in the ease of the execution of the mortgage curtailment option by borrowers. Additionally, servicer fixed effects may capture other elements related to borrower risk that are unobservable in the dataset.

For example, there may be a clientele effect among servicers or certain servicers may have a high concentration of loans containing exotic features that are not visible in dataset. I use a series of indicator variables to assign loans to one of the nineteen largest servicers[34] or to an additional category that encompasses all other smaller servicers' loans. Although I only observe servicer information at time of securitization, I believe this effect captures significant heterogeneity in lending practices as well as other unobservable information about borrowers.

2.4.3.11 Other Fixed Effects

Mortgagors' curtailment patterns may also vary significantly depending on when the loan is originated, where the collateral property is located, and the seasonality of the payment activity. I employ a series of indicator variables to control for fixed effects related to loan vintage, property location, and month of payment observation. The omitted category for loan vintage is 2004, the year with the most new loans entering the sample. The omitted category for payment month is December, and the omitted CS-20 city is Dallas. These variables are primarily used to provide additional controls for potentially unobserved heterogeneity of borrowers. A complete list of variables used is summarized in Table 2.2.

[34] As measured by percentage of loans in the BBx population serviced by a given institution.

Table 2.2: Variable Descriptions

Variable	Description
payment status	categorical variable indicating payment choice of borrower:
	delinquent, current, contains curtailment, or fully prepaid
curtail	1 if the observation contains a curtailment, 0 otherwise
curtail_amt	dollar amount of the curtailment
CLTV	Estimated current loan to value ratio for loan
neg_eq	1 if loan has CLTV>=1, 0 otherwise
pos_eq	1 if loan has CLTV<1, 0 otherwise
savings premium	current interest rate minus current 12 month LIBOR
neg(pos)_eq savings premium	interaction of neg(pos)_eq and savings premium
arm	1 if adjustable rate mortgage, 0 if fixed rate mortgage
term_30	1 if 30 year loan, 0 if 15 year loan
fico	borrower FICO score at origination
rate premium	initial interest rate minus comparable market
	rate at origination
jumbo	1 if original loan balance is larger than conforming loan
	limits for that county at time of origination, 0 otherwise
prepay_penalty	1 if loan contains a prepayment penalty, 0 otherwise
documentation_full	1 if loan is fully documented, 0 otherwise
documentation_low	1 if low documentation loan, 0 otherwise
documentation_unknown	1 if documentation of loan unknown, otherwise
city	1 if property located in a given CS-20 city, 0 otherwise
vintage	1 if loan originated in a given year, 0 otherwise
activity year	1 if remittance report occurs in a given year, 0 otherwise
activity month	1 if remittance report occurs in a given month,0 otherwise
servicer	1 if loan is handled by a given servicer, 0 otherwise

2.4.4 Summary Statistics

Summary statistics for selected variables are presented in Table 2.3 for monthly observations that exhibit curtailment behavior (curtail=1), those that do not (curtail=0), as well as the whole sample.

There are several notable differences between the characteristics of the observations that contain curtailment payments and those that do not. Observations that have curtailment payments are more likely to be adjustable rate mortgages. Lower interest rates, which are associated with ARMs, translate into smaller monthly payments, relative to similar FRM borrowers. (Borrowers who curtail adjustable rate mortgages will have the additional benefit of reducing their future required monthly payment after the interest reset date in a declining interest rate regime.) Financially non-constrained ARM borrowers may respond to the lower interest rate by devoting some of their interest savings to reduce their mortgage debt outstanding.

Additionally, the average savings premium positive equity borrowers with curtailment is higher than loans with positive equity than those without curtailment. The same is true for the savings premium for borrowers with negative equity. However, the two groups are similar on some other dimensions, including likelihood of having a 30 versus 15 year mortgage, documentation levels, and number of borrowers with jumbo loans.

To address any concerns about multicollinearity, a correlation matrix for all key independent variables is included in the Appendix. These correlations show there is no concern about multicollinearity problems amongst these variables (the highest correlation is 0.6373, most are below 0.2). In unreported results, the correlations between all independent variables used were considered, including for all of the fixed effects variables. Most of the correlations are quite low, and none exceed 0.35.

Table 2.3: Summary Statistics

	No Curtail		Curtail		All	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
neg_eq	0.1985	0.3989	0.2397	0.4269	0.2055	0.4041
neg_eq savings premium*	4.0750	1.7766	4.4486	1.7578	4.1487	1.7791
pos_eq savings premium*	2.8690	2.0230	3.2557	2.1678	2.9315	2.0521
LTV_origination	72.7808	15.2873	74.0575	14.8740	72.9965	15.2258
arm	0.5766	0.4940	0.6581	0.4743	0.5904	0.4918
term_30	0.9480	0.2221	0.9568	0.2034	0.9495	0.2190
FICO	688.4406	71.2190	673.2841	77.3188	685.8796	72.5086
risk premium	−0.4797	1.7763	−0.4666	2.3045	−0.4776	1.8760
jumbo	0.1810	0.3850	0.1663	0.3724	0.1785	0.3830
prepay_penalty	0.2252	0.4177	0.2422	0.4284	0.2281	0.4196
documentation low	0.4560	0.4980	0.4604	0.4984	0.4567	0.4981
documentation unknown	0.1852	0.3884	0.1570	0.3638	0.1804	0.3845

*neg_eq (pos_eq) savings premium summary statistics are reported for observations where neg_eq=1(pos_eq=0).

2.5 Results

This section presents and discusses regression results from multinominal regressions in Table 2.4 and the results from two-limit tobit regressions in Table 2.5. For the approximately

75 million single family monthly remittance records for properties located in CS-20 cities for which the curtailment dummy variable is populated, approximately 65 million have non-missing values for all variables of interest in my regression specification. Due to computational constraints, we take a 25% random sample by loan identifier.[35] The regression results for this full sample are presented in Figure 2.4. Complete results, including estimates for all fixed effects, are included in the Appendix. For all regression results, standard errors reported are robust to heteroskedasticity and clustered on the loan identifier level.

2.5.1 Multinomial Logit Results

I present the main results from the multinomial logistic estimations in Table 2.4. (The full results, including all fixed effects estimates, are presented in the Appendix.) Moreover, Table 2.4 contains the results from two multinomial regressions. The first multinomial regression uses the definition of curtailment of $100 or more (positive curtailments of less than $100 would be treated as current, the base case). The second multinomial regression uses the definition of curtailment of $1,000 or more (positive curtailments of less than $1,000 would be treated as current, the base case).

The rationale for the different thresholds are to see if the results are sensitive to large changes in the definition of curtailment and to try to separate large from small curtailment decisions.[36] Presumably, borrowers who make large curtailment payments do so more strategically than individuals who may make small curtailment decisions based on diverse behavioral criteria (dislike of debt, upward rounding of the mortgage payment to the nearest thousand, and so forth).

[35]This is about 875,000 loans corresponding to approximately 18.5 million remittance reports.

[36]I also estimated the model with a curtailment minimum of $10 and results are largely similar to the model with $100 minimum curtailment value.

Table 2.4: Late, Curtailment, and Prepayment Multinomial Logit Estimates

		$100 Min.			$1,000 Min.	
Variables	Late	Curtail	Prepay	Late	Curtail	Prepay
neg_eq	0.3191	−0.4628	−1.0500	0.3326	−0.8518	−1.0342
	25.7979	−20.7940	−45.8078	26.8959	−17.7728	−45.1896
neg_eq savings	0.1616	0.0561	0.2142	0.1545	0.2151	0.2054
premium	56.6626	10.5121	40.3583	54.2679	18.7095	38.7957
pos_eq savings	0.1482	0.0092	0.2920	0.1420	0.1160	0.2837
premium	66.2065	2.5457	116.2488	63.6208	16.3028	113.6475
LTV_origination	0.0161	−0.0032	−0.0013	0.0162	−0.0066	−0.0011
	70.7840	−8.5220	−9.0222	71.5308	−9.5794	−7.4893
arm	0.3371	0.1462	0.4314	0.3313	0.5083	0.4241
	53.8720	11.5977	82.9419	52.9618	20.9231	82.2001
term_30	0.1316	−0.2210	0.0482	0.1401	−0.6307	0.0572
	7.0075	−9.0427	4.5294	7.4574	−14.9945	5.4384
fico	−0.0084	0.0041	0.0004	−0.0085	0.0066	0.0003
	−197.3644	45.8155	11.5260	−200.2674	37.0783	8.0266
risk premium	−0.0019	0.2544	0.0873	−0.0182	0.2598	0.0683
	−1.1037	92.9931	51.6478	−10.8541	51.9495	41.1729
jumbo	−0.2965	0.2594	0.0451	−0.2972	1.0552	0.0469
	−36.5108	21.1403	8.4374	−36.7160	51.8114	8.9040
prepay_penalty	0.0547	0.0974	−0.6072	0.0475	0.2513	−0.6181
	10.2906	9.6178	−124.9288	8.9510	12.6060	−127.6516
documentation_low	0.1444	−0.0805	−0.1885	0.1479	−0.0444	−0.1839
	24.9183	−7.2871	−36.6477	25.5470	−2.1628	−36.2699
documentation_unknown	−0.4143	−0.2432	1.2965	−0.4058	−0.2196	1.3090
	−49.1349	−14.1921	215.2107	−47.9764	−6.2290	219.0656
constant	2.0710	−6.2123	−5.4977	2.1077	−10.1327	−5.4522
	47.6154	−71.4391	−147.6197	48.4804	−58.7720	−147.2812
N observations	18,476,303			18,476,303		
N curtailment	1,323,825			257,298		
N loans	815,827			815,827		
Pseudo-R^2	0.1511			0.1651		

This table presents the multinomial logistic results for the minimum curtailment amounts of $100 and $1,000 with the competing choices of delinquency, current payment, curtailment, or full prepayment. The base case for both regressions is current payment status. Coefficients reported with t-statistics below. Standard errors reported are robust to heteroskedasticity and clustered on the loan identifier level.

The regression incorporates several variables that theoretically should affect the probability of curtailment as well as many control variables. The main pecuniary consideration modeled involves the potential desire to curtail mortgages that charge a higher rate than the rate on savings, as specified by LIBOR. However, individuals with negative equity may wish to preserve their option to default and so may not wish to curtail even if rates are favorable. To model the effects of savings and the different incentives faced by those with positive and negative equity, I allow for a linear trend in the predicted log-odds by including both negative equity (*neg_ eq*) and negative equity interacted with the difference between the current mortgage rate and LIBOR (*neg_ eq savings premium*).

I repeated this exercise with positive equity which led to the variable *pos_ eq savings premium* (but allowed the positive equity to be part of the intercept since the *neg_ eq* and *pos_ eq* indicator variables summed together would equal a constant). Although for both curtailment multinomial regressions, the savings premium for negative equity borrowers has a larger magnitude than the savings premium for positive equity borrowers (0.215 versus 0.116 for the larger curtailment payment), when allowing for the large negative effect for the negative equity indicator variable (-0.852) the relative predicted log-odds of curtailment for those with negative equity is lower (provided the difference between the current mortgage rate and LIBOR is under 8.6%). Therefore, borrowers with positive equity who pay a higher rate for their mortgage compared to LIBOR have increased relative odds of curtailment.

As another pecuniary variable, most prepayment penalties allow some principal reduction before imposing the penalty, and therefore curtailment offers a way to decrease the penalty. The results show that, as anticipated, prepayment penalties increase the relative log-odds of late payments and curtailment (0.048, 0.251), but decrease the relative log-odds of prepayment (-0.618).

In terms of other important mortgage-specific control variables, an increase in the LTV ratio at origination increases the relative log-odds of late payments and decreases relative odds of curtailment and prepayment for both curtailment thresholds. In contrast, ARM

status raises the relative log-odds of late payments, curtailment, and prepayment relative to the base case. Borrowers with 30 year mortgages have higher relative log-odds of being late or prepayment, but lower relative odds of curtailment. Borrowers with higher FICO scores have lower relative log-odds of being late, and higher relative log-odds of curtailing or prepaying relative to the base case.

Borrowers with a higher initial spread have a lower relative log-odds of being late (although in the $100 curtailment case this is not statistically different from the base case) and higher relative log-odds of curtailment and prepayment. Borrowers with jumbo loans have lower relative odds of being late and higher relative odds of curtailment and prepayment. Low documentation status increases the relative odds of late payments, but decreases relative odds of curtailment and prepayment. In contrast, unknown documentation status has higher relative odds of late payments and curtailment, but lower relative odds of prepayment. Note, even though curtailment represents partial prepayment the log-odds coefficient for prepayment and the log-odds coefficient for curtailment do not always share the same signs. Overall, these results are consistent with the hypotheses presented in Section 2.4.3.1– 2.4.3.8.

2.5.2 Full Sample Fixed Effects

To control for various sources of heterogeneity, I include geography, vintage and servicer fixed effects. I control for location fixed effects by using indicators for city of property location. The variation at the servicer level is controlled with indicators for the 19 largest primary loan servicers, plus an additional category that encompasses all the smaller servicers. I also account for unobservable differences in lending standards across time by including indicator variables for year of loan origination. All loans originated in 1998, 1999, or 2000 are included in the *Vintage 2000 or earlier* variable and all loans originated in 2007 or later are included in the *Vintage 2007* group.[37]Results for fixed effects estimates for are included in the Appendix.

[37]Both of these groups include less than 1% of the total sample each, and results do not substantially change if pre-2000 or post-2007 observations are instead excluded. A small portion of the database containing loans

Date of loan payment observation is controlled for in two groups of variables, month fixed effects (discussed in Section 2.5.2.1) and year fixed effects (discussed in Section 2.5.2.2). The base case for each of these four groups of fixed effects is as follows: for servicer fixed effect the base case is the largest primary servicer, Countrywide Home Loans, for location effects the base case is Dallas, for vintage effects the base case is 2004, for activity year effects the base case is 2011, and for month effects the base case is December.

With regard to the servicer indicator variables, relative to Countrywide (the excluded category), almost all of the servicers have significant negative relative odds of prepayment and significantly positive relative odds of curtailment. LaSalle has positive relative odds of both curtailment and prepayment. Litton and PHH have curtailment relative odds that are not statistically significant for the larger curtailment definition.

For the vintage indicator variables, all of the vintages after 2000 (with the exception of 2005) show positive relative log-odds of curtailment for the larger curtailment amount as compared to 2004, the year with the greatest number of new originations. For prepayment, it shows significantly positive relative odds ratios from 2000-3 vintages, but significantly negative relative log-odds ratios from 2005-7.

With regard to the city indicator variables, Boston, Los Angeles, Miami, New York, San Diego, San Francisco, and Washington D.C. all have higher relative log-odds of curtailment and prepayment for both definitions of curtailment whereas Charlotte, Phoenix, and Portland show lower relative log-odds of curtailment and higher relative log-odds of prepayment for both definitions of curtailment, relative to the base case city of Dallas. The coefficients on the larger curtailment amounts for Atlanta, Chicago, Cleveland, Denver, Las Vegas, Minneapolis, Seattle, and Tampa are not statistically significant. Again, the interest for these variables is in capturing heterogeneity in individual loans rather than testing absolute and relative magnitudes of these effects.

originated before 1998 are completely excluded from the sample.

2.5.2.1 Seasonal Effects

The seasonal effects of curtailment are shown in Figure 2.4. These estimates offer some interesting insights to borrower behavior and suggest some possible motivations for the timing of curtailment.[38] As shown in the graph, the probability of curtailment is most likely in December, but also reaches a local maximum in April. Curtailment probabilities show a generally increasing trend from June to the end of the year. Since curtailment is a use of discretionary income and is a form of savings, it makes sense that the likelihood of curtailment is associated with times of the year where borrowers have more available discretionary income or a higher desire to save relative to desire to engage in consumption.

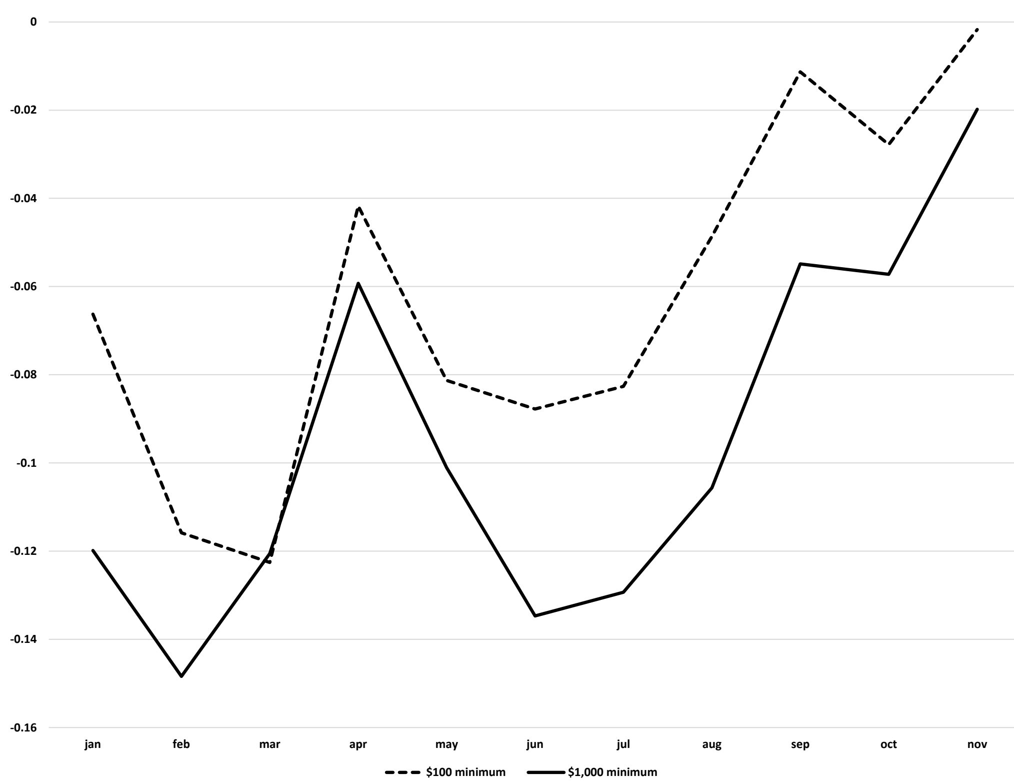

Figure 2.4: Parameter Estimates for Seasonal Effects

Base case is December

[38]Budinger and Fan (1995) present similar results for the seasonality of curtailment in more general terms.

The higher probability of curtailment in December may be associated availability and use of end of the year bonuses, an irregular source of income that financially non-constrained borrowers may choose to devote to accelerated debt repayment. Additionally, end of year curtailment rates may be related to holiday employment. The spike in April may be associated with tax refunds, another source of irregular income that borrowers may devote to mortgage curtailment. Although there is significant seasonal variation in the timing of curtailment choices, partial prepayments are observed throughout the year.

2.5.2.2 Observation Year Effects

The yearly indicator variables capture the effects of time after controlling for many individual level characteristics, geography, loan vintage, servicers, and seasonality of payments. The yearly indicator variables show a pattern of statistically significant, negative relative log-odds of curtailment that become more positive over time for both definitions of curtailment. For example, for the $1,000 curtailment amounts the estimated coefficient for 2002 and before is -21.59 and this rises to -0.078 in 2010. The patterns of relative log-odds for late payments and prepayment do not show such a consistent pattern.

Compared to the dramatic jump in curtailment presented in the raw curtailment data in Figure 2.1, the graph of the parameter estimates for observation year effects also included in Figure 2.1 presents a much smoother pattern of the popularity of curtailment over the sample period. After controlling for borrower and loan variables as well as city, vintage, and seasonal fixed effects, there is no longer a sharp jump curtailment rates in 2006. The probability of curtailment shows a constant pattern of growth of curtailment behavior beginning in 2002.

2.5.3 Curtailment Amount

I use the two-limit tobit specification described in Equation 2.3 to estimate the effects of borrower characteristics on the amount a borrower chooses to curtail. The results from the

full sample as well as splits on loan type and loan term are presented in Table 2.5.[39] In each of the tobit estimations presented I set the minimum curtailment amount to be \$1,000. The signs of each of the variables agrees with the multinomial estimates; the amount of curtailment is positively associated with savings premiums, FICO scores, adjustable rate loans, the rate premium, prepayment penalty, and jumbo loans and is negatively associated with negative equity, original leverage, and low or unknown loan documentation levels. When \$100 is instead used as the minimum value for curtailment, the estimates remain largely similar with the exception of the two savings premium variables, which become insignificant.[40] This supports the notion that large curtailers have more of a savings motivation relative to borrowers who make small curtailment payments.

Within the tobit setting I examine the effects of different term (15 year versus 30 year) and type (FRM versus ARM) on the amount a borrower chooses to curtail. For the loan term comparison we create interaction variables between indicator variables for 15 and 30 year loans and each of the key variables and then estimate a single model containing all of the interaction terms as well as all of the fixed effects. The coefficient estimates for each of the key variables for both 15 and 30 year loans are reported in the second and third column of Table 2.5. I then test if the estimates of each variable is different for the two loan terms and report if the estimates are significantly different in the subsequent column. Borrowers with 15 year loans have significantly different coefficients from borrowers with 30 year loans for savings premium (among borrowers with positive equity), leverage at origination, FICO scores, initial rate premiums, and prepayment penalties.

