Public Policy
Discussion Papers

FEDERAL RESERVE BANK OF BOSTON™

No. 09-1

Making Sense of the Subprime Crisis

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Abstract:
This paper explores the question of whether market participants could have or should have anticipated the large increase in foreclosures that occurred in 2007 and 2008. Most of these foreclosures stem from loans originated in 2005 and 2006, leading many to suspect that lenders originated a large volume of extremely risky loans during this period. However, the authors show that while loans originated in this period did carry extra risk factors, particularly increased leverage, underwriting standards alone cannot explain the dramatic rise in foreclosures. Focusing on the role of house prices, the authors ask whether market participants underestimated the likelihood of a fall in house prices or the sensitivity of foreclosures to house prices. The authors show that, given available data, market participants *should* have been able to understand that a significant fall in prices would cause a large increase in foreclosures, although loan-level (as opposed to ownership-level) models would have predicted a smaller rise than actually occurred. Examining analyst reports and other contemporary discussions of the mortgage market to see what market participants thought would happen, the authors find that analysts, on the whole, understood that a fall in prices would have disastrous consequences for the market but assigned a low probability to such an outcome.

JEL Classifications: D11, D12, G21

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This paper, which may be revised, is available on the web site of the Federal Reserve Bank of Boston at http://www.bos.frb.org/economic/ppdp/index.htm.

This paper was prepared for the Brookings Panel on Economic Activity, September 11–12, 2008. We thank Debbie Lucas and Nick Souleles for excellent discussions, the editors for their suggestions, advice, and patience, and the Brookings Panel and various other academic and non-academic audiences for their helpful comments. We thank Christina Pinkston for valuable help programming the First American LoanPerformance data. Any remaining errors are our own responsibility.

This version: December 22, 2008

1 Introduction

Had market participants anticipated the increase in defaults on subprime mortgages originated in 2005 and 2006, the nature and extent of the current financial market disruptions would be very different. *Ex ante*, investors in subprime mortgage-backed securities would have demanded higher returns and greater capital cushions. As a result, borrowers would not have found credit as cheap or as easy to obtain as it became during the subprime credit boom of 2005–2006. Rating agencies would have had a similar reaction, rating a much smaller fraction of each deal investment grade. *Ex post*, the increase in foreclosures would have been significantly smaller, with fewer attendant disruptions to the housing market. In addition, investors would not have suffered such outsized, and unexpected, losses. To make sense of the subprime crisis, one needs to understand why, when accepting significant exposure to the creditworthiness of subprime borrowers, so many smart analysts, armed with advanced degrees, data on the past performance of subprime borrowers, and state-of-the-art modeling technology did not anticipate that so many of the loans they were buying, either directly or indirectly, would go bad.

Our bottom line is that the problem largely had to do with house price expectations. Had investors known the trajectory of house prices, they would have predicted large increases in delinquency and default and losses on subprime mortgage-backed securities (MBS) roughly consistent with what we have seen. We show this by using two different methods to travel back to 2005, when subprime was still thriving, and look forward. The first method is to forecast performance with only data available in 2005 and the second is to look at what market participants wrote at the time. The latter "narrative" analysis, which appears in Section 4 below, provides strong evidence against the claim that investors lost money by purchasing loans which, because they were originated by others, could not be evaluated properly.

We proceed by first addressing the question of whether the loans themselves were *ex ante* unreasonable. Loans made in 2005–2006 were not that different from loans made earlier, which, in turn had performed well, despite carrying a variety of serious risk factors. We show that lenders did make riskier loans, and describe in detail the dimensions along which risk increased. In particular, we find that borrower leverage increased and, further, did so in a way that was relatively opaque to investors. However, we find that the change in the mix of mortgages originated is too mild to explain the huge increase in defaults. Put simply, the average default rate on loans originated in 2006 exceeds the default rate on the riskiest category of loans originated in 2004.

We then focus on the collapse in house price appreciation (HPA) that started in the spring of 2006.[1] Lenders must either have expected that HPA would remain high (or at least that house prices would not collapse), or have expected subprime defaults to be insensitive to a big drop in house prices. More formally, if we let f represent foreclosures, p represent prices, and t represent time, then we can decompose the growth in foreclosures over time, df/dt, into a part corresponding to the change in prices over time and a part reflecting the sensitivity of foreclosures to prices:

$$df/dt = df/dp \times dp/dt.$$

Our goal is to determine whether market participants underestimated df/dp, the sensitivity of foreclosures to prices, or whether dp/dt, the trajectory of house prices, came out much worse than they expected.

We begin with data that were available, *ex ante*, on mortgage performance to determine whether it was possible to estimate df/dp on subprime mortgages accurately. Because severe house price declines are relatively rare and the subprime market is relatively new, one plausible theory is that the data did not contain sufficient variation to estimate df/dp in scenarios in which dp/dt is negative and large. We put ourselves in the place of analysts in 2005, using data through 2004 to estimate the type of hazard models commonly used in the industry to predict mortgage defaults. We use two datasets. The first is a loan-level dataset from First American LoanPerfomance that is used extensively in the industry to track the performance of mortgages in MBS; this dataset has sparse information on loans originated before 1999. The second is an ownership-level dataset from the Warren Group, which tracked the fates of homebuyers in Massachusetts from the late 1980s forward. These data were not (so far as we can tell) widely used by industry but were, at least in theory, available. The Warren Group data do contain information on the behavior of homeowners in an environment of falling prices.

We find that it was possible, although not easy, to measure df/dp with some degree

[1] Examples include Gerardi, Shapiro, and Willen (2007), Mayer, Pence, and Sherlund (2008), Demyanyk and van Hemert (2007), Doms, Furlong, and Krainer (2007), and Danis and Pennington-Cross (2005).

of accuracy. Essentially, a researcher with perfect foresight about the trajectory of prices from 2005 forward would have forecast a large increase in foreclosures starting in 2007. Perhaps the most interesting result is that, despite the absence of negative HPA in 1998–2004, when almost all subprime loans were originated, we could still determine, albeit not exactly, the behavior of subprime borrowers in a falling house price environment. In effect, the out-of-sample (and out-of-support) performance of default models was sufficiently good to have predicted large losses in a falling house price environment.

However, while it was possible to estimate df/dp, we also find that the relationship was less exact when using data on *loans* rather than data on *ownerships.* A given borrower might refinance his original loan several times before defaulting. All of the loans bar the final one would have been seen as successful by lenders. An ownership spans multiple loans and terminates only when the homeowner sells and moves or is foreclosed upon and evicted. Thus, while the same foreclosure would appear as a default in both loan-level and ownership-level data, intermediate refinancings between purchase and foreclosure would not appear as happy endings in an ownership-level database.

In the last section of the paper, we discuss what analysts of the mortgage market said in 2004, 2005, and 2006 about the loans that eventually got into trouble. Our conclusion is that investment analysts had a good sense of df/dp and understood, with remarkable accuracy, how falling dp/dt would affect the performance of subprime mortgages and the securities backed by them. As an illustrative example, consider a 2005 analyst report published by a large investment bank: it analyzed a representative deal composed of 2005 vintage loans and argued it would face 17 percent cumulative losses in a "meltdown" scenario in which house prices fell 5 percent over the life of the deal. Their analysis is prescient: the ABX index (an index that represents a basket of credit default swaps on high-risk mortgages and home equity loans) currently implies that such a deal will actually face losses of 18.3 percent over its life. The problem was that the report only assigned a 5 percent probability to the meltdown scenario, whereas it assigned a 15 percent probability and a 50 percent probability to scenarios in which house prices grew 11 percent and 5 percent, respectively, over the life of the deal.

We argue that house prices outweigh other changes in driving up foreclosures. However, we do not take a position on why prices rose so rapidly, fell so fast, and why they peaked in mid-2006. Other researchers have examined whether factors such as lending standards can affect house prices.[2] Broadly speaking, we maintain the assumption that while, in the aggregate, lending standards may indeed have affected house price dynamics (we are agnostic on this point), no individual market participant felt that he could affect prices with his actions. Nor do we analyze whether the housing market was overvalued in 2005 and 2006, and whether a collapse of house prices was therefore, to some extent, predictable. There was a lively debate during that period, with some arguing that housing was reasonably valued (see Himmelberg, Mayer, and Sinai 2005 and McCarthy and Peach 2004) and others arguing that it was overvalued (see Gallin 2006, Gallin 2008, and Davis, Lehnert, and Martin 2008).

Our results in Sections 2 and 3 suggest that some borrowers were more sensitive than others to a single macro risk factor (here: house prices). This comports well with the findings of Musto and Souleles (2006), who argue that average default rates are only half the story; they argue that correlations across borrowers, perhaps driven by macro factors, are also an important factor in valuing portfolios of consumer loans.

In this paper, we focus almost exclusively on subprime mortgages. However, many of the same arguments might apply to prime mortgages. Lucas and McDonald (2006) computed the volatility of the underlying assets of the housing-related government-sponsored enterprises (GSEs), which concentrate mainly on prime and near-prime mortgages, using information on the firms' leverage and their stock prices. They found that risk was quite high (and, as a result, the value of the implicit government guarantee on GSE debt was also quite high).

Many have argued that a major driver of the subprime crisis was the increased use of securitization.[3] In this view, the "originate to distribute" business model of many mortgage finance companies separated the underwriter making the credit extension decision from exposure to the ultimate credit quality of the borrower and thus created an incentive to maximize lending volume without concern for default rates. In addition, information asymmetries, unfamiliarity with the market, or other factors prevented investors who were buying the credit risk from putting in place effective controls for these incentives. While this argument is intuitively persuasive, our results are not consistent

[2]Examples of this include Pavlov and Wachter (2006), Coleman IV, Lacour-Little, and Vandell (2008), Wheaton and Lee (2008), Wheaton and Nechayev (2008), and Sanders, Chomsisengphet, Agarwal, and Ambrose (2008).

[3]See, for example, Keys, Mukherjee, Seru, and Vig (2008) and Calomiris (2008).

with such an explanation. One of our key findings is that most of the uncertainty about losses stemmed from uncertainty about the evolution of house prices and not from uncertainty about the quality of the underwriting. All that said, our models do not perfectly predict the defaults that occurred, and these often underestimate the number of defaults. One possible explanation is that there was an unobservable deterioration of underwriting standards in 2005 and 2006.[4] But another possible explanation is that our model of the highly non-linear relationship between prices and foreclosures is wanting. No existing research successfully separates the two explanations.

The endogeneity of prices does present a problem for our estimation. One common theory is that foreclosures drive price falls by increasing the supply of homes for sale, in effect introducing a new term into the decomposition of df/dt, namely, dp/df. However, our estimation techniques are, to a large extent, robust to this issue.[5] In fact, as we show in Section 3, it is possible to estimate the effect of house prices on foreclosures even in periods when there were very few foreclosures, and when foreclosed properties sold quickly.

No discussion of the subprime crisis of 2007 and 2008 is complete without mention of the interest rate resets built into many subprime mortgages that virtually guaranteed large payment increases. Many commentators have attributed the crisis to the payment shock associated with the first reset of subprime 2/28 mortgages. However, the evidence from loan-level data shows that resets cannot account for a significant portion of the increase in foreclosures. Both Mayer, Pence, and Sherlund (2008) and Foote, Gerardi, Goette, and Willen (2007) show that the overwhelming majority of defaults on subprime adjustable-rate mortgages (ARM) occur long before the first reset. In other words, many lenders would have been lucky had borrowers waited until the first reset to default.

The rest of the paper is organized as follows. In Section 2, we document changes in underwriting standards on mortgages. In Section 3 we explore what researchers could have learned with the data they had in 2005. We review contemporary analyst reports in Section 4. Section 5 concludes.

[4] An explanation favored by Demyanyk and van Hemert (2007).

[5] As discussed in Gerardi, Shapiro, and Willen (2007), most of the variation in the key explanatory variable, homeowner's equity, is within-town (MSA), within-quarter variation, and thus could not be driven by differences in foreclosures over time or across towns (MSAs)

2 Underwriting Standards in the Subprime Market

In this section, we begin with a brief background on subprime mortgages, including the competing definitions of "subprime."[6] We then turn to a discussion of changes in the apparent credit risk of subprime mortgages originated from 1999 to 2007, and we link these to the actual performance of the underlying loans. We argue that the increased number of subprime loans originated with high loan-to-value rations (LTV) was the most important observable risk factor that increased over the period. Further, we argue that the increases in leverage were to some extent masked from investors in mortgage-backed securities. Loans originated with less than complete documentation of income or assets, and particularly those originated with both high leverage and incomplete documentation, exhibited sharper rises in defaults than other loans. A more formal decomposition exercise, however, confirms that the rise in defaults can be only partly explained by observed changes in underwriting standards.

2.1 Background on subprime mortgages

One of the first notable features encountered by researchers working on subprime mortgages is the dense thicket of jargon surrounding the field, particularly the multiple competing definitions of "subprime." This hampers attempts to estimate the importance of subprime lending.

There are, effectively, four useful ways to categorize a loan as subprime. First, mortgage servicers themselves recognize that certain borrowers require more frequent contact in order to ensure timely payment; they charge higher fees to service these loans. Second, some lenders specialize in loans to financially troubled borrowers. The Department of Housing and Urban Development maintains a list of such lenders. Loans originated by these so-called "HUD list" lenders are often taken as a proxy for subprime loans. Third, "high cost" loans are defined as loans that carry fees and rates significantly above those charged to typical borrowers. Fourth, the loan may be sold into an asset-backed security marketed as containing subprime mortgages.

Table 1 provides two measures of the importance of subprime lending in the United States. The first column shows the percent of loans in the Mortgage Bankers Association (MBA) delinquency survey that are classified as "subprime." Because the MBA

[6] For a more detailed discussion, see Mayer and Pence (2008).

surveys mortgage servicers, this column represents the servicer definition of a subprime loan. As shown, over the past few years, subprime mortgages have accounted for about 12 to 14 percentage of outstanding mortgages. The second and third columns show the percent of loans tracked under the Home Mortgage Disclosure Act that are classified as "high cost." As shown, in 2005 and 2006 roughly 25 percent of originations were subprime under this definition.[7]

These two measures point to an important discrepancy between the *stock* and the *flow* of subprime mortgages (although source data and definitions also account for some of the difference). Subprime mortgages were a growing part of the U.S. mortgage market, so that the flow of new mortgages should naturally exceed their presence in the stock of outstanding mortgages. In addition, subprime mortgages, for a variety of reasons, tend to last for a shorter period of time than prime mortgages, so they form a larger share of the flow of new mortgages than of the stock of outstanding mortgages. Furthermore, until the mid-2000s most subprime mortgages were typically used to refinance an existing loan and, simultaneously, to increase the principal balance (allowing the homeowner to borrow against accumulated equity), rather than to finance the purchase of a home.

In this section we focus on changes in the kinds of loans made over the period 1999 to 2007. We use loan-level data on mortgages sold into private-label mortgage-backed securities marketed as subprime. These data are provided by First American LoanPerformance and were widely used in the financial services industry. We further limit the set of loans to the three most popular products: those carrying fixed interest rates to maturity, and so-called "2/28s" and "3/27s." A 2/28 is a mortgage in which the contract rate is fixed at an initial "teaser" rate for two years, after which it adjusts to the six-month Libor rate plus a predetermined margin (often around 6 percentage points). A "3/27" is similar.[8] We refer to this database as "the ABS data" for simplicity.

In this section, the outcome variable of interest is whether a mortgage defaults within 12 months of its first payment due date. There are several competing definitions of "default"; here, we define a mortgage as having defaulted by month 12 if, as of

[7]HMDA data are taken from Federal Reserve *Bulletin* articles; see Avery, Canner, and Cook (2005), Avery, Brevoort, and Canner (2006), Avery, Brevoort, and Canner (2007), and Avery, Brevoort, and Canner (2008). Note that the high-cost measure was only introduced to the HMDA data in 2004; for operational and technical reasons, the reported share of high cost loans in 2004 may be depressed relative to its share in later years.

[8]These three loan categories accounted for more than 98 percent of loans in the original data.

its twelfth month of life, it had terminated following a foreclosure notice; if the loan was listed as real estate owned by the servicer (indicating a transfer of title from the borrower); if the loan was still active but foreclosure proceedings had been initiated; or if the loan was 90 or more days past due. Note that some of the loans we count as defaults might subsequently revert to current status if the borrower made up missed payments. In effect, any borrower who manages to make 10 of the first 12 mortgage payments or who refinances or sells without a formal notice of default having been filed is assumed *not* to have defaulted.

The default rate is shown in Figure 1. Conceptually, default rates differ from delinquency rates in that they track the fate of mortgages originated in a given month by their twelfth month of life; in effect, the default rate tracks the proportion of mortgages originated at a given point that are “dead” by month 12. Delinquency rates, by contrast, track the proportion of all active mortgages that are “sick” at a given point in calendar time. Further, because we close our dataset in December 2007, we can track only the fate of mortgages originated through Deccember 2006. The continued steep increase in mortgage distress is not reflected in our data here, nor is the fate of mortgages originated in 2007, although we do track the underwriting characteristics of these mortgages.

