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Draft - Understanding the Subprime Mortgage Crisis

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Abstract

Using loan-level data, we analyze the quality of subprime mortgage loans by adjusting their performance for differences in borrower characteristics, loan characteristics, and macroeconomic conditions. We find that the quality of loans deteriorated for six consecutive years before the crisis and that securitizers were, to some extent, aware of it. We provide evidence that the rise and fall of the subprime mortgage market follows a classic lending boom-bust scenario, in which unsustainable growth leads to the collapse of the market. Problems could have been detected long before the crisis, but they were masked by high house price appreciation between 2003 and 2005.

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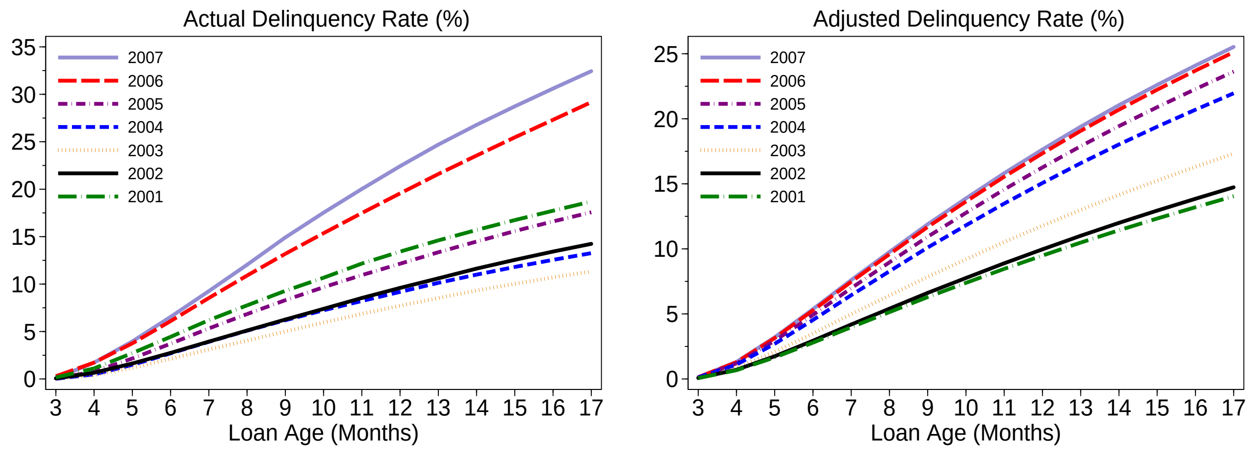
1 Introduction

The subprime mortgage crisis of 2007 was characterized by an unusually large fraction of subprime mortgages originated in 2006 and 2007 becoming delinquent or in foreclosure only months later. The crisis spurred massive media attention; many different explanations of the crisis have been proffered. The goal of this paper is to answer the question: "What do the data tell us about the possible causes of the crisis?" To this end we use a loan-level database containing information on about half of all U.S. subprime mortgages originated between 2001 and 2007.

The relatively poor performance of vintage 2006 and 2007 loans is illustrated in Figure 1 (left panel). At every mortgage loan age, loans originated in 2006 and 2007 show a much higher delinquency rate than loans originated in earlier years at the same ages.

Figure 1: Actual and Adjusted Delinquency Rate

The figure shows the age pattern in the actual (left panel) and adjusted (right panel) delinquency rate for the different vintage years. The delinquency rate is defined as the cumulative fraction of loans that were past due 60 or more days, in foreclosure, real-estate owned, or defaulted, at or before a given age. The adjusted delinquency rate is obtained by adjusting the actual rate for year-by-year variation in FICO scores, loan-to-value ratios, debt-to-income ratios, missing debt-to-income ratio dummies, cash-out refinancing dummies, owner-occupation dummies, documentation levels, percentage of loans with prepayment penalties, mortgage rates, margins, composition of mortgage contract types, origination amounts, MSA house price appreciation since origination, change in state unemployment rate since origination, and neighborhood median income.



We document that the poor performance of the vintage 2006 and 2007 loans was not confined to a particular segment of the subprime mortgage market. For example, fixed-rate, hybrid, purchase-money, cash-out refinancing, low-documentation, and full-documentation loans originated in 2006 and 2007 all showed substantially higher delinquency rates than loans made the prior five years. This contradicts a widely held belief that the subprime mortgage crisis was mostly confined to hybrid or low-documentation mortgages.

We explore to what extent the subprime mortgage crisis can be attributed to different loan characteristics, borrower characteristics, macroeconomic conditions, and vintage (origination) year effects. The most important macroeconomic factor is subsequent house price appreciation, measured as the MSA-level house price change between the time of origination and the time of loan performance evaluation. For the empirical analysis, we run a proportional odds duration model with the probability of (first-time) delinquency a function of these factors and loan age.

We find that loan and borrower characteristics are very important in terms of explaining the cross-section of loan performance. However, because these characteristics were not sufficiently different in 2006 and 2007 compared with the prior five years, they cannot explain the unusually weak performance of vintage 2006 and 2007 loans. For example, a one-standard-deviation increase in the debt-to-income ratio raises the likelihood (the odds ratio) of a current loan turning delinquent in a given month by as much as a factor of 1.14. However, because the average debt-to-income ratio was just 0.2 standard deviations higher in 2006 than its level in previous years, it contributes very little to the inferior performance of vintage 2006 loans. The only variable in the considered proportional odds model that contributed substantially to the crisis is the low subsequent house price appreciation for vintage 2006 and 2007 loans, which can explain about a factor of 1.24 and 1.39, respectively, higher-than-average likelihood for a current loan to turn delinquent.[1] Due to geographical heterogeneity in house price changes, some areas have experienced larger-than-average house price declines and therefore have a larger explained increase in delinquency and foreclosure rates.[2]

The coefficients of the vintage dummy variables, included as covariates in the proportional odds model, measure the quality of loans, adjusted for differences in observed loan characteristics, borrower characteristics, and macroeconomic circumstances. In Figure 1 (right panel) we plot the adjusted delinquency rates, which are obtained by using the estimated coefficients for the vintage dummies and imposing the requirement that the average actual and average adjusted delinquency rates are equal for any given age. As shown in Figure 1 (right panel), the adjusted delinquency rates have been steadily rising for the

[1]Other papers that research the relationship between house prices and mortgage financing include Genesove and Mayer (1997), Genesove and Mayer (2001), and Brunnermeier and Julliard (2007).

[2]Also, house price appreciation may differ in cities versus rural areas. See for example Glaeser and Gyourko (2005) and Gyourko and Sinai (2006).

past seven years. In other words, loan quality—adjusted for observed characteristics and macroeconomic circumstances—deteriorated monotonically between 2001 and 2007. Interestingly, 2001 was among the worst vintage years in terms of actual delinquency rates, but is in fact the best vintage year in terms of the adjusted rates. High interest rates, low average FICO credit scores, and low house price appreciation created the "perfect storm" in 2001, resulting in a high actual delinquency rate; after adjusting for these unfavorable circumstances, however, the adjusted delinquency rates are low.

In addition to the monotonic deterioration of loan quality, we show that over time the average combined loan-to-value ratio increased, the fraction of low documentation loans increased, and the subprime-prime rate spread decreased. The rapid rise and subsequent fall of the subprime mortgage market is therefore reminiscent of a classic lending boom-bust scenario.[3] The origin of the subprime lending boom has often been attributed to the increased demand for so-called private-label mortgage-backed securities (MBSs) by both domestic and foreign investors. Our database does not allow us to directly test this hypothesis, but an increase in demand for subprime MBSs is consistent with our finding of lower spreads and higher volume. Mian and Sufi (2008) find evidence consistent with this view that increased demand for MBSs spurred the lending boom.

The proportional odds model used to estimate the adjusted delinquency rates assumes that the covariate coefficients are constant over time. We test the validity of this assumption for all variables and find that it is the most strongly rejected for the loan-to-value (LTV) ratio. High-LTV borrowers in 2006 and 2007 were riskier than those in 2001 in terms of the probability of delinquency, for given values of the other explanatory variables. Were securitizers aware of the increasing riskiness of high-LTV borrowers?[4] To answer this question, we analyze the relationship between the mortgage rate and LTV ratio (along with the other loan and borrower characteristics). We perform a cross-sectional ordinary least squares (OLS) regression, with the mortgage rate as the dependent variable, for each quarter from 2001Q1 to 2007Q2 for both fixed-rate mortgages and 2/28 hybrid mortgages. Figure 2 shows that the coefficient on the first-lien LTV variable, scaled by the standard deviation of the first-lien LTV ratio, has been increasing over time. We thus find evidence that securitizers were aware of the increasing riskiness of high-LTV borrowers, and

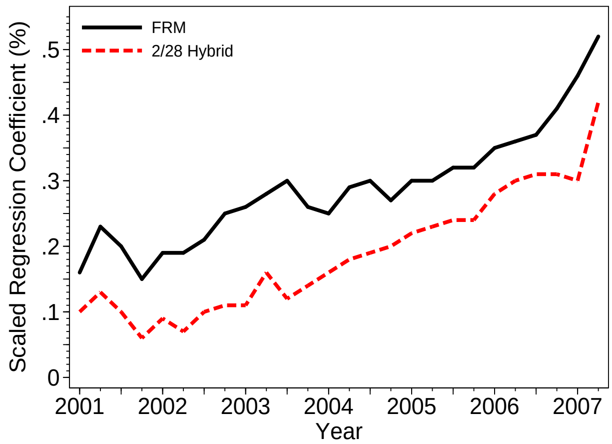
[3] Berger and Udell (2004) discuss the empirical stylized fact that during a monetary expansion lending volume typically increases and underwriting standards loosen. Loan performance is the worst for those loans underwritten toward the end of the cycle. Demirgüç-Kunt and Detragiache (2002) and Gourinchas, Valdes, and Landerretche (2001) find that lending booms raise the probability of a banking crisis. Dell'Ariccia and Marquez (2006) show in a theoretical model that a change in information asymmetry across banks might cause a lending boom that features lower standards and lower profits. Ruckes (2004) shows that low screening activity may lead to intense price competition and lower standards.

[4] For loans that are securitized (as are all loans in our database), the securitizer effectively dictates the mortgage rate charged by the originator.

adjusted mortgage rates accordingly.

Figure 2: Sensitivity of Mortgage Rate to First-Lien Loan-to-Value Ratio

The figure shows the effect of the first-lien loan-to-value ratio on the mortgage rate for first-lien fixed-rate and 2/28 hybrid mortgages. The effect is measured as the regression coefficient on the first-lien loan-to-value ratio (scaled by the standard deviation) in an ordinary least squares regression with the mortgage rate as the dependent variable and the FICO score, first-lien loan-to-value ratio, second-lien loan-to-value ratio, debt-to-income ratio, missing debt-to-income ratio dummy, cash-out refinancing dummy, owner-occupation dummy, prepayment penalty dummy, origination amount, term of the mortgage, prepayment term, and margin (only applicable to 2/28 hybrid) as independent variables. Each point corresponds to a separate regression, with a minimum of 18,784 observations.



We show that our main results are robust to analyzing mortgage contract types separately, focusing on foreclosures rather than delinquencies, and specifying the empirical model in numerous different ways, like allowing for interaction effects between different loan and borrower characteristics. The latter includes taking into account risk-layering—the origination of loans that are risky in several dimensions, such as the combination of a high LTV ratio and a low FICO score.