[39] All geographic, vintage, observation year, observation month, and servicer fixed effects used in the multinomial model were included in estimation, but the output is omitted.

[40] Results from \$100 minimum curtailment value are omitted from Table 2.5, but available upon request.

Table 2.5: Tobit Global and Subsample Estimates

Variables	Global	15 yr	30 yr	Δ	FRM	ARM	Δ
neg_eq	−1,984.4910	−1,388.6090	−1,956.0300		−1,597.3940	−1,982.1330	
	−18.1122	−0.7336	−17.8272		−7.0537	−16.1800	
neg_eq savings premium	533.2325	−35.8444	525.1784		103.3266	568.1202	***
	20.2472	−0.0839	20.0762		1.7566	19.7579	
pos_eq savings premium	323.6201	47.2302	328.7429	***	63.5712	355.0056	***
	17.9115	0.7517	17.7707		2.0106	17.2053	
LTV_origination	−19.2147	8.0738	−22.5075	***	−1.4079	−30.8042	***
	−11.3685	1.7941	−12.7523		−0.5904	−14.1948	
arm	1,247.1800	2,059.6880	1,293.5821		.	.	
	21.6219	2.9432	22.2382		.	.	
term_30	−1,674.4240	.	.		−1,884.5811	−2,225.5248	**
	−16.4637	.	.		−17.7934	−5.3229	
fico	15.7525	16.6913	15.6538	*	13.3307	17.0335	***
	35.5233	26.2136	35.1927		22.6992	34.9980	
rate premium	630.9389	260.3274	632.4170	**	295.7174	622.8852	***
	48.6696	2.1148	48.5500		5.5112	46.7163	

Table 2.5 continued

Variables	Global	15 yr	30 yr	Δ	FRM	ARM	Δ
prepay_penalty	515.5441	−308.1352	593.8134	**	−216.2385	784.3930	***
	10.9988	−0.9385	12.4095		−1.8775	15.0902	
jumbo	2,846.7000	3,106.5090	2,796.6070		2,869.0190	2,788.8460	***
	48.8610	16.0987	46.9568		33.8649	39.7518	
documentation_low	−135.6321	−449.6538	−90.5241		−318.6525	−21.0109	
	−2.7549	−2.4024	−1.7799		−4.1676	−0.3288	
documentation_unknown	−778.6440	−1,210.7930	−501.4495		−304.1952	−573.9149	**
	−9.8610	−2.9203	−6.2316		−1.9020	−6.5361	
Left-censored observations	16,284,395						
Right-censored observations	11,448						
Pseudo-R^2	0.0545	0.0554			0.0558		

Coefficients reported with t-statistics below. *,**,*** indicate subsamples significantly different at 5%, 1%, and 0.1% levels, respectively. Vintage, observation year, observation month, servicer, and city fixed effects included but not reported. Standard errors reported are robust to heteroskedasticity and clustered at the loan level.

Additionally, several variables that are predictive of 30 year loan curtailment amount are insignificant among 15 year borrowers. Although in the global model 30 year loans were associated with smaller curtailment amounts, as mentioned in Section 2.4.3.5, 15 year loans may tend to have more behavioral reasons for curtailment while 30 year loans may have more pecuniary motives, given the greater interest expenses associated with longer term loans.

I then follow the same procedure for testing the differential effects of fixed and adjustment rate mortgage on the amount curtailed. In this specification the sample is more evenly split with 59% of the sample containing observations for adjustable rate loans. In this specification all of the coefficients for the key variables are significantly different between FRMs and ARMs, except for the negative equity indicator and the indicator for low documentation loans. Also, some of the variables that are highly predictive of ARM curtailment amounts are not significant for FRM loans (*neg_ eq savings premium*, *LTV_ origination*, *prepay_penalty*, and *documentation_ unknown*). However, the remaining variables are still significantly predictive of the amount of curtailment chosen by fixed rate borrowers, suggesting that factors such as higher creditworthiness, larger loans, and positive equity positions are the primary considerations of higher curtailment amount for FRM loans.

In general, the results from the multinomial and tobit models are consistent; the same variables that are predictive of the curtailment choice are also predictive of the amount a borrower chooses to curtail.

2.6 Conclusions and Future Research

Historically, curtailment has been a prominent borrower behavior in Asian markets, but largely absent from or considered to be of little significance in the US mortgage market. However, the rate of curtailment for US borrowers experienced tremendous growth in the past decade. In fact, curtailment is a fairly common behavior that I observe in 6% or more of all mortgages each month from 2006 onwards. Additionally, 30% of all mortgages in my

sample have at least one remittance report containing a curtailment payment.

I develop a model to identify borrower and loan specific variables that are associated with a higher probability of making a curtailment payment. I show that curtailment is more likely for borrowers with higher credit scores, shorter loan terms, lower leverage at origination, and current positive equity, all characteristics associated with lower default risk. Borrowers with a prepayment penalty have an increased probability of curtailment (and lower probability of prepayment in full), illustrating that curtailment can be an attractive choice for borrowers desiring to reduce debt outstanding, but facing substantial financial penalties for full prepayment of their loan. Additionally, I provide support to the savings hypothesis of curtailment by presenting evidence that borrowers accelerate repayment of relatively expensive debt.

Most importantly, after controlling for borrower and loan-level variables, as well as fixed effects for geography, year of origination, servicers, and seasonality, I show that the propensity to curtail has increased over the sample period. Interestingly, the increase in curtailment behavior predates the deleveraging trend observed in aggregate consumer debt. I show that mortgage curtailment is both common enough and has enough economic significance to warrant additional attention, which may lead to new insights.

For example, the question of do borrowers who curtail (low current value of default option) but subsequently default provide a control group of non-strategic defaulters is examined in Chapter 3. Additionally, could curtailment act as a barometer of local housing market fundamentals? Does curtailment predict prepayment motivation (moving versus interest rate savings)?

Chapter 3. Mortgage Curtailment and Strategic Default

3.1 Introduction

Mortgage default may be motivated by the inability of a borrower to continue making payments, perhaps due to an idiosyncratic liquidity shock, such as job loss or unexpected medical expenses. Alternatively, mortgage default may also be a reaction to a decline in housing prices that renders the mortgage balance outstanding greater than the property's current value. Liquidity defaults can occur at any time, but the option to strategically default, or for the borrower to exercise the put option on their loan, only becomes valuable in an environment where there are large housing price declines. As home-equity shortfalls increase, borrowers have been shown to increase their willingness to strategically default (Guiso, Sapienza, and Zingales, 2013; Bhutta, Dokko, and Shan, 2010). However, in such a world, both motivations for default exist and it becomes difficult to differentiate between the two.

The difficulty in distinguishing between liquidity and strategic default arises in part because much of the information known about individual borrowers is only collected at the time of origination. Both lenders and policymakers face a substantial informational problem in developing solutions to assist borrowers in an environment where negative equity is prevalent because it is difficult to determine which homeowners would benefit most from a measure of relief to prevent foreclosure (Foote, Geraldi, and Willen, 2008).

There is ample recent evidence that consumers behave strategically in financial decision making. For example, borrowers have changed their relative prioritization, or the pecking order, of repayment of credit card and mortgage debt from 2001 to 2009 (Andersson et al., 2013). Furthermore, the announcement of any modification program may exacerbate potential strategic behavior, such as the 10% relative increase in delinquency rates following

the announcement of the 2008 Countrywide legal settlement, which agreed to offer modifications to severely delinquent mortgagors (Mayer et al., 2014). Therefore, the ability to better predict strategic default behavior is important in developing better responses to observed delinquencies and defaults.

To help circumvent the problem stemming from lack of dynamically updated borrower information, I use monthly payment histories to glean additional insights about loans after origination. Specifically, I identify a group of borrowers engage in mortgage curtailment, or the act of voluntarily making payment in excess of amount the contractually due. These curtailments reveal additional post-origination information about the borrower, namely that the borrower has funds available in excess of the amount due and makes the choice to put some portion of such (unobservable) discretionary income towards the repayment of their mortgage.

In the US market, curtailment has historically been treated as a rare event of little economic consequence, but in recent years it has been shown to be an important household savings mechanism (Adelman, Cross, and Shrider, 2010). Additionally, curtailment is now a common behavior, approximately 35% of first lien mortgages outstanding as of 2012 have made at least one curtailment payment. Curtailment began to increase in popularity as early as 2003; indeed, curtailment is an example of consumer deleveraging behavior that began prior to the Great Recession, as shown in Chapter 2. Additionally, because the borrower has the choice each remittance cycle of whether he wishes to make a partial prepayment or not; curtailment provides dynamically updated information about a borrower's repayment preferences and abilities.

From the perspective of the borrower, curtailing mortgage debt and subsequently defaulting on the loan likely results in a total loss of the excess payments, thus such defaults would be inconsistent with the concept of strategic default. I exploit this mortgage curtailment behavior to show that curtailing borrowers display only approximately half as much sensitivity to current mortgage leverage in their default decisions relative to non-curtailing

borrowers. This result is robust to both the frequency and dollar amount of past curtailments. Additionally, the result is consistent for subsamples of different types of loans, the inclusion of additional demographic and geographic information, as well as a propensity score matched sample. The difference in leverage sensitivity provides support to the concept of using mortgage curtailment to identify loans that are less likely to strategically default. Thus, I contribute to a better understanding of default decisions during the recent mortgage crisis.

The remainder of this chapter is organized as follows: Section 3.2 discusses previous studies that relate to curtailment, mortgage options, and strategic default, Section 3.3 and gives an overview of the data, variables and summary statistics, Section 3.4 presents the empirical models and results, Section 3.5 presents various robustness tests, and Section 4.6 concludes.

3.2 Literature Review

Section 3.2.1 provides an overview of the existing literature on mortgage curtailment. Section 3.2.2 provides discussion on some previous studies on strategic mortgage default. Section 3.2.3 briefly discusses option pricing in the context of mortgage payment decisions.

3.2.1 Mortgage Curtailment

Mortgage curtailment has not received much attention in the real estate literature. Campbell (2006) notes that despite the importance of housing and mortgage debt for households, there is a limited amount of research on mortgage decisions from the perspective of individual households. By using curtailment history to help explain loan-level default, I contribute to the literature on personal mortgage payment choices in the context of household finance.

The first study to investigate mortgage curtailment, Hayre and Lauterbach (1991) highlights the importance of accounting for partial prepayments in calculating the weighted average maturities (WAM) of mortgage pools; failing to account for curtailment will upwardly bias the average age of the mortgage pool. Budinger and Fan (1995) examine curtailments in the context of pools of jumbo loans. They find that curtailments seldom occur early in the life of the mortgage and that curtailment rates significantly increase in the later years of a mortgage and three variables (mortgage interest rate, loan size, and loan to value ratio) help predict future curtailments. Additionally, a borrower's liquidity, value of retiring debt, loan age, and available alternative uses of discretionary funds help predict the likelihood of engaging in curtailment behavior (Abrahams, 1997).

Mortgage curtailment is always an option, not an obligation. Since borrowers are never obligated to curtail their mortgage, the amount of money observed to be used as a curtailment payment is some unknown portion of a given borrower's discretionary income. A household that engages in this behavior has the choice to spend discretionary income in any manner they see fit, but has elected to apply funds towards the principal outstanding on their mortgage. Curtailment payments are part of an intertemporal household maximization decision in which households must choose monthly from a menu of options ranging from default to complete prepayment (Chinloy, 1993). Therefore, rational borrowers engaging in this behavior must be of the belief that curtailment payments provide the most utility for a given amount of discretionary income at a given point in time.

Unlike default or prepayment, which end in loan termination, a borrower who makes a curtailment payment may choose to repeat this behavior several times over the course of the life of the loan. Fu (1997) finds that records of previous curtailment for a given mortgage greatly increases the chances that loan will make a curtailment in the future. Although they do not specifically study curtailment, Amromin, Huang, and Sialm (2007) document the reluctance of households to participate in financial markets and how paying down existing debt can be viewed as an alternate method of personal savings.

A few recent studies have documented the growth and importance of curtailment behavior in the US mortgage market. In a study of this behavior by American homeowners using survey data, a household's propensity to save is found to be highly positively correlated with the probability of mortgage curtailment and liquidity risk also factors into the decision to make a curtailment payment (Adelman, Cross, and Shrider, 2010). In the exotic loan market, over 30% of all borrowers with an interest-only feature make a principal curtailment during the IO period (Janowiak, 2013). Across all loan types, mortgage curtailment has grown in popularity; controlling for a large set of loan characteristics and local economic variables, the probability of making curtailment payments increased dramatically since 2003, with approximately 8% of all monthly mortgage observations containing a curtailment payment and over 30% of all active loans have made at least one curtailment payment as of June 2011, as previously shown in Chapter 2.

Two previous studies have looked at curtailment and mortgage outcomes in Asian markets. Curtailment is a popular choice in Asian markets with high household savings rates. Lin and Yang (2005) find individuals who curtail their mortgages exhibit different behaviors than those who do not; curtailment is associated with a 85% reduction in default risk and a 23% higher probability of future prepayment. These behaviors have implications for both the pricing of and investment in mortgaged backed securities. In a similar study Lin et. al (2005b) find that curtailment is the most significant factor in predicting default probabilities of a seasoned mortgage pool. They conclude that mortgage modeling for Asian countries should be different than mortgage modeling for western countries.

3.2.2 Strategic Default

In order for a mortgage default to be, at least in part, strategic, it is necessary, but not sufficient that the value of the mortgage exceeds the value of the home.[1]It is unlikely that

[1]This is strictly true in non-recourse states.

a borrower will default if the current value of the home exceeds the current balance of the mortgage, because if a borrower finds himself unable to make payments he may sell the home for more than the mortgage balance.

Even if a borrower has a negative equity position, he may choose to continue repayment of the loan because he has a low current value on the mortgage default option. There is mixed evidence on what depth of negative equity is necessary to induce a borrower to default.[2] Given the uncertainty about the true market price of a property (given infrequency of transactions) it is reasonable to assume that the borrower may not know the exact point in time in which a negative equity position is reached.

However, homeowners with negative equity seem to largely be aware of and respond to their negative equity position; Melzer (2012) finds borrowers with mortgage debt overhang respond by reducing investment in home improvements and mortgage principal payments. Also, related to market prices is the role of liquidity in the housing market. As housing prices decline, it becomes harder to sell a home; Elul et al. (2010) cite rising illiquidity as an important factor (in addition to depth negative equity) in strategic default decisions.

Guiso, Spienza, and Zingales (2013) develop a model that shows that strategic default is a function of three categories of variables: the magnitude of the negative equity position, the pecuniary (which vary by jurisdiction, see Ghent and Kudlyak (2011)) and non-pecuniary costs of defaulting (see White (2010) and Seiler et al. (2012)), and the option value of not defaulting in the current period. In this paper, I acknowledge the potential impact of all of these components of strategic default, but focus on empirically testing differences of the impact of the magnitude of the negative equity position (using estimated current loan to value ratios) between borrowers with a history of curtailment and borrowers without a history of curtailment.

[2]See Vandell (1995) for a review of this literature.

3.2.3 Mortgage Option Pricing

A mortgage contract may be broadly described as a series of one month options, where at the beginning of each month the borrower may choose one of several actions ranging from paying nothing to complete prepayment (Chinloy, 1993). If a borrower chooses to default on his loan, this is roughly equivalent to the exercise of the embedded put option in the mortgage contract because in default, the borrower gives up his claim to the underlying asset, the property. More specifically, default can be characterized as a European compound put option because default only occurs at the time of payment (expiration of the option) and a borrower who does not default today has the opportunity to default at a later date (Kau and Keenan, 1995). Alternatively, if the borrower completely prepays the loan (analogous to a call option), he terminates the mortgage contract. When considering mortgage curtailment, the borrower is partially prepaying the loan in the current period, but retaining the full range of options in the next period.

All else equal, the partial prepayment of the mortgage in the current period implies that the borrower assigns a low value to the default option in the near future; if this was not the case, the borrower should retain the funds used to undertake partial prepayment because if the borrower curtails his loan and then defaults, he will not have access to those funds. At the point a loan enters into negative equity territory, the rational borrower must view any past curtailments as a sunk cost in the current period; this sunk cost view may become more pervasive as the negative equity position depends or equivalently the expectation of future increases in housing prices becomes lower. However, if the curtailment is not simply a monetary investment, but a signal of the borrower's attachment to the property or an expression of household preference for lower leverage, then a borrower with past curtailments may have a lower sensitivity to current price in the decision to default.

Option theory predicts that a borrower will default if the put option is "in the money" by some specific amount. However, as illustrated by Deng, Quigley, and Order (2000),

the significant amount of unobserved borrower heterogeneity in the market is important is explaining the exercise of mortgage options (payment choices). The decision to make curtailment payments is a source of individual heterogeneity which may cause differences in default choices, particularly in how default probabilities are impacted by current leverage levels for borrowers with previous curtailment payments versus those with no history of mortgage curtailment. Mortgage option value changes for borrowers who engage in curtailment not only through mechanical changes in outstanding balance and future payment schedules as shown by Chinloy (1993), but also through revelation of updated borrower commitment to loan repayment.

3.3 Data, Variables, and Summary Statistics

I describe data sources in Section 3.3.1, discuss variables used in Section 3.3.2, and present summary statistics in Section 3.3.3.

3.3.1 Data

The primary data used in this study is from individual monthly loan-level records from Blackbox Logic, LLC (BBx).[3] BBx covers over 90% of non-agency residential securitized mortgages including prime, Alt-A, and subprime loans. BBx has detailed mortgage contract information at loan origination and monthly records of mortgage payment information. BBx contains information at origination for over 21 million loans as well as approximately 800 million monthly remittance reports[4] as of December 2013. The primary sample period of this study is from June 2006 to June 2012.

The sample is further limited by only examining loans where the mortgaged property is located in one of the twenty MSAs tracked by the S&P-Case-Shiller Composite 20 home

[3] Detailed BBx data information is available at http://www.bbxlogic.com/data.htm.

[4] BBx contains remittance reports from February 1999 to the present.

price index (CS-HPI). To be included in the sample, a loan must be for a single family residential property and originated no earlier than January 2001, which reduces the sample size to approximately 4.3 million loans. Additionally, I only include loans with 15 or 30 year terms; BBx includes loans with alternate terms (i.e. 10 years, 20 years, or 40 years), but such loans comprise less than 2% of all loans in the database.

Monthly home price index levels for the twenty major metropolitan areas come from the S&P Case-Shiller Composite 20 (CS-20) index. I limit my study to the metropolitan statistical areas represented in the CS-20 index.[5] The Case-Shiller index methodology provides a list of counties included in each of the CS-20 areas; loans in the BBx database are also identified by county as one of the list of variables recorded about the loan at origination. Included in the sample are loans in these geographic areas for which loan characteristics at origination and monthly payment information is available. New observations enter the sample as additional loans are originated and securitized. Mortgages may be seasoned before they appear as observations in my sample since they only enter the database at the point of securitization.

To be included in the sample, a loan must be for a single family residential property and originated no earlier than January 2002, which reduces the sample size to approximately 4.3 million loans. The city specific monthly CS-HPI price levels are used to calculate estimates of borrowers' current loan to value (CLTV) ratios. Restricting the sample to loans with valid observations for all of the variables needed to estimated CLTV, the final sample is between approximately 0.7 millions and 1.3 million loans for each of the seven years in the sample period (2006–2012). There are many reasons an observation could leave the sample during my period of study, including but not limited to foreclosure or complete prepayment due to refinance or sale of the property. Since the shortest loan term I include is 15 years and the earliest loan origination date we allow is 2002, no loans will leave our

[5] Detailed information about Case-Shiller geographic coverage and methodology is available at http://www.standardandpoors.com/indices/sp-case-shiller-home-price-indices/en/us/?indexId=spusa-cashpidff–p-us—-.

sample due to completion of the amortization schedule. Given that the CS-20 index is based on single family residential transactions (which include 1-4 home properties), I exclude large investment properties (such as apartment complexes) from this analysis.

The city specific monthly CS-HPI price levels are used to calculate estimates of borrowers' current loan to value (CLTV) ratios. Restricting the sample to loans with valid observations for all of the variables needed to estimated CLTV, the final sample is between approximately 0.7 millions and 1.3 million loans for each of the seven years in the period of observation (2006–2012).

3.3.2 Variables

This section describes the construction of my dependent variable (default) , my key independent variable (an interaction of curtailment and current leverage), and a host of control variables.

3.3.2.1 Default

Default occurs when a borrower becomes seriously delinquent; in this study I consider any borrower who is 90+ days delinquent to be in default. This definition also includes borrowers currently in foreclosure or bankruptcy proceedings or if the mortgage is currently being liquidated. The rationale for this broad definition of default is that for my primary analysis using logistic regression models I use a cross-section of data to examine a borrower's repayment status in a single month (June) of each year 2006–2012.