Note that this measure of default is designed to allow us to compare the *ex ante* credit risk of various underwriting terms. It is of limited usefulness as a predictor of defaults because it considers only what happens by the twelfth month of life and does not consider the changing house price, interest rate, and overall economic environment faced by households. Further, this measure does not consider the changing incentives to refinance. The competing risk, duration models we estimate in Section 3 are, for these reasons, far better suited to determining the credit and prepayment outlook for a group of mortgages.

2.2 Changes in underwriting standards

During the credit boom, lenders published daily “rate sheets” with various combinations of loan risk characteristics and the associated interest rates they would charge to make such loans. A simple rate sheet, for example, might be a matrix of credit scores and loan-to-value ratios; borrowers with lower credit scores or higher LTVs would be charged higher interest rates or be forced to pay larger fees up front. Certain cells of the matrix such as combinations of low score and high LTV, might not be available at all.

Unfortunately, we do not have access to information on the evolution of rate sheets over time, but underwriting standards can change in ways observable in the ABS data. Of course, underwriting standards can also change in ways observable to the loan originator but not reflected in the ABS data, or in ways largely unobservable by even the loan originator (for example, an increase in the number of borrowers getting home equity lines of credit (HELOCs) after origination). In this section, we consider the evidence that more loans with *ex ante*, observable risky characteristics were originated. Throughout, we use loans from the ABS database described earlier.

We consider trends over time in borrower credit scores, loan documentation, leverage (as measured by the combined loan-to-value ratio or CLTV at origination), and other factors associated with risk, such as a loan's purpose, non-owner occupancy, and amortization schedules. We find that, from 1999 to 2007, borrower leverage, loans with incomplete documentation, loans used to purchase homes (as opposed to refinance an existing loan), and loans with non-traditional amortization schedules grew. Borrower credit scores increased while loans to non-occupant owners remained essentially flat. Of these, the increase in borrower leverage appears to have contributed the most to the increase in defaults, and we find some evidence that leverage was, in the ABS data at least, opaque.

Credit Scores Credit scores, which essentially summarize a borrower's history of missing debt payments, are the most obvious definition of "subprime." The commonly used scalar credit score is the FICO score originally developed by Fair, Isaac & Co. It is the only score contained in the ABS data, although subprime lenders often used scores and other information from all three credit reporting bureaus.

Under widely accepted industry rules of thumb, borrowers with FICO scores of 680 or above are not usually considered subprime without another accompanying risk factor; borrowers with credit scores between 620 and 680 may be considered subprime, while those with credit scores below 620 are rarely eligible for prime loans. Note that subprime pricing models typically used more information than just a borrower's credit score; they also considered the nature of the missed payment that led a borrower to have a low credit score. For example, a pricing system might assign greater weight to missed mortgage payments than to missed credit card payments.

Figure 2 shows the proportion of newly originated subprime loans falling into each of these three categories. As shown, loans to borrowers with FICO scores of 680 and above grew over the sample period, while loans to traditionally subprime borrowers (those with scores below 620) accounted for a smaller share of originations.

Loan Documentation Borrowers (or their mortgage brokers) submit a file with each mortgage application documenting the borrower's income, liquid assets, other debts, and the value of the property being used as collateral. Media attention has focused on the rise of so-called "low doc" or "no doc" loans, which contained incomplete documentation of income or assets. (These are the infamous "stated income" loans.) The top left panel of Figure 3 shows the proportion of newly originated subprime loans carrying less than full documentation. As shown, this proportion rose from around 20 percent in 1999 to a high of more than 35 percent by mid-2006. While reduced doc lending was a part of subprime lending, it was by no means the majority of the business, nor did it increase dramatically during the credit boom.

As we discuss in greater detail below, until about 2004, subprime loans were generally backed by substantial equity in the property. This was especially true for subprime loans with less than complete documentation. Thus, in some sense, the lender accepted less complete documentation in exchange for a greater security interest in the underlying property.

Leverage The leverage of a property is, in principle, the total value of all liens divided by the mark-to-market value of the property. This is often referred to as the property's combined loan-to-value ratio, or CLTV. Both the numerator and denominator of the CLTV will fluctuate over a borrower's tenure in the property: the borrower can amortize the original loan, refinance or take on junior liens, and the potential sale price of the house will also, of course, change over time. However, all of these variables ought to be known at the time of a loan's origination. The lender undertakes a title search to check for the presence of other liens on the property and hires an appraiser to confirm either the price paid (when the loan is used to purchase a home) or the potential sale price of the property (when the loan is used to refinance an existing loan).

In practical terms, high leverage was also accompanied by additional complications and opacity. Rather than originate a single loan for the desired amount, originators often preferred to originate two loans: one for 80 percent of the property's value, and the other for the remaining desired loan balance. In the event of a default, the holder of the first lien would be paid first from sale proceeds, with the junior lien holder getting the remaining proceeds (if any). Lenders may have split loans in this way for the same reason that asset-backed securities are tranched into a AAA-rated piece and a below investment-grade piece. Some investors might specialize in credit risk evaluation and hence prefer the riskier piece, while other investors might prefer to forgo credit analysis and purchase the less risky loan.

The reporting of these junior liens in the ABS data appears to be spotty. This could be the case if, for example, the junior lien was originated by a different lender than the first lien, because the first lien lender might not properly report the second lien, while the second lien lender might not report the loan at all. If the junior lien was an open-ended loan, such as a home equity line of credit (HELOC), it appears not to have been reported in the ABS data at all, perhaps because the amount drawn was unknown at origination.

Further, there is no comprehensive national system for tracking liens on any given property. Thus, homeowners could take out a second lien shortly after purchasing or refinancing, raising their CLTV. While such borrowing should not affect the original lender's recovery, it does increase the probability of a default and thus the value of the original loan.

The top right panel of Figure 3 shows the growth in the number of loans originated with a high CLTV (defined as CLTV≥ 90 percent or the presence of a junior lien); in addition, the figure shows the proportion of loans originated for which a junior lien was recorded.[9] As shown, both measures of leverage rose sharply over the past decade. High CLTV lending accounts for roughly 10 percent of originations in 2000, rising to over 50 percent by 2006. The incidence of junior liens also rose.

The presence of a junior lien has a powerful effect on the CLTV of the first lien. As shown in Table 2, loans without a second lien reported a CLTV of 79.9 percent,

[9]The figures shown here and elsewhere are based on first liens only; where there is an associated junior lien that information is used in computing CLTV and for other purposes, but the junior loan itself is not counted.

while those with a second lien reported a CLTV of 98.8 percent. Moreover, loans with reported CLTVs of 90 percent or above were much likelier to have associated junior liens, suggesting that lenders were leery of originating single mortgages with LTVs greater than 90 percent.

Later, we will discuss the evidence that there was even more leverage than reported in the ABS data.

Other Risk Factors A variety of other loan and borrower characteristics may have contributed to increased risk. The bottom left panel of Figure 3 shows the fraction of loans originated with a non-traditional amortization schedule, to non-occupant owners, and to borrowers who used the loan to purchase a property (as opposed to refinancing an existing loan).

A standard, or "traditional," U.S. mortgage self-amortizes; that is, a portion of each month's payment is used to reduce the principal owed on the loan. As shown in the bottom left panel of Figure 3, non-traditional amortization schedules became increasingly popular among subprime loans. These were mainly loans that lowered payments by not requiring sufficient principal payments (at least in the early years of the loan) to amortize over the 30-year term of the loan. Thus, some loans had interest-only periods, while others were amortized over 40 years, with a balloon payment due at the end of the 30-year term. The effect of these terms was to slightly lower payments, especially in the early years of the loan.

Subprime loans had traditionally been used to refinance an existing loan. As shown in the bottom left panel of Figure 3, loans used to purchase homes also increased over the period, although not dramatically. Loans to non-occupant owners, for example, loans backed by a property held for investment purposes, are, all else equal, riskier than loans to owner occupiers because the borrower can default and not face eviction from his primary residence. As shown, such loans never accounted for a large fraction of subprime originations, nor did they grow over the period.

Risk Layering As we discuss below, leverage is a key risk factor for subprime mortgages. An interesting question is the extent to which high leverage loans were combined with other risk factors; this practice was sometimes known as *risk layering.* As shown in the bottom right panel of Figure 3, risk layering grew over the sample period.

In particular, loans with incomplete documentation *and* high leverage had an especially notable rise, increasing from essentially zero in 2001 to almost 20 percent of subprime originations by the end of 2006. Highly leveraged loans to borrowers purchasing homes also increased over the period.

2.3 Effect on default rates

We now turn to considering the performance of the various risk factors that we outlined earlier. We start with simple univariate descriptions before turning to a more formal decomposition exercise. Here, we continue to focus on 12-month default rates as our outcome of interest. In the next section we present results from dynamic models that consider the ability of borrowers to refinance as well as default.

Documentation Level The upper left panel of Figure 4 shows the default rates over time for loans with complete and incomplete documentation. As shown, the two loan types performed roughly in line with one another until the current cycle, when default rates on loans with incomplete documentation rose far more rapidly than default rates on loans with complete documentation.

Leverage The top right panel of Figure 4 shows default rates on loans with high CLTVs (defined, again, as a CLTV≥ 90 *or* having a junior lien present at origination). Again, loans with high leverage performed approximately in line with other loans until the most recent episode.

As we highlighted in the earlier discussion, leverage is often opaque. To dig deeper into the correlation between leverage at origination and subsequent performance, we estimated a pair of simple regressions relating CLTV at origination to default probabilities and the initial contract interest rate charged to the borrower. The results are shown in Table 3. For all loans in the sample, we estimated a probit model of default and an OLS model of the initial contract rate. The list of explanatory variables contained various measures of leverage, including an indicator variable for having a reported CLTV in the dataset of *exactly* 80 percent, as well as a few other controls. We estimated two versions of the simple model: model 1 simply contains the CLTV measures and the initial contract rate itself; model 2 adds state and origination-date fixed effects. These results are designed purely to highlight the correlation among variables of interest and not as fully fledged risk models. Model 1 can be thought of as the simple multivariate correlation across the entire sample, while model 2 compares loans originated in the same state at the same time. The results are shown in Figure 6. (When plotting the expected default probability from model 2, we assume that the loan was originated in California, in June 2005.)

As shown, default probabilities generally increase with increasing leverage. Note, however, that loans with reported CLTVs of *exactly* 80 percent, which account for 15.7 percent of subprime loans, have substantially higher default probabilities than loans with CLTVs of, for example, 79.9 percent or 80.01 percent. Indeed, under model 2, which includes time and state fixed effects, such loans are among the riskiest originated. As shown by the bottom panel of Figure 6, there is no compensating increase in the initial contract rate charged to the borrower, although the lender may have charged points and fees upfront (not measured in this dataset) to compensate for the increased risk.

This evidence suggests that borrowers with apparently reasonable CLTVs were, in fact, using junior liens to increase their leverage in a way not easily visible to investors, nor apparently compensated by higher mortgage interest rates.

Other Risk Factors The bottom three panels of Figure 4 show the default rates associated with the three other risk factors we described earlier: owner non-occupancy, loan purpose, and non-traditional amortization schedules. As shown, loans to non-occupant owners were not (in this sample) markedly riskier than loans to owner occupiers. The 12-month default rates on loans originated from 1999 to 2004 did not vary much between those originated for home purchase (as opposed to refinance), and those carrying a non-traditional amortization schedule. However, among loans originated in 2005 and 2006, purchase loans and those with non-traditional amortization schedules defaulted at much higher rates.

Risk Layering Figure 5 shows the default rates on loans carrying the multiple risk factors we discussed earlier. As shown in the top panel, loans with high CLTVs *and* low FICO scores have always defaulted at higher rates than other loans. Loans with high CLTVs used to purchase homes also had a worse track record, and saw their default rates climb sharply over the last two years of the sample. Loans with high CLTVs and incomplete documentation (panel c), however, showed the sharpest increase in defaults relative to other loans. This suggests that within the group of high leverage loans, those with incomplete documentation were particularly prone to default.

2.4 Decomposing the increase in defaults

As shown in Figure 1, the default rates on subprime loans originated in 2005 and 2006 were much higher than the rates on those originated earlier in the sample. The previous discussion suggests that this increase is not related to observable underwriting factors. For example, high CLTV loans originated in 2002 defaulted at about the same rate as other loans originated that same year. However, high CLTV loans originated in 2006 defaulted at much higher rates than other loans.

Decomposing the increase in defaults into a portion due to the mix of types of loans originated and a portion due to house prices requires data on how all loan types behave under a wide range of house price scenarios. If loans originated in 2006 were truly novel, then there would be no unique decomposition between house prices and underwriting standards. We have shown that at least some of the riskiest loan types were already being originated (albeit in low numbers) by 2004.

To more formally test this idea, we divide the sample into two groups: an "early" group of loans originated in the years 1999 to 2004, and a "late" group of loans originated in 2005 and 2006. We estimate default models separately on the early group and the late group and also track changes in risk factors over these groups. We measure the changes in risk factors between the two groups, and the changes in the coefficients of the risk model. We find that increases in high-leverage lending and risk layering can account for some, but by no means all, of the increase in defaults.

Table 4 provides variable means across the two groups. As shown, a much higher fraction of loans originated in the late group defaulted: 9.28 percent as opposed to 4.60 percent. The differences between the two groups on other risk factors are in line with the discussion earlier: FICO scores, CLTVs, the incidence of 2/28s, low documentation, non-traditional, and purchase loans rose from the early group to the late group.

Table 5 gives the results of a loan-level probit model estimated using data from the early group and the late group. The table shows marginal effects and standard errors;

the model also includes a set of state fixed effects (not shown). The differences in estimated marginal effects when using data from the early group as opposed to the late group are striking. Defaults are more sensitive in the late group to a variety of other risk factors, such as leverage, credit score, loan purpose, and non-traditional amortization schedules.

The slopes in Table 5 correspond roughly to the returns in a Blinder-Oaxaca decomposition, while the sample means correspond to the differences in endowments between the two groups. However, because the underlying model is nonlinear, we cannot perform the familiar Blinder-Oaxaca decomposition.

As a first step, Table 6 provides the predicted default rate in the late group using the model estimated against data from the early group, as well as other combinations. As shown, the early group model does not predict a significant rise in defaults based on the observable characteristics of the late group.

These results are consistent with the view that a factor other than underwriting changes was primarily responsible for the increase in mortgage defaults. However, because these results mix up changes in the distribution of risk factors between the two groups as well as changes in the riskiness of certain characteristics, it can be useful to consider the increase in riskiness of a typical loan after varying a few characteristics in turn. Again, because of the non-linearity of the underlying model, we have to consider just one set of observable characteristics and vary each characteristic in turn.

To this end, we consider a typical 2/28 originated in California with observable characteristics set to their early-period sample means. We change each risk characteristic in turn to its late-period sample mean, or a value suggested by the experience in the late period.

The results are shown in Table 7. As shown, even with the worst combination of underwriting characteristics, the predicted default rate is about half of the actual default rate experienced by this group of loans. The greatest increases in default probability are associated with higher-leverage scenarios. (Note that decreasing the CLTV to exactly 80 percent increases the default probability, for reasons we discussed earlier.)

3 What Could be Learned from the Data in 2005?

In this section, we focus on whether market participants could reasonably have estimated the sensitivity of foreclosures to house price decreases. We estimate standard competing risk, duration models using data on the performance of loans originated through the end of 2004; presumably this is the information set available to lenders as they were making decisions about loans originated in 2005 and 2006. We produce out-of-sample forecasts of foreclosures, assuming the house price outcomes that the economy has actually experienced. In Section 4 below, we address the question of what house price expectations investors had, but here we assume market participants had perfect foresight about future HPA.

In conducting our forecasts, we use two primary data sources. First, we use the ABS data discussed in Section 2 above. These data are national in scope, and have been widely used by mortgage analysts to model both prepayment and default behavior in the subprime mortgage market, so it is not unreasonable to use these data as an approximation of market participants' information set. The second source of data is publicly available, individual-level data on both housing and mortgage transactions in the state of Massachusetts, and these data come from county-level registry of deeds offices. While these data are not national in scope and do not have the level of detail in terms of mortgage and borrower characteristics that the ABS data have, their historical coverage is far superior. Specifically, the deed-registry data extend back to the early 1990s, a period in which the Northeast experienced a significant housing downturn. In contrast, the ABS data have very sparse coverage before 2000, as the non-agency, subprime MBS market did not become relevant until the turn of the century. Hence, for the vast majority of the coverage of the ABS data, the economy was in the midst of a significant housing boom. In the next section we discuss the potential implications of this data limitation for predicting mortgage defaults and foreclosures.