As an extension, we estimate our proportional odds model using data just through year-end 2005 and again obtain the continual deterioration of loan quality from 2001 onward. This means that the seeds for the crisis were sown long before 2007, but detecting them was complicated by high house price appreciation between 2003 and 2005—appreciation that masked the true riskiness of subprime mortgages.

In another extension, we find an increased probability of delinquency for loans originated in low- and moderate-income areas, defined as areas with median income below 80 percent of the larger Metropolitan Statistical Area median income. This points toward a negative by-product of the 1977 Community Reinvestment Act and Government Sponsored Enterprises housing goals, which seek to stimulate loan origination in low- and moderate-income areas.

There is a large literature on the determinants of mortgage delinquencies and foreclosures, dating back to at least Von Furstenberg and Green (1974). Recent contributions include Cutts and Van Order (2005) and Pennington-Cross and Chomsisengphet (2007).[5] Other papers analyzing the subprime crisis include Gerardi, Shapiro, and Willen (2008), Mian and Sufi (2008), DellAriccia, Igan, and Laeven (2008), and Keys, Mukherjee, Seru, and Vig (2008). Our paper makes several novel contributions. First, we quantify how much different determinants have contributed to the observed high delinquency rates for vintage 2006 and 2007 loans, which led up to the 2007 subprime mortgage crisis. Our data enables us to show that the effect of different loan-level characteristics as well as low house price appreciation was quantitatively too small to explain the poor performance of 2006 and 2007 vintage loans. Second, we uncover a downward trend in loan quality, determined as loan performance adjusted for differences in loan and borrower characteristics and macroeconomic circumstances. We further show that there was a deterioration of lending standards and a decrease in the subprime-prime mortgage rate spread during the 2001–2007 period. Together these results provide evidence that the rise and fall of the subprime mortgage market follows a classic lending boom-bust scenario, in which unsustainable growth leads to the collapse of the market. Third, we show that the continual deterioration of loan quality could have been detected long before the crisis by means of a simple statistical exercise. Fourth, securitizers were, to some extent, aware of this deterioration over time, as evidenced by changing determinants of mortgage rates. Fifth, we detect an increased likelihood of delinquency in low- and middle-income areas, after controlling for differences in neighborhood incomes and other loan, borrower, and macroeconomic factors. This empirical finding seems to suggest that the housing goals of the Community Reinvestment Act and/or Government Sponsored Enterprises—those intended to increase lending in low- and middle-income areas—might have created a negative by-product, that is associated with higher loan delinquencies.

The structure of this paper is as follows. In Section 2 we show the descriptive statistics for the subprime mortgages in our database. In Section 3 we discuss the empirical strategy we employ. In Section 4 we present the baseline-case results and in Section 5 we discuss extensions and robustness checks. In Section 6 we demonstrate the increasing riskiness of high-LTV borrowers, and the extent to which securitizers were aware of this risk. In Section 7 we analyze the subprime-prime rate spread and in Section 8 we conclude. We provide several additional robustness checks in the appendices.

[5] Deng, Quigley, and Van Order (2000) discuss the simultaneity of the mortgage prepayment and default option. Campbell and Cocco (2003) and Van Hemert (2007) discuss mortgage choice over the life cycle.

2 Descriptive Analysis

In this paper we use the First American CoreLogic LoanPerformance (henceforth: LoanPerformance) database, as of June 2008, which includes loan-level data on about 85 percent of all securitized subprime mortgages; (more than half of the U.S. subprime mortgage market).[6]

There is no consensus on the exact definition of a subprime mortgage loan. The term subprime can be used to describe certain characteristics of the borrower (e.g., a FICO credit score less than 620),[7] lender (e.g., specialization in high-cost loans),[8] security of which the loan can become a part (e.g., high projected default rate for the pool of underlying loans), or mortgage contract type (e.g., no money down and no documentation provided, or a 2/28 hybrid). The common element across definitions of a subprime loan is a high default risk. In this paper, subprime loans are those underlying subprime securities. We do not include less risky Alt-A mortgage loans in our analysis. We focus on first-lien loans and consider the 2001 through 2008 sample period.[9]

We first outline the main characteristics of the loans in our database at origination. Second, we discuss the delinquency rates of these loans for various segments of the subprime mortgage market.

2.1 Loan Characteristics at Origination

Table 1 provides the descriptive statistics for the subprime mortgage loans in our database that were originated between 2001 and 2007. In the first block of Table 1 we see that the annual number of originated loans increased by a factor of four between 2001 and 2006 and the average loan size almost doubled over those five years. The total dollar amount originated in 2001 was $57 billion, while in 2006 it was $375 billion. In 2007, in the wake of the subprime mortgage crisis, the dollar amount originated fell sharply to $69 billion, and was primarily originated in the first half of 2007.

In the second block of Table 1, we split the pool of mortgages into four main mortgage contract types.

[6]Mortgage Market Statistical Annual (2007) reports securitization shares of subprime mortgages each year from 2001 to 2006 equal to 54, 63, 61, 76, 76, and 75 percent respectively.

[7]The Board of Governors of the Federal Reserve System, The Office of the Controller of the Currency, the Federal Deposit Insurance Corporation, and the Office of Thrift Supervision use this definition. See e.g. http://www.fdic.gov/news/news/press/2001/pr0901a.html

[8]The U.S. Department of Housing and Urban Development uses HMDA data and interviews lenders to identify subprime lenders among them. There are, however, some subprime lenders making prime loans and some prime lenders originating subprime loans.

[9]Since the first version of this paper in October 2007, LoanPerformance has responded to the request by trustees' clients to reclassify some of its subprime loans to Alt-A status. While it is not clear to us whether the pre- or post-reclassification subprime data are the most appropriate for research purposes, we checked that our results are robust to the reclassification. In this version we focus on the post-classification data.

Table 1: Loan Characteristics at Origination for Different Vintages

Descriptive statistics for the first-lien subprime loans in the LoanPerformance database.

	2001	2002	2003	2004	2005	2006	2007
				Size			
Number of Loans (*1000)	452	737	1,258	1,911	2,274	1,772	316
Average Loan Size (*$1000)	126	145	164	180	200	212	220
				Mortgage Type			
FRM (%)	33.2	29.0	33.6	23.8	18.6	19.9	27.5
ARM (%)	0.4	0.4	0.3	0.3	0.4	0.4	0.2
Hybrid (%)	59.9	68.2	65.3	75.8	76.8	54.5	43.8
Balloon (%)	6.5	2.5	0.8	0.2	4.2	25.2	28.5
				Loan Purpose			
Purchase (%)	29.7	29.3	30.1	35.8	41.3	42.4	29.6
Refinancing (cash out) (%)	58.4	57.4	57.7	56.5	52.4	51.4	59.0
Refinancing (no cash out) (%)	11.2	12.9	11.8	7.7	6.3	6.2	11.4
				Variable Means			
FICO Score	601.2	608.9	618.1	618.3	620.9	618.1	613.2
Combined Loan-to-Value Ratio (%)	79.4	80.1	82.0	83.6	84.9	85.9	82.8
Debt-to-Income Ratio (%)	38.0	38.5	38.9	39.4	40.2	41.1	41.4
Missing Debt-to-Income Ratio Dummy (%)	34.7	37.5	29.3	26.5	31.2	19.7	30.9
Investor Dummy (%)	8.2	8.1	8.1	8.3	8.3	8.2	8.2
Documentation Dummy (%)	76.5	70.4	67.8	66.4	63.4	62.3	66.7
Prepayment Penalty Dummy (%)	75.9	75.3	74.0	73.1	72.5	71.0	70.2
Mortgage Rate (%)	9.7	8.7	7.7	7.3	7.5	8.4	8.6
Margin for ARM and Hybrid Mortgage Loans (%)	6.4	6.6	6.3	6.1	5.9	6.1	6.0

Most numerous are the hybrid mortgages, accounting for more than half of all subprime loans in our data set originated between 2001 and 2007. A hybrid mortgage carries a fixed rate for an initial period (typically 2 or 3 years) and then the rate resets to a reference rate (often the 6-month LIBOR) plus a margin. The fixed-rate mortgage contract became less popular in the subprime market over time and accounted for just 20 percent of the total number of loans in 2006. In contrast, in the prime mortgage market, most mortgage loans were of the fixed-rate type during this period.[10] In 2007, as the subprime mortgage crisis hit, the popularity of FRMs rose to 28 percent. The proportion of balloon mortgage contracts jumped substantially in 2006, and accounted for 25 percent of the total number of mortgages originated that year. A balloon mortgage does not fully amortize over the term of the loan and therefore requires a large final (balloon) payment. Less than 1 percent of the mortgages originated over the sample period were adjustable-rate (non-hybrid) mortgages.

In the third block of Table 1, we report the purpose of the mortgage loans. In about 30 to 40 percent of cases, the purpose was to finance the purchase of a house. Approximately 55 percent of our subprime mortgage loans were originated to extract cash, by refinancing an existing mortgage loan into a larger new mortgage loan. The share of loans originated in order to refinance with no cash extraction was relatively small.

In the final block of Table 1, we report the mean values for the loan and borrower characteristics that we will use in the statistical analysis (see Table 2 for a definition of these variables). The average FICO credit score rose 20 points between 2001 and 2005. The combined loan-to-value (CLTV) ratio, which measures the value of all-lien loans divided by the value of the house, slightly increased over 2001–2006, primarily because of the increased popularity of second-lien and third-lien loans. The (back-end) debt-to-income ratio (if provided) and the fraction of loans with a prepayment penalty were fairly constant. For about a third of the loans in our database, no debt-to-income ratio was provided (the reported value in those cases is zero); this is captured by the missing debt-to-income ratio dummy variable. The share of loans with full documentation fell considerably over the sample period, from 77 percent in 2001 to 67 percent in 2007. The mean mortgage rate fell from 2001 to 2004 and rebounded after that, consistent with movements in both the 1-year and 10-year Treasury yields over the same period. Finally, the margin (over a reference rate) for adjustable-rate and hybrid mortgages stayed rather constant over time.

[10] For example Koijen, Van Hemert, and Van Nieuwerburgh (2007) show that the fraction of conventional, single-family, fully amortizing, purchase-money loans reported by the Federal Housing Financing Board in its Monthly Interest Rate Survey that are of the fixed-rate type fluctuated between 60 and 90 percent from 2001 to 2006. Vickery (2007) shows that empirical mortgage choice is affected by the eligibility of the mortgage loan to be purchased by Fannie Mae and Freddie Mac.

We do not report summary statistics on the loan source, such as whether a mortgage broker intermediated, as the broad classification used in the database rendered this variable less informative.