Given that I am examining a single time point in each year, I may not be observing the point in time where a borrower enters into serious delinquency; my aim is instead to ascertain a borrower's repayment status at a single uniform point in time. My dependent variable, default, is treated as an indicator variable, taking the value 1 if the loan is currently in a state of default and 0 otherwise. A summary of the default rates for the curtailment and

non-curtailment groups is presented in Figure 3.1. Note, these default rates are not yearly averages, but the default rate for June of each year.

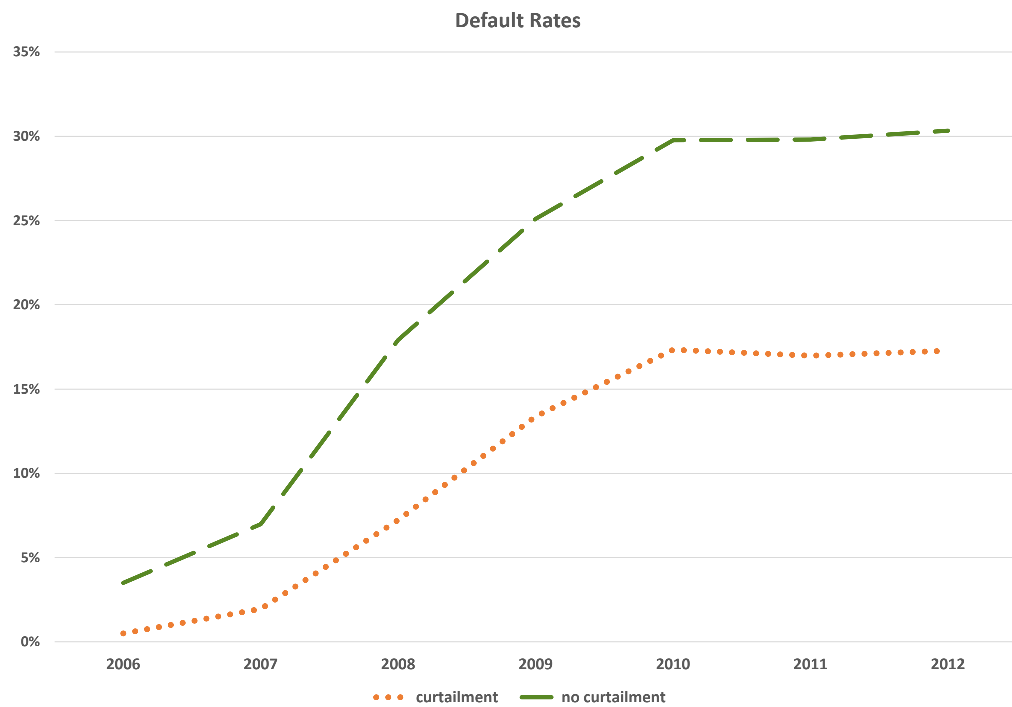

Figure 3.1: Default by group 2006–2012

A snapshot default rates in the month of June presented for the curtailment and non-curtailment groups for each year in the sample.

3.3.2.2 Measure of Historic Curtailment

The key independent variable, historic curtailment, is measured in several different ways. First the remittance records for a loan are searched for a curtailment payment at any point in itself history. In order for a curtailment event to be considered valid, it must meet the several criteria.

First, the excess payment in a given month must be at least \$100 and the sum of all curtailments must be greater than \$100 for a loan to be identified as a mortgage that exhibits

curtailment behavior.[6] The purpose for setting a minimum value for curtailment is that in the data set there were many observations that had very small payments that likely resulted from the borrower rounding the payment amount to the nearest dollar, or even forgetting the exact amount due; these small amounts likely do not reflect a conscious effort on the part of the borrower to make an effort to make additional principal payment and increase home equity.

Secondly, there were some observations in which a partial prepayment is recorded for a given month, and then the following month had an offsetting negative partial prepayment recorded. This likely represents a regular payment made early or a similar recording error that was corrected in the following period. These observations are excluded as are observations for which the sum of all curtailment payments for a given individual loan is negative.

The records of curtailment payments in our dataset become unreliable when borrower is behind on payments, and this issue is exacerbated the greater the delinquency becomes. This is due in part to not knowing what portion of a payment made by a delinquent borrower in excess of the amount past due is related to late fees and other related charges. Therefore, I do not include any curtailment observations for borrowers who are more than 30 days delinquent in their payments. These loans are still observed in our sample, and if they exhibited curtailment behavior before becoming delinquent, those curtailment payments would still be included in my analysis.

Lastly, the partial prepayment must be for less than 90% of the outstanding balance to be considered a curtailment in our sample. The rationale for this criterion is that a large partial prepayment of 90% or more of the balance outstanding is effectively a prepayment in full and therefore not representative of curtailment behavior as I have defined it. Although

[6] I also set the monthly minimum at $10 and $1,000. Additionally, I undertook a similar analysis where I did not consider a loan to exhibit curtailment behavior unless the cumulative curtailment amount was at least $1,000 or the cumulative number of curtailments was above the median number of curtailments for all borrowers with at least one curtailment. In each of these cases, the results do not materially change.

individual curtailment payment amounts have a wide range of values[7], I treat curtailment as a dummy variable equal to 1 if the borrower makes a curtailment payment for a given monthly remittance report, 0 otherwise. At the first observance of a curtailment record that fits these criteria, the variable *curt_ind* takes the value 1 and retains that value for all subsequent loan observations, reflecting that loan has a history of curtailment. Additionally, the number of curtailment payments fitting the above criteria was tabulated and is summarized in the previous chapter in Figure 2.3. The median number of curtailments for a loan where *curt_ind*=1 is 8.

In addition to the concept of curtailment as an indicator variable, I consider the cumulative dollar amount of curtailment for each loan, with the thought that the total amount of funds the borrower has previously committed to the loan as partial prepayments may impact his sensitivity to price in default. Taking the group of borrowers with previous curtailments, I divide these borrowers into one of three categories at each year based on the sum of all their previous curtailment payments. Each variable represents the interaction of an indicator variable taking the value 1 if the borrower is a member of a given payment group in a given year, and 0 otherwise and the estimated CLTV for that loan.

The first group (*curt0_50_cltv*) is comprised of all borrowers whose previous curtailments put them in the 0-50 percentile of all curtailing borrowers that year. The second group (*curt50_75_cltv*) is comprised of the group of borrowers whose previous curtailment place them above the 50th percentile up to the 75th percentile of all curtailing borrowers for that year. The final group (*curt75_100_cltv*) have the largest relative cumulative curtailment amounts for that year, above the 75th percentile of all curtailing borrowers.

The cut-offs for each group are adjusted annually to account for the effects of an additional 12 payment periods in which a borrower had the option to make additional payments. For example, the 50th percentile value for dollar amount of cumulative curtailments ranges from $982.47 in 2006 to $1,936.69 in 2012. The cut-off points are presented in Figure 3.2.

[7]Individual curtailment amounts are allowed to range from $100 to 90% of current loan balance outstanding.

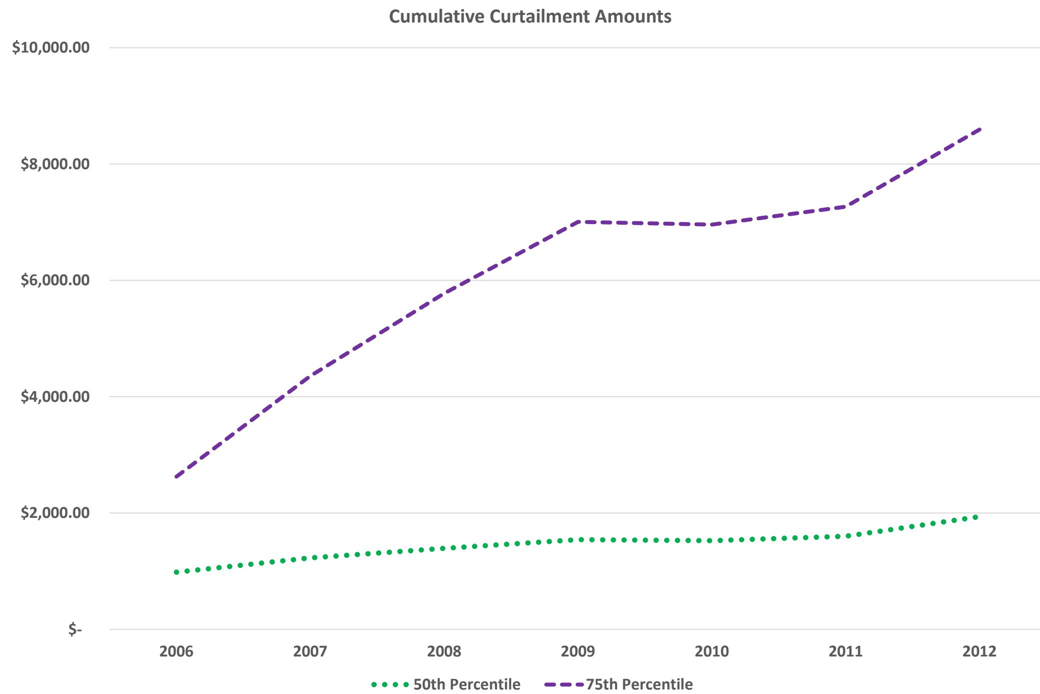

Figure 3.2: Cutoffs for Curtailment Groups 2006-2012

This graph presents the 50th and 75th percentile values for cumulative curtailment amount, which are calculated each year.

3.3.2.3 Current Loan to Value Estimate

Estimated current loan to value (CLTV) is an estimate of current loan to value ratio at each monthly observation, t=m. This variable is constructed with five key data points, the LTV at origination, which includes the mortgage balance at origination, ($MB_{t=0}$), and value of the home at time of origination ($V_{t=0}$), mortgage balance outstanding at time of observation, ($MB_{t=m}$), the Case-Shiller index level for a given city, i, at origination (${CS^i}_{t=0}$), and the Case-Shiller index level for that city, i, at the time of the observation (${CS^i}_{t=m}$). A precise monthly measure of LTV is not possible, since property appraisals are conducted infrequently, and even when they are conducted, that information is not part of the data set. Since each individual's true loan to value ratio is not updated continuously, the measure I

use for estimating current leverage provides a reasonable proxy for the changing home price environment the borrower encounters.

The current loan to value estimate (CLTV) is given by:

$$current\_ltv_{it} = \left(\frac{(MB_{t=0} + \Delta MB)}{(V_{t=0} \cdot (1 + \Delta CS^i)} \right) \tag{3.1}$$

where ΔMB equals the change in mortgage balance from t=0 to t=m and ΔCS^i is the percentage change in the Case-Shiller index for city i from t=0 to t=m.

Examining how CLTV influences the propensity to default can offer insight to the borrowers reacting to not only the change in value of their properties over time, but the amount of equity they have in their properties. As a borrower's CLTV increases, he is losing equity to negative price movements faster than he is gaining equity through reducing the mortgage balance outstanding through making regularly scheduled payments. We would expect such a borrower may be at higher risk of default.[8]

3.3.2.4 Negative Equity

A house is considered to have negative equity, or be "underwater" if it is currently worth less than the outstanding mortgage balance owed on the property. Stated differently, a house negative equity is underwater. I calculate an estimate of current equity using the CLTV measure:

$$CurrentEquity_{it} = 1 - CLTV_{it} \tag{3.2}$$

If *CurrentEquity* < 0 then the indicator variable underwater takes the value of 1, otherwise underwater equals 0. All else equal, I would expect a borrower that is currently in a negative

[8] I exclude loans with current loan to value estimates of greater than 2 (approximately 0.4% of the sample) from our sample because these observations likely have erroneous values for some of the inputs used to calculate this variable. Additionally, we exclude loans with CLTV of less than 0.2, since these loans are relatively close to being fully repaid and likely exhibit different behavior that the larger sample. I also set the minimum at 0.1 and 0.3 and the results do not materially change.

equity position, or “underwater", to be more likely to enter default than a borrower who is currently estimated to have positive equity in his property.

3.3.2.5 Measurement of Credit Risk

The borrower's credit quality at origination is largely captured by his FICO score. FICO scores provide a method of ranking potential borrowers by the probability of having a negative credit event in the next two years, typically on a scale from 400 to 850. (Most scores are between 550 and 800.) A negative credit event can be as small as a single missed payment, or can be a large scale event like foreclosure or bankruptcy.

Borrowers with lower scores have a greater chance of all types and magnitudes of negative credit events than borrowers with higher scores. Previous studies (e.g.LaCour-Little (1999),(Pennington-Cross, 2003), and (Ghent and Kudlyak, 2011)) have shown that FICO score at origination is positively associated with prepayments and negatively associated with defaults in both the prime and subprime mortgage markets. I would anticipate high credit quality to be associated with a lower probability of default, all else equal. I use the log of the FICO score at origination, *log_fico*.

In my sample, the FICO score variable has the highest missing rate among the variables I use in my analysis (approximately 10% of all loans in the database are missing borrower origination credit score). Another measure of credit risk, credit category is available for approximately 98% of loans. Credit categories (prime, alt-a, subprime) are assigned by the lender at the time of origination based on borrower credit risk and level of loan documentation. The results do not materially change if I use the larger sample and use credit category as my measure of credit risk. I chose to present my results with the continuous FICO variable.

3.3.2.6 Other control variables

I include several additional control variables in our default models. I include several time invariant variables, such as the loan's interest rate at origination (*origintrtcalc*) and dummy variables for loan type (*arm*), lien number (*lien_2*), interest-only loans (*io_d*), prepayment penalty (*prepayment_penalty*), loan term (*term_30*), loan purpose (*purchase, cash_refi, reg_refi*), loan origination year (*vintage_X*), and city where the property is located (*city_X*). Additionally, I include some time varying control variables for loan age (*loanage*), current interest rate (*currentintrtcalc*)[9], and a dummy variable for curtailment history (*curt_ind*). A complete list of variables is summarized in Table 3.1.

3.3.3 Summary Statistics

A summary of the default rates for the curtailment and non-curtailment groups is presented in Figure 3.1. Across all years of the sample period, the loans with past curtailment have a lower rate of default than loans with no curtailment. Less than 2% of loans with curtailment defaulted in pre-crisis years, but in 2009 through 2012 between 15% and 19% of loans with curtailment experience default. However, this is much lower than the non-curtailment group, which in the same period ranged between 27% and 31% of loans in default, versus less than 5% in the pre-crisis period.

Additional summary statistics by observation year are presented in Table 3.2. The two groups also vary in terms of other characteristics; for example, borrowers with past curtailment have higher FICO scores. However this difference is not large and attenuates over time (a difference of 32 points in loans observed 2006 versus a 7 point difference in loans active in 2012). Loans with curtailment histories have larger appraisal values, but again the difference becomes smaller between the two groups in towards the end of the sample period.

[9] Of course, current interest rate will only be time-variant for adjustable rate mortgages.

Table 3.1: Variable Descriptions

Variable	Description
curtail_ind	1 if borrower has made at least one curtailment, 0 otherwise
cum_curt	Number of curtailment payments in a loan's history
current_ltv	Estimate of current loan to value ratio at time of observation
curtail_currentltv	CLTV for borrowers where curt_ind equals 1
nocurtail_currentltv	CLTV for borrowers where curt_ind equals 0
curt0_50_cltv	CLTV for borrowers where cumulative curtailment amount up to 50th percentile
curt50_75_cltv	CLTV for borrowers where cumulative curtailment amount 50-75th percentile
curt75_100_cltv	CLTV for borrowers where cumulative curtailment amount 75-100th percentile
arm	1 if adjustable rate mortgage, 0 if fixed rate mortgage
ln_fico	log of borrower FICO score at origination
lien_2	1 if loan is second lien, 0 otherwise
loanage	Age of loan from origination in months
origintrtcalc	Loan's interest rate at origination
currentintrtcalc	Loan's interest rate at time of observation
appraisal	Appraisal value of property at loan origination
purchase	1 if loan's purpose was new purchase, 0 otherwise
cash_refi	1 if cash-out refinance was loan's stated purpose, 0 otherwise
reg_refi	1 if refinance (no cash-out) was loan's stated purpose, 0 otherwise
io_d	1 if loan is interest-only, 0 otherwise
prepay_penalty	1 if loan contains a prepayment penalty, 0 otherwise
term_30	1 if 30 year loan, 0 if 15 year loan
city_X	1 if property located in given CS-20 city, 0 otherwise
vintage_X	1 if loan originated in a given year, 0 otherwise

Table 3.2: Summary Statistics By Year

2006	**No curtailment**			**Curtailment**		
Variable	N	Mean	Std Dev	N	Mean	Std Dev
fico	1,452,926	677	72	197,417	709	64
appraisal	1,724,338	439,995	457,547	196,425	573,337	488,230
LTV_orig	1,724,333	0.74	0.45	196,425	0.72	0.35
current_ltv	1,515,548	0.65	0.22	180,974	0.65	0.22
arm (d)	1,972,110	0.41	0.49	225,606	0.54	0.50
term 30 (d)	1,972,110	0.89	0.31	225,606	0.91	0.29
lien 2 (d)	1,972,110	0.08	0.27	225,606	0.03	0.18
2007	**No curtailment**			**Curtailment**		
Variable	N	Mean	Std Dev	N	Mean	Std Dev
fico	1,828,481	678	70	307,320	707	64
appraisal	2,046,801	443,292	448,041	329,035	596,344	554,322
LTV_orig	1,724,333	0.74	0.45	329,031	0.77	0.51
current_ltv	1,780,084	0.70	0.28	300,413	0.67	0.27
arm (d)	2,367,209	0.40	0.49	382,641	0.54	0.50
term 30 (d)	2,367,209	0.89	0.32	382,641	0.91	0.29
lien 2 (d)	2,367,209	0.12	0.33	382,641	0.04	0.20

Table 3.2 continued

2008	No curtailment			Curtailment		
Variable	N	Mean	Std Dev	N	Mean	Std Dev
fico	1,637,823	682	69	372,871	706	65
appraisal	1,822,854	449,932	457,772	393,260	593,615	532,681
LTV_orig	1,822,833	0.81	0.69	393,257	0.82	0.59
current_ltv	1,608,527	0.81	0.32	352,714	0.80	0.32
arm (d)	2,133,225	0.38	0.49	467,230	0.52	0.50
term 30 (d)	2,133,225	0.90	0.30	467,230	0.91	0.28
lien 2 (d)	2,133,225	0.10	0.31	467,230	0.04	0.21

2009	No curtailment			Curtailment		
Variable	N	Mean	Std Dev	N	Mean	Std Dev
fico	1,294,804	684	69	384,738	701	66
appraisal	1,431,956	457,471	465,551	411,584	577,960	530,664
LTV_orig	1,431,937	0.82	0.68	411,581	0.84	0.61
current_ltv	1,257,687	0.95	0.38	361,263	0.94	0.37
arm (d)	1,692,979	0.36	0.48	487,626	0.53	0.50
term 30 (d)	1,692,979	0.91	0.29	487,626	0.92	0.27
lien 2 (d)	1,692,979	0.09	0.28	487,626	0.04	0.21

Table 3.2 continued

2010	No curtailment			Curtailment		
Variable	N	Mean	Std Dev	N	Mean	Std Dev
fico	1,007,248	682	69	369,025	695	67
appraisal	1,131,850	451,766	460,095	406,202	552,521	513,141
LTV_orig	1,131,834	0.80	0.60	406,199	0.84	0.58
current_ltv	1,001,947	0.92	0.36	357,608	0.92	0.36
arm (d)	1,330,908	0.35	0.48	481,634	0.54	0.50
term 30 (d)	1,330,908	0.92	0.28	481,634	0.92	0.27
lien 2 (d)	1,330,908	0.08	0.27	481,634	0.05	0.21

2011	No curtailment			Curtailment		
Variable	N	Mean	Std Dev	N	Mean	Std Dev
fico	804,408	681	69	366,444	688	68
appraisal	907,292	442,130	444,053	411,945	513,484	482,339
LTV_orig	907,287	0.79	0.53	411,942	0.85	0.56
current_ltv	808,539	0.95	0.37	361,140	0.97	0.36
arm (d)	1,060,677	0.33	0.47	489,427	0.55	0.50
term 30 (d)	1,060,677	0.92	0.28	489,427	0.93	0.26
lien 2 (d)	1,060,677	0.07	0.26	489,427	0.04	0.20

Table 3.2 continued

2012	**No curtailment**			**Curtailment**		
Variable	N	Mean	Std Dev	N	Mean	Std Dev
fico	657,146	680	69	357,336	682	69
appraisal	750,458	431,598	426,923	412,292	480,866	449,100
LTV_orig	750,456	0.77	0.47	412,290	0.85	0.54
current_ltv	671,225	0.93	0.35	363,692	0.96	0.35
arm (d)	870,695	0.32	0.46	487,945	0.56	0.50
term 30 (d)	870,695	0.92	0.27	487,945	0.94	0.25
lien 2 (d)	870,695	0.07	0.25	487,945	0.04	0.20

Interestingly, the group with curtailment has a higher average leverage at origination than the non-curtailment group, and the gap widens in later years. The average current leverage is similar between the groups and is lower that the originally leverage for the first three years of the sample; from 2009–2012 the average current leverage is higher than the average original leverage. This is presented graphically in Figure 3.3. Properties with second

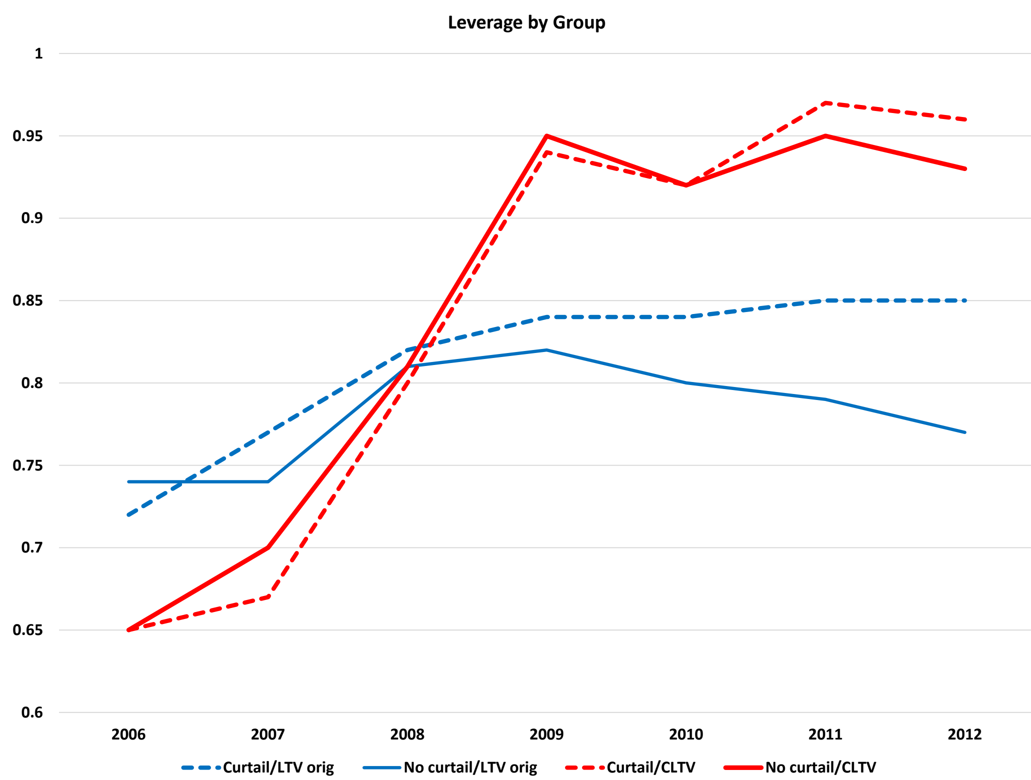

Figure 3.3: Original and Current Leverage by Group

lien loans are more prevalent among non-curtailing borrowers, but curtailing borrowers are more likely to have adjustable rate mortgages. Both groups have a similar proportion of 15 and 30 year loans.