3.1 Relationship between housing equity and foreclosure

Economic theory tells us that the relationship between equity and foreclosure is highly nonlinear. For a homeowner with positive equity in his home who needs to terminate his mortgage a strategy of either refinancing the mortgage or selling the house dominates a strategy of defaulting and allowing foreclosure to occur. However, for an "underwater" homeowner, that is, one with negative equity, the optimal decision from an economic perspective is sometimes to default and face foreclosure.[10] Thus, the theoretical relationship between equity and foreclosure is not linear. Rather, the sensitivity of default to equity should be approximately zero for positive values of equity but negative for negative values of equity. These observations imply that the relationship between housing prices and foreclosure is very sensitive to the housing cycle. In a house price boom, even borrowers in extreme financial distress have more appealing options than foreclosure, as house price gains result in positive equity. However, with house prices falling, highly leveraged borrowers will often find themselves in a position of negative equity, which implies fewer options.

As a result, estimating the relationship between housing prices and foreclosures requires, in principle, data that span a house price bust as well as a boom. Furthermore, analysts using loan level data must account for the fact that even as foreclosures *rise* in a house price bust, prepayments will also *fall*.

Given that the ABS data did not contain a house price bust through the end of 2004, and that, as loan level data, they could not track the experience of an individual borrower across many loans, we expect (and find) that models estimated using the ABS data only through 2004 have a harder time predicting foreclosures in 2007 and 2008 than models that include a house price bust and can track ownerships.

3.2 Forecasts Using the ABS Data

As described in Section 2, the ABS data are loan-level data that track mortgages held in securitized pools marketed as alt-A or subprime. We restrict our attention to first-lien, 30-year subprime mortgages originated from 2000 to 2007.

A key difference between the model we estimate in this section and the decomposition exercise from Section 2 is the definition of *default* and *prepayment*. The data track the performance of these mortgages over time. Delinquency status (current, 30 days late, 60 days late, 90 days or more late, or in foreclosure) is recorded monthly for active loans. The data also differentiate between types of mortgage termination: foreclosure or prepayment (without a notice of foreclosure). Here, we define *default* as a mortgage that terminates after a notice of foreclosure was served, and *prepayment* as a mortgage

[10] See Foote, Gerardi, and Willen (2008) for a more detailed discussion of this topic.

that terminates without such a notice (presumably through refinancing or home sale). Thus, loans can cycle through various delinquency stages and even have a notice of default served, but whether they are classified as happy endings (that is, prepayments) or unhappy endings (that is, defaults) will depend on their status at termination.

To model default and prepayment behavior, we augment the ABS data with MSA-level house price data from S&P/Case-Shiller, where available, and state-level house price data from the Office of Federal Housing Enterprise Oversight (OFHEO) otherwise. These data are used to construct mark-to-market CLTV ratios and measures of house price volatility. Further, we augment the data with state-level unemployment rates, monthly oil prices, and various interest rates to capture other pressures on household balance sheets. Finally, we include zip code level data on average household income, share of minority households, share of households with a high school education or less, and the child share of the population, all from the U.S. Census.

3.2.1 Empirical model

We now use the ABS data to estimate what an analyst with perfect foresight about house prices, interest rates, oil prices and so on would have predicted for prepayment and foreclosures in 2005–2007, given information on mortgage performance available at the end of 2004. We estimate a competing hazards model over the 2000–2004 period and simulate mortgage defaults and prepayments over the 2005–2007 period. The baseline hazard functions for prepayment and default are assumed to follow the PSA guidelines, which is fairly standard in the mortgage industry.[11]

The factors that can affect prepayment and default include mortgage and borrower characteristics at loan origination, such as CLTV and payment-to-income ratios, contractual mortgage rate, state-level unemployment rate, oil prices, the fully indexed contract rate (6-month LIBOR plus loan margin for adjustable-rate mortgages), the borrower's credit score, loan documentation, and occupancy status. We also include variables indicating whether the loan has any prepayment penalties, interest-only features, piggyback mortgages, refinance or purchase, and the type of property. Further, we include indicator variables to identify loans characterized by both high leverage and poor documentation, loans with credit scores below 600, and an interaction term between occupancy status and cumulative HPA over the life of the mortgage. A non-occupant

[11] For the specific forms of the PSA guidelines, see Sherlund (2008).

owner ought to be, all else being equal, more willing to default when it is in his narrow financial interest to do so, because he would not lose his primary residence.

Similarly, we include dynamically updated mortgage and borrower characteristics that vary month-to-month *after* loan origination. Most importantly, we include an estimate of the mark-to-market CLTV; changes in house prices will primarily affect default and prepayment rates through this variable. In addition, we include the current mortgage contract rate, house price volatility, state-level unemployment rates, oil prices, and the fully indexed mortgage rate (that is, the index plus the margin on ARMs).

Because of the focus on payment changes, we include three indicator variables to capture the effects of rate resets. The first is set to unity in the three months around the first mortgage rate reset (one month before, the month of, and the month after reset). The second captures whether the loan has passed its first mortgage rate reset date. The third is an indicator variable for changes in monthly mortgage payments of more than 5 percent from the original monthly mortgage payment to capture any potential large payment shocks.

Variable names and definitions for models using the ABS data are shown in Table 8, and summary statistics are shown in Table 9.

3.2.2 Estimation strategy and results

We estimate a competing-risks, proportional hazard model for six subsamples of our data. First, the data are broken down by subprime product type: hybrid 2/28s, hybrid 3/27s, and fixed-rate mortgages. Second, for each product type, estimation is carried out separately for purchase mortgages versus refinance mortgages.

Estimation results for the default hazard functions are contained in Table 10.[12] The results are similar to those reported in Sherlund (2008). As one would expect, house prices (acting through the mark-to-market CLTV term) are extremely important. In addition, non-occupant owners are, all else equal, more likely to default. The payment shock and reset window variables have relatively small effects, possibly because so many subprime borrowers defaulted in 2006 and 2007, ahead of their resets. Aggregate variables such as oil prices and unemployment rates do push up defaults, but by relatively small amounts, once we control for loan-level observables.

[12] For brevity, we do not display the parameter estimates for the prepayment hazard functions. They are available upon request from the authors.

3.2.3 Simulation results

With the estimated parameters in hand, we turn to the question of how well the model performs over the 2005–2007 period. In this exercise, we focus on the 2004 and 2005 vintages of subprime mortgages contained in the ABS data. To construct the forecasts, we use the estimated model parameters to calculate predicted foreclosure (and prepayment) probabilities for each mortgage, in each month during 2005–2007. These simulations assume perfect foresight, in that the assumed paths for house prices, unemployment rates, oil prices, and interest rates follow those that actually occurred. The average default propensity each month is used to determine the number of defaults each month, with the highest propensities defaulting first (similarly for prepayments). We then take the cumulative incidence of simulated defaults and compare them with the actual incidence of defaults via cumulative default functions (that is, the percent of original loans that default by loan age t).

The two vintages differ on many dimensions: underwriting standards, the geographic mix of loans originated, oil price shocks experienced by the loans and so on. However, the key difference between the two is the fraction of active loans in each vintage that experienced the house price bust that started, in some regions, as early as 2006. Loans from both vintages were tied to properties whose prices declined; however, loans from the later vintage were much more exposed. As we show, cumulative defaults on the 2004 vintage were reasonable, while those on the 2005 vintage skyrocketed. Thus the comparison of the 2004 and 2005 vintages provides a tough test of a model's ability to predict defaults. Any results we find here would be larger when comparing vintages farther apart; for example, the 2003 vintage experienced much greater and more sustained house price gains than did the 2006 vintage.

The results of this vintage simulation exercise are displayed in Figure 7. As shown, the model overpredicts defaults among the 2004 vintage and underpredicts defaults among the 2005 vintage. Comparing the 2005 simulation with the 2004 simulation, the model would have predicted that, after 36 months, 9.3 percent of the 2005 vintage would have defaulted, compared with 7.9 percent of the 2004 vintage, an increase of 18 percent. While this is fairly significant, it is dwarfed by the *actual* increase in defaults between vintages, both because the 2005 vintage performed so poorly, and because the 2004 vintage performed better than expected.

The cash flows from a pool of mortgages are greatly affected by prepayments. Loans that prepay (because the underlying borrower either refinanced or moved) deliver all unpaid principal to the lender, as well as, in some cases, prepayment penalties. Further, loans that prepay are not at risk of future defaults. As shown in the bottom panel of Figure 7, prepayment rates for the two vintages fell dramatically from 2004 to 2005. The model predicted that 68 percent of loans originated in 2004 would have prepaid by month 36, while only 57 percent of loans originated in 2005 would have prepaid, a 16 percent drop.

Thus, the simulations predict an 18 percent increase in cumulative defaults and a 16 percent drop in cumulative prepayments for the 2005 vintage of loans relative to the 2004 vintage. These swings would have had a large impact on the cash flows from the pool of loans.

As a further explanation of the effect of house prices on the model estimated here, we compute the conditional default and prepayment rates for the generic hybrid 2/28 mortgage we described in Table 7. By focusing on a particular mortgage type, we eliminate the potentially confounding effects of changes in the mix of loans originated, oil prices, interest rates, and so on between the two vintages and isolate the pure effect of house prices. We let house prices, oil prices, unemployment rates, and so on proceed as they did in 2004 to 2006. We then keep everything else constant, but replace *house prices* with their 2006 to 2008 trajectories. The resulting conditional default and prepayment rates are shown in Figure 8. As shown, for this type of mortgage at least, there is extreme sensitivity to house price changes. The gap between the default probabilities increases over time because house prices operate through the mark-to-market CLTV, and this particular loan started with a CLTV at origination of just over 80 percent. The gyrations in default and prepayment probabilities around month 24 are associated with the loan's first mortgage rate reset.

3.3 Forecasts using the registry of deeds data

In this section, we use data from the Warren Group, which collects mortgage and housing transaction data from Massachusetts registry of deeds offices, to analyze the foreclosure crisis in Massachusetts and to determine whether a researcher armed with this data at the end of 2004 could have successfully predicted the rapid rise in foreclosures that subsequently transpired. We focus on the state of Massachusetts in this section mostly because of data availability. The Warren Group currently collects deed-registry data for many of the northeastern states, but their historical coverage of foreclosures is limited to Massachusetts. However, the underlying micro-level housing and mortgage historical data are publicly available in many U.S. states, and a motivated researcher certainly could have obtained the data had he or she been inclined to do so before the housing crisis occurred. Indeed, several vendors sell such data in an easy-to-use format for many states, albeit at significant cost.

The deed-registry data include every residential sale deed, including foreclosure deeds, as well as every mortgage originated in the state of Massachusetts from January 1990 through December 2007. The data contain transaction amounts and dates for mortgages and property sales, but do not contain information on mortgage terms or borrower characteristics. The data do contain information about the identity of the mortgage lender, which we use in our analysis to construct indicators for mortgages that were originated by subprime lenders.

With these data we are able to construct a panel dataset of homeowners, in which we follow each homeowner from the date when the owner purchased the home to the date when the owner sold the home, experienced a foreclosure, or reached the end of our sample. We use the term "ownership experience" to refer this interval.[13] Since the data contain all residential sale transactions, we are also able to construct a collection of town-level, quarterly, weighted, repeat-sales indexes, using the methodology of Case and Shiller (1987).[14]

We use a slightly different definition of foreclosure in the deed-registry data than in the loan-level analysis above. We use a foreclosure deed, which signifies the very end of the foreclosure process, when the property is sold at auction to a private bidder or to the mortgage lender. This definition is not possible in the loan-level analysis, in part because of a large degree of heterogeneity across states in foreclosure laws, which results in significant heterogeneity in the time span between the beginning of the foreclosure process and its end.

[13] See Gerardi, Shapiro, and Willen (2007) for more details regarding the construction of the dataset.

[14] There are many Massachusetts towns that are too small to enable us to construct precise house price indexes. To deal with this issue, we group the smaller towns together, based on both geographic and demographic criteria. Altogether, we are able to estimate just over 100 indexes for the state's 350 cities and towns.

3.3.1 Comparison with the ABS Data

The deed-registry data differ significantly from the ABS data. The ABS data track individual mortgages over time, while the deed-registry data track homeowners in the same residence over time. Thus, with the registry of deeds data, the researcher can follow the same homeowner across different mortgages in the same residence and determine the eventual outcome of the ownership experience. With the ABS data, in contrast, if the mortgage terminated in a manner other than foreclosure, such as a refinance or sale of the property, the borrower drops out of the dataset and the outcome of the ownership experience is unknown. Gerardi, Shapiro, and Willen (2007) argue that analyzing ownership experiences rather than individual mortgages has certain advantages, depending on the ultimate question being addressed.

Another major difference between the deed-registry data and ABS data is the period of coverage. The deed-registry data encompass the housing bust of the early 1990s in the Northeast, when there was a severe decrease in nominal house prices as well as a significant foreclosure crisis. Figure 9 displays the evolution of house price appreciation and the foreclosure rate in Massachusetts. Foreclosure deeds began to rise rapidly beginning in 1991 and peaked in 1992, with approximately 9,300 foreclosures statewide. The foreclosure rate remained high through the mid-1990s, until nominal HPA became positive in the late 1990s. The housing boom in the early 2000s is evident, with double-digit annual house price appreciation and extremely low levels of foreclosure. We see evidence of the current foreclosure crisis at the very end of our sample, as foreclosure deeds began rising in 2006 and by 2007 were approaching the levels witnessed in the early 1990s.

The final major difference between the two data sources is the coverage of the subprime mortgage market. Since the ABS data encompass pools of non-agency, mortgage-backed securities, a subprime mortgage is simply defined as a loan contained in a pool of mortgages labeled "subprime." In the deed-registry data, there is no information pertaining to whether the mortgage is securitized or not, and thus, we cannot use the same subprime definition. Instead, we use the identity of the lender in conjunction with a list of lenders who originate mainly subprime mortgages; this is constructed by the Department of Housing and Urban Development (HUD) on an annual basis. The two definitions are largely consistent with each other.[15] Table 13 displays the top 10 Massachusetts subprime lenders for each year going back to 1999. The composition of the list does change a little from year-to-year, but for the most part, the same lenders consistently occupy a spot on the list. It is evident from the table that subprime lending in Massachusetts peaked in 2005 and fell sharply in 2007. The increasing importance of the subprime purchase mortgage market is also very clear from Table 13. During the period from 1999 to 2001 the subprime mortgage market consisted mostly of mortgage refinances. In 1999 and 2000, home purchases with subprime mortgages made up only 25 percent of the Massachusetts subprime market, and only 30 percent in 2001. By 2004, however, purchases made up almost 78 percent of the subprime mortgage market, and in 2006 they made up 96 percent of the market. This is certainly evidence supporting the idea that over time the subprime mortgage market opened up the opportunity of homeownership to many households, at least in the state of Massachusetts.

3.3.2 Empirical model

The empirical model we implement is drawn from Gerardi, Shapiro, and Willen (2007) and is similar to previous models of mortgage termination, including Deng, Quigley, and Order (2000), Deng and Gabriel (2006), and Pennington-Cross and Ho (2006). It is a duration model similar to the one used in the above analysis of the ABS data, with a few important differences. As in the loan-level analysis, we use a competing risks, proportional hazard specification, which assumes that there are baseline hazards common to all ownership experiences. However, because we are now analyzing ownership experiences rather than individual loans, the competing risks correspond to the two possible terminations of an ownership experience, sale and foreclosure, as opposed to the two possible terminations of a mortgage, prepayment and foreclosure. As discussed above, the major difference between the two specifications comes in the treatment of refinances. In the loan-level analysis, when a borrower refinances, he drops out of the dataset, as the mortgage is terminated. However, in the ownership experience analysis, when a borrower refinances, he remains in the data. Thus, a borrower who defaults on a refinanced mortgage will show up as a foreclosure in the deed-registry dataset, whereas his first mortgage will show up in the ABS data as a prepayment, and his second mort-

[15] See Gerardi, Shapiro, and Willen (2007) for a more detailed comparison of different subprime mortgage definitions. Mayer and Pence (2008) also conduct a comparison of subprime definitions, and reach similar conclusions.

gage may or may not show up in the data (depending on whether the mortgage was sold into a private-label MBS), but either way, the two mortgages will not be linked together. Thus, perforce, for the same number of eventual foreclosures, the ABS data will show a lower apparent foreclosure rate.

Unlike mortgage terminations, ownership terminations lack a generally accepted standard baseline hazard. Therefore, we specify both the foreclosure and sale baseline hazards in a non-parametric manner, including a dichotomous variable for each year after the purchase of the home. In effect, we model the baseline hazards with a set of age dummies.[16]

The list of explanatory variables is different than in the loan-level analysis. We have detailed information regarding the CLTV at the time of purchase for each homeowner in the data, and we include this information as a right-hand-side variable. We also combine the initial CLTV with cumulative HPA since purchase, in the town where the house is located, to construct a measure of household equity, E_{it}:

$$E_{it} = \frac{(1 + C_{jt}^{HPA}) - CLTV_{i0}}{CLTV_{i0}}, \tag{1}$$

where $CLTV_{i0}$ corresponds to household i's initial CLTV, V_{i0} is the purchase price of the home, and C_{jt}^{HPA} corresponds to the cumulative amount of HPA experienced in town j from the date of house purchase through time t.[17] Based on our above discussion of the theory of default, the effect of an increase in equity should be significantly different on a borrower in a position of negative equity than on a borrower who has positive equity in his or her home. For this reason, we assume a specification that allows for the effect of equity on default to change depending on the equity level of the borrower. To do this, we specify equity as a linear spline, with six intervals: (-∞, -10%), [-10%, 0%), [0%, 10%), [10%, 25%), and [25%, ∞).[18]

Since detailed mortgage and borrower characteristics are not available in the deed-registry data, we use zip code level demographic information from the 2000 U.S. Census, including median household income and the percentage of minority households in

[16] Gerardi, Shapiro, and Willen (2007) and Foote, Gerardi, and Willen (2008) use a third-order polynomial in the age of the ownership. The non-parametric specification has the advantage of not being affected by the non-linearities in the tails of the polynomials for old ownerships, but the results for both specifications are very similar.