2.2 Performance of Loans by Market Segments

We define a loan to be delinquent if payments on the loan are 60 or more days late, or the loan is reported as in foreclosure, real estate owned, or in default. We denote the ratio of the number of vintage k loans experiencing a first-time delinquency at age s over the number of vintage k loans with no first-time delinquency for $age < s$ by $\tilde{P}_s^k$. We compute the actual (cumulative) delinquency rate for vintage k at age t as the fraction of loans experiencing a delinquency at or before age t

$$Actual_t^k = 1 - \prod_{s=1}^{t} \left(1 - \tilde{P}_s^k\right) \tag{1}$$

We define the average actual delinquency rate as

$$\overline{Actual}_t = 1 - \prod_{s=1}^{t} \left(1 - \bar{P}_s\right), \text{ where} \tag{2}$$

$$\bar{P}_s = \frac{1}{7} \sum_{i=2001}^{2007} \tilde{P}_s^k \tag{3}$$

In Figure 1 (left panel) we show that for the subprime mortgage market as a whole, vintage 2006 and 2007 loans stand out in terms of high delinquency rates. In Figure 3, we again plot the age pattern in the delinquency rate for vintages 2001 through 2007 and split the subprime mortgage market into various segments. As the figure shows, the poor performance of the 2006 and 2007 vintages is not confined to a particular segment of the subprime market, but rather reflects a (subprime) market-wide phenomenon.

In the six panels of Figure 3 we see that for hybrid, fixed-rate, purchase-money, cash-out refinancing, low-documentation, and full-documentation mortgage loans, the 2006 and 2007 vintages show the highest delinquency rate pattern. In general, vintage 2001 loans come next in terms of high delinquency rates, and vintage 2003 loans have the lowest delinquency rates. Notice that the scale of the vertical axis differs across the panels. The delinquency rates for the fixed-rate mortgages (FRMs) are lower than those for hybrid mortgages but exhibit a remarkably similar pattern across vintage years.

In Figure 4 we plot the delinquency rates of all *outstanding* mortgages. Notice that the fraction of FRMs that are delinquent remained fairly constant from 2005Q1 to 2007Q2. Delinquency rates in this

Figure 3: Actual Delinquency Rate for Segments of the Subprime Mortgage Market

The figure shows the age pattern in the delinquency rate for different segments. The delinquency rate is defined as the cumulative fraction of loans that were past due 60 or more days, in foreclosure, real-estate owned, or defaulted, at or before a given age.

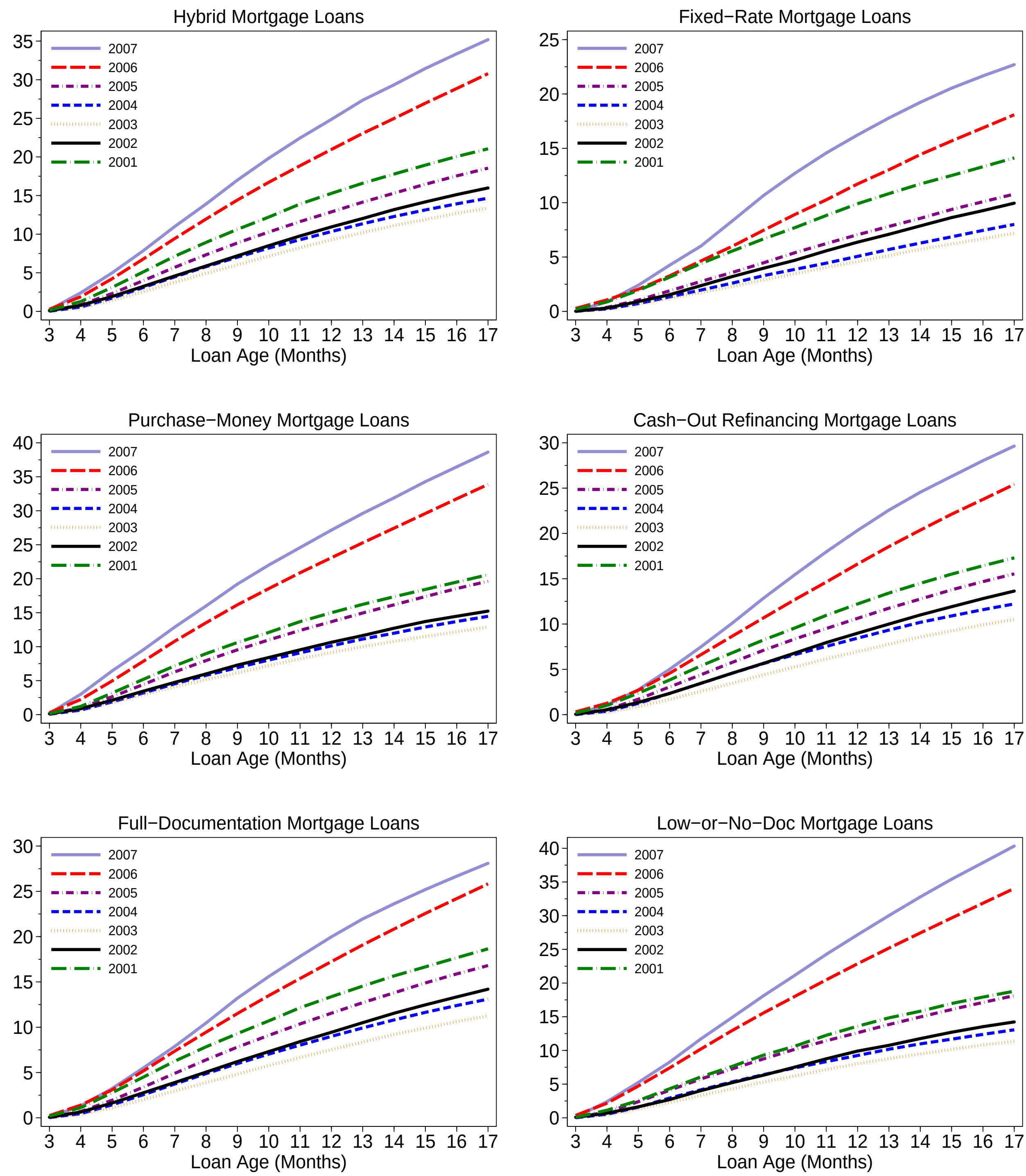
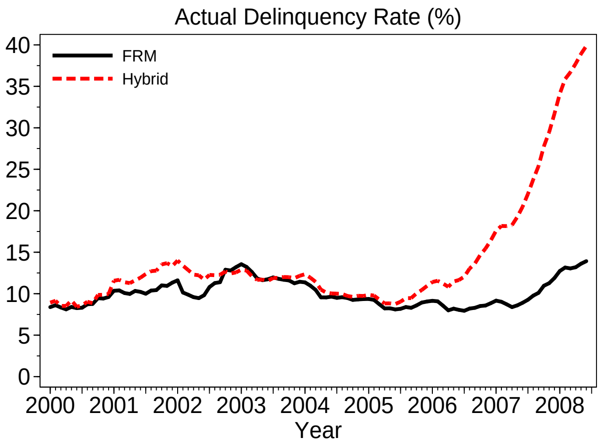


figure are defined as the fraction of loans delinquent at any given time, not cumulative. These rates are consistent with those used in an August 2007 speech by the Chairman of the Federal Reserve System (Bernanke (2007)), who said "For subprime mortgages with fixed rather than variable rates, for example, serious delinquencies have been fairly stable." It is important, though, to realize that this result is driven by an aging effect of the FRM pool, caused by a decrease in the popularity of FRMs from 2001 to 2006 (see Table 1). In other words, FRMs originated in 2006 in fact performed unusually poorly (Figure 3, upper-right panel), but if one plots the delinquency rate of outstanding FRMs over time (Figure 4, left panel), the weaker performance of vintage 2006 loans is masked by the aging of the overall FRM pool.

Figure 4: Actual Delinquency Rates of Outstanding Mortgages

The Figure shows the actual delinquency rates of all outstanding FRMs and hybrids from January 2000 through June 2008.



3 Statistical Model Specification

The focus of our paper is on the performance of subprime mortgage loans in the first 17 months after origination, for which we already have data for the vintages of particular interest: 2006 and 2007. Given this focus on young loans, we include delinquency—the earliest stage of payment problems—in our non-performance measure. Delinquency is an intermediate stage for a loan in trouble; the loan may eventually cure or terminate with a prepayment or default.

Our paper is related to the vast literature on empirical mortgage termination. Termination occurs either through a prepayment or a default. An analysis of mortgage termination lends itself naturally to duration (i.e., survival) models, with prepayment and default as competing reasons for termination. Important contributions to this literature include Deng (1997), Ambrose and Capone (2000), Deng, Quigley, and Van Order (2000), Calhoun and Deng (2002), Pennington-Cross (2003), Deng, Pavlov, and Yang (2005), Clapp, Deng, and An (2006), and Pennington-Cross and Chomsisengphet (2007).

We apply the duration model methodology to the intermediate status of delinquency by defining non-survival as "having ever been 60 days delinquent or worse," which includes formerly delinquent loans that are prepaid or cured. Transition from survival to non-survival will occur when a loan becomes 60 or more days delinquent or defaults *for the first time*. As a robustness check, we used "being *currently* 60 or more days delinquent or in default" as the non-performance measure, ran a standard logit regression, and found qualitatively similar results for the effect of explanatory variables and the effect of vintage year dummies (unreported results).

3.1 Empirical Model Specification

We are interested in the number of months (duration) until a loan becomes at least 60 days delinquent or defaults for the first time. Denoting this time by T, we define the probability that at age t loan i with covariate values $x_{i,t}$ becomes delinquent for the first time, conditional on not having been delinquent before, as

$$P_{i,t} = \Pr\{T = t | T \geq t, x_{i,t}\} \tag{4}$$

Because the monthly choice whether to make a mortgage payment is discrete, we use a proportional odds model, the discrete-time analogue to the popular proportional hazard model:

$$\log\left(\frac{P_{i,t}}{1 - P_{i,t}}\right) = \alpha_t + \beta' x_{i,t} \tag{5}$$

where α_t is an age-dependent constant and β is a vector of coefficients. The name "proportional odds" arises from the fact that the vector of coefficients, β, does not have an age subscript and thus the log odds are proportional to the covariate values at any age.

3.2 Estimation

The proportional odds model, Equation 5, is typically estimated for the full panel at once using either partial likelihood (see Cox (1972)) or maximum likelihood methodologies. The small sample properties for these two estimation methods are potentially different, but for a sample size of $10,000$ loans the methods already provide very similar estimates for β. For larger sample sizes the computational burden of the partial likelihood function quickly becomes unmanageable. This is a result of heavily tied data in our discrete time setup, where the term "tied" refers to loans experiencing first-time delinquency at the exact same age. We therefore estimate the proportional odds model using maximum likelihood, which has the added advantage that it provides estimates of the loan age effect, α_t. We use a random sample of 1 million loans for this exercise.

We use the PROC LOGISTIC procedure in SAS for the maximum likelihood estimation. This method is able to handle both left censoring (loans entering the sample at a later age) and right censoring (loans leaving the sample prematurely, not due to a prepayment or default), using the non-informative censoring assumption.[11] In order to generate unbiased delinquency rate plots (as in Figure 1, right panel), we classify prepaid loans as non-delinquent and non-censored, because we know for sure that they will never experience a first-time delinquency.

Because we include vintage year dummies as covariates we have to restrict the maximum age considered in our analysis to 17 months, the latest age for which we have an observation for the 2007 origination year; the maximum likelihood estimation requires each covariate, including the vintage 2007 dummy, have some dispersion in the covariate values for each age.[12] For the adjusted delinquency rate plots viewed at the end of 2005 and 2006 (Figure 5), we restrict the analysis to a maximum age of 11 months.