3.4 Empirical Model and Results

I estimate a logistic regression for each year from 2006 to 2012 using the mortgage status as observed in June[10] of each year to examine if borrowers in the curtailment group differ in their sensitivity to current market conditions in their default decisions as compared to the group without previous curtailments. To examine the impact of loan and borrower characteristics on default, I use the following specification:

$$Pr(D_{it} = 1) = \phi\left(X_{it}\beta + Y_i\gamma + \delta_{fe} +\right) \tag{3.3}$$

The dependent variable, default (D_{it}), is a dummy variable that takes the value 1 if a state of serious delinquency or foreclosure is observed for loan i at time t, and 0 otherwise. $Pr(D_{it})$ is the probability that default is observed for loan i at time t. The vector of mortgage characteristics that vary by time and by individual is given by X_{it} and includes a curtailment indicator variable to estimate the effect of individuals' past curtailments on current default decisions. This includes if the loan the key independent variables, the interaction between *curt_ind* and *current_ltv* to examine the sensitivity of each group to current leverage, as well as the current interest rate on the loan, if the loan currently has a prepayment penalty, and the age of the loan.

The vector of mortgage characteristics Y_i, is time invariant. This vector includes all of the origination borrower characteristics including interest rate type and term of the loan, the purpose of the loan at origination, if the mortgage is a second lien loan, the borrower's FICO score, and the interest rate at origination. I also control for fixed effects, δ_{fe}, including vintage fixed effects (base case is 2004) and city fixed effects (base case is Dallas), both of which are known at origination. I expect the curtailment group to respond less to changes in leverage when predicting their probability of default than the group with no curtailment.

[10] The choice of June as the yearly point of observation is arbitrary, the results are similar if other months are chosen.

Results from the logistic regressions presented in Table 3.3 show that for the key independent variables *curtail_ currentltv* and *nocurtail_ currentltv*, each group's probability of default rises with the estimated current loan to value ratio. Across the sample period, the variable *curtail_ currentltv* has a smaller coefficient than *nocurtail_ currentltv*, which suggests that the curtailment group is less sensitive to negative changes in equity than the non-curtailment group. However, both the curtailment and non-curtailment groups, have a positive and significant coefficient on their respective current leverage (CLTV) variables. This suggests that both groups are sensitive to changing house prices. In other words, even the curtailment group has some element of strategic behavior in their default decision, but the effect is smaller in magnitude than that for the non-curtailment group.

For ease of interpretation, I estimate the elasticities of our key variables at different values of current loan to value ratio. These results are presented in Figure 3.4 and Table 3.4. These results clearly illustrate the impact of being underwater on the likelihood of default for the two groups.

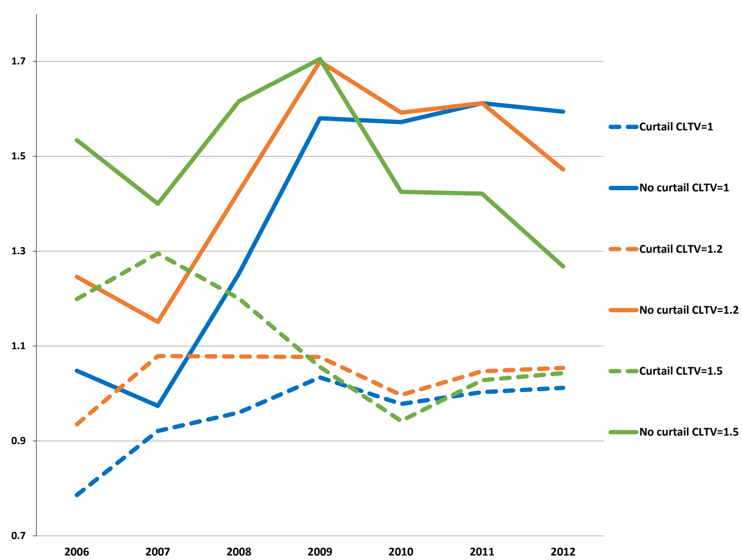

Figure 3.4: Elasticity Estimates

Marginal effects, expressed as elasticities, are estimated for three leverage levels (1, 1.2, and 1.5) for both the curtailment and non-curtailment groups. A current leverage level of 1 (CLTV=1) corresponds to the instance in which the estimated house value is exactly equal to the remaining balance on the mortgage.

Table 3.3: Logistic Regressions for Default

	2006	2007	2008	2009	2010	2011	2012
nocurtail_currentltv	1.093***	1.058***	1.567***	2.218***	2.535***	2.637***	2.850***
	(44.92)	(84.23)	(144.12)	(183.94)	(189.75)	(184.76)	(184.73)
curtail_currentltv	0.834***	1.059***	1.416***	2.071***	2.189***	2.059***	2.034***
	(6.73)	(27.67)	(66.95)	(109.86)	(123.75)	(117.22)	(119.05)
curt_ind	-1.276***	-0.999***	-0.657***	-0.516***	-0.363***	-0.198***	0.00604
	(-14.11)	(-28.16)	(-27.85)	(-22.52)	(-17.49)	(-9.28)	(0.29)
arm	0.205***	0.187***	0.346***	0.333***	0.288***	0.294***	0.310***
	(15.68)	(22.13)	(56.07)	(57.53)	(48.22)	(44.95)	(44.41)
term_30	0.277***	0.106***	-0.0634***	0.153***	0.146***	0.118***	-0.0101
	(10.61)	(6.63)	(-4.89)	(10.25)	(9.19)	(6.53)	(-0.56)
lien_2	-0.0438	-0.229***	0.0548***	0.934***	0.952***	0.786***	1.052***
	(-1.35)	(-12.11)	(3.58)	(57.25)	(57.30)	(41.94)	(55.50)
currentintrtcalc	0.274***	0.352***	0.507***	0.395***	0.286***	0.270***	0.226***
	(61.05)	(139.09)	(225.59)	(152.10)	(132.41)	(137.47)	(122.22)
origintrtcalc	0.0773***	0.0646***	-0.0166***	-0.0930***	-0.107***	-0.119***	-0.108***
	(21.23)	(38.95)	(-11.62)	(-52.53)	(-61.98)	(-67.57)	(-62.03)
lnfico	-5.357***	-4.547***	-3.574***	-4.317***	-4.876***	-4.399***	-3.989***
	(-80.29)	(-108.00)	(-106.36)	(-136.66)	(-156.06)	(-133.28)	(-116.24)
purchase	0.417***	0.323***	0.272***	-0.0219***	-0.0547***	-0.00894	0.0165*
	(27.97)	(34.76)	(39.24)	(-3.30)	(-8.00)	(-1.19)	(2.08)
cash_refi	-0.268***	-0.369***	-0.362***	-0.356***	-0.249***	-0.118***	-0.0548***
	(-16.41)	(-35.16)	(-47.32)	(-50.97)	(-35.52)	(-15.77)	(-6.99)
io_d	-0.100***	0.194***	0.334***	0.235***	0.193***	0.213***	0.203***
	(-5.48)	(20.06)	(50.79)	(38.20)	(30.72)	(31.45)	(28.19)
prepay_d	0.132***	0.161***	0.270***	0.331***	0.262***	0.188***	0.137***
	(10.40)	(19.25)	(43.16)	(55.71)	(43.41)	(29.17)	(20.32)
loanagecalc	0.0642***	0.0567***	0.0131***	0.00750***	0.00426***	0.00480***	0.00201*
	(35.77)	(50.48)	(15.69)	(9.20)	(5.24)	(5.42)	(2.20)
_cons	26.02***	20.26***	14.54***	20.88***	25.97***	22.94***	20.82***
	(57.78)	(71.03)	(63.17)	(95.12)	(119.78)	(98.69)	(84.97)
pseudo R^2	0.226	0.197	0.236	0.209	0.198	0.194	0.188
N	1,288,117	1,608,273	1,385,111	1,125,392	971,050	847,803	763,722

t statistics in parentheses, standard errors robust to heteroskedasticity
vintage and city fixed effects included, loans with CLTV>2 or CLTV<0.2 excluded
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4: Elasticities for Current Loan to Value in Curtailment and Non-curtailment groups

	2006	2007	2008	2009	2010	2011	2012
Estimates at CLTV=1							
nocurtail_currentltv	1.048***	0.974***	1.253***	1.580***	1.572***	1.612***	1.594***
	(0.023)	(0.011)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
curtail_currentltv	0.786***	0.921***	0.960***	1.034***	0.978***	1.003***	1.012***
	(0.131)	(0.030)	(0.010)	(0.004)	(0.003)	(0.004)	(0.005)
N	1,288,117	1,608,273	1,385,111	1,125,392	971,050	847,803	763,722
Estimates at CLTV=1.2							
nocurtail_currentltv	1.246 ***	1.151***	1.426***	1.700***	1.592***	1.612***	1.472***
	(0.270)	(0.130)	(0.008)	(0.007)	(0.005)	(0.004)	(0.003)
curtail_currentltv	0.935***	1.079***	1.078***	1.077***	0.997***	1.047***	1.054***
	(0.131)	(0.033)	(0.010)	(0.003)	(0.002)	(0.005)	(0.004)
N	1,288,117	1,608,273	1,385,111	1,125,392	971,050	847,803	763,722
Estimates at CLTV=1.5							
nocurtail_currentltv	1.534***	1.400***	1.616***	1.705***	1.425***	1.421***	1.268***
	(0.032)	(0.013)	(0.008)	(0.004)	(0.002)	(0.003)	(0.003)
curtail_currentltv	1.199***	1.295***	1.200***	1.056***	0.942***	1.028***	1.043***
	(0.153)	(0.015)	(0.008)	(0.002)	(0.002)	(0.002)	(0.002)
N	1,288,117	1,608,273	1,385,111	1,125,392	971,050	847,803	763,722

Delta-method standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The elasticities are estimated at three points corresponding to different levels of negative equity positions, CLTV=1, CLTV=1.2, and CLTV=1.5.[11] At CLTV=1, or the point where the borrower initially crosses the threshold into a negative equity position, a 10% increase in CLTV is associated with a 10.48% to 16.12% increase in the probability of default in the non-curtailment group versus a 7.86% to 10.34% increase in the probability of default for the curtailment group across the sample period.

As the CLTV rises over 1, the risk of default associated with becoming even further underwater on the loan increases for both groups, but remains consistently higher in the group without curtailment activity. At CLTV=1.5, a 10% increase in CLTV is associated with a 12.68% to 17.05% increase in the probability to default, whereas the same increase

[11] I exclude loans have estimated current loan to value ratios of greater than 2 from our sample. Loans with CLTVs greater than 2 comprise less than 0.5% of all observations across our sample period and are likely the result of data errors in one or more of the variables used to estimate CLTV.

in CLTV is associated with a 9.42% to 12.95% increase in the probability in default for the curtailment group. Across each of the three CLTVs at which the elasticities are estimated for the years 2008–2012, the non-curtailment group always has a statistically significant higher estimated elasticity than the curtailment group.[12] Borrowers in the curtailment group display on average approximately 30-40% less sensitivity to current leverage, relative to borrower the non-curtailment group.

Note that I am not making any claims about the absolute magnitude of strategic behavior on the default decisions; I am only examining the impact of changes in leverage on the two groups. If the two groups had the same unobservable propensity to engage in strategic behavior I would expect the coefficients/elasticities on the two CLTV variables to be the same. Since I observe consistently lower (and significantly different) values on CLTV variables for the curtailment group, I assert that this group appears to be less strategic in their default decision than the non-curtailment group.

Stated differently, these results would suggest that the curtailment group provides a lower bound on sensitivity to current leverage (which is a function of borrower payments and changes in house prices since origination) in the default decision. Recall, the curtailment group had a low value on the default option at the time of the partial prepayment whereas the non-curtailment group had not revealed any additional new information about their commitment to loan repayment, so their option value of default was more uncertain.

The measure of sensitivity of the curtailment group to leverage provides an measure of the level of exigent strategic default in the market, or in other words this is the minimum price sensitivity that I would expect to see. By observing the difference on the estimates of the impact of leverage between the non-curtailment group and curtailment group I obtain an estimate of the magnitude of excess strategic default, or stated differently, this is the portion of strategic default that is more likely to be avoidable and therefore would be of interest to investors and policymakers.

[12]For the years 2006–2007 the non-curtailment group also has a higher estimated elasticity than the curtailment group, but this difference is not always statistically significant.

3.4.1 Cumulative Curtailment Amounts

Using the same methodology from the previous section, I examine the impact of the dollar amount of curtailment on the sensitivity of default. Regression results are presented in Table 3.3. As expected, the magnitude of the sensitivity of borrowers equity to default, decreases uniformly moving from the no curtailment group to the group with the highest dollar amount of curtailment. In the pre-crisis years of the sample, the sign of the sensitivity variable flips for higher levels of curtailment, although some of the coefficients are insignificant or marginally significant.

In estimating the elasticities at CLTV=1 and CLTV=1.5 (presented graphically in Figure 3.5, the biggest decline in sensitivity of price to default occurs as a borrower moves from the non-curtailment group to the lowest dollar amount curtailment group. At the point where the borrower is just crossing into negative equity territory (CLTV=1) belonging to higher dollar amount curtailment groups lowers sensitivity of price in default, and the difference is significant although relatively small in magnitude compared to the gap between the lowest curtailment group and the non-curtailment group. However, this form of the model illustrates a sharper contrast between default sensitivities that the previous form which considered all curtailing borrowers together. On average, the curtailing borrowers display only 50% of the sensitivity of the non-curtailing borrowers to current leverage in their default decisions.

Interestingly, as the negative equity position grows larger (CLTV=1.5) there is no significant difference in between the sensitivities to price between the three curtailment groups. However, there is still a large gap in leverage sensitivity between each of the curtailment groups relative to the non-curtailment group. On average, during the period 2008–2012, the borrowers in any curtailment group display half the the sensitivity to current leverage in default as borrowers in the non-curtailment group.

Table 3.5: Logistic Regressions for Default with Cumulative Curtailment Amounts

	2006	2007	2008	2009	2010	2011	2012
nocurt_cltv	1.127***	1.017***	1.471***	2.190***	2.434***	2.529***	2.696***
	(47.37)	(82.89)	(141.72)	(181.74)	(191.18)	(183.33)	(176.91)
curt0_50_cltv	1.006***	1.082***	1.494***	2.170***	2.213***	2.042***	2.059***
	(7.82)	(26.16)	(66.11)	(109.50)	(123.35)	(114.92)	(114.80)
curt50_75_cltv	-0.158	0.221**	1.007***	1.771***	1.928***	1.766***	1.680***
	(-0.66)	(2.94)	(34.05)	(78.71)	(96.91)	(90.49)	(85.71)
curt75_100_cltv	-0.967**	-1.865***	-0.194**	1.147***	1.523***	1.437***	1.324***
	(-2.62)	(-9.80)	(-3.13)	(38.30)	(63.43)	(64.33)	(62.04)
curt_ind	-1.219***	-0.847***	-0.601***	-0.487***	-0.267***	-0.0638**	0.0827***
	(-11.76)	(-20.68)	(-23.85)	(-20.64)	(-12.98)	(-2.99)	(3.81)
arm	0.234***	0.242***	0.347***	0.320***	0.242***	0.241***	0.263***
	(18.03)	(28.78)	(57.64)	(55.94)	(41.41)	(37.55)	(38.28)
term_30	0.403***	0.218***	0.0786***	0.141***	0.114***	0.0459**	-0.0708***
	(10.35)	(10.95)	(5.88)	(9.21)	(7.40)	(2.58)	(-3.68)
lien_2	-0.106	-0.184***	-0.164***	1.728***	0.926***	0.672***	0.787***
	(-1.93)	(-8.67)	(-11.01)	(110.82)	(58.57)	(36.62)	(39.29)
lnfico	-5.800***	-4.823***	-3.416***	-5.527***	-4.410***	-3.741***	-3.344***
	(-88.15)	(-115.68)	(-104.57)	(-179.29)	(-150.01)	(-121.19)	(-102.83)
currentintrtcalc	0.319***	0.393***	0.501***	0.385***	0.218***	0.207***	0.170***
	(75.53)	(150.79)	(237.49)	(206.50)	(120.41)	(125.21)	(104.56)
purchase	0.452***	0.313***	0.206***	0.0381***	-0.0267***	-0.0176*	-0.00687
	(28.84)	(32.22)	(30.10)	(5.77)	(-3.98)	(-2.40)	(-0.87)
cash_refi	-0.272***	-0.386***	-0.383***	-0.354***	-0.218***	-0.105***	-0.0545***
	(-16.37)	(-36.48)	(-51.11)	(-50.69)	(-31.72)	(-14.27)	(-6.99)
io_d	-0.0673***	0.244***	0.350***	0.181***	0.158***	0.163***	0.147***
	(-3.65)	(25.14)	(54.21)	(29.73)	(25.69)	(24.45)	(20.66)
prepay_d	0.115***	0.126***	0.270***	0.355***	0.315***	0.250***	0.183***
	(8.80)	(15.09)	(44.74)	(60.24)	(53.60)	(39.51)	(27.45)
loanagecalc	0.0578***	0.0499***	0.0126***	0.00202*	0.00317***	0.00470***	0.00164
	(31.47)	(43.45)	(14.99)	(2.47)	(3.93)	(5.41)	(1.78)
_cons	29.06***	22.28***	13.48***	31.01***	22.84***	18.42***	16.46***
	(65.80)	(79.09)	(60.28)	(147.09)	(112.22)	(85.19)	(71.17)
pseudo R^2	0.242	0.205	0.241	0.183	0.196	0.186	0.182
N	1,281,002	1,608,604	1,470,700	1,083,529	1,008,663	863,523	756,659

t statistics in parentheses, heteroskedasticity robust standard errors used
vintage and city fixed effects included, loans with CLTV>2 or CLTV<0.2 excluded
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

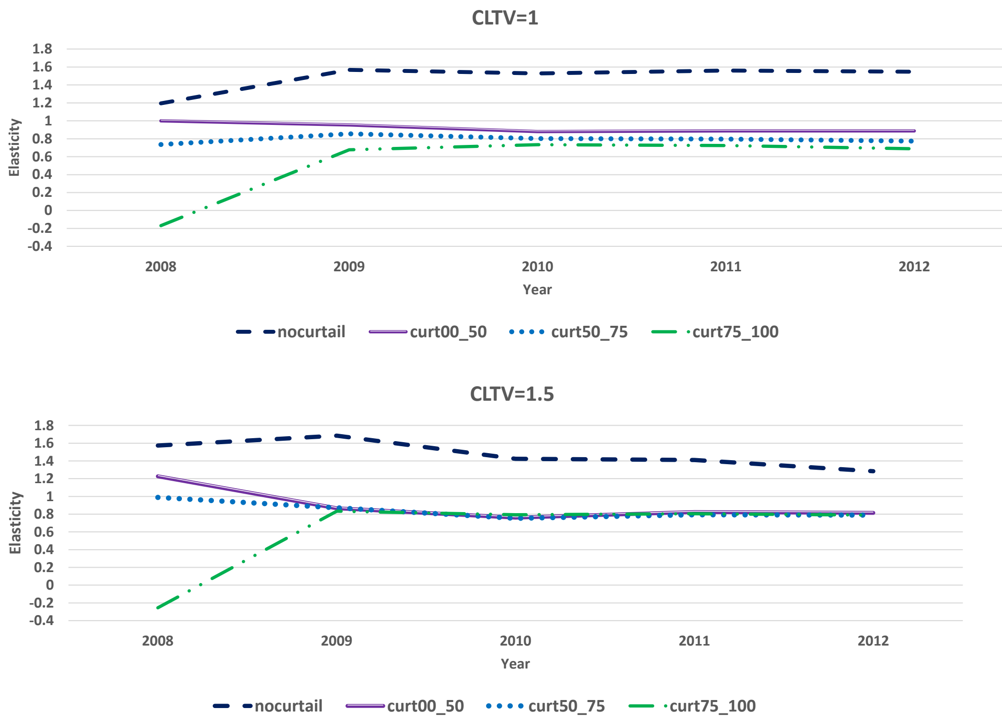

Figure 3.5: Elasticity Estimates by Curtailment Amount

These graphs report elasticity estimates for borrowers at current estimated leverage levels of 1 and 1.5 for three curtailment groups (by dollar amount) and the non-curtailment group.