[17] This equity measure is somewhat crude as it does not take into account amortization, cash-out refinances, or home improvements. See Foote, Gerardi, and Willen (2008) for a more detailed discussion of the implication of these omissions on the estimates of the model.

[18] See Foote, Gerardi, and Willen (2008) for a more detailed discussion of the selection of the intervals.

the zip code, and town-level, unemployment rates from the Bureau of Labor Statistics (BLS). We also include the 6-month LIBOR rate in the list of explanatory variables to capture the the effects of nominal interests rates on sale and foreclosure.[19] Finally, we include an indicator of whether the homeowner obtained financing from a lender on the HUD subprime lender list at the time of purchase. This variable is included as a proxy for the different mortgage and borrower characteristics that distinguish the subprime mortgage market from the prime mortgage market. It is important to emphasize that we do not assign a causal interpretation to this variable. Rather we interpret the estimated coefficient as a correlation that simply tells us the relative frequency of foreclosure for subprime purchase borrowers compared with the relative frequency for borrowers who use a prime mortgage.

Table 11 displays summary statistics for the number of new Massachusetts ownership experiences initiated and the number of sales and foreclosures, broken down by vintage. The two housing cycles are clearly evident in this table. Almost 5 percent of the ownerships initiated in 1990 eventually experienced a foreclosure, while fewer than 1 percent of the vintages between 1996 and 2002 experienced a foreclosure. Even though there is a severe right-censoring problem for the 2005 vintage of ownerships, as of December 2007 more than 2 percent had already succumbed to foreclosure. The housing boom of the early 2000s can also be seen in the ownership statistics, as between 80 and 100 thousand ownerships were initiated each year between 1998 and 2005, almost double the number that were initiated each year in the early 1990s and 2007.

Table 12 contains summary statistics for the explanatory variables included in the model, also broken down by vintage. It is clear from the loan-to-value statistics that homeowners became more leveraged on average over the period of our sample. Median initial CLTVs increased from 80 percent in 1990 to 90 percent in 2007. Even more striking, the percentage of CLTVs that are greater than or equal to 90 percent almost doubled from approximately 22.5 percent in 1990 to 41.6 percent in 2007. The table shows both direct and indirect evidence of the increased importance of the subprime purchase mortgage market. The last column of the table displays the percentage of borrowers who financed a home purchase with a subprime mortgage in Massachusetts.

[19] We use the 6-month LIBOR rate since the vast majority of subprime ARMs are indexed to this rate. However, using other nominal rates such as the 10-year treasury rate does not significantly affect the results.

Fewer than 4 percent of new ownerships used the subprime market to purchase a home before 2003. In 2003, the percentage increased to almost 7, and in 2005, at the peak of the subprime market, it reached almost 15. The increased importance of the subprime purchase market is also apparent from the zip code level income and demographic variables. The percentage of ownerships coming from zip codes with large minority populations (according to the 2000 Census) increased over time. Furthermore, the number of ownerships coming from lower-income zip codes increased over time.

3.3.3 Estimation Strategy

We use the deed-registry data to estimate the proportional hazards model for three separate sample periods. We then use the estimates from each sample to form predicted foreclosure probabilities for the 2004 and 2005 vintages of subprime and prime borrowers and compare the predicted probabilities to the actual foreclosure outcomes of the respective vintages. The first sample we use is the entire span of the data, January 1990 to December 2007. This basically corresponds to an in-sample, goodness of fit exercise, as some of the data being used would not have been available to a forecaster in real time when the 2004 and 2005 vintage ownerships were initiated. This period covers two housing downturns in the Northeast, and thus two periods when many households found themselves in positions of negative equity, where the nominal mortgage balance was larger than the market value of the home. From the peak of the market in 1988 to the trough in 1992, nominal housing prices fell by more than 20 percent statewide, implying that even some of the borrowers who put 20 percent down at the time of purchase found themselves in a position of negative equity at some point in the early 1990s. In comparison, nominal Massachusetts housing prices fell by more than 10 percent from their peak in 2005 through December 2007.

The second sample includes homeowners who purchased homes between January 1990 and December 2004. This is an out-of-sample exercise, as we are only using data that were available to a researcher in 2004 to estimate the model. Thus, with this exercise, we are asking the question of whether a mortgage modeler in 2004 could have predicted the current foreclosure crisis using only data available at that time. This sample does include the housing downturn of the early 1990s, and thus a significant number of negative equity observations.[20] However, it includes a relatively small num-

[20] See Foote, Gerardi, and Willen (2008) for a more detailed analysis of Massachusetts homeowners with

ber of subprime ownerships. It is clear from Table 13 that the peak of the subprime purchase mortgage market occurred in 2004 and 2005. However, the majority of the subprime purchase observations in the 1990–2004 sample come from the 2000 to 2002 vintages, which, combined, were approximately 50 percent of the 2005 vintage. Thus, while this sample period does include a significant housing price decline, it does not include the peak of the subprime market. Furthermore, Section 2 provided evidence that the underlying mortgage and borrower characteristics of the subprime market evolved over time. Thus, the subprime purchase mortgages in the 1990–2004 sample are likely different from those originated after 2004, and this could have a significant effect on the fit of the model.

The final sample covers ownership experiences initiated between January 2000 and December 2004, and corresponds to the sample period used in the loan-level analysis above. This was a time of extremely rapid house price appreciation, as can clearly be seen in Figure 9. House prices increased at an annual rate of more than 10 percent in Massachusetts during this period. Thus, the major difference between this sample and the 1990–2004 sample is the absence of a housing downturn.

3.3.4 Estimation results

The proportional hazard model is estimated at a quarterly frequency, in contrast to the monthly frequency used in the loan-level analysis above, because of the quarterly frequency of the town-level, house price indexes. The model is estimated using maximum likelihood. Since we are basically working with a panel dataset containing the population of Massachusetts homeowners, the number of observations is too large to conduct the estimation. Thus, to facilitate computation, we take three random samples of ownerships (10 percent of the 1990–2007 sample, 10 percent of the 1990–2004 sample, and 25 percent of the 2000–2004 sample). Finally, we truncate ownerships that last longer than 8 years, for two reasons. First, because there are relatively few of these long ownerships, the estimates of the baseline hazard are imprecise. Second, because of missing information regarding mortgage equity withdrawal, the equity measure becomes more biased as the length of the ownership experience increases.[21]

Figure 10 displays the estimates of both the foreclosure and the sale baseline haz-

negative equity in the early 1990s.

[21] The estimation results are not very sensitive to this 8-year cutoff. Assuming a 7-year or 9-year cutoff produces almost identical results.

ards. The foreclosure baseline is hump-shaped, and reaches a peak between the fourth and fifth year of the ownership experience. The sale baseline rises sharply over the first three years of the ownership, then flattens until the seventh year, when it continues to rise. In Table 14 we display the parameter estimates. The first panel contains estimates for the full sample (1990–2007); the second panel contains estimates for the period 1990–2004; and the third panel displays estimates for the period 2000–2004.[22] For the most part, the signs of the estimates are intuitive and consistent with economic theory. Higher interest and unemployment rates tend to raise foreclosures, although the coefficient estimate associated with the LIBOR rate switches signs in the 1990–2004 sample. Homeowners who finance their home purchase from subprime lenders are more likely to experience a foreclosure than those who use prime lenders. Borrowers who purchase a condominium or a multi-family property are more likely to experience a foreclosure than borrowers who purchase a single-family home, in both the full sample and the 1990–2004 samples. This likely reflects the fact that the Massachusetts condominium market was hit especially hard by the housing downturn in the early 1990s, and the fact that many of the economically depressed cities in Massachusetts are characterized by housing stocks that are disproportionately made up of multi-family properties. In the 2000–2004 sample, homeowners in condominiums are actually less likely to experience a foreclosure. Finally, ownerships located in zip codes with relatively larger minority populations and lower median income levels are more likely to experience a foreclosure.

The quantitative implications of the parameter estimates are displayed in Table 16. The table displays the effect of a change in selected variables (one standard deviation for continuous variables and zero-one for dummies) on the probability of foreclosure. For example, the first panel shows that a homeowner who purchased his house with a subprime mortgage is approximately 7.3 times as likely to default, all else being equal, than a homeowner who purchased with a prime mortgage, and 1.1 times as likely to experience a foreclosure if the unemployment rate is one standard deviation above average. The functional form of the proportional hazard model implies that the effect of several different changes on the hazard is multiplicative. For example, the combined effect of a subprime purchase ownership and one-standard deviation higher

[22] For brevity we do not display the parameter estimates for the sale hazard. They are available upon request from the authors.

unemployment is $7.3 \times 1.1 = 8.0$.

There are some interesting differences across the different sample periods, most notably associated with the estimate of the subprime purchase indicator. In the full sample period, subprime purchase ownerships are more than 7 times as likely to experience foreclosure, but in the earlier sample period (1990–2004), they are only 3.4 times as likely to default. Based on the analysis from Section 2, this likely reflects differences in mortgage and borrower characteristics between the two samples. For example, increases in debt-to-income ratios and low documentation loans, as well as increases in mortgages with discrete payment jumps, have characterized the subprime market over the past few years. This has likely had a lot to do with the deterioration in the performance of the subprime purchase market. Of course, there are other possible explanations such as a deterioration in unobservable lender-specific underwriting characteristics. Another possibility is a higher sensitivity to declining house prices relative to prime purchase ownerships. Although the subprime market existed in the early 1990s, most of the activity came in the form of refinances (as evidenced by Figure 13). Thus, not many subprime purchase ownerships from the 1990–2004 sample actually experienced a significant decline in house prices, whereas the vast majority of subprime ownerships took place in 2004 and 2005, and many of these were exposed to large price declines. The performance of subprime purchases is better in the 2000–2004 sample than in the full sample but worse than in the 1990–2004 sample, as they are approximately 5.5 times as likely to experience foreclosure.

Since housing equity E_{it} is estimated with a spline, the estimates are not shown in Table 16. Instead, we graph the predicted foreclosure hazard as a function of equity relative to a baseline subprime purchase ownership in Figure 11. The covariates for the baseline ownership have have been set to their full sample averages. Each panel corresponds to a different sample period. There were virtually no equity values below zero in the 2000–2004 sample to estimate the spline, so instead we were forced to use a single parameter.

The takeaway from the figure is that increases in E_{it} have a large and negative effect on foreclosures for the range of equity values between -50 and 25 percent of the purchase mortgage. For ownerships with nominal equity values above 25 percent, further increases in equity have a much smaller effect on the foreclosure hazard. This is consistent with the intuition presented above. Homeowners with positive equity who are either in financial distress or need to move for another reason are not likely to default, since they are better off selling their homes instead. Thus, if a homeowner already has a significant amount of positive equity, additional equity is likely to matter little in the default decision. However, when one takes into account the potential transactions costs involved in selling a property, such as the real estate broker commission (usually 6 percent of the sale price) as well as moving expenses, the equity threshold at which borrowers will default may be greater than zero. Therefore, the apparent kink in the foreclosure hazard at 25 percent equity is not necessarily inconsistent with the discussion above.

The estimated non-linear relationship is similar for the full sample and the 1990–2004 sample. The scale is higher and the non-linearity is more pronounced in the full sample, as that sample includes the recent foreclosure crisis. But, perhaps the most surprising observation from Figure 11 is the shape of the predicted hazard from the 2000–2004 sample (lower left panel). While the predicted hazard is necessarily smooth because of the single parameter that governs the relationship, it has a very similar shape and scale to the other samples. This is surprising because the sensitivity of foreclosure to equity is being estimated with only positive equity variation in this sample. On the face of things, the figure seems to suggest that one could estimate the sensitivity using positive variation in equity and then extrapolate to negative equity values and obtain findings that are similar to those obtained using a sample with housing price declines. This is, of course, in part, a result of the non-linear functional form of the proportional hazard model, and it would be impossible in a linear framework (for example, a linear probability model). The implications of this in terms of forecasting ability is discussed below.

3.3.5 Simulation results

With the estimated parameters in hand, we turn to the question of how well the model performs, both in-sample and out-of-sample. In this exercise, we focus on the 2004 and 2005 vintages of subprime purchase borrowers. The choice of these vintages is motivated both by performance and by data availability. The summary statistics in Table 11 suggest that the 2004 vintage was the first to suffer elevated foreclosure rates in the current housing crisis, and the 2005 vintage is experiencing even higher foreclosure rates. Unfortunately, we do not have enough data at this time to conduct a thorough analysis of the 2006 or 2007 vintages.

To construct the forecasts, we use the estimated model parameters to calculate predicted foreclosure probabilities for each individual ownership in the vintages of interest between the time that the vintage was initiated and 2007:Q4. We then take the individual predicted probabilities and aggregate them to obtain cumulative foreclosure probabilities for each respective vintage, and we compare the predicted foreclosure probabilities to the probabilities that actually occurred.[23] The results for the subprime purchase vintages are displayed in Figures 12 and 13.

The model consistently overpredicts foreclosures for the 2004 subprime vintage (top left panel in Figure 12) in the full sample, as approximately 9.2 percent of the vintage had succumbed to foreclosure as of 2007:Q4, while the model predicts 11.2 percent. For the out-of-sample forecasts, the model underpredicts Massachusetts foreclosures, but there are significant differences between the two different sample periods. The model estimated using data from 1990–2004 is only able to account for a little over half of the foreclosures experienced by the 2004 vintage, while the model estimated using data from 2000–2004 accounts for almost 85 percent of the foreclosures. The reason for the better fit can likely be attributed to the larger coefficient estimate associated with the subprime mortgage indicator variable for the 2000–2004 sample compared with the 1990–2004 (see Table 14). In Table 13 we see similar patterns for the 2005 subprime vintage, although the in-sample forecast slightly underpredicts cumulative foreclosures, and the out-of-sample forecasts are markedly worse for both sample periods compared with the 2004 subprime vintage forecasts. The 1990–2004 out-of-sample forecast accounts for only one-third of the foreclosures experienced by the 2005 subprime vintage, while the 2000–2004 does better, accounting for more than 60 percent of the foreclosures. However, this is not as good as the 2004 vintage forecast.

To summarize, the model, estimated using data from the 2000–2004 vintages, does very well in its 2005–2007 out-of-sample foreclosure predictions for the 2004 vintage of subprime purchase borrowers, accounting for approximately 85 percent of cumulative foreclosures in 2007:Q4. The model does not perform quite as well for the 2005 vintage, as it accounts for only 63 percent of cumulative foreclosures in 2007:Q4.

[23] See Gerardi, Shapiro, and Willen (2007) for more details.

There are significant differences between the performance of the model estimated using data from different sample periods. The model estimated using the 2000–2004 sample performs much better than model estimated using data from the 1990–2004 sample period. This is despite the fact that the latter sample period includes a decline in housing prices, while the former does not. Based on observations from Figure 11, the proportional hazards model is able to estimate the nonlinear relationship between equity and foreclosure, even when there are no negative equity observations in the data. Thus, the primary explanation for the difference in the out-of-sample forecasts is the different coefficient estimates associated with the HUD subprime purchase indicator.

4 What Did the Participants Say in 2005 and 2006?

In this section, we attempt to understand why the investment community did not anticipate the subprime mortgage crisis. We do this by looking at written records from market participants in the period from 2004 to 2006.

These records include analyst reports from investment banks, publications by rating agencies, and discussions in the media. We have chosen not to identify the five major banks (J.P. Morgan, Citigroup, Morgan Stanley, UBS, and Lehman Brothers) individually, but rather by alias (Bank A, Bank B, etc.)[24] Five basic themes emerge in this section. First, the subprime market was viewed by market insiders as a great success story in 2005. Second, subprime mortgages were viewed, in some sense correctly, as lower risk than prime mortgages because of their more stable prepayment behavior. Third, analysts used fairly sophisticated tools, but were hampered by the absence of episodes of falling prices in their data. Fourth, many analysts anticipated the crisis in a qualitative way, laying out in various ways a roadmap of what could happen, but they never fleshed out the quantitative implications. Finally, analysts were remarkably optimistic about HPA.