3.3 Reported Output

The *AgeEffect* statistic is defined as the proportional odds ratio for first-time delinquency at a particular age t for the average (over the full sample) vector of covariate values at age t, $\bar{x}_t$:

$$AgeEffect_t = exp\left(\alpha_t + \beta' \bar{x}_t\right) \tag{6}$$

The $Marginal$ statistic is defined as the log proportional odds ratio associated with a one standard

[11]Loans securitized several months after origination are not observed in our data between the origination date and the securitization date; therefore, they are left censored. In addition, if the securitizer goes out of business we stop observing their loans and therefore they are right censored.

[12]For more information on this, see page 126 of Allison (2007).

deviation increase in variable j, σ_j:

$$Marginal_j = \beta_j \sigma_j = \log\left(\frac{\exp\left(\alpha_t + \beta' x_{i,t} + \beta_j \sigma_j\right)}{\exp\left(\alpha_t + \beta' x_{i,t}\right)}\right) \tag{7}$$

The advantage of taking the log in Equation 7 is that the effect of an increase of σ_j in covariate j is minus the effect of a decrease of σ_j, and thus the absolute effect is invariant to the chosen direction of change.

The *Deviation* statistic measures the difference between the mean value of a variable in a particular vintage year and the mean value of that variable measured over the entire sample, expressed in the number of standard deviations of the variable. For example, for vintage 2001 and variable j it is the difference between the mean value for variable j in 2001, $\overline{x01}_j$, and the mean value over all vintages, $\bar{x}_j$, expressed in the number of standard deviations:

$$Deviation_j = \frac{\overline{x01}_j - \bar{x}_j}{\sigma_j} \tag{8}$$

The *Contribution* statistic measures the deviation of the (average) log proportional odds of first-time delinquency in a particular vintage year from the (average) log proportional odds of first-time delinquency over the entire sample that can be explained by a particular variable. For example for vintage 2001 and variable j we have:

$$\begin{aligned} Contribution_j = \beta_j\left(\overline{x01}_j - \bar{x}_j\right) &= \log\left(\frac{\exp\left(\alpha_t + \beta' x_{i,t} + \beta_j\left(\overline{x01}_j - \bar{x}_j\right)\right)}{\exp\left(\alpha_t + \beta' x_{i,t}\right)}\right) \\ &= Marginal_j * Deviation_j \end{aligned} \tag{9}$$

As a straightforward generalization of Equation 9, the combined contribution of two variables is simply the sum of the individual contributions. This property will be used for reporting the total contribution of all covariates in Table 3.

The probability of experiencing a first-time delinquency at or before $age = t$ is given by

$$\Pr\left\{T \leq t | x_t, x_{t-1}, ..\right\} = 1 - \prod_{s=1}^{t}\left(1 - P_s\right) \tag{10}$$

To visualize the magnitude of the vintage year effect, we evaluate the above expression for the value of

P_s that satisfies

$$\log\left(\frac{P_s}{1-P_s}\right) = \log\left(\frac{\bar{P}_s}{1-\bar{P}_s}\right) + D^k - \bar{D} \tag{11}$$

where D^k is the estimated coefficient for for the vintage year k dummy variable and $\bar{D}$ is the average estimated vintage dummy variable. This expression uses the proportional odds property for explanatory variables, including vintage year dummies, illustrated in Equation 5. Combining Equations 10 and Equation 11 we obtain the adjusted delinquency rate for vintage year k at age t

$$Adjusted_t^k = 1 - \prod_{s=1}^{t} \frac{1}{1 + \left(\frac{\bar{P}_s}{1-\bar{P}_s}\right)\exp\left\{D^k - \bar{D}\right\}} \tag{12}$$

Notice that for an average vintage year, $D^k = \bar{D}$, Equation 12 simplifies to

$$\overline{Adjusted}_t = 1 - \prod_{s=1}^{t}\left(1-\bar{P}_s\right) = \overline{Actual}_t \tag{13}$$

4 Empirical Results for the Baseline-Case Specification

In this section we investigate to what extent the proportional odds model model can explain the high levels of delinquencies for the vintage 2006 and 2007 mortgage loans in our database. All results in this section are based on a random sample of one million first-lien subprime mortgage loans, originated between 2001 and 2007.

4.1 Variable Definitions

Table 2 provides the definitions of the variables (covariates) included in the baseline-case specification of the proportional odds model.

The borrower and loan characteristics we use in the analysis are: the FICO credit score; the combined loan-to-value ratio; the value of the debt-to-income ratio (when provided); a dummy variable indicating whether the debt-to-income ratio was missing (reported as zero); a dummy variable indicating whether the loan was a cash-out refinancing; a dummy variable indicating whether the borrower was an investor (as opposed to an owner-occupier); a dummy variable indicating whether full documentation was provided; a dummy variable indicating whether there is a prepayment penalty on a loan; the (initial) mortgage rate;

Table 2: Baseline-Case Variable Definitions

This table presents definitions of the baseline-case variables (covariates) used in the proportional odds duration model. The first two variables are used as dependent variables. The other variables are used as independent variables. We report the expected sign for the independent variables in parentheses and sometimes provide a brief motivation.

Variable (Expected Sign)	Explanation
FICO Score (-)	Fair, Isaac and Company (FICO) credit score at origination.
Combined Loan-to-Value Ratio (+)	Combined value of all liens divided by the value of the house at origination. A higher combined loan-to-value ratio makes default more attractive.
Debt-to-Income Ratio (+)	Back-end debt-to-income ratio, defined by the total monthly debt payments divided by the gross monthly income, at origination. A higher debt-to-income ratio makes it harder to make the monthly mortgage payment.
Missing Debt-to-Income Dummy (+)	Equals one if the back-end debt-to-income ratio is missing and zero if provided. We expect the lack of debt-to-income information to be a negative signal on borrower quality.
Cash-Out Dummy (-)	Equals one if the mortgage loan is a cash-out refinancing loan. Pennington-Cross and Chomsisengphet (2007) show that the most common reasons to initiate a cash-out refinancing are to consolidate debt and to improve property.
Investor Dummy (+)	Equals one if the borrower is an investor and does not owner-occupy the property.
Documentation Dummy (-)	Equals one if full documentation on the loan is provided and zero otherwise. We expect full documentation to be a positive signal on borrower quality.
Prepayment Penalty Dummy (+)	Equals one if there is a prepayment penalty and zero otherwise. We expect that a prepayment penalty makes refinancing less attractive.
Mortgage Rate (+)	Initial interest rate as of the first payment date. A higher interest rate makes it harder to make the monthly mortgage payment.
Margin (+)	Margin for an adjustable-rate or hybrid mortgage over an index interest rate, applicable after the first interest rate reset. A higher margin makes it harder to make the monthly mortgage payment.
Product Type Dummies (+)	We consider four product types: FRMs, Hybrids, ARMs, and Balloons. We include a dummy variable for the latter three types, which therefore have the interpretation of the probability of delinquency relative to FRM. Because we expect the FRM to be chosen by more risk-averse and prudent borrowers, we expect positive signs for all three product type dummies.
Origination Amount (?)	Size of the mortgage loan. We have no clear prior on the effect of the origination amount on the probability of delinquency, holding constant the loan-to-value and debt-to-income ratio.
House Price Appreciation (-)	MSA-level house price appreciation from the time of loan origination, reported by the Office of Federal Housing Enterprise Oversight (OFHEO). Higher housing equity leads to better opportunities to refinance the mortgage loan.
Change Unemployment Rate (+)	State-level change in the unemployment rate from the time of loan origination, reported by the Bureau of Economic Analysis. An increase in the state unemployment rate increases the probability a homeowner lost his job, which increases the probability of financial problems.
Neighborhood Income (-)	Zip-code-level median income in 1999 from the U.S. Census Bureau 2000. The better the neighborhood, as proxied by the median income, the more motivated a borrower may be to stay current on a mortgage.

and the margin for adjustable-rate and hybrid loans.[13]

In addition, we use three macro variables in the baseline-case specification. First, we construct a variable that measures house price appreciation from the time of origination until the time we evaluate whether a loan is delinquent. To this end we use metropolitan statistical area (MSA) level house price indexes from the Office of Federal Housing Enterprise Oversight (OFHEO) and match loans with MSAs by using the zip code provided by LoanPerformance.[14] Second, we include the state-level change in the unemployment rate from the time of loan origination until the time of performance evaluation, reported by the Bureau of Economic Analysis. An increase in the state unemployment rate increases the probability a homeowner lost his or her job, which increases the probability of financial problems. Third, we use a measure for the quality of the neighborhood: zip-code-level median household income in 1999. The data are from U.S. Census Bureau 2000 and are collected every 10 years. The better the neighborhood the more motivated a borrower may be to stay current on a mortgage. In Table 2 we report the expected sign for the regression coefficient on each of the explanatory variables in parentheses.

4.2 Determinants of Delinquency

In Tables 3, 4 and 5 we present the determinants of delinquency using the proportional odds methodology. The tables report the output of a single estimation; due to limited page size, the output is spread over three separate tables. The first column of Table 3 lists the covariates included (other than the vintage and age dummies which are reported in Tables 4 and 5). Column two documents the marginal effect of the covariates (Equation 7). All marginal effects have the expected sign, as shown in Table 2. Except for the hybrid and ARM dummies, all variables are statistically significant at the 1% level. The four explanatory variables with the largest (absolute) marginal effects and thus the most important for explaining cross-sectional differences in loan performance, are the FICO score, the combined loan-to-value ratio, the mortgage rate, and house price appreciation. According to the estimates, for example, a one standard deviation increase in the FICO score decreases the log odds of first-time delinquency by 47.94 percent; or, equivalently, changes the odds by a factor $\exp(-0.4794) = 0.6192$. The product type has a relatively small effect on the performance of a loan, beyond what is explained by other characteristics. In Figure

[13]We also studied specifications that included loan purpose, reported in Table 1, and housing outlook, defined as the house price accumulation in the year prior to the loan origination. These variables were not significant and did not materially change the regression coefficients on the other variables.

[14]Estimating house price appreciation on the MSA-level, as opposed to the individual property level introduces a potential measurement error of this variable. To the best of our knowledge, there is no data available to estimate the size of this measurement error or to evaluate its impact on the results.

3 we show that FRMs experience a much lower delinquency rate than hybrid mortgages, which therefore must be driven by borrowers with better characteristics selecting into FRMs.[15]

The contributions of each covariate to explaining different delinquency rates for each vintage year are given in columns 3 through 9 of Table 3. The very high delinquency rate for vintage 2001 loans can be explained in large part by a near perfect storm of unfavorable lending and economic conditions: low FICO scores, high mortgage rates, relatively low house price appreciation, and low (negative) change in unemployment, all contributing to a higher probability of delinquency. In total, the different covariates contributed to a 51.71 percent increase in the log odds of delinquency, compared to a situation with average covariate values. This is slightly higher than the 45.06 percent for vintage 2006 and slightly smaller than the 56.09 percent for vintage 2007—years for which low house price appreciation and high mortgage rates increased the probability of delinquency. For vintage years 2003 and 2005, high house price appreciation contributed to a reduced probability of delinquency compared to a situation with average covariate values. Therefore, we can say that high house price appreciation between 2003 and 2005 masked the true riskiness of subprime mortgages for these vintage years.[16]

By construction, the weighted-average contribution of a variable over 2001–2007 is zero, with weights equal to the number of originated loans in a particular vintage year. Because the number of loans originated differs across vintages years, the equal-weighted average contribution is not zero, hence rows for the contribution variable in Table 3 do not add up to zero.