3.5 Robustness Tests

In this section, I present several robustness tests to help verify that the main results are not driven by subsamples of the data, potential important omitted variables, or by observable group differences. First in Section 3.5.1, I present illustrative results for various subsamples, including splits on loan origination year, loan size, loan type, and credit quality at origination. Next, in Section 3.5.2 I show results that incorporate zipcode fixed effects and census variables for demographic characteristics at the zipcode level. Finally, I present results for propensity score matched samples in Section 3.6. In each of these sections, I present for the

estimated marginal effects for each group at the point where estimated current leverage is equal to 1.[13]

3.5.1 Data subsamples

In this section, I examine several subsamples of borrowers for both the curtailment and non-curtailment groups to verify that the main result is not driven by the inclusion or exclusion of an identifiable subsample of borrowers. First, I examine loans by origination year. This is to address the concern that borrowers originating loans in 2004 (in the middle of the real estate boom) are fundamentally different than borrowers originating loans in 2007, in ways beyond observable origination characteristics, which I control for in all specifications. In Figure 3.6, I present results for loans originated in the years 2004-2007 whose payment status is observed in 2008, 2010, and 2012.

In general, the main result of non-curtailing borrowers having higher sensitivity to current leverage than curtailing borrowers remains consistent for all loan vintages. Like in the main sample, the two groups begin to diverge in 2008 and for the later years, the differences are quite large. Interestingly although the pattern of the differences is consistent overage loan vintage and observation year, the magnitude of the difference is the largest for loans originated in 2007.

Borrowers who originated loans closer to point when house prices reached their peak values saw their equity wiped out sooner than borrowers who had been in loans for a longer period of time before the crisis. Therefore observing borrowers who curtail, even after their original equity is likely erased, probably is a stronger indication of intent to repay than borrowers who chose first chose a curtailment action while prices were still rising. Therefore, conditioning group membership on any past curtailment instead of recent past curtailment likely provides a conservative estimate of the magnitude of our results.

[13]Results are quantitatively consistent for CLTV=1.2 and CLTV=1.5, and are available upon request.

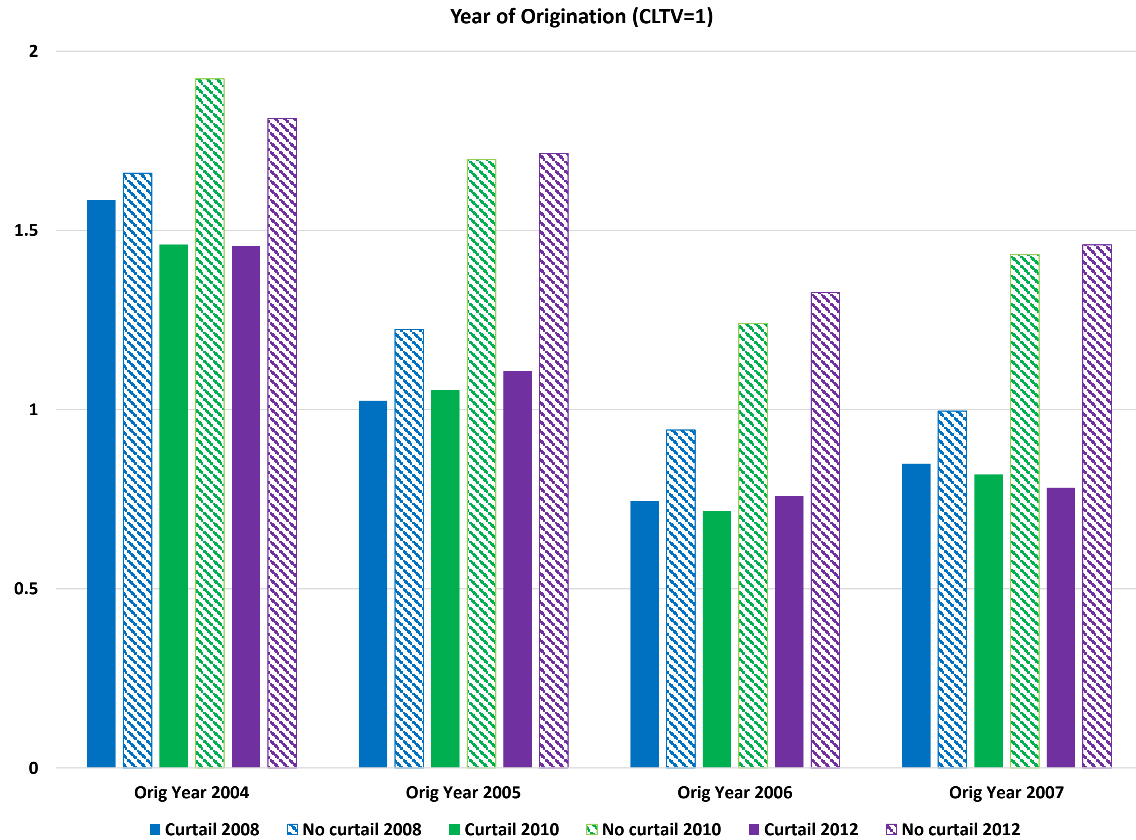

Figure 3.6: Marginal effects by origination year

Marginal effects by origination year are presented for the curtailment and non-curtailment groups. For each origination year (2004-2007) elasticities are estimated for the curtailment and non-curtailment groups each year, but only three years are included for ease of presentation.

Next, I examine subsamples of observations based on the original balance of the loan. I broadly classify the loans into jumbo and conforming sized loans. This designation is based on the dollar amount of the loan, date of origination, and physical location of the property.[14] For the majority of loans in the sample, the conforming loan limit is \$417,000. For both jumbo and conforming loans the sensitivity to current leverage differs in the curtailment and non-curtailment groups (see Figure 3.7).

[14]Historical loan limits can be found at $https://www.fanniemae.com/content/fact_sheet/historical-loan-limits.pdf$. Differential limits on geography (high cost areas) did not begin until 2008.

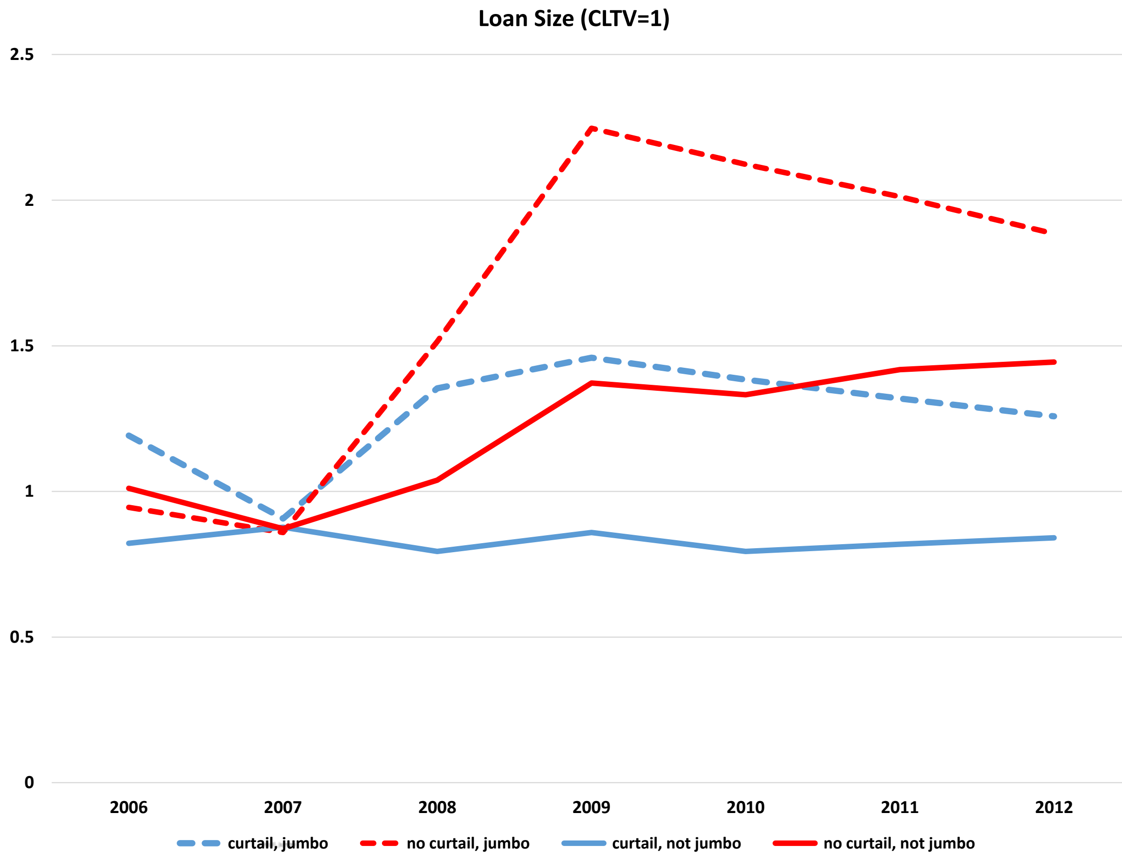

Figure 3.7: Marginal effects by loan size

These results present results both jumbo and conforming sized loans for the curtailment and non-curtailment groups. In most geographic areas and during the majority of the time frame of the analysis the conforming loan limit is $417,000.

I now focus on differences in loan types, namely fixed rate mortgages (FRMs) and adjustable rate mortgages (ARMs). As shown in Figure 3.8, the differences between curtailers and non-curtailers remain for both types of loans. However, the differences in leverage sensitivity between the curtailment and non-curtailment fixed rate borrowers are more dramatic than those for adjustable rate borrowers.

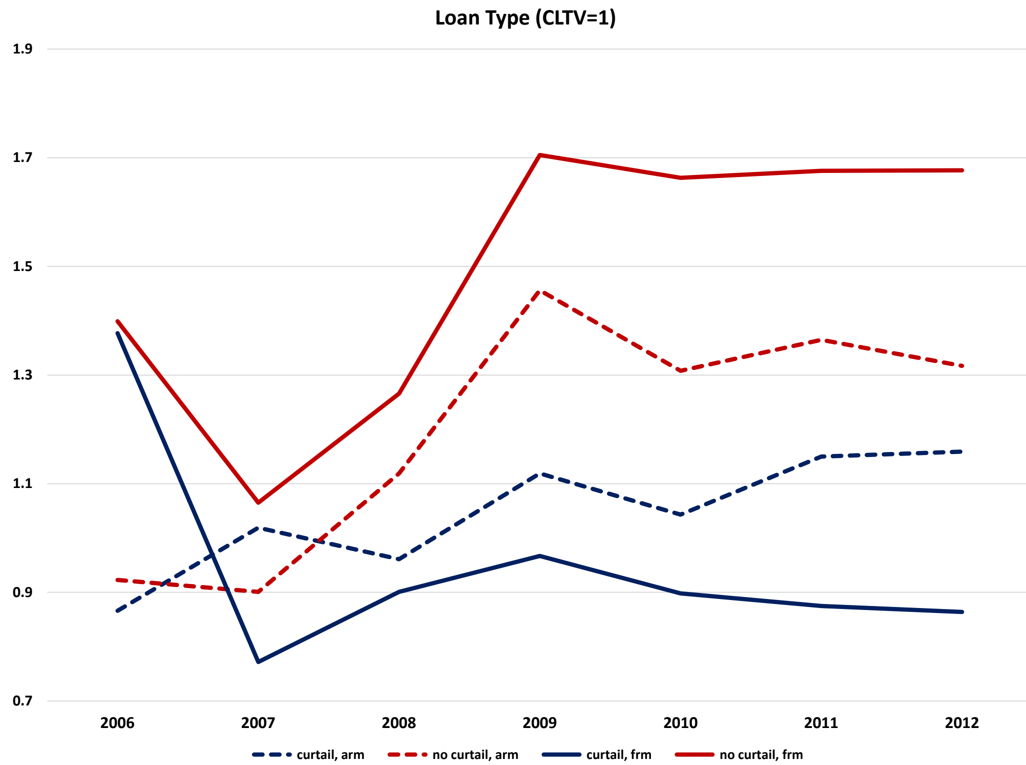

Figure 3.8: Marginal effects for loan types

Presents results for fixed rate mortgages (FRM) and adjustable rate mortgages (ARM).

Finally, I split the sample on credit quality at origination. For simplicity, I group borrowers into prime and non-prime groups, as designated by the lender at origination.[15] As shown in Figure 3.9 the non-curtailment groups for both prime and non-prime borrowers are more sensitive to current leverage in their default decisions that their respective curtailing counterparts. I also considered credit quality based on origination FICO score, and the results are materially similar, but I chose to present these results based on prime designation because there is not consensus on what minimum credit score is needed to be a prime borrower across lenders and time.

[15]The non-prime group contains both alt-a and subprime loans.

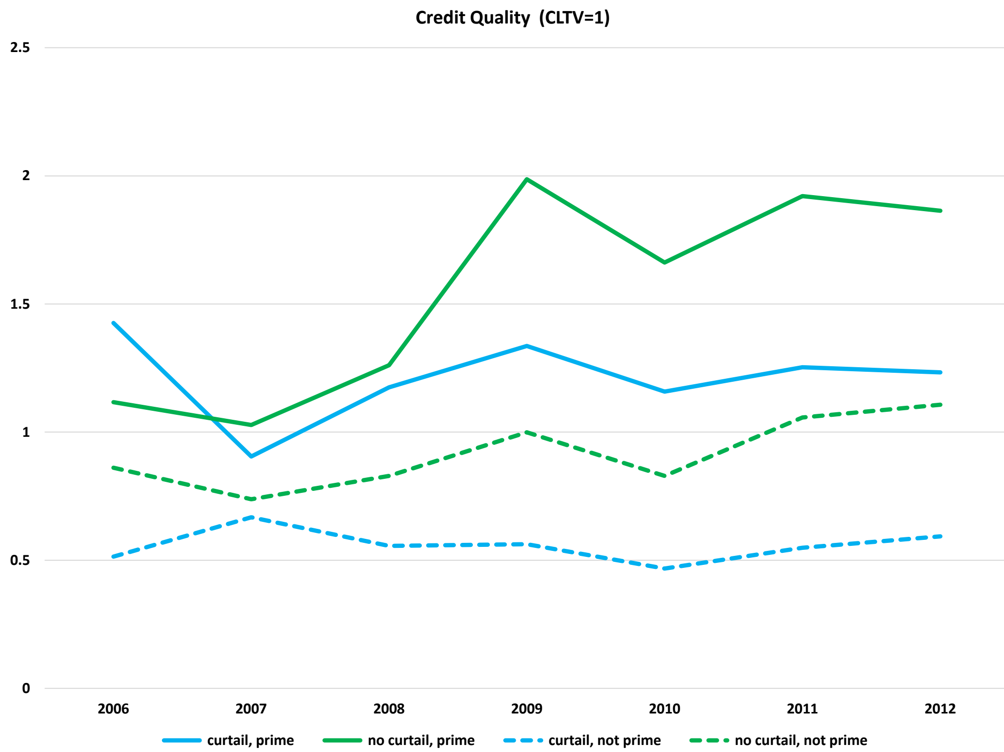

Figure 3.9: Marginal effects for different credit categories

These results present results for prime and non-prime loans, as designated by lender at origination.

3.5.2 Demographic and Geographic Variation

Although ideally I would like to know detailed demographic characteristics about each household, this information is unobservable. To help address concerns that both curtailment and default decisions are impacted by variables such as age, education, income, or race I incorporate these variables as the most detailed level possible, given data constraints. For approximately 95% of the mortgage sample, the finest level locational detail I am able to observe for individual properties is the zipcode in which the house is located. I then obtain variables of interest at the zipcode level from the 2010 US Census and 2011 American Community Survey and match these variables to the mortgage data by zipcode.

Given that new demographic information is unavailable yearly at the zipcode level, I have only one time invariant set of zipcode level characteristics for each loan. The zipcode level variables included are presented in Table 3.6. I then estimate the default model, now including the demographic variables and compare in to the results without the inclusion of the Census variables. Note, the comparison group is slightly different than the main result due to approximately 5% of the observations not having zipcode information available. For this section I use only the observations with valid zipcodes in both the base and comparison groups.[16]

Table 3.6: Census Variables

Variable	Description
log_age	log median age
per_male	percent male (base is percent female)
per_white	percent white and black (base is percent other race)
per_black	
per_children	percent of household with children under 18
per_single	percent of unmarried households
per_occupied	percent of housing stock occupied
per_owner	percent of housing owner occupied
avg_rooms	average number of rooms per house
per_1year	percent of households living in same resident for greater than 1 year
log_income	log of median income
per_EDU	percent of residents with a given highest level of educational achievement: high school, some college, associates, bachelors, graduate or professional (base is less than high school diploma

All variables measured at the zipcode level

Results for the variable of interest, current leverage sensitivity for curtailment and non-curtailment groups, are presented graphically in Figure 3.10. As I expect, the zipcode level time-invariant demographic variables add little predictive power to the model, but coefficients on these variables are either in the expected directions (e.g. higher education levels or higher incomes negatively associated with probability of default) or insignificant. The inclusion of

[16]These results are virtually identical to the original results.

these variables does not substantially change the marginal effects on current leverage for our two groups of borrowers.

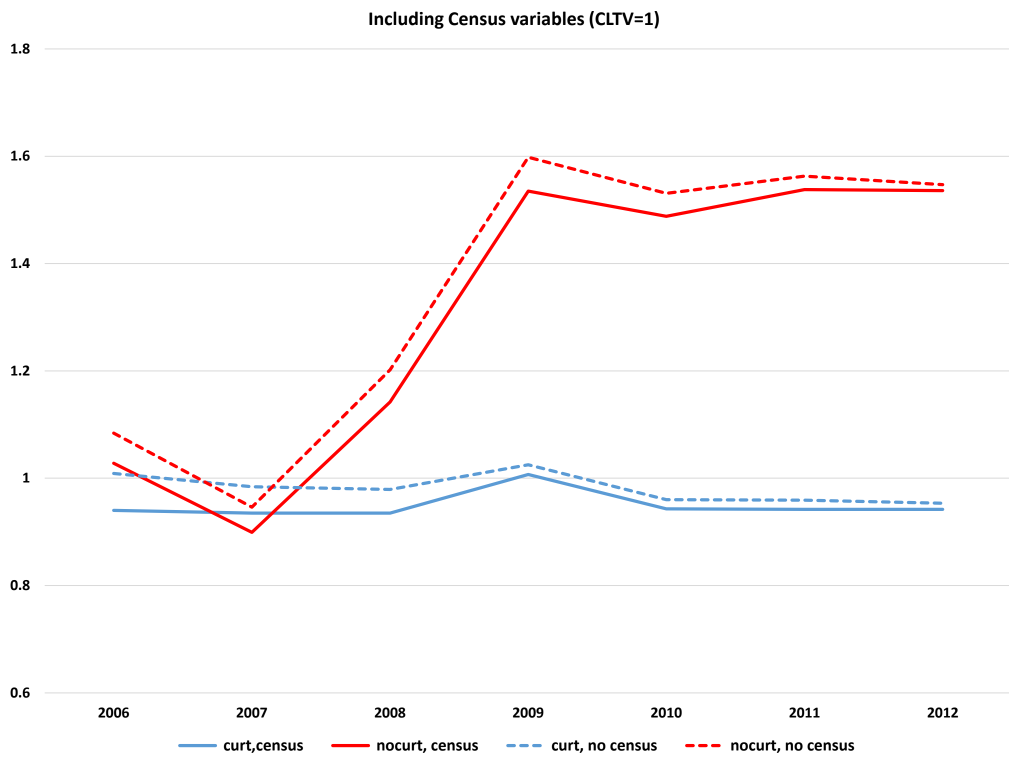

Figure 3.10: Marginal effects with Census variables included

This figure presents results for the curtailment and non-curtailment groups for both a model that includes zipcode level Census variables and a model without these variables.