Figure 14 provides a timeline for this discussion. The top part shows HPA using the Case-Shiller 20-city composite index. In the first half of 2005, HPA for the nation as a whole was positive but in the single digits and so well below the record pace set in 2004 and 2005. By the end of the third quarter, HPA was negative, although, given the reporting lag in the Case-Shiller numbers, market participants would

[24] Researchers interested in verifying the sources should contact the authors.

not have had this datapoint until the end of the fourth quarter. The bottom part of the figure shows the prices of the ABX-HE 06-01-AAA and ABX-HE 06-01-BBB indexes which measure the cost of insuring, respectively, AAA-rated and BBB-rated subprime-mortgage-backed securities issued in the second half of 2005, and containing mortgages originated throughout 2005. One can arguably date the subprime crisis to the first quarter of 2007 when the cost of insuring the BBB-rated securities, which had not changed throughout all of 2006, started to rise. The broader financial market crisis, which started in August, coincides with another spike in the BBB index and the first signs of trouble in the AAA index. The purpose of this section is to try and understand why market participants did not appreciate the impending crisis, as evidenced by the behavior of the ABX indexes in 2006.

4.1 General state of the subprime market

In 2005, market participants viewed the subprime market as a success story along many dimensions. Borrowers had become much more mainstream. Bank A analysts referred to the subprime borrower as "Classic Middle America," writing:

> The subprime borrower today has a monthly income above the national median and a long tenure in his job and profession. His home is a three-bedroom, two bathroom, typical American home, valued at the national median home price. Past credit problems are the main reason why the subprime borrower is ineligible for a prime loan.[25]

Analysts noted that the credit quality of the typical subprime borrower had improved. The average FICO score of a subprime borrower had risen consistently from 2000 to 2005.[26] But other aspects got better too.

> ...collateral credit quality has been improving since 2000. FICO scores and loan balances increased significantly implying a mainstreaming of the subprime borrower. The deeply subprime borrowers of the late 1990s have been replaced by the average American homeowner...[27]

Lenders had improved as well. Participants drew a distinction between the seedy subprime lenders of the mid-late 1990s and the new generation of lenders that they saw

[25] Bank A, October 10, 2005.
[26] *ibid* and Bank E, February 15, 2005.
[27] Bank A, October 10, 2005.

as well-capitalized and well-run.

> The issuer and servicer landscape in the HEL market has changed dramatically since the liquidity crisis of 1998. Large mortgage lenders or units of diversified financial services companies have replaced the small specialty finance companies of the 1990s.[28]

Lenders, analysts believed, could weather a storm:

> ...today's subprime issuer/servicers are in much better shape in terms of financial strength. If and when the market hits some kind of turbulence, today's servicers are in a better position to ride out the adverse market conditions.[29]

Another dimension along which the market had improved was the use of data. Many market participants were using loan-level data and modern statistical techniques. Bank A analysts expressed a widely held view when they wrote:

> An increase in the sophistication of all market participants — from lenders to the underwriters to the rating agencies to investors. All of these participants now have access to quantitative models that analyze extensive historical data to estimate credit and prepayment rates.[30]

Contemporary observers placed a fair amount of faith in the role of credit scoring in improving the market. FICO scores did appear to have significant predictive power for credit problems. In particular, statistical evidence showed that FICO scores, when combined with LTV, could "explain a large part of the credit variation between deals and groups of subprime loans."[31] The use of risk-based pricing made origination decisions more consistent and transparent across originators, and thus resulted in more predictable performance for investors.

> *We believe that this more consistent and sophisticated underwriting is showing up as more consistent performance for investors. An investor buying a subprime home equity security backed by 2001 and 2002 (or later*

[28] Bank A, October 10, 2005. Here and elsewhere, "HEL" is used by market participants to refer to "home equity loan", the typical market participant term for either a junior lien to a prime borrower, or senior lien to a subprime borrower. Although the two loan types appear quite different, from a financial engineering standpoint both prepaid relatively quickly but were not that sensitive to prevailing interest rates on prime first-lien mortgages.

[29] Bank E, January 31, 2006.

[30] Bank A, October 10, 2005.

[31] Bank E, February 15, 2005.

> *vintage) loans is much more likely to get the advertised performance than buying a deal from earlier years.* [Italics in the original] [32]

One has to remember that the use of credit scores such as the FICO model emerged as a crucial part of residential mortgage credit decisions only in the mid-1990s.[33] And as late as 1998, one observer points out, FICO scores were absent for more than 29 percent of the mortgages in their sample, but by 2002, this number had fallen to 6 percent.[34]

Other things had also made the market more mature. One reason given for the rise in average FICO scores was that "the proliferation of state and municipal predatory lending laws has made it more onerous to fund very low credit loans."[35]

Finally, market participants' experience with rating agencies through mid-2006 had been exceptionally good. Rating agencies had what appeared to be sophisticated models of credit performance using loan-level data and state of the art statistical techniques. S&P, for example, used a database, "which compiles the loan level and performance characteristics for every RMBS (residential mortgage-backed security) transaction that we have rated since 1998."[36] Market participants appeared to put a lot of weight on the historical stability of HEL credit ratings.[37] And indeed, through 2004, the record of the major rating agencies was solid. Table 15 shows S&P's record from their first RMBS rating in 1978 to the end of 2007 and illustrates that the probability of a downgrade was quite small and far smaller than the probability of an upgrade.

4.2 Prepayment risk

Investors allocated appreciable fractions of their portfolios to the subprime market because, in one key sense, it was considered less risky than the prime market. The issue was prepayments, and the evidence showed that subprime borrowers prepaid much less efficiently than prime borrowers, meaning that they did not immediately exploit advantageous changes in interest rates to refinance into lower rate loans. Thus, the sensitivity of the income stream from a pool of subprime loans to interest rate changes was lower than the sensitivity of a pool of prime mortgages. According to classical finance theory,

[32] Bank E, February 15, 2005.
[33] Mester, 1997
[34] Bank E, February 15, 2005.
[35] Bank A, Dec. 16, 2003.
[36] "A More Stressful Test Of A Housing Market Decline On U.S. RMBS," S&P, May 15, 2006.
[37] Bank A, October 20, 2005.

one could even argue that subprime loans were less risky in an absolute sense. While subprime borrowers had a lot of idiosyncratic risk, as evidenced by their problematic credit histories, such borrower-specific shocks can be diversified away in a large enough pool. In addition, the absolute level of prepayment (rather than its sensitivity to interest rate changes) of subprime loans is quite high, reflecting the fact that borrowers with such loans either resolve their personal financial difficulties and graduate into a prime loan or encounter further problems and refinance again into a new subprime loan, terminating the previous loan. However, this prepayment was also thought to be effectively uncorrelated across borrowers and not tightly related to changes in the interest rate environment. Mortgage pricing revolved around the sensitivity of refinancing to interest rates; subprime loans appeared to be a useful class of assets whose cash flow was not particularly correlated with interest rate shocks. Thus, Bank A analysts wrote, in 2005:

> [Subprime] prepayments are more stable than prepayments on prime mortgages adding appeal to [subprime] securities.[38]

A simple way to see the difference between prepayment behavior of prime and subprime borrowers is to look at variation in a commonly used mortgage industry measure, the so-called constant prepayment rate, or CPR, which is the annualized probability of prepayment. According to Bank A analysts, the minimum CPR for subprime fixed-rate mortgages was 18 percent, and for ARMs it was 29 percent. By contrast, for Fannie Mae mortgages, the minimums were 7 and 15 percent, respectively. As mentioned above, this was attributed to the fact that even in a stable interest rate environment, subprime borrowers will refinance in response to household-level shocks. At the other end, the maximum CPRs for subprime fixed and ARM borrowers are 41 and 54 percent, respectively, compared with 58 and 53, respectively, for Fannie Mae borrowers. The lower CPR for subprime reflects, at least partly, the prevalence of prepayment penalties. More than 66 percent of subprime borrowers face prepayment penalties. Historically, the prepayment penalty period often lasted five years, but in most cases, it had shortened to two years for ARMs, and three for fixed-rate mortgages, by 2005.

[38] Bank A, October 10, 2005.

4.3 Data

Correctly modeling (and thus pricing) prepayment and default risk requires good underlying data, giving market participants every incentive to acquire data on loan performance. As mentioned above, analysts at every firm we looked at, including the rating agencies, had access to loan-level data. One major problem, however, was that these data, for the most part, did not include any examples of sustained price declines. The fact that the Trends database only dates back to 1998 is typical. Bank A's RAMP-RS, for example, dates back to 1998. And the problems were particularly severe for subprime loans, since there essentially were none before 1998. Furthermore, to add to the problems, analysts believed that the experience of pre- and post-2001 subprime loans were not necessarily comparable. In addition, in one sample, analysts identified a major change in servicing, pointing in particular to a new rule that managers needed to have four-year college degrees, as explaining significant differences in default behavior before and after 2001.

Analysts recognized that their modeling was constrained by lack of data on the performance of loans through house price downturns. Some analysts simply focused on the cases for which they had data — high and low positive HPA experiences. In one Bank A report, the highest current LTV bin examined was "$>$ 70 percent."[39] The worst case examined in a Bank E analyst report in the fall of 2005 was 0–5 percent HPA.[40]

But, in truth, most analysts appear to have been aware that the lack of examples of negative HPA was not ideal. Bank A analysts wrote in December of 2003 that,

> Because of the strong HPA over the past five years, high LTV buckets of loans thin out fast, limiting the history.[41]

And they knew this was a problem. In June of 2005, an analyst at Bank A wrote:

> We do not project losses with home appreciation below 2.5% because the dataset on which the model was fitted contains no meaningful home price declines and few loans with LTVs in the high 90s. Therefore, model projections for scenarios that take LTVs well above 100% are subject to significant uncertainty. [42]

[39] Bank A, March 17, 2004.
[40] Bank E, December 13, 2005.
[41] Bank A, December 13, 2005.
[42] Bank A, June 3, 2005.

However, eventually, some analysts overcame these problems. In a debate that we discuss in more detail below, S&P and Bank A analysts considered scenarios with significant declines in house prices. An S&P report in September of 2005 considered a scenario in which house prices fell on the coasts by 30 percent and in the interior of the country by 10 percent.[43] Bank A analysts also examined the same scenario, illustrating that by December they were able to overcome the lack of meaningful price declines identified in June.[44]

4.4 Role of HPA

Market participants clearly understood that HPA played a central role in the the dynamics of foreclosures. They identified at least three key facts about the interaction between HPA and foreclosures. First, HPA provided an "exit strategy" for troubled borrowers. Second, analysts identified a close relationship between refinance activity and prepayment speeds for untroubled borrowers, which also reduced losses. Third, they knew high HPA meant that even when borrowers did default, losses would be small. Finally, they understood that the exceptionally small losses on recent vintage subprime loans were due to exceptionally high HPA and that a decline in HPA would lead to higher losses.

The role of HPA in preventing defaults was well understood. Essentially, high HPA meant borrowers were very unlikely to have negative equity, and this, in turn, implied that defaulting was never optimal for a borrower who could profitably sell the property. In addition, high HPA meant that lenders were willing to refinance. The following view was widely echoed in the industry:[45]

> Because of strong HPA, many delinquent borrowers have been able to sell their house and avoid foreclosure. Also, aggressive competition among lenders has meant that some delinquent borrowers have been able to refinance their loans on more favorable terms instead of defaulting.[46]

The "double-trigger" theory of default was the prevailing wisdom:

[43] Simulated Housing Market Decline Reveals Defaults Only in Lowest-Rated US RMBS Transactions, Standard and Poor's, September 13, 2005.

[44] Bank A, December 2, 2005.

[45] See also Bank E, December 13, 2005.

[46] Bank A, October 20, 2005.

> Borrowers who are faced with an adverse economic event — loss of job, death, divorce or large medical expense — and who have little equity in the property are more likely to default than borrowers who have large equity stakes.[47]

Participants also identified the interaction between HPA and prepayment as another way that HPA suppressed losses. As a Bank A analyst explained in the fall of 2005:

> Prepayments on subprime hybrids are strongly dependent on equity build-up and therefore on HPA. Slower prepayments extend the time a loan is outstanding and exposed to default risk.[48]

Quantitatively, the analyst claimed that a fall in HPA from 15 percent to -5 percent would reduce CPR, the annualized prepayment rate of the loan pool, by 29 percentage points.

Analysts seem to have understood both that high HPA of recent years accounted for the exceptionally strong performance of recent vintages, and that lower HPA represented a major risk going forward. A Bank E analyst wrote in the fall of 2005:

> Double-digit HPA is the major factor supporting why recent vintage mortgages have produced lower delinquencies and much lower losses.[49]

An analyst at Bank C wrote:

> ...the boom in housing translated to a build-up of equity that benefited subprime borrowers, allowing them to refinance and/or avoid default. This has been directly reflected in the above average performance of the 2003 and 2004 HEL ABS vintages.[50]

And in a different report, another Bank E analyst argued that investors did understand its importance:

> If anyone questioned whether housing appreciation has joined interest rates as a key variable in mortgage analysis, attendance at a recent CPR/CDR conference would have removed all doubts. Virtually every speaker, whether

[47] Bank A, December 2, 2005.
[48] Bank A, December 2, 2005.
[49] Bank E, December 13, 2005.
[50] Bank C, April 11, 2006.

> talking about prepayments or mortgage credit, focuses on the impact of house prices.[51]

Analysts did attempt to measure the quantitative implications of slower HPA. In August of 2005, analysts at Bank B evaluated the performance of 2005 deals in five HPA scenarios. In the "meltdown" scenario, which involved -5 percent HPA for the life of the deal, they concluded that cumulative losses on the deals would be 17.1 percent of the original principal balance. Because the "meltdown" is roughly what actually happened, we can compare their forecast with actual outcomes. Implied cumulative losses for the deals in the ABX-06-01, which are deals made in 2005, are between 17 and 22 percent, depending on the assumptions. [52]

The lack of examples of price declines in their data did not prevent analysts from appreciating the importance of HPA, consistent with the results of the previous section. In an April 2006 report, analysts at Bank C pointed out that the cross-section of MSAs illustrated the importance of HPA:

> The areas with the hottest real estate markets experienced low single-digit delinquencies, minimal LTD losses, [and] low loss severity, ... a sharp contrast to performance in areas at the low end of HPA growth.[53]

Greeley, Colorado, had 6 percent HPA since origination and 20 percent delinquency. At the other extreme was Bakersfield, California, with 87 percent HPA and 2 percent delinquency. Their estimated relationships between delinquency rates and loss rates and cumulative HPA since origination using the 2003 vintage, are plotted in the top and bottom panels, respectively, of Figure 15. Even in their sample, there was a dramatic difference in performance between low and high levels of cumulative HPA. The figure suggests that it was possible to use variation across regions in positive levels of cumulative HPA to extrapolate to situations with negative levels of cumulative HPA. For example, if we used the tables to forecast delinquencies in May of 2008 with a 20 percent fall in house prices (roughly what happened), we would get a 35 percent delinquency rate and 4 percent cumulative loss rate. The actual numbers for the 2006-1 ABX are 3.37 percent losses and a 37 percent delinquency rate.

In some ways, most interestingly, some analysts seem to have understood that the

[51] Bank E, November 1, 2005.
[52] See Bank C, August 21, 2008 and Bank B, 9/2/2008.
[53] Bank C, April 11, 2006.

problems might extend beyond higher losses on some subprime ABS. In the fall of 2005, Bank A analysts mapped out almost exactly what happened in the summer of 2007, but the analysis is brief and not the centerpiece of their report. They started by noting, "As of November 2004, only three AAA-rated RMBS classes have ever defaulted..." And, indeed, to that point, almost no AAA rated RMBS had defaulted. But, they understood that even without such defaults, problems could be severe:

> Even though highly rated certificates are unlikely to suffer losses, poor collateral or structural performance may subject them to a ratings downgrade. For mark-to-market portfolios the negative rating event may be disastrous, leading to large spread widening and trading losses. Further down the credit curve, the rating downgrades become slightly more common, and need to be considered in addition to the default risk.[54]

The only exception to the claim that analysts understood the magnitude of df/dp comes from the rating agencies. As a rating agency, S&P was forced to focus on the worst possible scenario rather than the most likely one. And their worst-case scenario is remarkably close to what actually happened. In September of 2005, they considered the following:

- a 30 percent house price decline over two years for 50 percent of the pool
- a 10 percent house price decline over two years for 50 percent of the pool.
- an economy that was"slowing but not recessionary"
- a cut in Fed Funds rate to 2.75 percent
- a strong recovery in 2008.

In this scenario, they concluded that cumulative losses would be 5.82 percent. Interestingly, their predictions of losses for the first three years are around 3.43 percent, which is in line with both the estimates from Bank C's estimated relationship (Figure 15) and the data from deals in the 2006-1 ABX.[55] Their problem was in forecasting the major losses that would occur later. As a Bank C analyst recently said, "The steepest part of the loss ramp lies straight ahead."[56]

S&P concluded that none of the investment grade tranches of RMBSs would be affected at all — that is, no defaults or downgrades would occur. In May of 2006,

[54] Bank A, October 10, 2005.
[55] "Simulated Housing Market Decline Reveals Defaults Only In Lowest-Rated US RMBS Transactions," S&P, September 13, 2005.
[56] Bank C, September 2, 2008.

they updated their scenario to include a minor recession in 2007, and they eliminated both the rate cut and the strong recovery. They still saw no downgrades of any A-rated bonds or most of the BBB-rated bonds. They did expect widespread defaults, but this was, after all, a scenario they considered "highly unlikely." Although S&P does not provide detailed information on their model of credit losses, it is impossible to avoid concluding that their estimates of df/dp were way off. They obviously appreciated that df/dp was not zero, but their estimates were clearly too small.