As shown in Table 4, the coefficients of the vintage dummy variables increase every year, which demonstrates that loan quality deteriorated after adjusting for the other covariates included in the specification. This deterioration is illustrated by the adjusted delinquency rates depicted in Figure 1 (right panel), which is computed using Equation 12. This picture is in sharp contrast with that obtained from actual rates, where 2003 was the year with the lowest delinquency rates, and 2001 was the year with the third-highest rates (see Figure 1, left panel). We test whether the differences between every subsequent vintage year dummy coefficients are statistically significant. We find that the yearly change (increase) in the dummy variables are statistically significant at the 1% confidence level, except for the small increase from 2006 to 2007. The vintage dummy coefficients reported in Table 4 are in the same units as the contribution of the different variables presented in Table 3. For example, comparing vintages 2001 and 2007, the total

[15] Consistent with this finding, LaCour-Little (2007) shows that individual credit characteristics are important for mortgage product choice.

[16] Shiller (2007) argues that house prices were too high compared to fundamentals in this period and refers to the house price boom as a classic speculative bubble largely driven by an extravagant expectation for future house price appreciation.

Table 3: Determinants of Delinquency, Variables Other Than Vintage and Age Dummy Variables

The table shows the output of the proportional odds duration model. The first column reports the covariates included, other than the vintage and age dummies which are reported separately in Table 4. The second column reports the marginal effect, defined in Equation 7. A "$*$" indicates statistical significance at the 1% level. Columns three through nine detail the contribution of a variable to explain a different probability of delinquency in 2001–2007 (Equation 9).

Explanatory Variable	**Marginal Effect, %**	**Contribution, %**						
	2001–2007	2001	2002	2003	2004	2005	2006	2007
FICO Score	−47.94∗	13.74	6.74	−0.36	−1.00	−3.09	−1.04	3.00
Combined Loan-to-Value Ratio	24.02∗	−7.44	−5.92	−2.52	0.23	2.20	3.29	−1.43
Debt-to-Income Ratio	12.86∗	−2.76	−2.73	−0.66	0.31	−0.63	2.86	0.04
Missing Debt-to-Income Dummy	12.59∗	2.17	2.35	0.24	−0.51	0.85	−2.40	0.67
Cash-Out Dummy	−12.73∗	−0.98	−0.60	−0.69	−0.35	0.59	0.78	−0.93
Investor Dummy	3.86∗	0.04	−0.03	−0.01	0.02	0.00	−0.02	−0.03
Documentation Dummy	−13.79∗	−3.42	−1.49	−0.54	0.01	0.78	0.90	−0.52
Prepayment Penalty Dummy	6.13∗	0.50	0.37	0.18	0.05	−0.06	−0.32	−0.46
Mortgage Rate	29.21∗	39.51	16.86	−4.78	−13.00	−8.25	11.34	13.68
Margin	11.84∗	−2.07	0.19	−1.81	0.32	1.10	0.32	−2.43
Hybrid Dummy	1.81	−0.23	0.03	−0.12	0.29	0.34	−0.53	−0.95
ARM Dummy	0.36	0.00	0.00	−0.01	0.00	0.00	0.00	0.00
Balloon Dummy	3.70∗	−0.16	−0.71	−0.94	−1.02	−0.48	2.48	2.95
Origination Amount	15.91∗	−7.31	−5.03	−2.64	−0.62	2.05	3.31	4.08
House Price Appreciation	−29.96∗	7.24	5.32	−10.52	−16.40	−2.24	21.38	32.86
Change Unemployment	7.69∗	12.76	3.03	−1.85	−2.40	−2.31	2.25	5.18
Neighborhood Income	−8.81∗	0.11	−0.40	−0.53	−0.11	0.11	0.48	0.38
Total	–	51.71	17.99	−27.55	−34.19	−9.04	45.06	56.09

Table 4: Determinants of Delinquency, Vintage Dummy Variables

The table shows the output of the proportional odds duration model. The first column reports the vintage dummies included. The values for the other covariates are outlined in Tables 3 and 5. The second column shows the estimated coefficients. The vintage 2001 dummy was not included as covariate; hence the coefficients on the other covariates are relative to the 2001 vintage and we report a zero value for the coefficient of 2001. A "$*$" indicates statistical significance at the 1% level.

Explanatory Variable	**Estimate, %**
Vintage 2001	0.00
Vintage 2002	5.12*
Vintage 2003	23.64*
Vintage 2004	49.71*
Vintage 2005	57.93*
Vintage 2006	64.65*
Vintage 2007	66.69*

Table 5: Determinants of Delinquency, Age Dummy Variables

The table shows the output of the proportional odds duration model. Each column reports the corresponding odds ratio, *AgeEffect*, estimated for each age dummy variable based on Equation 6. The values for the other covariates are reported in Tables 3 and 4.

Age, Months	3	4	5	6	7	8	9	10
***AgeEffect* (*100)**	0.04	0.31	0.55	0.67	0.72	0.72	0.73	0.72

Age, Months	11	12	13	14	15	16	17	–
***AgeEffect* (*100)**	0.73	0.72	0.73	0.71	0.70	0.69	0.67	–

contribution of the (non-vintage dummy) covariates increased by 4.38 percent (from 51.71 percent to 56.09 percent). This pales in comparison to the 66.69 percent increase in the vintage dummy variable over 2001–2007.

To illustrate the effect of age on the conditional probability of first-time delinquency, in Table 5 we report the odds statistic defined in Equation 6. We see that the odds of first-time delinquency peaks around age of 7–13 months.

Next we study the following question: Based on information available at the end of 2005, was the dramatic deterioration of loan quality since 2001 already apparent? Notice that we cannot answer this question by simply inspecting vintages 2001 through 2005 in Figure 1 (right panel), because the computation of the adjusted delinquency rate for, say, vintage 2001 loans, makes use of a regression model estimated using data from 2001 through 2008. Hence, we re-estimate the proportional odds model underlying Figure 1 (right panel) making use of only 2001–2005 data. The resulting age pattern in adjusted delinquency rates is plotted in Figure 5 (left panel). We again obtain the result that the adjusted delinquency rate rose monotonically from 2001 onward. We therefore conclude that the dramatic deterioration of loan quality in this decade should have been apparent by the end of 2005. Figure 5 (right panel) depicts the situation when we use data available at the end of 2006. Again, the deterioration is clearly visible.[17]

The finding of a continual decline in loan quality also occurs when analyzing foreclosure rates (Appendix A), and analyzing hybrid mortgages and FRMs separately (Appendix B). Moreover, the main result documenting the monotonic rise in adjusted delinquency rates is found based on numerous alternative model specifications discussed in Section 5.

5 Empirical Results for Alternative Specifications

In this Section we explore various alternative model specifications.

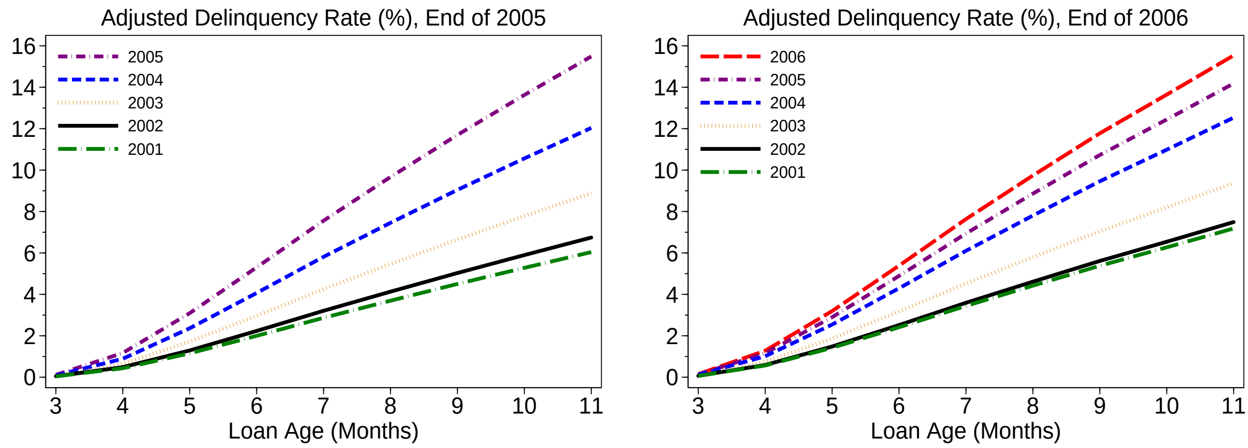
5.1 Different Loan and Borrower Characteristics

We explore numerous alternative loan and borrower characteristics as covariates for robustness. First, we consider as covariates those of the baseline case presented in Table 3, plus the 10 interaction and quadratic terms that can be constructed from the four most important variables: the FICO score, the CLTV ratio,

[17] One reason why investors did not massively start to avoid or short subprime-related securities is that the timing of the subprime market downturn may have been hard to predict. Moreover, a short position is associated with a high cost of carry (Feldstein (2007)).

Figure 5: Adjusted Delinquency Rate, Viewed at the End of 2005 and 2006

The figure shows the adjusted delinquency rate using data available at the end of 2005 (left panel) and 2006 (right panel). The delinquency rate is defined as the cumulative fraction of loans that were past due 60 or more days, in foreclosure, real-estate owned, or defaulted, at or before a given age. The adjusted delinquency rate is obtained by adjusting the actual rate for year-by-year variation in FICO scores, loan-to-value ratios, debt-to-income ratios, missing debt-to-income ratio dummies, cash-out refinancing dummies, owner-occupation dummies, documentation levels, percentage of loans with prepayment penalties, mortgage rates, margins, composition of mortgage contract types, origination amounts, MSA house price appreciation since origination, change in state unemployment rate since origination, and neighborhood median income.



the mortgage rate, and subsequent house price appreciation. Allowing for these additional terms, we take into account the effect of *risk-layering*—such as, for example, the effect of a combination of a borrower's low FICO score and a high CLTV ratio—on the probability of delinquency. It is in this case not a priori clear what the sign on the FICO-CLTV interaction variable should be. A negative sign would mean that a low FICO and a high CLTV reinforce each other and give rise to a predicted delinquency probability that is higher than that without interaction effect. A positive sign could be explained by lenders who originate a low FICO and high CLTV loan only if they have positive private information on the loan or borrower quality. We find that the coefficient on the FICO-CLTV interaction term is close to zero and insignificant.

More certain is the sign we expect on the HPA-CLTV variable. Low house price appreciation is expected to especially give rise to a higher delinquency probability for a high CLTV ratio, because the borrower is closer to a situation with *negative equity* in the house (combined value of the mortgage loans larger than the market value of the house). Consistent with this intuition, we find a negative and significant (at the 1% level) coefficient on this interaction term. The vintage dummy variables are still increasing every year. Inclusion of the 10 interaction covariates does not substantially increase the overall fit of the model, as measured by the log likelihood ratio.

Second, we included a dummy for the presence of a second-lien loan. We find that the coefficient is positive and statistically significant and that it inherits some of the statistical power of the CLTV variable. The coefficients of the other covariates are virtually unchanged. Inclusion of the dummy does not substantially increase the overall fit of the model, as measured by the log likelihood ratio.