Next, to further address the possibility that the results could be driven by observable differences in loans in various geographical answers, I examine a model that excludes the Census variables, but includes zipcode fixed effects. First, I identify all zipcodes present in the sample in the first year of payment observation, 2006. Then I rank the zipcodes on number of observations and keep only those loans that are located within the 250 zipcodes with the most observations at that point in time.[17] Although including zipcode fixed effects improves model fit noticeably (approximately 4-7% increase in pseudo-R2, depending on the

[17] There are over 40,000 zipcodes in the US, and over 7,300 with at least one loan observation in the twenty large MSAs included in our sample.

year of observation), the relationship between the marginal effects for the two groups of borrowers remains consistent.

3.6 Propensity Score Matching

Finally, in my series of robustness tests I consider the possibility that the curtailment and non-curtailment groups of borrowers may be different on observable characteristics, and I wish to control for the observable differences in groups. To do so, I employ propensity score matching. This method is appropriate given that there are far more non-curtailing borrowers than curtailing borrowers(Dehejia and Wahba, 2006); even in 2012, the year with the highest percentage of observations belonging to the curtailment group, only about 30% of borrowers have previous curtailments. I employ 1 to 1 matching on all observable characteristics (i.e. all control variables used in the base model) to form a sample of non-curtailing borrowers that is the most similar to curtailing borrowers.

Such a sample selection creates a bias against finding a difference between the two groups because variables that are predictive of curtailment (see Chapter 2) are also predictive of default (albeit in the opposite direction). As shown in Figure 3.11, given that I drop a large portion of our observations to match the relatively rare curtailing borrowers with the most similar non-curtailing borrowers, the magnitude of the difference between the groups somewhat attenuates attenuates, but the curtailing group of borrowers is still much less sensitive to current leverage in default than the non-curtailing group. Even when I compare the non-curtailers that are the most similar to the curtailing borrowers on all known characteristics, there is still a substantial difference in leverage sensitivity between these groups that can be attributed to unobservable differences between the two groups of borrowers which is only revealed in their choice to previously curtail their mortgage.

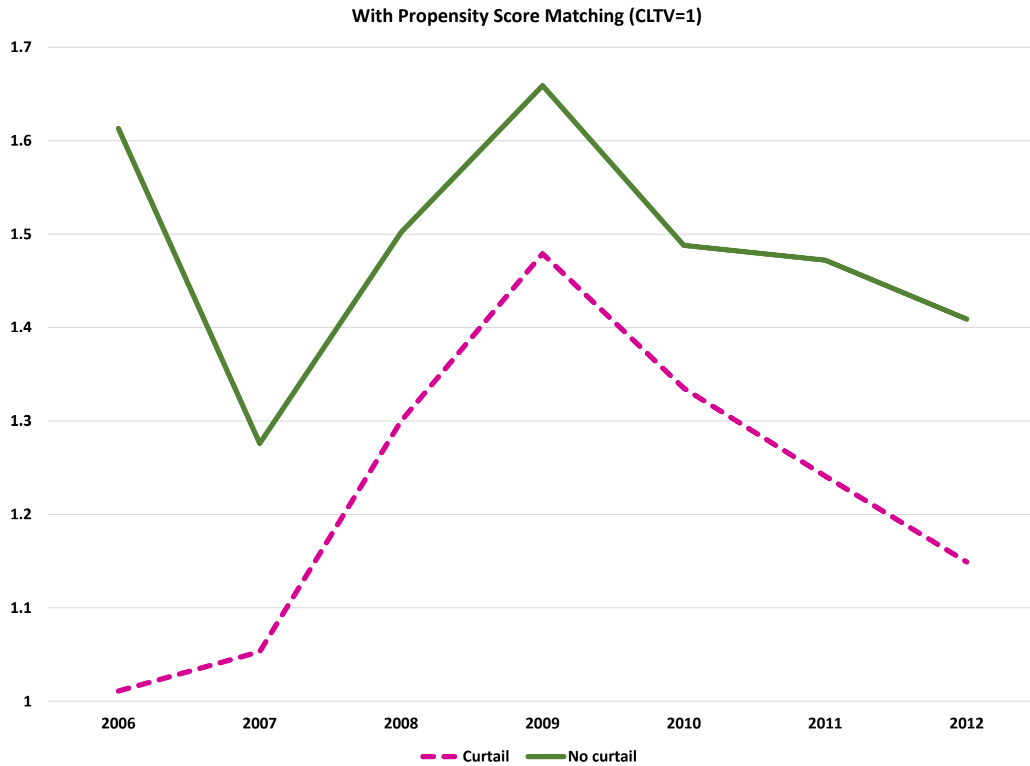

Figure 3.11: Marginal effects for matched sample

This figure presents marginal effects for the matched sample formed using propensity scores.

3.7 Conclusion

In this study, I identify a group of borrowers who have previously revealed a low value on the default (put) option on their mortgages by making voluntary curtailment payments. Even though the probability of default is lower for mortgages with a history of curtailment, many of these previously 'good' borrowers experienced default during the recent housing crisis in spite of having previously engaged in mortgage curtailment.

I find evidence that borrowers with past curtailments are less sensitive to current leverage than borrowers without past curtailments. In other words, borrowers who previously curtailed their mortgages but do ultimately default, are less likely to engage in strategic

default than borrowers who have not made any curtailment payments. Although increases the dollar amount of cumulative curtailment amount seems to lower the sensitivity to price, this effect lessens as the estimate of current leverage increases. However, the large difference in sensitivity of default between borrowers with and without a history of curtailment is large and significant over a wide range of estimated current leverage values. This suggests that the act of curtailment can also be viewed as a dynamically updated signal to the lender of the borrower's intent and ability to repay the mortgage loan.

The use of curtailment payment information from mortgage remittance reports can provide new insights into default behavior for both securitizers of and investors in mortgage backed securities. The information content of curtailment has yet to be fully exploited and numerous potential other applications and extensions for research exist. Given the findings that borrowers who curtail default at lower rates and appear to be less strategic in their choices when they are observed to default, this behavior could be important in loan modification policies and decisions. Given the difficulties of disentangling the impact of negative equity on default choices (Foote, Geraldi, and Willen, 2008), a possible extension of this study is to examine effects of curtailment in the approval of loan modifications and the resulting subsequent re-default rates.

Additionally, evidence relating to strategic behavior in borrowers is important in formulating an appropriate policy response to observed widespread defaults. Differentiating between the relative prevalence of strategic or liquidity motivations for default allows for policymakers to identify the relative importance of house price declines and borrower ability to pay in defaults.

Given that most information on an individual borrower is collected only at loan origination, examining borrower payment histories is useful in better understanding borrower choices post-origination. Specifically, examining the mortgage curtailment behavior of borrowers provides a setting in which we can identify borrowers who are less likely to strategically default, which contributes to a better understanding of borrower default decisions.

Chapter 4. Income Stability and Mortgage Default

4.1 Introduction

Were declining house prices the major culprit in mortgage default during the Great Recession or was default largely a natural outcome of borrower job losses? Answering this question is surprisingly difficult since very little information is collected on the individual borrower after mortgage origination. Personal income and employment status are known by lenders at the time of mortgage loan origination; however, as time passes these variables can change and impact the ability of the borrower to repay the loan. Therefore, only having information about the borrower and the loan at time of origination makes it difficult to ascertain if a later default is more related to liquidity constraints (current ability to pay) or strategic behavior (current value of the asset).

Negative equity (owing more on the mortgage than the property is currently worth) is a necessary, but not a sufficient condition for default. Conditional upon negative equity, the ability to pay should impact default rates. This dual trigger (negative equity and job loss) hypothesis is not new to the mortgage literature (Jackson and Kaserman, 1980; Campbell and Dietrich, 1983; DeVaney and Lytton, 1995; Elmer and Seelig, 1999; Getter, 2003), but has received a great deal of attention recently (Foote, Geraldi, and Willen, 2008; Foote, Kristopher Geraldi, and Willen, 2010; Elul et al., 2010). Among other insights, this research has highlighted the difficultly of disentangling the relative effects of price declines and income shocks in borrower default decisions.

Although job loss (or equivalently, the loss of the ability to make regularly scheduled loan payments) is anecdotally cited as a leading reason for mortgage default, empirical estimates on the effects of income and unemployment are small compared to the effect of

financial characteristics such as FICO scores or loan-to-value ratios. However, individual information for income and employment status, although collected by lenders at origination, is not dynamically updated. Debt-to-income (DTI) ratios from loan applications do not offer much in the way of predictive power in the default models, particularly as time passes since origination (Foote, Kristopher Geraldi, and Willen, 2010).

The use of proxies for individual level income shocks, such as county or MSA level unemployment, often result in coefficients that are insignificant or very small in magnitude in default models. Theoretically, income shocks are important in mortgage default (Campbell and Cocco, 2011); by using proxies for individual level proxies for unemployment status, unemployment is the strongest predictor of default (Gerardi et al., 2013). Recent research indicates that the role of unemployment status (and by extension, current income) may be underestimated due to omitted variables problems (Gyourko and Tracy, 2014).

Such omitted variables problems can lead to bias in estimated parameters when the omitted variables are correlated with the included variables, or inflate the disturbance term. In addition, omitting uncorrelated variables essentially provides a source of unmodeled heterogeneity. For limited dependent variable models, however, unmodeled heterogeneity yields attenuated (shrunk towards zero) parameter estimates (Yatchew and Griliches, 1985), regardless of sample size. Attenuation bias does not necessarily affect estimation of the marginal effects, but it can affect classification or prediction (Ramalho and Ramalho, 2010).

To avoid the complexities posed by interactions among house prices, employment status, and income, I propose the natural experiment of examining the default decisions of workers with job security. Specifically, I follow governmental workers (including police, firefighters, city administrators, lawyers, public school teachers, and college professors) employed in Clark County Nevada in 2009, during the midst of the Great Recession, to examine the sensitivity of their default decisions to house prices relative to the general population. Currently employed governmental workers not only have an income, but also have more security with regard to future income, and are less likely to have experienced a material pay cut than private sector

workers. In addition, governmental workers have health insurance and often enough paid sick leave so that short term health problems do not trigger loss of income. In other words, all individuals in the government employees portion of our sample are employed in FY2009-10 and on average have relatively low expected future income volatility. Consequently, the potentially confounding effects of income shocks in mortgage payment decisions should be minimized among this group as compared to the general population.

Traditional mortgage data has great detail on the loan and property, but little on the borrower. Moreover, this information is known at loan origination, but it may become less relevant as time passes. Insofar as mortgage research struggles with omitted variables problems, I augment my data with public records to include individual specific characteristics of the homeowner's sex, age, marital status, and political affiliation. Additionally, for governmental workers, we observe their current salary, job title, and place of employment. Although variables such as profession and income may directly affect the propensity to default, all of the variables may be correlated with other unobserved variables, such as wealth and risk preferences.

The purpose of this paper is to examine (1) whether including a measure of post-origination income stability makes a fundamental difference in the estimated sensitivity of the default decision to housing prices; and (2) what difference including additional variables (employment status, income, personal characteristics) makes to improving the fit of mortgage default models.

I find that borrowers with known income stability and documented income are equally sensitive to price in the default decision as the general population of borrowers, whose current income and employment status is unknown. This result is robust to marital status, house price range, and several definitions of default.

Additionally, I find that age, sex, marital status, profession, and political affiliation all exert a statistically significant impact on the default decision. Collectively, these variables materially improve model fit, particularity in samples with higher levels of borrower hetero-

geneity. For example, employment as a professor or K-12 teacher lowers the probability of default relative both as compared to other governmental employees and well as compared to the general population. Nonetheless, we find that introduction of these previously omitted variables does not greatly change the importance of house prices in predicting default. Therefore, it appears that the new variables used in this study are not heavily correlated with house prices. Consequently, the new variables have more of an influence on fit than on the marginal effect of housing prices on default.

The remainder of this chapter is organized as follows. I present motivation for using the controlled setting of government employees to study mortgage defaults and detail the data used in this study in Section 4.2. Section 4.3 describes key variables and presents summary statistics, section 4.4 introduces the empirical models employed, and section 4.5 presents results. Finally, section 4.6 summarizes the relevant findings and suggests areas for future research.

4.2 Data

Section 4.2.1 outlines the setting for this study. The different data sources used in this paper are described in Sections 4.2.2- 4.2.4. Section 4.2.2 describes the wage data, section 4.2.3 describes the property and foreclosure records, and section 4.2.4 describes data obtained from voter registration records. Lastly, section 4.2.5 describes how the individual datasets were combined.

4.2.1 Clark County

Using the setting of Clark County Nevada for this analysis is helpful in many ways. A major metropolitan statistical area, Las Vegas, is located entirely within the county. Therefore, I only need to obtain one county of public employment records, voter registration records,

and property records to conduct inference about a large city. This is in contrast to cities like Denver, CO (10 counties), Charlotte, NC (6 counties), or Dallas, TX (12 counties). Clark County is geographically large, so anyone employed in Clark County almost certainly resides within county limits and residents of the county, if they are employed, are likely to be work within the county.

Additionally, Clark County has well organized digitized public records that make construction of our individual level dataset containing property, employment, and demographic records feasible.[1] Also, the Las Vegas metropolitan area was one of the hardest hit areas in the mortgage crisis. The overall high frequency of mortgage delinquency helps in the estimation of the default models in this study.

4.2.2 Wage Data

There are several advantages to studying financial decisions of public sector employees. Perhaps most importantly, for these workers the name, job title, place of employment, and salary is information of public record. There is a broad spectrum of job categories represented within the public sector including lawyers, accountants, administrative assistants, IT professionals, custodians, teachers, police, and firefighters. Also, public employees typically have higher job security than private sector employees in comparable positions as well as less income volatility. Additionally, medical and sick leave benefits typically available to full-time governmental employees help insulate these borrowers against default due to illness or medical expenses. While this is true in cities across the nation, it is especially pertinent in Clark County. Since the Las Vegas metropolitan area has a large portion of the population that is employed by industries (such as hospitality, gaming, and entertainment) that are quite sensitive to business cycle fluctuations. In comparison, public sector employees have much less income volatility and uncertainty. Therefore, a public sector employee has

[1] I would especially like to thank the employees of the non-profit organization TransparentNevada for making many of the public employment records for 2009 available in a spreadsheet format.

the knowledge that in absence of voluntary job change, her future employment status and salary level are relatively stable and predictable as compared to private sector employees and should factor in that knowledge when making major financial decisions, such as purchasing a home.

Public sector salary records were collected from eight different sources including county employees, city of Las Vegas employees, and colleges located within Clark County, Nevada. Many employers had several years of salary records available, but the largest sample during the housing crisis was obtained using employment records from 2009. Employment records are described in further detail in Table 4.1.

Table 4.1: Clark County Public Sector Employers, 2009

Employer	Total Observations	Homeowner & Matched	Proportion
Clark County- General	11,591	1,472	0.1270
Clark County School District	32,953	3,930	0.1193
College of Southern Nevada	1,260	246	0.1952
Desert Research Institute	310	14	0.0451
Nevada State College	149	16	0.1074
Nevada System of Higher Education System Admin.	210	9	0.0429
University of Nevada at Las Vegas	3,487	629	0.1804
Metro Las Vegas	6,276	1,004	0.1599
Total	56,242	7,333	0.1304

4.2.3 Property and Foreclosure Data

Information about individual homeownership and housing transactions was collected from the Clark County Property Assessor's Records, which is composed of three parts: assessor records, sales records, and default records. The records are complete through 2011, but since I am using salary records from 2009-10, I exclude 2011 sales records from the sample. The first set, property assessor records, contains information on housing characteristics including

a recent assessment of market value of the property, the age of the property as well as information on variables such as address, number of bedrooms and bathrooms, and square footage of the structure and the lot.

Sales records include information on property transactions for every single family property in Clark County. Variables I use from sales records include original date of sale of each property, information about additional liens on each property, loan amount at time of the original transaction, and the loan type (fixed or adjustable rate mortgage).

Default records include the date of each notice of default filed against each property in Clark County. Using this information I can ascertain if a individual received a notice of default during the relevant time period or not. We use this information as the dependent variable in the empirical specifications predicting default.

Each of these datasets has unique identifiers for each property and each transaction so that a property or individual can be linked across the three property records datasets. Therefore, I can match a default with a particular individual at a particular address to the record of the same individual buying the same property in the sales records as well as have all the (largely) time invariant characteristics about the specific property.

4.2.4 Voter Registration and Additional Demographic Data

Voter registration records contain several demographic variables of interest. Much of the information supplied by individuals upon registering to vote in a particular county is a matter of public record. In Nevada, voter registration is often conducted concurrently with driver's license and motor vehicle registration, which improves voter registration rates. Voter records obtained from the Clark County Department of Elections are currently as of September 2013 and include records of both active and inactive voters.

An inactive voter is defined as a voter who has been sent some official correspondence by Clark County and as a result of that correspondence the county has determined that

the individual no longer resides at that residence. When an individual moves within Clark County he may update his address (and never reach inactive status) or re-register under his new address (and thus have an active and an inactive record for the same individual). If an individual moves outside of Clark County he will eventually be classified as inactive. Periodically, inactive voting records are purged from the system; I have records of inactive voters back to 2009.

Overall, there are 864,772 active voters in Clark County as of September 2013, as well as approximately 300,000 inactive voting records, many of which are for individuals who have an active record. To put this in perspective, as of July 2013, Clark County had a total population of approximately 2 million (including residents under the age of 18).[2] Thus, the voting records provide information on the vast majority of adult residents of the county.[3]

In addition to information that is specific to elections (congressional district, school board district, record of participation in past four years of elections) the data set provides information on the registered political affiliation of each individual. The full name, address (current as of 2013 or date that inactive status begun), gender, year of birth, date of original voter registration are provided for each voter.[4]

To infer martial status, I use the raw name records from the property assessor records. If an individual is legally married at the time the property is purchased, in Clark County both spouses names must appear on the deed. In the case of a property that is jointly owned the property records list both names with an "&" symbol between the names. Therefore, if a property record does not contain an ampersand, we infer that the owner is single. Additionally, individuals who are not married but choose to own property jointly will be counted as married by this criteria. Of course, since these values are taken from assessor records, it is possible that singles may have gotten married or married couples may have

[2] From 2013 Census Bureau estimates.

[3] Many thanks to Lorena Portillo of the Clark County Department of Elections for assistance in obtaining and interpreting the registration and elections data.

[4] Most of these variable field are well populated; however, a value for gender is missing for approximately 30% of all voter records.

divorced since the deed was recorded, but using this variable to infer marital status is still informative.

4.2.5 Matching Criteria

First, employment records are combined into single dataset that includes fields for first name, middle name (if available), last name, job title, and 2009 wages. A unique identifier was generated for each employee. Next, employment records are filtered in an attempt to exclude records from employees who are not full time. First, if the employee has “temporary" in their job title, they are dropped from the sample. Next, if the employee has a wage of less than $15,000 they are dropped from the sample.[5]

Property sales records are filtered so that only individuals owning residential property remain in the sample. If the owner's name included any of the following words, it is dropped: LLC, Inc, Residential, Property, Properties, Construction, Finance, Resort, Vacation, Mortgage, Financial, Global, Bank, Home, Security, Securities, Services, Servicing, Nevada, Fund, Wells Fargo, Consultant, or Series. All of the public property records also include identifiers so that information can later be extracted from the sales, assessor, and foreclosure datasets.

Next, exact matches using names are found between property sales records and voter registration records. On the first pass, here the first, middle, and last name must match between both datasets. The match will be considered unique if it matches only a single identifier given for each individual on the voter registration records. An individual may have multiple voter registration records, due to change of address or change in other personal information, but each person will have a unique ID number.

[5]Minimum wage changed from $6.55 to $7.25 in July 2009. A full-time employee (40 hours per week/52 weeks per year) earning minimum wage would have earned $14,456 in 2009. (For additional details on the minimum wage see: http://www.dol.gov/whd/minwage/chart.htm.)