The problems with the S&P analysis did not go unnoticed. Bank A analysts disagreed sharply with S&P:

> Our loss projections in the S&P scenario are vastly different from S&P's projections with the same scenario. For 2005 subprime loans, S&P predicts lifetime cumulative losses of 5.8 percent, which is less than half our number... We believe that S&P numbers greatly understate the risk of HPA declines.[57]

The irony of this is that both S&P and Bank A ended up quite bullish, but for different reasons. S&P apparently believed that df/dp was low, whereas most analysts appear to have believed that dp/dt was unlikely to fall substantially.

4.5 House price appreciation

Virtually everyone agreed in 2005 that the record HPA pace of recent years was unlikely to be repeated. However, many believed that price *growth* would simply revert to its long run average, not that price *levels* or *valuations* would. At worst, some predicted a prolonged period of subpar nominal price growth.

A Bank A report in December of 2005 expressed the prevailing view on house prices that, "A slowdown of HPA seems assured." The question was by how much. In that report, the Bank A analysts stated:

> ...the risk of a national decline in home prices appears remote. The annual HPA has never been negative in the United States going back at least to 1992.

The authors acknowledge that there had been regional falls,

[57] Bank A, December 12, 2005.

> In each one of these regional corrections, the decline of home prices coincided with a deep regional recession.

The conclusion that prices were unlikely to fall follows from the fact that "few economists predict a near-term recession in the U.S."[58] An analyst at Bank D described the future as a scenario in which house prices would "rust but not bust."[59]

Bank B analysts actually assigned probabilities to various house price outcomes.[60] They considered five scenarios:

Name	Scenario	Probability
(1) Aggressive	11% HPA over the life of the pool	15%
(2) [No name]	8% HPA over the life of the pool	15%
(3) Base	HPA slows to 5% by year-end 2005	50%
(4) Pessimistic	0% HPA for the next 3 years, 5% thereafter	15%
(5) Meltdown	-5% for the next 3 years, 5% thereafter	5%

Over the relevant period, HPA actually came in a little below the -5 percent of the meltdown scenario, according to the Case-Shiller index. Reinforcing the idea that they viewed the meltdown as implausible, the analysts devoted no time to discussing the consequences of the meltdown scenario even though it is clear from tables in the paper that it would lead to widespread defaults and downgrades, even among the highly rated investment grade subprime ABS.

The belief that such a widespread and steep decline in house prices could not occur persisted even long after prices began to fall. The titles of a series of analyst reports entitled "HPA Update" from Bank C tell the story:[61]

Date of	Data from	Title
12/8/06	10/06	"More widespread declines with early stabilization signs"
1/10/07	11/06	"Continuing declines with stronger stabilization signs"
2/6/07	12/06	"Tentative stabilization in HPA"
3/12/07	1/07	"Continued stabilization in HPA"
9/20/07	7/07	"Near bottom on HPA"
11/2/07	9/07	"UGLY! Double digit declines in August and September"

[58] Bank A, December 2, 2005.
[59] Bank D, November 27, 2006.
[60] Bank B, August 15, 2005.
[61] Bank C, "HPA Update," dates as noted.

By 2008, Bank C analysts had swung to the opposite extreme; their position in May was, "We expect another 15 percent drop in home prices over the next 12 months."[62]

However, the belief that a national decline was unlikely was not shared universally. Bank E analysts took issue with the views expressed above, writing that:

> Those bullish on the housing market often cite the historic data... to show that only in three quarters since 1975 have U.S. home prices (on a national basis) turned negative, and for no individual year have prices turned negative.[63]

But they went on to point out, correctly, that those claims are only true in nominal terms and that in real terms house prices had fallen on many occasions.

4.6 What they anticipated

With the exception of the S&P analysts, it seems everyone understood that a major fall in HPA would lead to a dramatic increase in problems in the subprime market. Thus, understanding df/dp does not appear to have been a problem. In a sense, this more or less implies that dp/dt was the problem, and the evidence confirms it. Most analysts simply thought that a 20 percent nationwide fall in prices was impossible, let alone the even larger falls we have seen in certain regions — Arizona, California, Florida and Nevada — which accounted for a disproportionate share of subprime lending.

One can argue that the basic pieces of the story were all there. Analysts seem to have understood that house prices could fall. They seem to have understood that HPA played a central role in the performance of subprime loans. Some seem, in many cases, to have understood how large that role was. Others seem to have understood that even downgrades of RMBSs would have serious consequences for the market. However, none of the analyst reports we found seem to have put the whole story together in 2005 or 2006.

5 Conclusion

The subprime mortgage crisis leads one naturally to wonder how large and sophisticated market participants badly underestimated the credit risk of heterodox mortgages.

[62] Bank C, May 16, 2008.
[63] Bank E, November 1, 2005.

As we showed in Section 2, subprime lending only incrementally added risk features, and the underlying leverage of loans was, at least in some data sources, somewhat obscure. Thus, rather than plunging into uncharted waters, investors may have felt increasing comfort with each successive round of weaker underwriting standards.

The buoyant house price environment that prevailed through mid-2006 certainly held down losses on subprime mortgages. Nonetheless, as we showed in Section 3, even with just a few years of data on subprime mortgage performance, containing almost no episodes of outright price declines, loan-level models reflect the sensitivity of defaults to house prices. Loss models based on these data should have warned of a significant increase in losses, albeit smaller than the actual increase. Of course, making the effort to acquire property records from a region afflicted by a major price drop, such as Massachusetts in the early 1990s, would have allowed market participants significantly more precise estimates of the likely increase in foreclosures following a drop in house prices. Nonetheless, even off-the-shelf data and models, from the point of view of early 2005, would have predicted sharp increases in subprime defaults following a drop in house prices. However, these models are sensitive to specification and assumptions about the future, so by choosing the specification that gave the lowest default rates, one could have maintained a sanguine outlook for subprime mortgage performance.

In the end, one has to wonder whether market participants underestimated the probability of a house price collapse or misunderstood the consequences of such a collapse. Thus, in Section 4, we describe our reading of the mountain of research reports, media commentary, and other written records left by market participants of the era. Investors were focused on issues such as small differences in prepayment speeds that, in hindsight, appear of secondary importance to the credit losses stemming from a house price downturn. When they did consider scenarios with house price declines, market participants as a whole appear to have correctly identified the subsequent losses. However, such scenarios were labeled as "meltdowns" and ascribed very low probabilities. At the time, there was a lively debate over the future course of house prices, with disagreement over valuation metrics and even the correct index with which to measure house prices. Thus, at the start of 2005, it was genuinely possible to be convinced that nominal U.S. house prices would not fall substantially.

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Table 1: Subprime Share of U.S. Mortgage Market. Table gives measures of the penetration of subprime mortgages in the U.S., 2004 to 2008:Q1. *Outstandings* are taken at from the MBA's national delinquency surveys for Q4 of the indicated years. *Originations* are taken from data collected under the Home Mortgage Disclosure Act (HMDA). In this dataset, a subprime loan corresponds to a mortgage classified as "high cost" (roughly speaking, carrying APRs 3 percent above the yield on the 30 year Treasury bond). The high cost fraction was unusually low in 2004 because of the configuration of the yield curve and operational issues. First liens, not weighted by loan value.

	Subprime loans as a % of total		
Period	Outstanding Loans	New originations	
2004	12.3	11.5	15.5
2005	13.4	24.6	25.7
2006	13.7	25.3	31.0
2007	12.7	14.0	21.7
2008:Q2	12.2	–n.a.–	

Table 2: Joint Distribution of CLTV and Second Liens. Joint distribution of the combined loan-to-value ratio (CLTV) at origination and the indicator variable for the presence of a second lien.

Second Lien	No	Yes
Mean CLTV	79.92%	98.84%
Fraction of loans with CLTV...		
< 80	0.35	0.01
$= 80$	0.18	0.00
> 80 & < 90	0.18	0.01
$= 90$	0.15	0.01
> 90 & < 100	0.08	0.16
≥ 100	0.05	0.80

Table 3: The Effect of Leverage. Top panel shows marginal probabilities from a probit model where the dependent variable is an indicator of whether the loan had defaulted by its 12th month of life. Bottom panel coefficients from an OLS regression where the dependent variable is the loan's initial contract interest rate. Results are from a 10 percent random sample of the ABS data. Standard errors are not shown.

(1) Probability of Default within 12 months of origination

Variable	**Model 1**	**Model 2**	**Mean**
Default Rate			0.0655
Marginal Effects			
CLTV	0.00219	0.00223	82.6929
$CLTV^2/100$	-0.00103	-0.00103	70.3912
$CLTV = 80$	0.00961	0.01036	0.1572
$80 < CLTV < 90$	0.00014	-0.00302	0.1556
$CLTV = 90$	0.00724	-0.00041	0.1286
$90 < CLTV < 100$	0.00368	-0.00734	0.0968
$CLTV \geq 100$	0.00901	-0.00740	0.1620
Second lien recorded	0.05262	0.04500	0.1452
Initial contract rate	0.01940	0.02355	8.2037
Origination date effects?	N	Y	
State effects?	N	Y	
Observations	679,518	679,518	

(2) Initial Contract Rate

Variable	**Model 1**	**Model 2**
Constant	7.9825	10.4713
CLTV	.0093	.0083
$CLTV^2/100$	-.0063	-.0082
$CLTV = 80$	-.0127	-.0817
$80 < CLTV < 90$	.0430	.1106
$CLTV = 90$	.1037	.2266
$90 < CLTV < 100$	.0202	.3258
$CLTV \geq 100$	.0158	.3777
Second lien recorded	-.8522	-.6491
Origination date effects?	N	Y
State effects?	N	Y
Observations	707,823	707,823

Table 4: Sample Means. Table gives sample means and standard deviations of selected underwriting variables from the ABS data. The "early" group comprises loans originated from 1999 to 2004; the "late" group comprises loans originated in 2005 and 2006.

	All loans		Early		Late	
	Mean	StDev	Mean	StDev	Mean	StDev
Outcomes 12 months after origination						
Defaulted	0.0657	0.2478	0.0460	0.2095	0.0928	0.2901
Refinanced	0.1622	0.3686	0.1596	0.3663	0.1657	0.3718
Characteristics						
Contract rate	8.2059	1.5882	8.3763	1.7639	7.9721	1.2726
Margin	4.4539	2.9418	4.2815	3.1135	4.6904	2.6704
FICO score	610	60	607	61	615	58
CLTV	83	14	81	14	85	15
Mortgage types						
Fixed-rate	0.2814	0.4497	0.3230	0.4676	0.2243	0.4171
2/28	0.5854	0.4927	0.5340	0.4988	0.6558	0.4751
3/27	0.1333	0.3399	0.1430	0.3501	0.1199	0.3248
Documentation type						
Complete	0.6828	0.4654	0.7062	0.4555	0.6507	0.4768
No doc	0.0031	0.0558	0.0038	0.0612	0.0023	0.0475
Low doc	0.3071	0.4613	0.2782	0.4481	0.3468	0.4760
Other						
Non-traditional	0.1604	0.3669	0.0693	0.2540	0.2853	0.4515
Non-occ. owner	0.0657	0.2478	0.0651	0.2468	0.0666	0.2493
Refinance	0.6700	0.4702	0.7095	0.4540	0.6158	0.4864
Second lien	0.1459	0.3530	0.0750	0.2634	0.2432	0.4290
PP Pen	0.7355	0.4411	0.7400	0.4387	0.7293	0.4443
Observations	3,532,525		2,043,354		1,489,171	

Table 5: Results of Default Model. Marginal effects and standard errors from a probit model of default after 12 months on the indicated variables. Regressions also include a complete set of state fixed effects.

	Early		Late	
Variable	$\partial F/\partial x$	σ	$\partial F/\partial x$	σ
Contract rate	0.0097	0.0001	0.0328	0.0002
Margin	0.0013	0.0001	0.0016	0.0003
2/28	0.0036	0.0009	0.0158	0.0016
3/27	0.0030	0.0010	0.0105	0.0020
CLTV	0.0007	0.0001	0.0037	0.0002
CLTV^2/100	-0.0002	0.0001	-0.0018	0.0002
CLTV$= 80$	0.0035	0.0005	0.0225	0.0012
$80 <$CLTV< 90	-0.0017	0.0006	0.0119	0.0014
$90 \leq$CLTV< 100	-0.0014	0.0008	0.0154	0.0022
CLTV≥ 100	-0.0000	0.0015	0.0229	0.0029
Second lien	0.0165	0.0008	0.0391	0.0009
FICO	-0.0003	0.0000	-0.0003	0.0000
FICO< 620	-0.0015	0.0008	0.0202	0.0015
FICO$= 620$	-0.0012	0.0016	0.0194	0.0031
$620 <$FICO< 680	-0.0040	0.0006	0.0110	0.0010
Hi CLTV$\times$ low FICO	-0.0004	0.0006	0.0013	0.0010
Hi CLTV$\times$ Purchase	0.0053	0.0006	-0.0143	0.0010
Hi CLTV$\times$ low doc	0.0059	0.0007	0.0129	0.0010
Refi	-0.0064	0.0004	-0.0223	0.0009
Non-owner occ.	0.0113	0.0006	0.0158	0.0010
Low doc	0.0127	0.0004	0.0160	0.0007
No doc	0.0107	0.0027	0.0293	0.0059
PP Pen	0.0012	0.0003	0.0087	0.0006
Pmt to inc. rat 1	0.0003	0.0000	0.0008	0.0000
Pmt to inc. rat 2	0.0008	0.0008	0.0008	0.0001
Ratio 1 missing	0.0131	0.0007	0.0330	0.0014
Ratio 2 missing	0.0240	0.0006	0.0273	0.0017
Retail source	0.0036	0.0005	-0.0204	0.0012
Wholesale source	0.0050	0.0004	0.0044	0.0009
Broker source	0.0011	0.0011	-0.0055	0.0019
Non-trad.	0.0043	0.0005	0.0218	0.0006
Observations	2,043,354		1,489,171	
Pseudo R^2	0.0929		0.0971	

Table 6: Predicted Defaults Rates by Model. The first row gives model-predicted average default rates given observables in the early period from a model estimated against the early period (first column) and the later late period (second column). The second row does the same, but for observables from the late period. The subsequent columns repeat the exercise, but break out each origination year separately.

	Coeff. from model	
Observables in	Early	Late
Early	0.0460	0.0930
Late	0.0455	0.0927
Origination year		
1999	0.0666	0.1537
2000	0.0867	0.2000
2001	0.0652	0.1434
2002	0.0483	0.0986
2003	0.0349	0.0642
2004	0.0344	0.0605
2005	0.0396	0.0750
2006	0.0531	0.1155

Table 7: The Effect of Incremental Underwriting Changes. Table gives a variety of alternative risk characteristics and their associated 12-month default probabilities from the model estimated using data from the early period. In all cases, the loan is a 2/28 with an initial rate of 8.22 percent, a margin of 6.26 percent, originated in California and with other variables set to their sample means. The final column gives the actual 12-month default rate experienced by these types of loans in the late period.