Third, we considered as an additional covariate a dummy variable taking the value one whenever the CLTV equals 80 percent. With this variable, we are aiming to control for *silent seconds*, referring to a situation where an investor takes out a second-lien loan not reported in our database typically in combination with an 80 percent first-lien loan. This dummy variable is statistically significant but economically not very large and moreover hardly improved the overall fit.

Fourth, we excluded the loans where the debt-to-income ratio is missing from the sample to make sure the measurement error associated with this variable does not lead to a significant bias in the results. The estimates based on the smaller subsample, in which the debt-to-income variable has non-zero reported values, are statistically and economically similar to those based on the entire sample of loans.

Fifth, we performed several robustness checks regarding the reset rate for hybrid mortgages. The initial mortgage rate for hybrid mortgages is potentially lower during the initial fixed-rate period. For 99.57 percent of mortgages in our database, the duration of the initial fixed rate period is 24 months or more; the most common fixed period is 24 months, followed by 36 months. Since we focus on delinquency in the first 17 months, we expect the initial mortgage rate to be an important covariate. However, because households may have factored in the rise in the mortgage rate before the actual reset date, we include the post-reset margin as an additional covariate in the baseline case specification. The margin is in excess of a reference rate, which in 99.34 percent of the cases is the 6-month LIBOR rate. As a robustness check we performed the analysis for FRMs and Hybrid mortgages separately, with FRMs not being subject to resets, and in both cases obtain our main result that adjusted delinquency rates rose monotonically over 2001–2007 (see Figure 9).

We performed two additional robustness checks. First, instead of the margin we included a covariate defined as the margin plus the 6-month LIBOR interest rate at origination (obtained from Bloomberg). Second, instead of the margin we included a covariate defined as the margin plus the 6-month LIBOR interest rate at origination minus the initial mortgage rate. This captures the potential change in interest rate at the time of reset, based on the 6-month LIBOR rate at origination. For FRMs the values of the new covariates are set to zero. The marginal effect for the two new covariates is 12.27 percent and 7.83 percent respectively; the marginal effects for the margin covariates in the baseline case are 11.84 percent, as reported in Table 3. Among the other covariates, only the coefficient for the initial rate is slightly affected. The marginal effect of the initial rate is 29.58 percent and 33.60 percent for the two alternative specifications respectively, compared to a marginal effect of 29.21 percent in the baseline case, as reported in Table 3. The log likelihood of the different specifications is virtually identical.

5.2 Local house-by-house return volatility

In this section we study local house-by-house return volatility as as additional covariate. We obtained the data from the Office of Federal Housing Enterprise Oversight (OFHEO) at the state level.[18] OFHEO uses a repeated-sales methodology to compute house price appreciation in a geographical unit (like a state or MSA) and, as a by-product, obtains an estimate of the variation of the return around the mean in the geographical unit.[19]

[18] We would like to thank OFHEO for providing us with the data. MSA-level data exist but was not available for public release.

[19] For more details on this procedure, see the official OFHEO documentation by Calhoun (1996). Also De Jong, Driessen, and Van Hemert (2008) explain the interpretation and computation of the volatility parameters.

The house-by-house volatility is 8.05 percent, annualized and averaged over the full panel (50 states plus the District of Columbia in the 2001Q1-2008Q2 sample period). Most of the variation of the volatility is in the cross-section: the standard deviation of the volatility estimate across states (averaged over 2001Q1-2008Q2) is 0.75 percent. The standard deviation of the volatility estimate over time (averaged over the 50 states plus the District of Columbia) is only 0.18 percent.

Ambrose, LaCour-Little, and Huszar (2005) use the volatility estimate of OFHEO to compute the probability of negative equity. In the special case that the equity in the house is exactly zero, based on house price appreciation in the geographical area, there is a 50 percent probability the household actually has negative equity based on the (unobserved) house price appreciation of the individual house, assuming a symmetric (e.g., normal) distribution for the house-by-house deviation from the MSA mean. When the equity is positive based on house price appreciation in the geographical area, the higher the house-by-house return volatility, the higher the probability an individual house has negative equity. When the equity is negative, the situation is reversed.

While it is not just the probability of having negative equity for an individual house that matters, but in general the whole probability distribution, it does seem intuitive that the effect of local house-by-house return volatility may interact with HPA. Hence, in the empirical implementation we add both the house-by-house return volatility by itself and the interaction of this volatility with HPA as covariates. Consistent with Ambrose, LaCour-Little, and Huszar (2005), the estimated coefficient on the interaction term is positive; when house price appreciation is high in the geographical area, high volatility increases the probability of having negative equity for a specific house. The effect is statistically significant at the 1% level, but has a small Chi-squared statistic compared to the baseline case covariates and has a negligible impact on the coefficients of the other covariates.

5.3 CRA and GSE Housing Goals

In this section we explore additional covariates related to the Community Reinvestment Act (CRA) and Government Sponsored Enterprises (GSEs) housing goals. The 1977 Community Reinvestment Act (CRA) is a United States federal law designed to encourage commercial banks and savings associations to meet the needs of borrowers in all segments of their communities, including low- and moderate-income (LMI) households and neighborhoods. The CRA does not list specific criteria for evaluating the performance of financial institutions, but indicates that the evaluation process should accommodate the situation and context of each individual institution. An institution's CRA compliance record is, for example, taken into account when applying for deposit facilities.[20] LMI neighborhoods have a median income level that is less than 80 percent of the median income of a broader geographic area, e.g., the MSA for urban neighborhoods.[21] With a similar objective of helping poor and underserved individuals and neighborhoods, the Congress in 1992 established an affordable housing mission for Fannie Mae and Freddie Mac by directing the Department of Housing and Urban Developement (HUD) to create specific mortgage purchase goals for these Government Sponsored Enterprises (GSEs). The goals are primarily defined in terms of (i) household income relative to median MSA income (for urban neighborhoods), (ii) neighborhood median income relative to MSA median income, and (iii) minority concentration in the neighborhood.[22]

To isolate the effect of CRA and the GSE housing goals from pure neighborhood effects, we study the effect of LMI neighborhood status on the probability of delinquency, controlling for the baseline-specification covariates, including the neighborhood median income.

We either include an LMI dummy that equals one if the median neighborhood income is less than 80 percent of the MSA median income, or we add the MSA median income. We use zip-code level median household income and median MSA household income from the U.S. Census Bureau to compute the LMI dummy.[23]

The LMI dummy or MSA median income level pick up the difference in the probability of delinquency for loans in MSAs with different median incomes, but in neighborhoods with the same median income and with the same loan and borrower characteristics, giving rise to different incentives for CRA-complying institutions and the GSEs. We interpret any effect from the LMI dummy or MSA median income to come from the CRA and GSE housing goals, and thus assume that there is no direct effect of LMI status or MSA median income on borrower behavior after controlling for neighborhood median income.

The results are presented in Table 6. Specification I corresponds to the baseline case of Table 3 and is included as a benchmark. Of the baseline case covariates, we only report the neighborhood income to preserve space. In specification II we add the MSA median income to the baseline case covariates. A higher

[20] See http://www.federalreserve.gov/dcca/cra/

[21] See Laderman (2004) for a further discussion.

[22] See http://www.huduser.org/Datasets/GSE/gse2006.pdf Table 1 for the specific goals for 2000-2006.

[23] The precise identification of CRA and GSE targeted neighborhoods is not feasible in our analysis for several reasons: (i) the location of subprime lenders is not reported in the LoanPerformance data, thus we cannot identify the CRA targeted community; and (ii) most frequently, CRA and GSE targeted communities are defined using census tract-level measures (such as income, poverty level, and minority concentration). LoanPerformance data identifies each property location in zip codes, which do not directly match with census tracts. Therefore, in our analysis we identify neighborhoods that can *potentially* fall under CRA and GSE housing goals using either the LMI dummy variable or MSA-level median household income.

MSA median income increases the possibility a loan was made to advance CRA or GSE housing goals. The positive and statistically significant (at the 1% level) marginal effect reported in the table effect thus implies that CRA and GSE housing goal eligibility is associated with a higher probability of delinquency, ceteris paribus. In specification III we add the LMI dummy to the baseline case covariates. We find a positive and significant marginal effect, again implying that CRA and GSE housing goal eligibility raises the probability of delinquency. Finally in specification IV we interact the LMI dummy with vintage dummies to see how the LMI effect changed over time. For all vintage years the marginal effect is positive and statistically significant at the 1% level, except for 2003, which is positive and statistically significant at the 5% level. There is no clear trend over time.

Table 6: Low- and Moderate-Income Neighborhood Effect

This table reports marginal effects for different measures of neighborhood (median household) income relative to MSA (median household) income. In all four specifications we include the baseline case variables used in Table 3, of which we only report neighborhood income to preserve space. Specification I is the baseline case with no variable capturing the neighborhood income relative to the MSA income. Specification II includes MSA income. Specification III includes a dummy with value one if neighborhood income is less than 80 percent of MSA income; i.e., if it is a low- and moderate-income (LMI) neighborhood. Specification IV includes interaction variables of the LMI dummy with vintage year dummies. The marginal effect for the interaction terms is computed as the product of the estimated coefficient and the full sample standard deviations of LMI. A "∗" indicates statistical significance at the 1% level.

	I	II	III	IV
Neighborhood Income	−8.81%*	−9.10%∗	−6.95%∗	−6.94%∗
MSA Income	–	1.07%∗	–	–
LMI Dummy	–	–	2.82%∗	–
LMI 2001	–	–	–	6.26%∗
LMI 2002	–	–	–	4.52%∗
LMI 2003	–	–	–	1.75%
LMI 2004	–	–	–	3.64%∗
LMI 2005	–	–	–	2.67%∗
LMI 2006	–	–	–	1.79%∗
LMI 2007	–	–	–	3.79%∗

6 Non-Stationarity of the Loan-to-Value Effect

The proportional odds model used in Section 4 assumes that the covariate coefficients are constant over time. That is, the effect of a unit change in a given covariate on the probability of first-time delinquency is the same in, for example, 2006, as it is in 2001, holding constant the values of the other covariates. We test the validity of this assumption for all variables in our analysis and find that the strongest rejection of a constant coefficient is for the CLTV ratio. In this section we first discuss this finding and then turn to the question of whether lenders were aware of the non-stationarity of the loan-to-value effect, by investigating the relationship between the loan-to-value ratio and mortgage rates over time.

We estimate the proportional odds model with CLTV interacted with the seven vintage dummy variables, instead of just CLTV without interaction, as we have in the baseline case specification (Section 4). We compute the marginal effect for a particular loan vintage as the product of the estimated coefficient for the associated interaction variable and the standard deviation of CLTV for all vintages together, which totals 0.10, 0.11, 0.14, 0.15, 0.22, 0.35, 0.34 for years 2001 to 2007, respectively. All seven coefficients are highly statistically significant at the 1% level. Hence, the CLTV is an increasingly important determinant of delinquency over time.