An individual is allowed to match multiple property records because he may have moved several times during his tenure in the county. As a second check, first and last name must match exactly, but middle name is allowed to match only using initials, so long as the match is unique (In other words, in on data set if an individual's middle name is recorded as"N." and the other "Nathan," but first and last name match exactly and there are no duplicates, this is considered an exact match.)

Additionally, if one or both datasets have no value for middle name, but first and last name match and the match is unique, this will be considered a successful match. Although addresses on the voter records and property records typically correspond with one another, I do not use this information to match observations in forming the initial sample because of the possibility that the individual has moved since 2009 and the voter records used in the study go through October 2013. I attempt this matching technique first only using active voter records and then repeat the process using inactive voter records to obtain additional matches that had no record as an active voter. Then, using the same method we match employment records to the combined property and voting records by full name.

Next, using the unique identifiers on the property records, we merge in assessor record variables as well as foreclosure variables. In the case of multiple records in the sales dataset for a given individual, we keep only the first five records. In the sample, over 99% of property owners have five or less sales records for the same property. Subsequent records for the same address and same individual may indicate refinancing or new liens against the property. If a multiple lien indicator is present anywhere in the first five transactions, I consider the property to have a second lien. After capturing possible second liens on the property, we keep only the first records for the individual at that address and consider the date of that transaction to be the original sales date. Similarly for the foreclosure variable, I find default filing notices (up to five) for each owner at each property. If any of these default notices occurred in 2009, I assign a value of 1 for foreclosure_activity for that individual, else this variable will take a value of zero.

At this point, the single property record with sales, assessor, and foreclosure information may match several records on the voter data, due to registration or address changes in the voter registration process. It is entirely reasonable for a true exact match to have several records. However, a small subset of records several dozen matches, which indicates that a true exact match may not have been made. For example "John Smith" (with no middle name on both datasets) may have matched exactly, but because this is a common name, we may be capturing several individuals with the exact same name. Therefore, I drop individuals who have more than five records.[6] I then keep only one record for each individual, which is the sample I use for the analysis in this study. Overall, I consider this to be a conservative matching approach, which likely downward biases the true number of matches that exist in the data.

4.3 Variables and Summary Statistics

From 2008-2010 approximately 9% of all single family owner-occupied residential properties received at least one notice of default. Among the groups of county employees over the same time period, the Clark County School System employees defaulted at a significantly lower level (4.8%) than the general population and employees of the University of Nevada, Las Vegas or Nevada State College also defaulted at a much lower rate (3.2%) than the rest of the county. A complete list of variables used is provided in Table 4.2. Detailed summary statistics are provided in Table 4.3.

[6] I experimented with using different cutoffs for number of records and got similar sample sizes. However, using a cut off of less than 3 appears to exclude many unique matches and greater than 10 appears to include many non-unique matches.

Table 4.2: Variable Descriptions

Variable	Description	Source
foreclosure_activity	1 if a notice of default filed, 0 otherwise	Property Records: Foreclosures
lnmarketvalue	log of most recent home value	Property Records: Assessor
houseage	age of property, in years	Property Records: Assessor
lnloanamount	log of loan amount	Property Records: Sales
frm	1 if mortgage is fixed rate loan, 0 otherwise	Property Records: Sales
lien_2	1 if more than 1 lien on property, 0 otherwise	Property Records: Sales
yearssincepurchase	number of years since property first acquired by individual	Property Records: Sales
age_2009	age of individual in 2009, in years	Voter Registration Records
female	1 if individual female, 0 if male	Voter Registration Records
female_age	interaction of female and age_2009	Voter Registration Records
republican	1 if individual registered as Republican, 0 otherwise	Voter Registration Records
democrat	1 if individual registered as Democrat, 0 otherwise	Voter Registration Records
otherparty	1 if individual registered as member of a third party, 0 otherwise	Voter Registration Records
noparty	1 if individual has no registered political affiliation, 0 otherwise	Voter Registration Records
lnsalary	log of salary in FY2009-10	Employment Records
gvmt_emply	1 if individual employed by Clark County, 0 otherwise	Employment Records
lawyer	1 if individual employed as lawyer or judge, 0 otherwise	Employment Records
teacher	1 if individual employed as K-12 teacher, 0 otherwise	Employment Records
prof	1 if individual employed as a professor, 0 otherwise	Employment Records
police	1 if individual employed as police officer, 0 otherwise	Employment Records
fire	1 if individual employed as firefighter, 0 otherwise	Employment Records

4.4 Empirical Strategy

I estimate a series of logistic regressions to examine the impact of individual property, employment, and demographic variables on the probability of mortgage default. To examine the impact of property characteristics and individual demographics on default, I use the following specification:

$$Pr(D_i = 1) = \phi\left(X_i\beta + C_i\theta\right) \tag{4.1}$$

The dependent variable, default (D_i), is a dummy variable that takes the value 1 if a state of serious delinquency or foreclosure is observed for the property owned by individual i in the given time period, and 0 otherwise. $Pr(D_i{=}1)$ is the probability that a default is observed for individual i. The vector of characteristics that relate the mortgaged property owned by individual i in 2009-2010 is given by X_i and includes the log of property market value (*lnmarketvalue*), the log of the loan amount (*lnloanamount*), a dummy variable for mortgage type (*frm*), a dummy variable indicating if there is a second lien on the property (*lien_2*), the number of years the individual has owned the property (*yearsinhouse*), and the age of the property in 2009 (*houseage*). All of these variables, with the exception of current market value, are known by the lender at origination. I use interactions between government employment indicator variable and the loan amount and current property value to test if the two groups of borrowers differ in their sensitivity to price in their default decisions.

In addition to the property characteristics and salary information, the vector C_i contains a series of dummy variables for political affiliation (*republican, otherparty, noparty*[7]), a dummy variable for gender (*female* and *gender_unknown*[8], age of the individual in years (*age_2009*), an interaction between age and gender (*female_age*), a dummy variable for marital status (*single*), and a series of dummy variables for profession (*lawyer, teacher, prof, police, fire*[9]). These characteristics may be unknown by the lender (i.e. political affiliation) or known and

[7]The omitted category is *democrat*.
[8]The omitted category is male.
[9]The omitted category is *otherjob*.

Table 4.3: Summary Statistics

Default Variables	N	Mean	Std. Dev.
Government Employees 2008-2010	7,333	0.064	0.245
Other Clark County Residents 2008-2010	372,176	0.090	0.286
Government Employees 2009-2010	7,333	0.051	0.221
Other Clark County Residents 2009-2010	631,226	0.070	0.255
Demographic and Employment Variables	N	Mean	Std. Dev.
County Employees			
salary	7,333	64,743.70	34,484.57
frm	7,333	0.768	0.422
lien_2	7,333	0.100	0.300
lnloanamount	6,949	11.68	0.782
lnmarketvalue	7,322	11.805	0 .579
single	7,333	0.265	0.441
female	7,333	0.562	0.496
male	7,333	0.280	0.449
unknown_gender	7,333	0.158	0.365
yearssincepurchase	7,333	8.335	2.272
houseage	7,322	17.414	12.637
age_2009	7,333	46.685	12.270
republican	7,333	0.344	0.475
democrat	7,333	0.475	0.499
otherparty	7,333	0.044	0.204
noparty	7,333	0.138	0.345
lnsqft	7,300	7.209	0.429
Other Clark County Residents			
frm	372,176	0.697	0 .459
lien_2	372,176	0.113	0.316
lnloanamount	339,414	11.736	0.793
lnmarketvalue	371,390	11.758	0.647
single	372,176	0.384	0.486
female	372,176	0.338	0 .473
male	372,176	0.391	0.488
unknown_gender	372,176	0.271	0.444
age_2009	372,176	49.774	15.665
yearssincepurchase	372,176	7.903	2.526
houseage	371,308	16.962	13.349
lnsqft	369,011	7.19	0.454
republican	372,176	0.353	0.478
democrat	372,176	0.434	0.496
otherparty	372,176	0.051	0.220
noparty	372,176	0.162	0.369

not directly used in the lending decision process (i.e. gender, age, marital status). Again, they may be correlated with other variables used default models, or may affect fit. These personal characteristics may be correlated with unobservable variables, such as education, wealth, or personal risk-taking preferences.

Next, to examine the effect of adding information on current salary on probability of default, we estimate a similar model, but include the log of salary for individual i in 2009. It is important to note that all individuals included in the sample were employed by Clark County in FY2009-10, and thus all have positive values for income.

$$Pr(D_i = 1) = \phi\left(X_i\beta + lnsalary_i\gamma + C_i\theta\right) \tag{4.2}$$

I would expect that salary will be negatively related to the probability of default. Current salary is usually omitted from default models; if salary is predictive of default, it is either correlated with loan and property variables (such as those used in the model specified in Equation 4.1) or with the error term in such models.

Finally, as a robustness check, I estimate Equation 4.1 for several subsamples, including single and married borrowers.

4.5 Results

Tables 4.4– 4.6 present results for different groups of Clark County employees. For each group of employees, results are presented for the three groups of models described in Section 4.4.

Table 4.4 presents the main results. Consistent with theory and other mortgage default models, the probability of default is reduced for borrowers who have fixed rate loans (average marginal effect=-5.0%), higher current property market values (both among governmental employees and all other residents) and default risk is higher for borrowers with second lien loans (average marginal effect=5.9%) and borrowers with higher loan amount (among both

groups of employees). These results are similar for both specifications of default (2008-2010 and 2009-2010)[10]

Table 4.4: Clark County Residents, Full Sample

	default 2008-10	default 2009-10
frm	-0.647***	-0.498***
	(-30.37)	(-20.36)
lien_2	0.773***	0.620***
	(32.00)	(22.37)
govt_emply_lnloanamount	0.711***	0.737***
	(5.33)	(5.04)
not_govt_emply_lnloanamount	0.864***	0.814***
	(27.17)	(24.17)
govt_emply_lnmarketvalue	-0.838***	-0.793***
	(-7.17)	(-6.25)
not_govt_emply_lnmarketvalue	-0.822***	-0.776***
	(-29.48)	(-25.57)
govt_emply	1.830	0.953
	(1.35)	(0.64)
single	0.337***	0.287***
	(16.99)	(12.94)
female	0.249***	0.335***
	(4.96)	(6.10)
unknown_gender	0.0624***	0.0381*
	(3.91)	(2.17)

[10] For simplicity, the remainder of the models report results for the 2008-2010 period for default, however all results are robust to the 2009-2010 period as well as just the 2009 period.

Table 4.4 continued

	default 2008-10	default 2009-10
yearssincepurchase	-0.0128**	-0.0261***
	(-3.19)	(-6.06)
houseage	-0.008***	-0.008***
	(-9.04)	(-7.64)
age_2009	-0.008***	-0.007***
	(-14.31)	(-11.53)
female_age_2009	-0.008***	-0.010***
	(-7.95)	(-9.13)
republican	-0.209***	-0.179***
	(-13.22)	(-10.28)
otherparty	-0.103***	-0.080*
	(-3.64)	(-2.57)
noparty	-0.159***	-0.135***
	(-8.86)	(-6.82)
lnsqft	-0.134***	-0.166***
	(-5.23)	(-5.93)
police	-0.0563	-0.103
	(-0.33)	(-0.54)
prof	-1.304**	-1.063*
	(-2.82)	(-2.31)
teacher	-0.335*	-0.220
	(-2.13)	(-1.33)
lawyer	-0.828	-0.556
	(-1.07)	(-0.73)
fire	0.232	0.312

Table 4.4 continued

	default 2008-10	default 2009-10
	(0.85)	(1.08)
_cons	-1.106***	-1.091***
	(-3.88)	(-3.46)
pseudo R^2	0.131	0.103
AIC	186901.6	161888.4
N	344,413	344,413

t statistics in parentheses, standard errors robust to heteroskedasticity and clustered on the property level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The two interaction terms for *lnmarketvalue* as well as *lnloanamount* have similar coefficients for both government employees (those with secure, known incomes) and the remainder of the population (whose employment status and income are unknown). Formally, the coefficients for *govt_emply_lnloanamount* (average marginal effect=5.5%) and *not_govt_emply_lnloanamount* (average marginal effect=6.6%) are statistically indistinguishable (Wald test for equality of coefficients p=0.26). The coefficients for the two market value (price) coefficients (average marginal effects for government and general population are -6.4% and -6.3%, respectively) are also statistically indistinguishable (Wald test for equality of coefficients, p=0.89). These results provide evidence that both groups of borrower have similar sensitivities to price in default.

Among the demographic variables, the individual's age (average marginal effect=0.6%) is positively associated with default, as is being female (average marginal effect=1.9%). However, the interaction of gender and age reveals that higher default probability associated with females reverses with age (beginning at approximately age 32). As compared to the base group of individuals who are registered Democrats those registered as Republicans or

who have no declared party affiliation have a lower probability of default (average marginal effects= -1.6% and -0.7%, respectively). Additionally, single borrowers have a higher probability of default (average marginal effect=2.6%). House age, number of years since purchase, and house size are all negatively associated with default. Finally, job title or classification appears not to matter for most groups, with one notable exception, those employed as educators. Those employed as university professors have a significantly lower probability of default (average marginal effect= -10.0% as do those employed as K-12 teachers (average marginal effect=-2.6%).

Table 4.5 presents results only for individuals who are known government employees. This sample is a relatively homogeneous group of individuals. Among the characteristics they share are: homeowners in Clark County, Nevada, work in the public sector (have relatively low income volatility), and are known to be employed during FY2009-10. For this group of borrowers with known salary, the coefficient for the log of current salary is negatively related to default (but only marginally improves model fit.) Despite all the similarities of the workers in this sample, several individual characteristics are still informative in predicting default (gender, indicator for employment as a professor, martial status).[11] Other individual characteristics that were significant in the main model have similar point estimates, but are no longer statistically significant. If this analysis were extending to a group with greater heterogeneity, we would expect the predictive power of individual characteristics to increase.

Table 4.5: Clark County Residents, Government Employees

	With salary included	Without salary included
	default	default
lnsalary	—	-0.360***
		(-3.37)

[11] The standard errors in all the models presented in this analysis are robust to heteroskedasticity and clustered on the property level.

Table 4.5 continued

	With salary included	Without salary included
	default	default
frm	-0.866***	-0.863***
	(-7.23)	(-7.16)
lien_2	0.521***	0.538***
	(3.71)	(3.80)
lnloanamount	0.845***	0.839***
	(5.01)	(5.01)
lnmarketvalue	-0.762***	-0.719***
	(-4.96)	(-4.65)
single	0.456***	0.530***
	(3.75)	(4.25)
female	1.226**	1.131**
	(2.81)	(2.61)
unknown_gender	0.425**	0.337*
	(3.00)	(2.31)
yearssincepurchase	0.0284	0.0339
	(1.16)	(1.37)
houseage	0.000	-0.000
	(0.06)	(-0.03)
age_2009	0.00137	0.00211
	(0.27)	(0.41)
female_age_2009	-0.027**	-0.027**
	(-2.93)	(-2.95)
republican	-0.057	-0.058
	(-0.48)	(-0.49)

Table 4.5 continued

	With salary included	Without salary included
	default	default
otherparty	-0.216	-0.213
	(-0.88)	(-0.87)
noparty	-0.281	-0.278
	(-1.75)	(-1.73)
lnsqft	-0.224	-0.225
	(-1.49)	(-1.48)
police	-0.009	0.127
	(-0.05)	(0.68)
prof	-1.326**	-1.140*
	(-2.83)	(-2.39)
teacher	-0.319	-0.267
	(-1.92)	(-1.59)
lawyer	-0.808	-0.590
	(-1.06)	(-0.77)
fire	0.257	0.544
	(0.92)	(1.86)
_cons	-1.993	1.432
	(-1.16)	(0.75)
pseudo R^2	0.126	0.129
AIC	2935.0	2925.5
N	6,923	6,923

t statistics in parentheses, standard errors robust to heteroskedasticity and clustered on the property level
*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The final model, presented in Table 4.6, shows results by borrower martial status. The results are similar to the main specification. Although the coefficient estimates are less precise for single government employees (due to relatively small sample size of approximately 1,200), the coefficients are still statistically indistinguishable from the full sample both on loan amount and market value variables. Most importantly, for single borrowers (those who are unlikely to have substantial unobserved income, such as a spouse's salary) the results hold. Also of interest, the model has higher predictive power for the group of single borrowers.[12]

Table 4.6: Full Sample, by martial status

	Single Borrowers	Not Single Borrowers
	default	default
frm	-0.596***	-0.681***
	(-20.79)	(-21.55)
lien_2	0.738***	0.817***
	(24.06)	(21.24)
govt_emply_lnloanamount	0.751**	0.679***
	(2.87)	(4.43)
not_govt_emply_lnloanamount	1.103***	0.706***
	(22.21)	(17.67)
govt_emply_lnmarketvalue	-0.835***	-0.811***
	(-3.83)	(-5.63)
not_govt_emply_lnmarketvalue	-0.872***	-0.810***
	(-21.97)	(-20.24)
govt_emply	3.629	0.136

[12] The difference in model fit is even more stark for narrower definitions of default.

Table 4.6 continued

	Single Borrowers	Not Single Borrowers
	default	default
	(1.51)	(0.08)
female	0.231**	0.278***
	(3.13)	(4.10)
unknown_gender	0.0609**	0.0653**
	(2.75)	(2.82)
yearssincepurchase	-0.017**	-0.003
	(-3.19)	(-0.52)
houseage	-0.007***	-0.009***
	(-6.53)	(-6.37)
age_2009	-0.006***	-0.010***
	(-6.95)	(-12.86)
female_age_2009	-0.008***	-0.008***
	(-5.40)	(-5.81)
republican	-0.199***	-0.211***
	(-9.18)	(-9.22)
otherparty	-0.118**	-0.0813
	(-3.06)	(-1.95)
noparty	-0.140***	-0.177***
	(-5.78)	(-6.61)
lnsqft	-0.0556	-0.241***
	(-1.69)	(-5.68)
police	0.0465	-0.257
	(0.22)	(-0.85)
prof	-1.058*	-1.980

Table 4.6 continued

	Single Borrowers	Not Single Borrowers
	default	default
	(-2.00)	(-1.96)
teacher	-0.529	-0.360*
	(-0.48)	(-2.17)
lawyer	.	0.0299
	.	(0.04)
fire	0.427	-0.181
	(1.22)	(-0.39)
_cons	-3.717***	1.463***
	(-9.27)	(3.62)
pseudo R^2	0.131	0.103
AIC	87161.5	99386.5
N	125,972	218,422

t statistics in parentheses, standard errors robust to heteroskedasticity and clustered on the property level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.6 Conclusion

Although job loss is often anecdotally cited as motivation for mortgage default, the inability to observe individual ability to pay (through employment status or current income) after loan origination makes it difficult to empirically test the impact of unemployment on default probabilities. Controlling for employment status by a sample of individuals who are known to be employed in FY 2009-10 and have relatively low income volatility, we observe lower

levels of default than in the general public, but not an absence of default activity. I show that although homeowners with relatively high income stability and known employment have lower absolute rates of default, they are equally price sensitive in default as the general population. This suggests that these defaults are not solely liquidity defaults (inability to pay), but these defaults have at least some strategic component (sensitivity to price) to them. Also, I provide evidence that this strategic component is similar in magnitude for the entire sample. This finding suggests that even though current income and employment status are important to default decisions, all borrowers have a similar level of price sensitivity.

Additionally, borrowers' default decisions are sensitive to financial variables typically used in default models, such as home value and loan amount, but even after controlling for these variables, for the group of government employees with known salaries, we find that current salary amount is negatively associated with default. The inclusion of individual level demographic variables helps control for unobservable borrower heterogeneity, which can lead to parameter attenuation, as well as improve the predictive power of default models. Disentangling the effects of housing price declines and income shocks can aid policymakers as well as investors in developing better responses to observed mortgage defaults.

By moving away from reliance on aggregate proxies for theoretically important variables, such as income and employment, the understanding of the importance of borrower heterogeneity in financial outcomes can be better understood. Although this study focuses on a single US county, similar datasets could certainly be constructed for other locales. Incorporating individual level data from public records into mortgage models offers many possibilities for further research. The addition of financial and non-financial individual level characteristics gleaned from public records offers an avenue to reduce the omitted variables problem in mortgage research .

Chapter 5. Summary and Conclusions

5.1 Summary

This dissertation presents three essays that each contribute to the literature in mortgage debt payment choices. In the first chapter, I provide an overview of the American mortgage market in the context of aggregate consumer debt and household financial decisions. In the second chapter, I examine mortgage curtailment, or voluntary extra partial prepayments. I provide evidence that this behavior is associated with widening differentials in interest rates at origination and current interest rates as well as changes in housing prices. After controlling for these factors as well as a host of variables related to the loan terms, I show that the propensity to curtail mortgage debt has been increasing since 2004. This predates the aggregate trend of consumer deleveraging, which did not begin until the Great Recession.