Variable	Base	$CLTV$ $= 80$	$CLTV$ > 99	$FICO$ $= 573$	Low doc	Non-trad	Purchase	$CLTV > 99$ Low Doc	$CLTV > 99$ $FICO = 573$	$CLTV > 99$ Purchase	Actual
CLTV	81.3	80	99.23	81.3	81.3	81.3	81.3	99.23	99.23	99.23	81.3
Second lien	No	No	Yes	No	No	No	No	Yes	Yes	Yes	No
FICO	600	600	600	573	600	600	600	600	573	600	600
Refi	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes
Low doc	No	No	No	No	Yes	No	No	Yes	No	No	No
Non-trad	No	No	No	No	No	Yes	No	No	No	No	No
$\widehat{P}_{Early}$	0.0196	0.0228	0.0376	0.0247	0.0288	0.0196	0.0241	0.0617	0.0376	0.0522	0.1136

Table 8: ABS Data Variable Names and Definitions

Variable	Description
cash	Cash-out refinancing indicator
cltvnow	Current mark-to-market combined LTV (percent)
cltvorig	Combined LTV at origination (percent)
doc	Full loan documentation indicator
educ	Zip code level share of high-school (or less) educated persons
ficoorig	Credit (FICO) score at origination
frmnow	Current 30-year FRM rate (percent)
frmorig	30-year FRM rate at origination (percent)
hhincome	Zip code level average household income (dollars)
hpvol	House price volatility (percent, 2-year standard deviation HPA)
indnow	Current fully indexed rate (6-month LIBOR plus margin, percent)
indorig	Fully indexed rate at origination (percent)
invhpa	Cumulative house price appreciation if nonowner=1 (percent)
kids	Zip code level child share of population
lngwind	Mortgage past rate reset period indicator
lofico	Credit score $<$ 600 indicator
loqual	Risk layering of leverage and low doc (CLTV¿95 and doc=0 at orig)
mratenow	Current mortgage interest rate (percent)
mrateorig	Contract rate at origination (percent)
nonowner	Not owner-occupied indicator
oil	Change in oil prices since loan origination (percent)
origamt	Loan amount at origination (dollars)
piggyback	Second liens recorded at origination indicator
pmi	Private mortgage insurance indicator
pmt	Current monthly payment $>$5% larger than original indicator
ppnow	Prepayment penalty still in effect indicator
pporig	Prepayment penalty at origination indicator
proptype	Single-family home indicator
pti	Payment-to-income ratio at origination (percent)
race	Zip code level minority population share
refi	Refinancing (including cash-out) indicator
rstwind	Mortgages in reset period indicator
unempnow	Change in unemployment rate since origination (percent)
unorig	State-level unemployment rate at origination (percent)

Table 9: ABS Data Sample Averages, 2000–2004

	2000–2004				2004	2005
	Origination	Active	Default	Prepay	Origination	Origination
cash	0.57	0.57	0.52	0.58	0.58	0.54
cltvnow	81.91	73.59	66.10	0.00	83.76	84.90
cltvorig	81.91	83.15	81.61	79.81	83.76	84.90
doc	0.70	0.69	0.74	0.70	0.66	0.64
dti	38.99	38.87	39.09	39.18	39.41	40.07
educ	0.36	0.37	0.38	0.35	0.37	0.37
ficoorig	610	616	582	605	616	619
frmnow	6.28	5.75	5.75	5.75	5.88	5.85
frmorig	6.28	6.03	6.89	6.62	5.88	5.85
hhincome	43,110	42,421	39,116	44,945	43,007	42,379
hpvol	3.38	4.15	3.20	4.78	3.91	4.57
hpvorig	3.38	3.41	2.52	3.46	3.91	4.57
indnow	8.52	9.06	9.51	9.12	7.90	9.81
indorig	8.52	8.06	10.06	9.05	7.90	9.81
invhpa	1.63	1.14	2.31	2.38	0.55	0.16
kids	0.27	0.27	0.27	0.27	0.27	0.27
lngwind	0.00	0.09	0.20	0.11	0.00	0.00
loqual	0.05	0.07	0.03	0.03	0.09	0.12
mratenow	8.22	7.73	9.95	8.81	7.32	7.56
mrateorig	8.22	7.72	9.95	8.82	7.32	7.56
nonowner	0.08	0.09	0.10	0.07	0.09	0.08
oil	0.00	26.96	54.47	53.35	0.00	0.00
origamt	118,523	119,569	89,096	121,636	136,192	148,320
piggyback	0.08	0.11	0.05	0.04	0.14	0.23
pmi	0.27	0.24	0.35	0.31	0.19	0.23
pmt	0.00	0.04	0.03	0.00	0.00	0.00
ppnow	0.73	0.67	0.36	0.38	0.73	0.72
pporig	0.73	0.74	0.75	0.71	0.73	0.72
proptype	0.87	0.88	0.90	0.86	0.87	0.86
race	0.31	0.30	0.32	0.31	0.31	0.31
refi	0.68	0.67	0.64	0.70	0.65	0.60
rstwind	0.00	0.02	0.06	0.09	0.00	0.00
unempnow	0.00	-4.50	13.47	2.95	0.00	0.00
unorig	5.58	5.69	5.06	5.48	5.63	5.06
No. obs.	3,654,683	2,195,233	183,586	1,275,864	1,267,866	1,794,953

Table 10: ABS Data Default Hazard Function Estimates, 2000–2004

	Subprime 2/28		Subprime 3/27		Subprime FRM	
	Purch	Refi	Purch	Refi	Purch	Refi
constant	7.519*	4.143*	5.819*	-0.842	7.826*	3.213*
cltvorig	-0.032*	0.002	-0.010	-0.008	-0.027*	-0.011*
mrateorig	0.325*	0.273*	-0.786	-0.067	-0.255	0.159
pporig	0.033	0.115	-0.329	0.056	0.157	0.439*
unorig	-0.023	-0.040*	-0.028	-0.043	-0.080	-0.091*
indorig	-0.270*	-0.358*	-0.136*	-0.145*	—-	—-
ficoorig	-4.388*	-4.881*	-4.084*	-2.321*	-4.874*	-4.386*
doc	-0.185*	-0.378*	-0.012	-0.272*	-0.271*	-0.194*
nonowner	0.557*	0.281*	0.883*	0.351*	0.540*	0.431*
piggyback	0.287*	0.286*	0.300*	0.287	0.133	-0.329
cash	—-	0.016	—-	0.087	—-	-0.110*
proptype	0.143*	0.031	0.167	0.060	-0.128	-0.025
loqual	-0.039	-0.112	0.031	-0.331	-0.215	0.561*
invhpa	-0.032*	-0.012*	-0.064*	-0.015	-0.030*	-0.011*
origamt	0.298*	0.115*	0.489*	0.234*	0.480*	0.148*
kids	0.317	0.249	1.304	-0.635	0.521	-0.695
race	0.690*	-0.302*	0.182	-0.082	0.593*	-0.324*
educ	-0.439	-0.125	-1.401*	-0.376	-0.075	0.227
cltvnow	0.030*	0.008*	0.019*	0.025*	0.036*	0.028*
mratenow	-0.031	0.044	1.071*	0.376	0.468	0.109
ppnow	-0.156*	-0.056	0.148	-0.084	-0.141	-0.320*
rstwind	-0.239*	-0.150*	0.100	0.143	—-	—-
lngwind	0.139	0.059	0.683*	-0.027	—-	—-
hpvol	-0.034*	-0.038*	-0.046*	-0.029	-0.064*	-0.037*
unempnow	0.007*	0.009*	0.005*	0.004	0.000	-0.003*
indnow	0.291*	0.369*	0.217*	0.234*	—-	—-
hhincome	-0.575*	-0.256*	-0.758*	-0.223	-0.872*	-0.222*
oil	0.002	0.000	0.001	-0.001	0.006*	0.005*
pmt	0.525*	-0.149	1.478*	0.707*	1.144*	0.393
pmi	0.075*	0.174*	0.212*	0.074	0.311*	0.160*
frmorig	-0.105*	0.105*	-0.310*	-0.025	-0.209*	-0.198*
frmnow	-0.124*	-0.179*	0.054	0.109	0.181*	0.113*
dti	0.005*	0.009*	0.009*	0.007*	-0.002	0.006*
lofico	-0.151*	-0.056	-0.256*	0.056	-0.085	0.128*
ln L	-140,135	-297,352	-30,071	-50,544	-36,574	-170,927
No. obs.	1,095,227	2,015,104	241,511	373,976	324,431	1,582,146

Table 11: Deed-registry data Percentage of Foreclosures and Sales by Vintage

	# ownerships	foreclosure %	sale %
1990	46,723	4.79	29.63
1991	48,609	2.18	31.56
1992	57,414	1.33	32.10
1993	63,494	1.17	32.63
1994	69,870	1.07	33.81
1995	65,193	1.05	35.79
1996	74,129	0.87	37.30
1997	79,205	0.77	38.32
1998	89,123	0.59	39.09
1999	90,350	0.74	39.75
2000	84,965	0.90	39.74
2001	83,184	0.82	36.09
2002	86,648	0.88	30.70
2003	88,824	1.09	23.12
2004	97,390	1.75	15.60
2005	95,177	2.19	8.49
2006	80,203	1.34	4.00
2007	48,911	0.07	1.36

Table 12: Deed-registry data Summary Statistics by Vintage

	Initial cltv		minority % (zip code)		Median income (zip code)		condo %	multi-family %	subprime purchase %
	median	% $\geq$ 90	median	mean	median	mean	mean	mean	mean
1990	0.800	22.54	8.52	14.59	54,897	57,584	19.41	10.21	0.00
1991	0.800	24.20	7.98	13.39	56,563	59,784	17.08	7.69	0.00
1992	0.800	26.05	7.76	13.00	56,879	60,217	15.02	7.89	0.01
1993	0.849	30.47	7.77	13.33	56,605	59,714	14.77	8.86	0.10
1994	0.872	32.90	7.98	13.79	55,880	58,848	14.87	10.15	0.39
1995	0.874	35.29	8.26	14.49	55,364	58,089	16.01	10.97	0.43
1996	0.871	35.22	8.25	14.22	55,364	58,076	16.98	10.41	0.91
1997	0.850	33.87	8.26	14.39	55,358	57,864	17.64	10.59	1.92
1998	0.850	33.41	8.25	14.20	54,897	57,394	18.90	10.40	2.56
1999	0.850	33.28	8.63	14.88	54,677	56,742	20.15	11.11	2.43
2000	0.824	31.67	8.65	14.96	54,402	56,344	21.55	11.17	2.43
2001	0.850	34.42	8.63	14.98	53,294	55,524	21.34	11.46	2.89
2002	0.820	32.32	9.14	15.25	53,357	55,672	22.63	11.14	3.88
2003	0.850	34.47	9.14	15.51	53,122	55,337	22.68	11.20	6.86
2004	0.866	35.68	9.66	16.42	52,561	55,017	24.48	11.85	9.99
2005	0.899	39.40	10.19	17.07	52,030	54,231	28.29	11.83	14.81
2006	0.900	41.65	9.92	17.10	51,906	54,326	28.09	10.80	12.96
2007	0.900	41.62	9.92	16.64	53,122	55,917	29.95	8.54	3.95

Table 13: Massachusetts Subprime Lender Originations 1999–2007

Lender	# total originations	# purchase originations	Lender	# total originations	# purchase originations	Lender	# total originations	# purchase originations
	2007			2004			2001	
Summit	1,601	1,584	Option One	3,767	3,129	Option One	2,660	1,111
Option One	360	358	New Century	2,991	2,507	New Century	1,263	323
Equifirst	195	195	Freemont	2,895	2,461	Ameriquest	1,984	296
New Century	149	149	Argent	2,200	2,068	Citifinancial Services	1,040	140
Freemont	108	107	Fieldstone	1,131	1,023	Freemont	748	317
Accredited Home	75	74	Accredited Home	1,014	820	Household Financial Corp.	548	61
Argent	73	73	Mortgage Lender Net	972	536	Wells Fargo Finance	467	43
Aegis	54	53	Nation One	946	927	Argent	457	66
Wilmington Finance	46	43	WMC	888	586	First Franklin	367	251
Nation One	44	44	Long Beach	812	685	Meritage	349	333
Total	3,021	2,956	Total	23,761	18,481	Total	15,308	4,595
	2006			2003			2000	
Mortgage Lender Net	2,489	2,310	Option One	3,157	2222	Option One	2,773	1,000
Summit	2,021	1,948	New Century	1,694	1053	Ameriquest	2,047	287
Freemont	2,016	1,973	Freemont	1,519	1089	Citifinancial Services	1,275	112
New Century	1,978	1,942	Ameriquest	1,288	436	New Century	1,251	336
WMC	1,888	1,860	First Franklin	922	917	Freemont	773	267
Option One	1,616	1,552	Argent	836	536	Household Financial Corp.	761	55
Accredited Home	1,006	986	Mortgage Lender Net	802	381	Long Beach	470	289
Argent	640	626	Accredited Home	636	428	First Franklin	464	407
Southstar	632	624	Fieldstone	585	430	Mortgage Lender Net	464	36
Equifirst	598	564	Citifinancial Services	459	70	Argent	437	48
Total	18,211	17,489	Total	17,988	11,062	Total	15,870	3,982
	2005			2002			1999	
Option One	4,409	4,152	Option One	2,822	1502	Option One	2,828	1013
Freemont	3,927	3,675	Ameriquest	1,713	526	Ameriquest	1,929	229
New Century	3,125	2,906	New Century	1,261	443	Citifinancial Services	1,303	108
Argent	2,253	2,195	Freemont	1,071	595	New Century	1,273	340
WMC	1,846	1,681	First Franklin	657	622	Freemont	738	233
Accredited Home	1,601	1,498	Citifinancial Services	656	97	Household Financial Corp.	728	47
Long Beach	1,599	1,551	Mortgage Lender Net	627	170	Wells Fargo Finance	478	26
Summit	1,588	1,440	Argent	606	166	Mortgage Lender Net	452	44
Mortgage Lender Net	1,494	1,211	Wells Fargo Finance	411	27	Long Beach	413	202
Nation One	969	959	Accredited Home	358	184	Argent	410	38
Total	28,464	26,128	Total	15,296	6,459	Total	16,161	3,852

Table 14: Estimates of Foreclosure Hazard Using deed-registry data

	1990–2007 Sample		**1990–2004 Sample**		**2000–2004 Sample**	
	Coef	Std. Err.	Coef	Std. Err.	Coef	Std. Err.
initial LTV	-0.27	0.19	-1.40	0.22	-0.82	1.71
LIBOR (6-month)	$1.96e^{-02}$	$1.39e^{-02}$	$-3.09e^{-02}$	$1.52e^{-02}$	0.18	0.11
unemployment rate	$4.74e^{-02}$	$6.00e^{-03}$	$5.03e^{-02}$	$6.14e^{-03}$	$7.70e^{-02}$	$5.24e^{-03}$
% minority (2000 zip-code)	$9.23e^{-03}$	$1.03e^{-03}$	$1.09e^{-02}$	$1.20e^{-03}$	$6.30e^{-03}$	$4.31e^{-03}$
median income (2000 zip-code)	$-1.60e^{-05}$	$1.82e^{-06}$	$-1.71e^{-05}$	$2.05e^{-06}$	$-6.90e^{-05}$	$1.03e^{-05}$
condo indicator	0.33	0.05	0.44	0.05	-1.19	0.35
multi-family property indicator	0.54	0.05	0.54	0.06	-0.24	0.20
subprime purchase indicator	1.99	0.06	1.21	0.19	1.70	0.21
# observations	3,005,137		2,365,999		813,802	

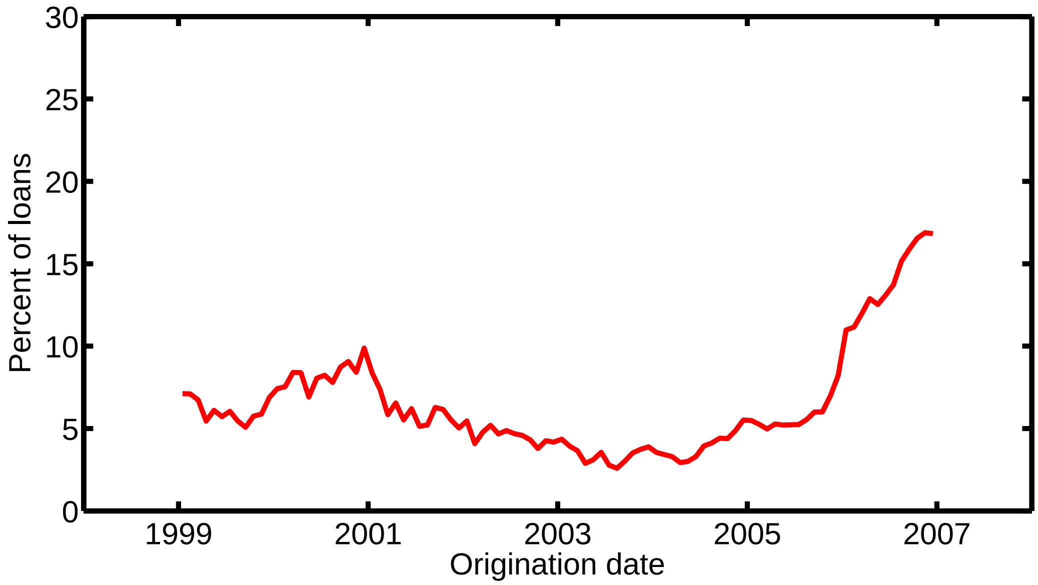
Table 15: The outcomes of S&P RMBS ratings, 1978–2004. From "Rating Transitions 2004: U.S. RMBS Stellar Performance Continues to Set Records," Standard and Poor's, January 21, 2005.