We examine whether lenders were aware that high LTV ratios were increasingly associated with riskier borrowers. The combined LTV ratio rather than the first-lien LTV ratio is believed to be the main determinant of delinquency because it is the burden of all the debt together that may trigger financial problems for the borrower. In contrast, the first-lien LTV is the more important determinant of the mortgage rate on a first-lien mortgage, because it captures the dollar amount at stake for the first-lien lender.[24] For this reason, we test whether the sensitivity of the lender's interest rate to the first-lien LTV ratio changed over time. We perform a cross-sectional OLS regression with the mortgage rate as the dependent variable, and loan characteristics, including the first-lien LTV and second-lien LTV (CLTV minus first-lien LTV), as independent variables.[25] We perform one such regression for each calendar quarter in our sample period. We can only expect to get accurate results when using relatively homogeneous groups of loans, and therefore consider fully amortizing FRM and 2/28 hybrid loans separately. Together these two contract types account for more than half of all mortgage loans in

[24] This is confirmed by our empirical results. To conserve space the results are not reported.

[25] Specifically, we use the FICO score, first-lien loan-to-value ratio, second-lien loan-to-value ratio, debt-to-income ratio, a dummy for a missing debt-to-income ratio, a cash-out refinancing dummy, a dummy for owner occupation, documentation dummy, prepayment penalty dummy, margin, origination amount, term of the mortgage, and prepayment term as the right-hand-side variables.

our database. Each cross-sectional regression is based on a minimum of 18,784 observations.

Figure 2 shows the regression coefficient on the first-lien LTV ratio for each quarter from 2001Q1 through 2007Q2.[26] We scaled the coefficients by the standard deviation of the first-lien LTV ratio, and they can therefore be interpreted as the changes in the mortgage rates when the first-lien LTV ratios are increased by one standard deviation. In the fourth quarter of 2006, a one-standard-deviation increase in the first-lien LTV ratio corresponded to about a 30-basis-point increase in the mortgage rate for 2/28 hybrids and about a 40-basis-point increase for FRMs, keeping constant other loan characteristics. In contrast, in the first quarter of 2001, the corresponding rate increase was 10 and 16 basis points, respectively. This provides evidence that lenders were to some extent aware of high LTV ratios being increasingly associated with risky borrowers.[27] In Appendix C we show that this result is robust to allowing for a non-linear relationship between the mortgage rate and the first-lien LTV ratio. Finally, notice that the effect of a one-standard-deviation increase in the first-lien LTV ratio on the 2/28 mortgage rate increased substantially in the wake of the subprime mortgage crisis: from 30 basis points in 2007Q1 to 42 basis points in 2007Q2.

7 Subprime-Prime Rate Spread

In general, interest rates on subprime mortgages are higher than on prime mortgages to compensate the lender for the (additional) default risk associated with subprime loans. In this section we analyze the time series of the subprime-prime rate spread, both with and without adjustment for changes in loan and borrower characteristics. We focus on FRMs for this exercise. For hybrid mortgages the subprime-prime comparison is more complicated because (i) both the initial (teaser) rate and the margin should be factored in, and (ii) we don't have good data on the prime initial rates and margins.

In Figure 6 we show the actual subprime-prime rate spread, defined in Equation (15) below. The subprime rate for this exercise is calculated as the average across individual loans initial mortgage rate for each calendar month (the data source is LoanPerformance); the prime rate is the contract rate on FRMs reported by the Federal Housing Finance Board (FHFB) in its Monthly Interest Rate Survey.[28] The subprime-prime spread—the difference between the average subprime and prime rates—decreased

[26] Our data extends to 2007Q3, but due to a near shutdown of the securitized subprime mortgage market we lack statistical power in this quarter.

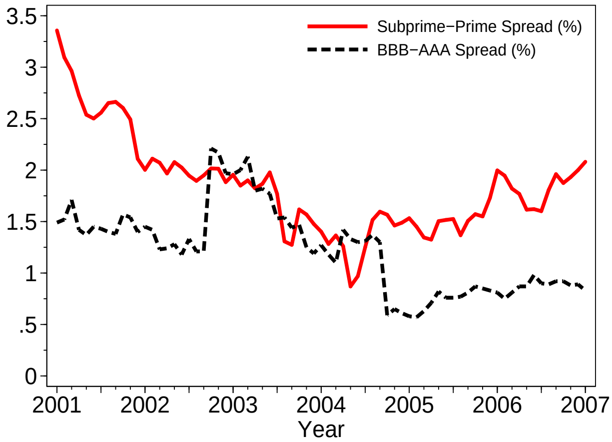
[27] The effects of other loan characteristics on mortgage rates have been much more stable over time, as unreported results suggest.

[28] Available at http://www.fhfb.gov/GetFile.aspx?FileID=6416.

substantially over time, with the largest decline between 2001 and 2004, which coincides with the most rapid growth in the number of loans originated (see Table 1). In Figure 6 we also plot the yield spread between 10-year BBB and AAA corporate bonds, which we obtained from Standard and Poor's Global Fixed Income Research. Compared to the corporate BBB-AAA yield spread, the actual subprime-prime rate spread declined much more and more steadily, hence the decline cannot just be attributed to a change in the overall level of risk aversion.

Figure 6: FRM Rate Spread and Corporate Bond Yield Spread

The figure shows the FRM subprime-prime rate spread and the yield spread between 10-year BBB and AAA corporate bonds.



We perform a cross-sectional OLS regression with the loan-level spread as the dependent variable and the prime rate and various subprime loan and borrower characteristics as the explanatory variables, using data from 2001 through 2006.[29]

$$spread_{it} = \beta_0 + \beta_1 prime_t + \beta_2' characteristics_{it} + error_{it}, \tag{14}$$

$$spread_{it} = subprime_{it} - prime_t \tag{15}$$

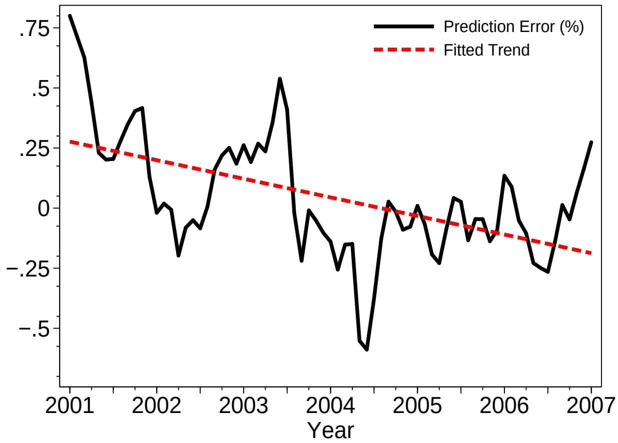
Notice that the $\beta_1 prime_t$ term corrects for the fact that the spread is affected by the prime rate itself, and thus changes over the business cycle, because a higher prime rate increases the default probability

[29]The explanatory factors in the regression are the FICO credit score, a dummy variable that equals one if full documentation was provided, a dummy variable that equals one if prepayment penalty is present, origination amount, value of debt-to-income ratio, a dummy variable that equals one if debt-to-income was not provided, a dummy variable that equals one if loan is a refinancing, a dummy variable that equals one if a borrower is an investor, loan-to-value ratio based on a first-lien, and loan-to-value ratios based on a second, third, etc. liens if applicable.

on subprime loans for a given spread. In Figure 7 we plot the prediction error, averaged per origination month t, along with a fitted linear trend.

Figure 7: Prediction Error in the Subprime-Prime Rate Spread

The figure shows the prediction error in the subprime-prime rate spread, determined in a regression of the spread on the prime rate and the following loan and borrower characteristics: the FICO credit score, a dummy variable that equals one if full documentation was provided, a dummy variable that equals one if a prepayment penalty is present, origination amount, value of debt-to-income ratio, a dummy variable that equals one if debt-to-income was not provided, a dummy variable that equals one if the loan is a refinancing, a dummy variable that equals one if a borrower is an investor, the loan-to-value ratio based on a first lien, and the loan-to-value ratio based on a second, third, etc. liens if applicable.



The downward trend in Figure 7 indicates that the subprime-prime spread, after adjusting for differences in observed loan and borrower characteristics, declined between 2001 to 2007. In Figure 1 (right panel) we showed that loan quality, obtained by adjusting loan performance for differences in loan and borrower characteristics and subsequent house price appreciation, deteriorated over the period, and thus the (adjusted) riskiness of loans rose. Therefore, on a per-unit-of-risk basis, the subprime-prime mortgage spread decreased even more than the level of the spread.

8 Concluding Remarks

The subprime mortgage market experienced explosive growth between 2001 and 2006. Angell and Rowley (2006) and Kiff and Mills (2007), among others, argue that this was facilitated by the development of so-called private-label mortgage backed securities (they do not carry any kind of credit risk protection by the Government Sponsored Enterprises). Investors in search of higher yields kept increasing their demand for private-label mortgage-backed securities, which also led to sharp increases in the subprime share of the mortgage market (from around 8 percent in 2001 to 20 percent in 2006) and in the securitized share of the subprime mortgage market (from 54 percent in 2001 to 75 percent in 2006).

In this paper we show that during the dramatic growth of the subprime (securitized) mortgage market, the quality of the market deteriorated dramatically. We measure loan quality as the performance of loans, adjusted for differences in borrower characteristics (such as the credit score, a level of indebtedness, an ability to provide documentation), loan characteristics (such as a product type, an amortization term, a loan amount, an mortgage interest rate), and macroeconomic conditions (such as house price appreciation, level of neighborhood income and change in unemployment).

The decline in loan quality was monotonic, but not equally spread among different types of borrowers. Over time, high-LTV borrowers became increasingly risky (their adjusted performance worsened more) compared to low-LTV borrowers. Securitizers seem to have been aware of this particular pattern in the relative riskiness of borrowers: We show that over time mortgage rates became more sensitive to the LTV ratio of borrowers. In 2001, for example, a borrower with a one standard deviation above-average LTV ratio paid a 10 basis point premium compared to an average LTV borrower. By 2006, in contrast, the premium paid by the high LTV borrower was around 30 basis points.

In principal, the subprime-prime mortgage rate spread (subprime mark-up) should account for the default risk of subprime loans. For the rapid growth of the subprime mortgage market to have been sustainable, the increase in the overall riskiness of subprime loans should have been accompanied by an increase in the subprime mark-up. In this paper we show that this was not the case: The subprime mark-up—adjusted and not adjusted for changes in differences in borrower and loan characteristics—declined over time. With the benefit of hindsight we now know that indeed this situation was not sustainable, and the subprime mortgage market crashed in 2007. In many respects, the subprime market experienced a classic lending boom-bust scenario with rapid market growth, loosening underwriting standards, deteriorating loan performance, and decreasing risk premiums.[30] Argentina in 1980, Chile in 1982, Sweden, Norway, and Finland in 1992, Mexico in 1994, Thailand, Indonesia, and Korea in 1997 all experienced the culmination of a boom-bust scenario, albeit in different economic settings.

Were problems in the subprime mortgage market apparent before the actual crisis erupted in 2007?

[30] A more detailed discussion, theory, and empirical evidence on such episodes is available in Dell'Ariccia and Marquez (2006), Demirgüç-Kunt and Detragiache (2002), Gourinchas, Valdes, and Landerretche (2001), and Kamisky and Reinhart (1999), among many others.

Our answer is yes, at least by the end of 2005. Using the data available only at the end of 2005, we show that the monotonic degradation of the subprime market was already apparent. Loan quality had been worsening for five years in a row at that point. Rapid appreciation in housing prices masked the deterioration in the subprime mortgage market and thus the true riskiness of subprime mortgage loans. When housing prices stopped climbing, the risk in the market became apparent.