The third and fourth chapters explore the concept of strategic mortgage default, or the instance of a borrower repudiating her outstanding mortgage debt, despite the ability to make payments, as a reaction to declines in housing values. The third chapter uses the concept of curtailment, first introduced in the second chapter, to identify a group of borrowers that should theoretically have lower instances of strategic default, or stated differently, contingent on their ability to make scheduled loan payments, they should be less sensitive to current levels mortgage leverage than their counterparts without previous curtailments. I empirically confirm this prediction by showing that borrowers with previous curtailments have 30-50% less sensitivity to current mortgage leverage than borrowers without previous curtailments in the decision to default.

The fourth chapter uses a similar framework of comparing two groups sensitivity to mortgage curtailment, but now examines the impact of income on borrowers' default decisions. I

collect information on a group of homeowners that are government employees whose income status and salaries are known during my sample period. Additionally, this group of employees has higher than average income stability. These homeowners have observable income to make mortgage payments during the sample period and given their professions, have much lower unemployment risk than the general population. Indeed, this group of borrower defaults less frequently than the general population, whose employment status after loan origination is observable. However, when I compare this group's sensitivity to current leverage in the default decision, I find that both groups are equally sensitive to current leverage levels. Both the third and fourth chapters results suggest that policies put in place to alleviate widespread defaults that target ability to pay (liquidity defaults) without addressing depressed property price levels (strategic defaults) will have limited effectiveness.

5.2 Concluding Remarks and Future Research

Will the trend of borrowers infusing extra equity into their mortgages via curtailment continue? Certainly this will be a function both changes in the mortgage market as well as in borrowers' perceived opportunity cost for their discretionary funds. If levels of disposable income remain constant, changes in curtailment behavior will depend largely on households consumption preferences and risk aversion levels. First, curtailment will depend on willingness to enter into riskier financial investments, such as the stock market. Additionally, the propensity to curtail will likely change as the low interest rate regime that has prevailed since the crisis eventually gives way to higher rates (although the timing of this change is unknown).

If rates of return on certificates of deposit or savings accounts increase above the household's current mortgage rate, the purely financial incentives to curtail lessen. However, since mortgage curtailment is a method to accelerate debt repayment, as more households enter retirement age and may have a reduced taste for debt, curtailment may continue at high

rates, irrespective of movements in the stock market or prevailing interest rates. To the extent that curtailment is a revelation of a households' changing preferences for holding debt, curtailment levels may increase as the recovery continues and household discretionary income increases.

Furthermore, although curtailment is an embedded option in the mortgage contract, the value of this option is not truly known. For example, a borrower who chooses a 30 year mortgage can structure his payments such that the loan is repaid over 15 years. However, such a borrower will repay a larger amount than an identical borrower who chose a 15 year loan because of interest rate differential between the two loan types, but will retain the right to revert to the lower payments required on the 30 year schedule if his financial position or preferences change during the life of the loan.

As the era of high defaults moves further into the past, eventually prepayment risk will regain prominence in the minds of lenders and investors. To the extent that curtailment is associated with a lower default risk, particularly a lower strategic default risk, what is its connection to full mortgage prepayment? To the extent that a borrower may choose to infuse equity into a mortgage in order to gain eligibility to refinance at a lower rate, curtailment may be positively associated with prepayment risk. However, when interest rates rise, the incentive for existing mortgagors to refinance for interest rate savings vanishes. In such an environment, observed curtailments may be primarily related to household savings behaviors, and could potentially have a negative relation to early termination through full prepayment.

Regardless of the future strength or weakness in the real estate market, it is likely that the demand for additional individual information that is predictive of mortgage outcomes will continue to grow. To this end, public records are a rich field for mining individual information that can be used by lenders and investors to update post-origination risk profiles of mortgages. Additionally, such information can be used to develop new investment products. To the extent that household wealth for homeowners continues to be largely concentrated in their residences, there are potentially additional insights in the area of household finance

that can be made by obtaining a better understanding of individual mortgage debt payment decisions.

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Appendix: Additional Tables

In this appendix, I provide additional tables. Table 5.1 presents a correlation matrix for the main variables used in the analysis undertaken in Chapter 2. Table 5.2 presents the full results for the main regression specification in Chapter 2 including coefficient estimates for all fixed effects used in the model.

Table 5.1: Correlation Matrix

Variable	neg_eq	sav prem	LTV_orig	arm	term_30	fico	risk prem	jumbo	pp_penalty	doc_low	doc_unk
neg_eq	1.0000										
sav prem	0.2357	1.0000									
LTV_orig	0.2323	0.1371	1.0000								
arm	0.0891	−0.0653	0.2174	1.0000							
term_30	0.1016	0.0460	0.2439	0.2605	1.0000						
fico	−0.0381	−0.2838	−0.1912	−0.1590	−0.0836	1.0000					
risk prem	−0.1206	−0.6373	−0.1841	0.1525	−0.0195	0.3867	1.0000				
jumbo	−0.0294	−0.1292	−0.1147	−0.0235	−0.0136	0.2487	0.1320	1.0000			
pp_penalty	0.0172	−0.0693	0.1181	0.1849	0.0809	−0.2242	0.0544	−0.1389	1.0000		
doc_low	0.1319	−0.0473	−0.1171	−0.0608	−0.0217	0.2292	0.1395	0.0381	−0.0387	1.0000	
doc_unk	−0.1466	0.0723	0.1210	0.1984	0.0442	−0.1853	−0.1174	−0.0886	0.0715	−0.4302	1.000

Table 5.2: Late, Curtailment, and Prepayment Multinomial Logit Estimates

	$100 Minimum			$1,000 Minimum		
Variables	Late	Curtail	Prepay	Late	Curtail	Prepay
neg_eq	0.3191	−0.4628	−1.0500	0.3326	−0.8518	−1.0342
	25.7979	−20.7940	−45.8078	26.8959	−17.7728	−45.1896
neg_eq savings premium	0.1616	0.0561	0.2142	0.1545	0.2151	0.2054
	56.6626	10.5121	40.3583	54.2679	18.7095	38.7957
pos_eq savings premium	0.1482	0.0092	0.2920	0.1420	0.1160	0.2837
	66.2065	2.5457	116.2488	63.6208	16.3028	113.6475
LTV_origination	0.0161	−0.0032	−0.0013	0.0162	−0.0066	−0.0011
	70.7840	−8.5220	−9.0222	71.5308	−9.5794	−7.4893
arm	0.3371	0.1462	0.4314	0.3313	0.5083	0.4241
	53.8720	11.5977	82.9419	52.9618	20.9231	82.2001
term_30	0.1316	−0.2210	0.0482	0.1401	−0.6307	0.0572
	7.0075	−9.0427	4.5294	7.4574	−14.9945	5.4384
fico	−0.0084	0.0041	0.0004	−0.0085	0.0066	0.0003
	−197.3644	45.8155	11.5260	−200.2674	37.0783	8.0266
risk premium	−0.0019	0.2544	0.0873	−0.0182	0.2598	0.0683
	−1.1037	92.9931	51.6478	−10.8541	51.9495	41.1729
jumbo	−0.2965	0.2594	0.0451	−0.2972	1.0552	0.0469
	−36.5108	21.1403	8.4374	−36.7160	51.8114	8.9040
prepay_penalty	0.0547	0.0974	−0.6072	0.0475	0.2513	−0.6181
	10.2906	9.6178	−124.9288	8.9510	12.6060	−127.6516
documentation_low	0.1444	−0.0805	−0.1885	0.1479	−0.0444	−0.1839
	24.9183	−7.2871	−36.6477	25.5470	−2.1628	−36.2699
documentation_unknown	−0.4143	−0.2432	1.2965	−0.4058	−0.2196	1.3090
	−49.1349	−14.1921	215.2107	−47.9764	−6.2290	219.0656
Atlanta	0.3071	−0.1842	0.3178	0.3125	−0.0816	0.3241
	18.4431	−4.8650	21.6995	18.7294	−0.9437	22.2411
Boston	0.4481	0.1004	0.8083	0.4487	0.4103	0.8075
	24.2692	2.6543	55.8253	24.2993	5.2646	56.2671
Charlotte	0.1585	−0.3433	0.3213	0.1638	−0.5496	0.3280
	6.0865	−5.7891	14.9027	6.2627	−4.0279	15.2479
Chicago	0.2346	0.0142	0.6944	0.2342	0.0915	0.6899
	15.3905	0.4064	54.1105	15.3368	1.1862	54.0367
Cleveland	0.1877	0.1866	0.1843	0.1834	0.1266	0.1778
	8.4313	3.7238	8.6041	8.2331	1.0004	8.3624
Denver	0.2199	−0.1150	0.4407	0.2278	−0.1605	0.4493
	11.2772	−2.8811	27.1379	11.6674	−1.7188	27.8896

Table 5.2 continued

	$100 Minimum			$1,000 Minimum		
Variables	Late	Curtail	Prepay	Late	Curtail	Prepay
Detroit	0.2732	0.1253	0.3366	0.2700	0.0320	0.3318
	16.7323	3.2745	22.0202	16.5159	0.3683	21.8334
Las Vegas	0.1423	−0.0945	0.7173	0.1491	−0.0499	0.7230
	7.8513	−2.2642	44.8622	8.2200	−0.5534	45.4986
Los Angeles	0.1691	0.1038	0.9511	0.1723	0.4707	0.9528
	12.1179	3.5510	80.2362	12.3298	7.3476	80.8542
Miami	0.2950	0.0784	0.6830	0.2947	0.2796	0.6797
	15.2746	1.8397	38.9895	15.2460	3.0168	38.9775
Minneapolis	0.2902	−0.0502	0.6350	0.2928	−0.0962	0.6362
	16.1048	−1.2961	41.2411	16.2394	−1.1132	41.6438
New York	0.3479	0.2000	0.6540	0.3459	0.7072	0.6491
	25.5191	6.8794	56.1105	25.3270	11.1126	55.9991
Phoenix	0.1039	−0.1381	0.7988	0.1093	−0.2080	0.8030
	6.4682	−3.7636	58.3829	6.7927	−2.5079	58.9524
Portland	−0.0254	−0.1151	0.7346	−0.0180	−0.2114	0.7416
	−1.1747	−2.6342	45.6509	−0.8318	−2.1645	46.3622
San Diego	0.1150	0.0946	0.8214	0.1178	0.4428	0.8230
	6.4490	2.7288	57.6989	6.6111	6.1185	58.2902
San Francisco	0.0958	0.0836	0.9281	0.0981	0.4498	0.9298
	5.8146	2.6484	71.9246	5.9562	6.7351	72.6523
Seattle	−0.0589	−0.0249	0.8118	−0.0540	0.1169	0.8161
	−3.2336	−0.6881	57.3464	−2.9614	1.5039	58.0610
Tampa	0.1499	0.0147	0.6211	0.1503	0.0874	0.6196
	8.4529	0.3697	39.6290	8.4587	0.9561	39.7328
Washington D.C.	0.1272	0.1292	0.9093	0.1261	0.4662	0.9055
	7.9787	3.9545	70.1652	7.9063	6.7320	70.3288
Bank of America	−2.0742	1.5746	−1.2582	−2.1135	1.0889	−1.3035
	−207.3206	50.5679	−159.8948	−211.0112	19.2202	−165.6796
Residential Funding Corp.	−1.8634	1.5581	−1.5595	−1.9011	0.9664	−1.6062
	−181.9885	46.5901	−193.5711	−185.4186	14.9690	−199.3818
Wells Fargo	−1.9143	1.7426	−1.6696	−1.9680	1.3353	−1.7344
	−188.8196	60.3717	−192.8570	−194.1806	26.0610	−201.7064
Aurora Loan Services	−1.9728	2.0909	−1.2952	−2.0869	1.3398	−1.4220
	−78.3386	59.1100	−105.5007	−83.1467	21.3220	−124.7107
Washington Mutual	−1.7211	2.0852	−1.5282	−1.8075	1.5484	−1.6388
	−138.4318	69.1103	−131.1909	−145.9099	28.9652	−142.7432
IndyMac	−1.4101	1.8236	−2.3410	−1.4630	1.4885	−2.3984
	−108.7012	50.0518	−180.0649	−112.9708	22.9921	−185.7240

Table 5.2 continued

	$100 Minimum			$1,000 Minimum		
Variables	Late	Curtail	Prepay	Late	Curtail	Prepay
Chase Manhattan Bank	−1.9128	1.5751	−1.7741	−1.9521	1.0331	−1.8174
	−151.1835	40.5486	−129.1677	−154.1895	14.3430	−132.6852
EMC Mortgage Corp	−1.6635	1.7062	−1.5048	−1.7289	0.9786	−1.5839
	−108.2580	51.9095	−121.5813	−112.9139	15.7568	−128.7640
Ocwen	−1.6219	1.3165	−1.7642	−1.6549	0.5797	−1.8041
	−122.3443	29.9779	−116.6599	−124.7039	6.4047	−119.5170
American Mortgage Corp	−1.9954	1.5092	−2.3210	−2.0319	1.2241	−2.3595
	−146.3125	42.2674	−133.6175	−148.9118	18.5696	−136.5088
Litton Loan Servicing	−2.5384	0.9105	−1.1777	−2.5719	−0.0654	−1.2216
	−118.3439	13.9846	−109.2189	−119.7003	−0.3910	−113.1569
GMAC	−1.7596	1.2031	−1.0135	−1.7898	0.8007	−1.0528
	−105.9562	18.8999	−91.5134	−107.7561	6.9458	−95.3424
Saxon Mortgage Services	−1.2544	1.1955	−2.0163	−1.2878	0.6863	−2.0616
	−61.1645	18.3835	−106.2681	−62.6022	4.8939	−108.5880
Wilshire Credit Corp	−1.7160	1.7624	−1.7411	−1.7718	1.4863	−1.8012
	−73.5004	44.6773	−96.6976	−76.0644	21.4918	−101.1952
Option One	−1.8991	1.4427	−1.3961	−1.9318	0.9344	−1.4370
	−111.9614	26.9815	−107.1624	−113.9134	7.7713	−110.8160
HomeEq Servicing Corp	−1.2898	1.2488	−3.2633	−1.3249	0.9504	−3.3075
	−32.3225	8.6411	−60.0682	−33.0572	2.9737	−60.9665
PHH Mortgage	−1.4402	1.0540	−3.1435	−1.4712	−0.0563	−3.1849
	−72.5890	13.9669	−98.8024	−74.1098	−0.3760	−100.3249
LaSalle Bank	0.5039	1.2218	1.3908	0.4786	0.7664	1.3602
	13.4731	9.1711	44.0843	12.8619	2.2797	43.5831
All other small servicers	−1.6701	1.6412	−1.3317	−1.7126	1.2566	−1.3813
	−166.7064	54.1508	−159.6983	−170.9393	23.2745	−166.2615
Vintage 2000 and earlier	1.3673	−0.2069	0.1235	1.3601	0.0381	0.1117
	31.5537	−0.8893	2.8861	31.3120	0.0695	2.6029
Vintage 2001	0.7861	0.2583	0.1812	0.7746	0.4007	0.1711
	27.8513	2.7477	9.2584	27.3673	2.7964	8.7599
Vintage 2002	0.5447	0.2667	0.3103	0.5384	0.3776	0.3040
	30.1337	6.5993	29.7669	29.8013	5.3789	29.5040
Vintage 2003	0.1766	−0.0099	0.1688	0.1794	0.1039	0.1741
	15.6500	−0.5007	28.0738	15.9178	2.8179	29.3368
Vintage 2005	−0.0135	−0.0302	−0.0432	−0.0089	−0.0001	−0.0378
	−1.5880	−2.2389	−8.4910	−1.0460	−0.0030	−7.5567
Vintage 2006	0.0423	−0.0576	−0.4240	0.0486	0.0803	−0.4111
	4.6348	−3.6685	−59.0539	5.3376	2.6673	−57.8224

Table 5.2 continued

	$100 Minimum			$1,000 Minimum		
Variables	Late	Curtail	Prepay	Late	Curtail	Prepay
Vintage 2007	−0.0629	0.1424	−0.7417	−0.0603	0.4544	−0.7325
	−5.5334	6.7395	−62.1395	−5.3178	12.2207	−61.7341
Obs. year 2002 and earlier	0.5225	−24.2016	−0.0042	0.5705	−21.5965	0.0603
	20.6902	−363.1883	−0.1453	22.4972	−194.3614	2.0652
Obs. year 2003	0.1915	−6.7637	−0.1423	0.2407	−21.5725	−0.0756
	10.2877	−24.5896	−7.2297	12.9133	−412.8135	−3.8510
Obs. year 2004	−0.0252	−3.2499	−0.0164	0.0214	−3.7948	0.0453
	−1.6741	−116.0028	−1.0041	1.4225	−52.5498	2.7872
Obs. year 2005	0.1653	−1.9581	0.9513	0.2024	−1.9430	0.9964
	11.5691	−97.3070	59.2511	14.1957	−44.3211	62.3696
Obs. year 2006	0.3691	−0.5963	1.6933	0.3783	−0.2483	1.7035
	26.3931	−33.9424	105.0308	27.1346	−6.8745	106.1784
Obs. year 2007	0.6073	−0.5418	1.8962	0.6161	−0.1413	1.9043
	46.9913	−34.3368	122.1541	47.8159	−4.3636	123.1789
Obs. year 2008	0.7838	−0.3049	1.0724	0.7909	−0.1306	1.0761
	70.9791	−26.9276	72.5120	71.7917	−5.5486	72.9764
Obs. year 2009	0.3281	−0.0991	0.5573	0.3290	−0.1387	0.5565
	33.7665	−11.1819	38.6425	33.8845	−7.4225	38.6668
Obs. year 2010	−0.0041	−0.0270	0.0018	−0.0055	−0.0782	−0.0001
	−0.4773	−4.2503	0.1179	−0.6353	−5.7362	−0.0090
Obs. month January	−0.0413	−0.1199	−0.1524	−0.0387	−0.0663	−0.1478
	−12.6119	−31.7905	−18.0993	−11.8154	−7.3490	−17.5687
Obs. month February	−0.1897	−0.1484	−0.1990	−0.1850	−0.1158	−0.1931
	−51.3851	−39.3932	−23.6279	−50.1492	−12.9049	−22.9414
Obs. month March	−0.1753	−0.1206	−0.2213	−0.1716	−0.1226	−0.2163
	−45.5449	−32.7297	−26.0617	−44.6026	−13.5765	−25.4835
Obs. month April	−0.3047	−0.0593	−0.0245	−0.3036	−0.0417	−0.0225
	−75.4927	−15.8292	−3.0003	−75.2495	−4.5979	−2.7577
Obs. month May	−0.2604	−0.1010	−0.0410	−0.2581	−0.0813	−0.0376
	−65.0295	−26.5057	−4.9955	−64.4759	−8.8451	−4.5831
Obs. month June	−0.1972	−0.1347	0.0541	−0.1936	−0.0878	0.0580
	−49.1080	−33.6425	6.6740	−48.2183	−9.4781	7.1569
Obs. month July	−0.1335	−0.1293	0.1501	−0.1297	−0.0826	0.1540
	−33.5719	−32.8557	18.7206	−32.6253	−9.0280	19.2001
Obs. month August	−0.1218	−0.1057	0.0381	−0.1185	−0.0486	0.0416
	−31.4563	−28.5990	4.6616	−30.6193	−5.4644	5.0885
Obs. month September	−0.0995	−0.0549	0.0408	−0.0988	−0.0113	0.0415

Table 5.2 continued

	$100 Minimum			$1,000 Minimum		
Variables	Late	Curtail	Prepay	Late	Curtail	Prepay
	−26.7530	−15.8408	4.9943	−26.5815	−1.2959	5.0861
Obs. month October	−0.0021	−0.0572	−0.0306	−0.0022	−0.0278	−0.0311
	−0.6078	−16.6548	−3.6573	−0.6279	−3.2272	−3.7117
Obs. month November	−0.0563	−0.0198	0.0342	−0.0557	−0.0017	0.0348
	−19.1040	−6.8664	4.1929	−18.9236	−0.2287	4.2676
constant	2.0710	−6.2123	−5.4977	2.1077	−10.1327	−5.4522
	47.6154	−71.4391	−147.6197	48.4804	−58.7720	−147.2812
N observations	18,476,303			18,476,303		
N curtailment	1,323,825			257,298		
N loans	815,827			815,827		
Pseudo-R^2	0.1511			0.1651		

This table presents the multinomial logistic results for the minimum curtailment amounts of $100 and $1,000 with the competing choices of delinquency, current payment, curtailment, or full prepayment. The base case for both regressions is current payment status. Coefficients reported with t-statistics below. Standard errors reported are robust to heteroskedasticity and clustered on the loan identifier level.

Vita

Meagan McCollum attended Samford University, where she earned a Bachelor of Arts in Music. Upon graduation Ms. McCollum worked in music and arts administration while earning an M.B.A., also at Samford University. In 2012 she completed her Master of Science in Finance, with a concentration in Real Estate from the University of Alabama. In August 2012 she entered the Ph.D. program in the Finance Department at Louisiana State University. Her research interests include real estate finance, household finance, and financial institutions. She is currently a candidate for the degree of Doctor of Philosophy in finance, which will be awarded in May 2015. Most recently, Ms. McCollum has accepted an assistant professor position at Baruch College, City University of New York, starting August 2015.