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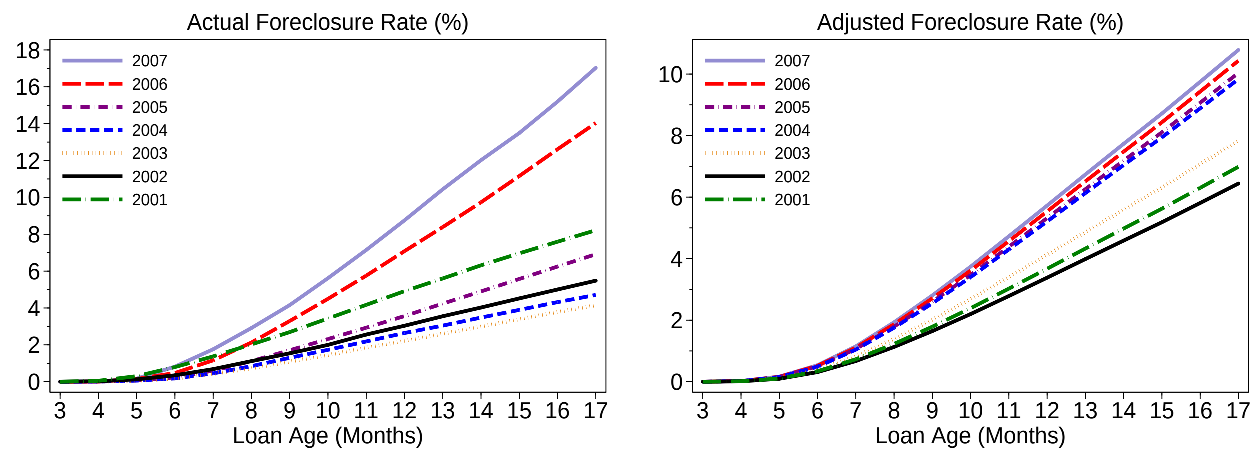
A Foreclosure Rates

In this Appendix we show the continual deterioration of adjusted loan performance using foreclosure, instead of delinquency, as a measure of loan performance. Foreclosure is defined as a loan being in foreclosure, real-estate owned, or in default. In Figure 8 we present actual (left panel) and adjusted (right panel) foreclosure rates. The actual foreclosure rate for loans age six months and younger is close to zero, in contrast to the actual delinquency rate at this age (presented in Figure 1 (left panel)). For older aged loans the actual foreclosure rate is roughly speaking twice as low as the actual delinquency rate. Similar to the actual delinquency rates (Figure 1 (left panel), the actual foreclosure rates (Figure 8, left panel) are highest for 2007, 2006, and 2001 and lowest for 2003 and 2004.

Using foreclosure instead of delinquency as a measure for non-performance, the adjusted foreclosure rates every vintage year starting in2002, as can be seen from Figure 8, right panel. The adjusted foreclosure rates of vintage 2001 loans are between vintages 2002 and 2003. The change for each year is statistically significant at the 1% confidence level.

Figure 8: Actual and Adjusted Foreclosure Rates

The figure shows the age pattern in the actual (left panel) and adjusted (right panel) foreclosure rate for the different vintage years. The foreclosure rate is defined as the cumulative fraction of loans that were in foreclosure, real-estate owned, or defaulted, at or before a given age. The adjusted foreclosure rate is obtained by adjusting the actual rate for year-by-year variation in FICO scores, loan-to-value ratios, debt-to-income ratios, missing debt-to-income ratio dummies, cash-out refinancing dummies, owner-occupation dummies, documentation levels, percentage of loans with prepayment penalties, mortgage rates, margins, composition of mortgage contract types, origination amounts, MSA house price appreciation since origination, change in state unemployment rate since origination, and neighborhood median income.

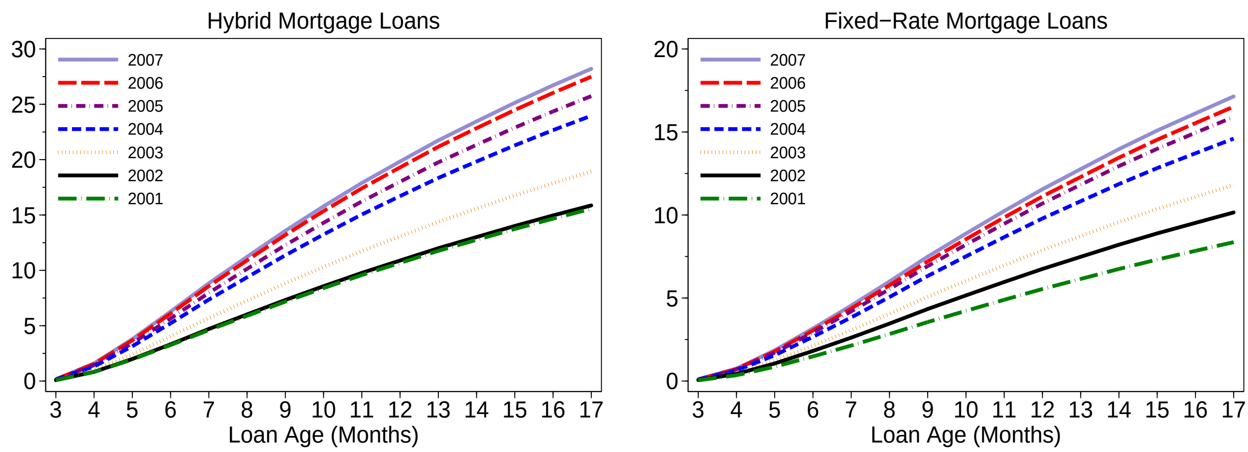


B Adjusted Delinquency Rate for Hybrids and FRMs Separately

In this Appendix we show that the continual deterioration of adjusted loan performance over the 2001–2007 period also occurs when estimating a separate proportional odds model for the main contract types, as opposed to the baseline case in the main text where we perform a single estimation for all loans together, but include contract type dummies in the regression specification. Figure 9 shows the adjusted delinquency rate for the two main contract types: 2/28 hybrids and FRMs. For both contract types, the adjusted delinquency rates have increased monotonically over time. Except for a level difference, the age pattern for the different vintage years looks very much the same for the two contract types.

Figure 9: Adjusted Delinquency Rates for Hybrids and FRMs Separately

The figure shows the adjusted delinquency rates based on hybrid mortgages (left panel) and FRMs (right panel) separately. The delinquency rate is defined as the cumulative fraction of loans that were past due 60 or more days, in foreclosure, real-estate owned, or defaulted, at or before a given age. The adjusted delinquency rate is obtained by adjusting the actual rate for year-by-year variation in FICO scores, loan-to-value ratios, debt-to-income ratios, missing debt-to-income ratio dummies, cash-out refinancing dummies, owner-occupation dummies, documentation levels, percentage of loans with prepayment penalties, mortgage rates, margins, composition of mortgage contract types, origination amounts, MSA house price appreciation since origination, change in state unemployment rate since origination, and neighborhood median income.



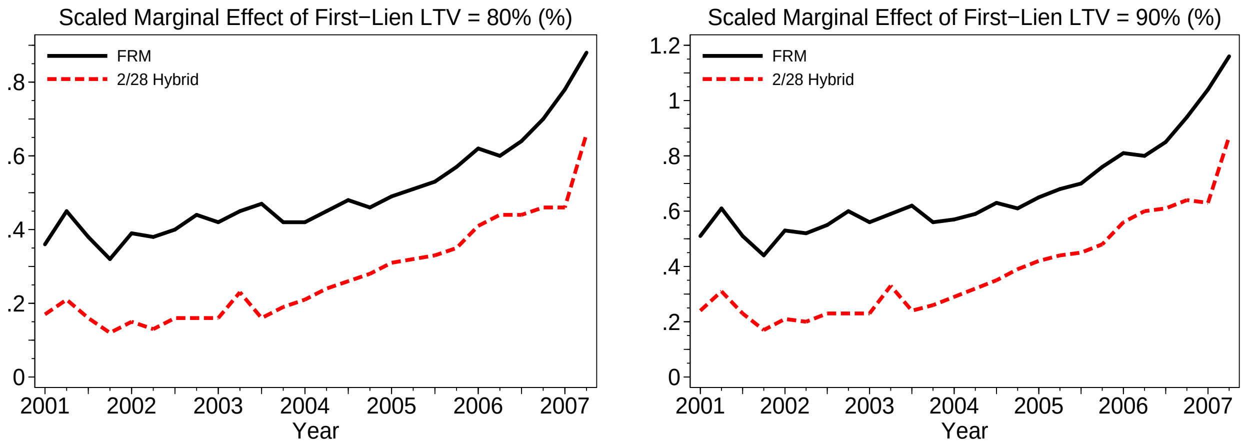
C Non-Linearity in the Sensitivity of the Mortgage Rate to the LTV

In Figure 2 we plotted the sensitivity of the fixed-rate and 2/28 hybrid mortgage rates to the first-lien LTV ratio. The sensitivity is defined as the regression coefficient on the first-lien LTV (scaled by the standard deviation) in a regression with the mortgage rate as dependent variable and the first-lien LTV, the second-lien LTV, and the other loan and borrower characteristics listed in Section 6, as independent variables.

In this appendix we study the robustness of this result to adding the square of the first-lien LTV and the square of the second-lien LTV as independent variables, therefore allowing for a non-linear functional form. In Figure 10 we report the resulting scaled marginal effect of the first-lien LTV for fixed-rate and 2/28 hybrid mortgages evaluated at a first-lien LTV of 80 percent (left panel) and 90 percent (right panel). Without non-linear terms the marginal effect is simply given by the regression coefficient. This is what we plotted in Figure 2. With the quadratic terms, the marginal effect is given by $\beta_{LTV} + 2\beta_{LTV^2}X$, where the βs are the regression coefficients and X is the first-lien LTV ratio at which the marginal effect is evaluated.

Figure 10: Sensitivity of Mortgage Rate to First-Lien LTV Ratio Allowing for Non-Linearity

The figure shows the scaled marginal effect of the first-lien loan-to-value (LTV) ratio on the mortgage rate for first-lien fixed-rate and 2/28 hybrid mortgages, evaluated at a first-lien LTV of 80 percent (left panel) and 90 percent (right panel). The effect is determined using an OLS regression with the interest rate as dependent variable and the FICO score, first-lien LTV (and the square), second-lien LTV (and the square), debt-to-income ratio, missing debt-to-income ratio dummy, cash-out refinancing dummy, owner-occupation dummy, prepayment penalty dummy, origination amount, term of the mortgage, prepayment term, and margin as independent variables.



As shown in Figure 10, the marginal effect is rising over time, consistent with the baseline case results presented in Figure 2. Moreover, we find that there is a statistically and economically significant non-linear effect of the first-lien LTV on the mortgage rate. Comparing the left and right panels in Figure 10, the higher the first-lien LTV ratio, the more sensitive is the mortgage rate to changes in the first-lien LTV. The largest difference between the results based on specifications with and without non-linearity is observed for 2/28 hybrid mortgages in 2007 at a first-lien LTV of 90 percent (right panel). The scaled marginal effect increases by 27 basis points over the course of 3 months in 2007 when the model allows for non-linearity. In contrast, in the case without non-linearity, as in Figure 2, the increase in the scaled marginal effect is only 13 basis points.