	# rated	Upgrade	Downgrade	Default
AAA	6,137	–	0.5	0.07
AA	5,702	22.4	3.6	0.5
A	4,325	16.2	1.3	0.7
BBB	4,826	11.1	2.0	1.2
BB	2,042	17.9	2.3	1.4
B	1,687	14.1	4.1	3.1

Table 16: Standardized Elasticities from Estimates Using deed-registry data

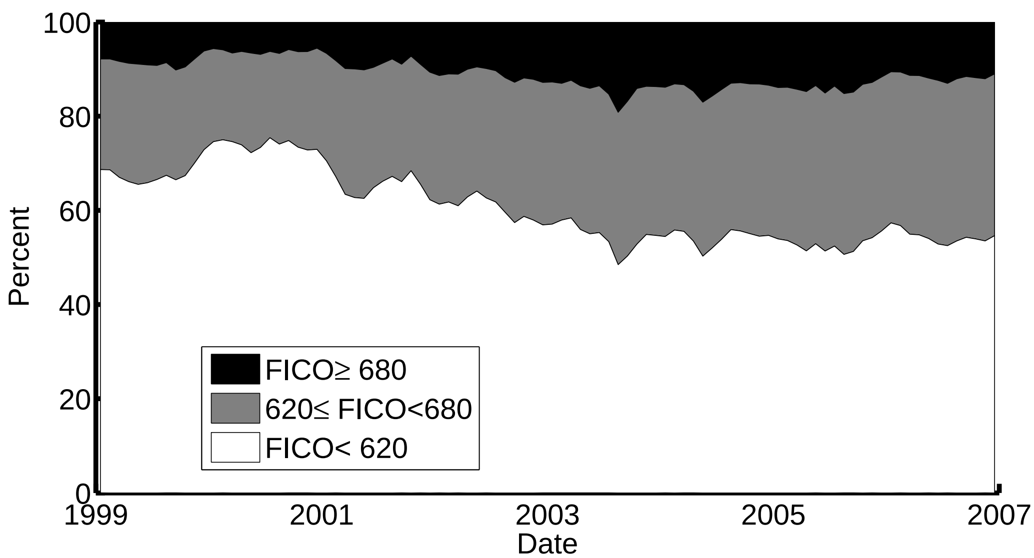
		1990–2007	**1990–2004**	**2000–2004**
	(+/-) std. dev.	factor change in hazard	factor change in hazard	factor change in hazard
Unemployment rate	(+) 2.06	1.10	1.12	1.17
% minority (2000 zip-code)	(+) 19.58	1.20	1.24	1.13
Median income (2000 zip-code)	(−) $24,493	1.49	1.53	5.60
Multi-family indicator	.	1.72	1.72	0.79
Condo indicator	.	1.39	1.55	0.30
Subprime purchase indicator	.	7.32	3.35	5.47

Figure 1: Twelve-Month Default Rate on Subprime Mortgages



NOTE. Figure shows the percent of loans that default within 12 months of origination, by month of origination, from Jan. 1999 to Dec. 2006, from the ABS data.

Figure 2: FICO Distribution of Subprime Mortgage Borrowers



NOTE. Figure shows distribution of subprime loans by credit score at origination, by month, from January 1999 to December 2007, from the ABS data.

Figure 3: Evolving Underwriting Characteristics on Subprime Mortgages. Source: LP ABS data.

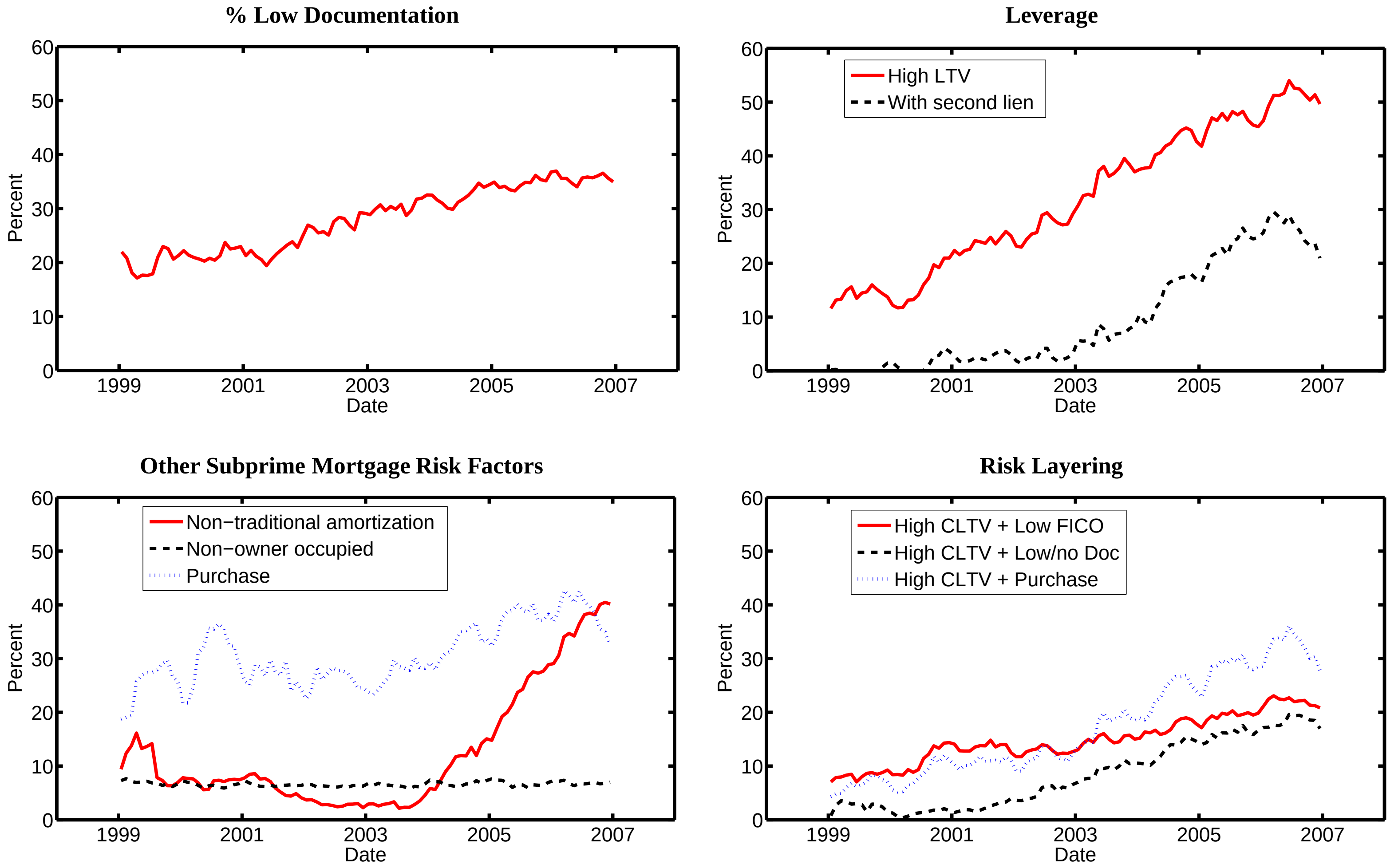


Figure 4: Default Characteristics on Subprime Mortgages by Month of Origination. Source: LP ABS data.

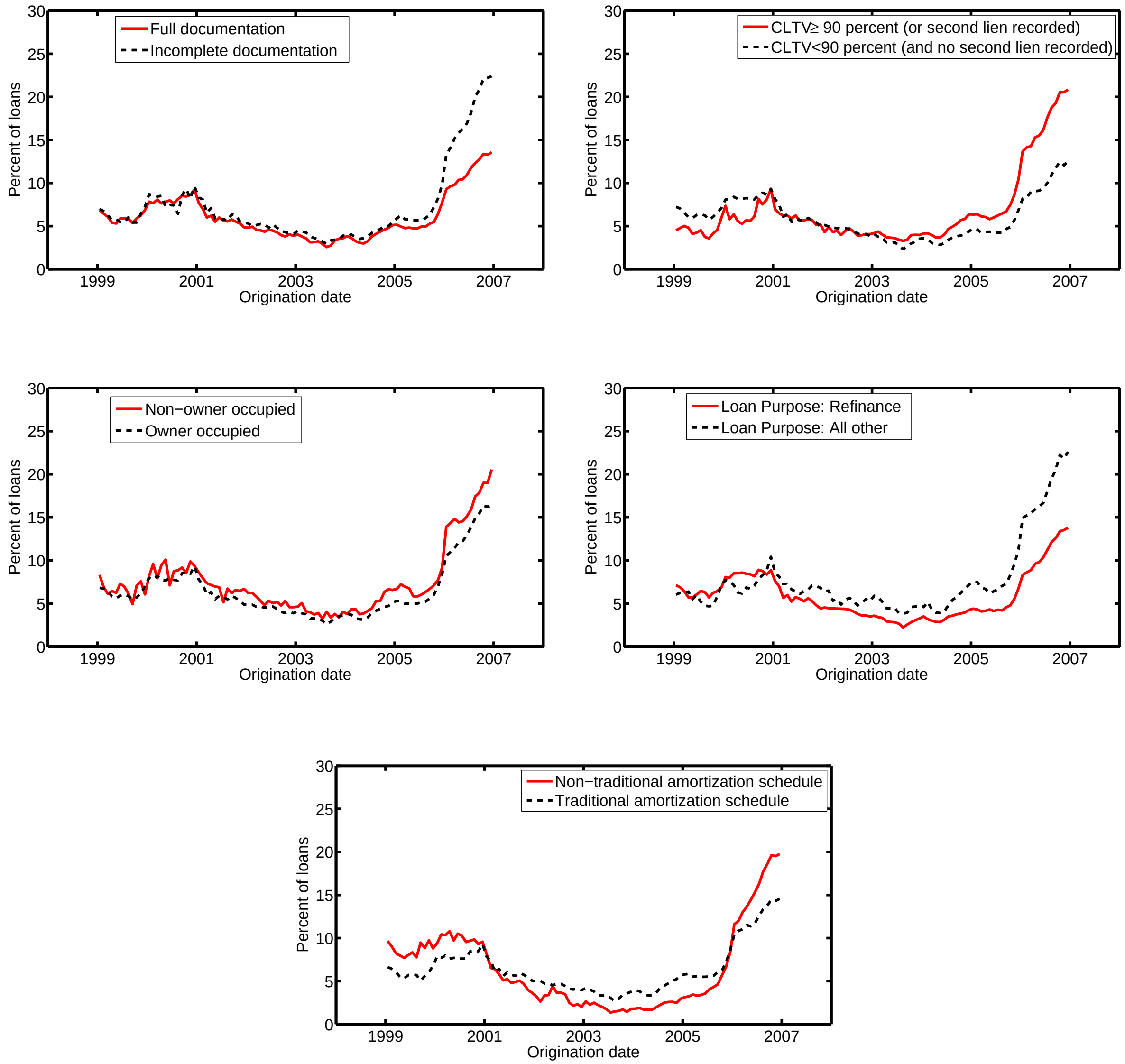
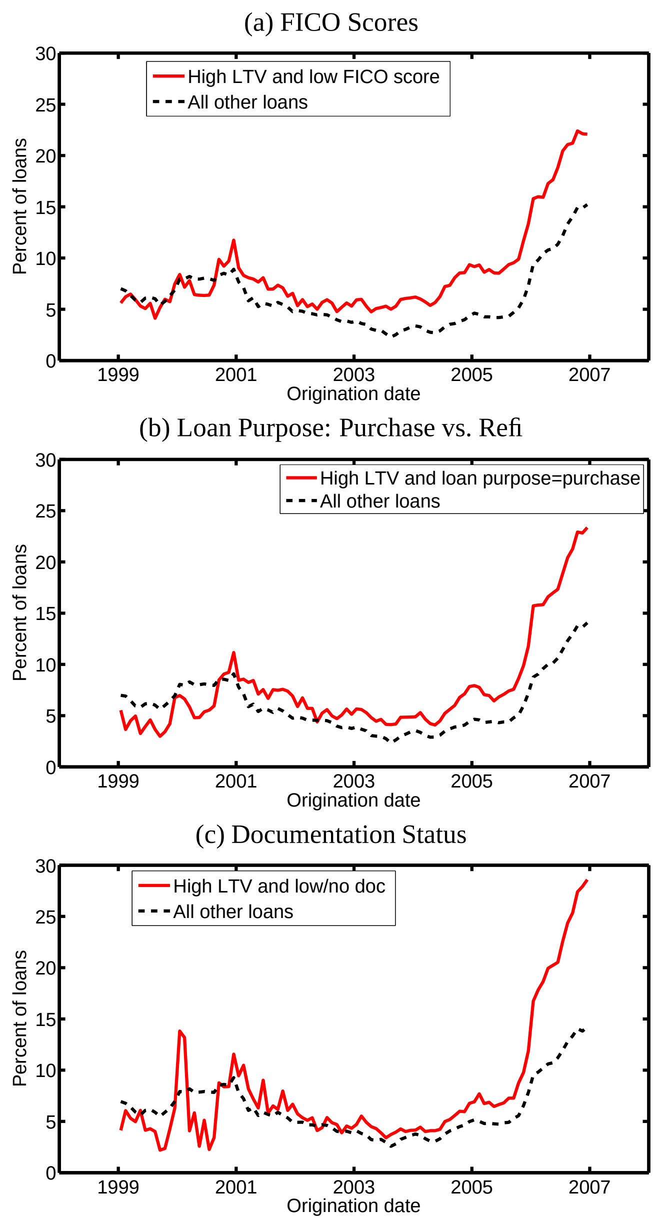
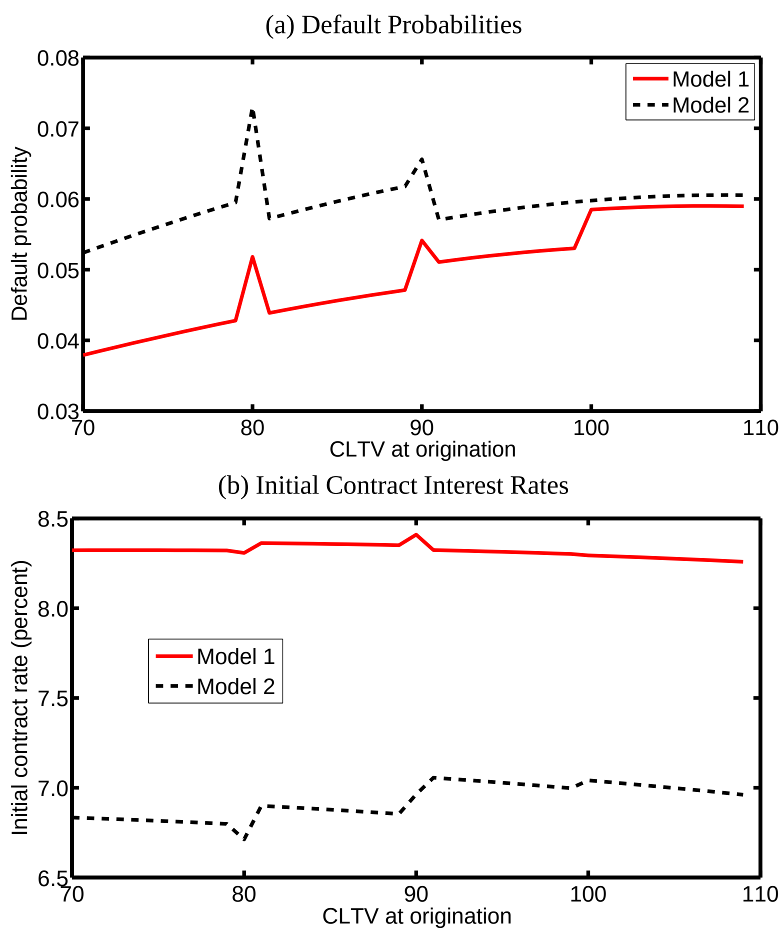


Figure 5: Twelve-Month Default Rates on Loans with Risk Layering



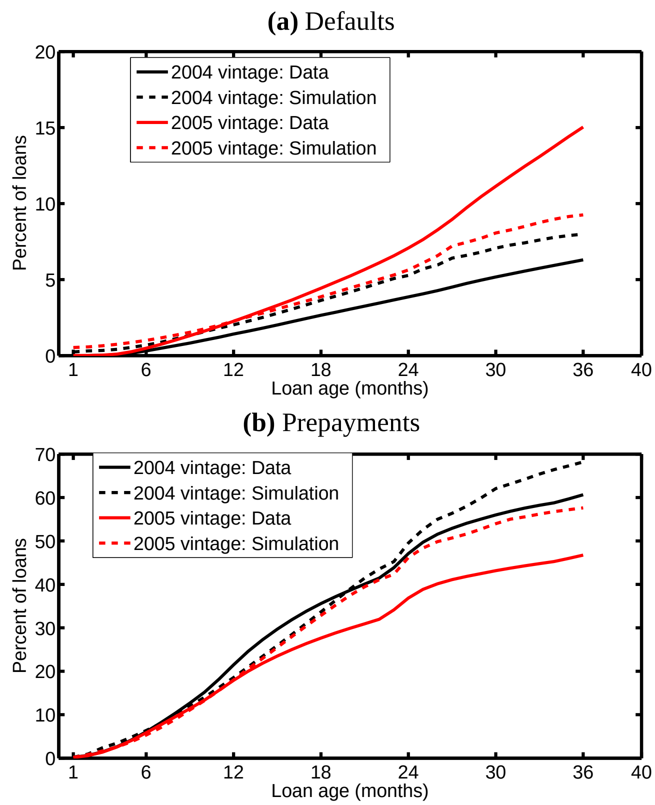
NOTE. Figure shows the percentage of loans that default within 12 months of origination conditional on three risk factors, by month of origination, from Jan. 1999 to Dec. 2006, from the ABS data. Panel (a) gives results by owner occupancy, panel (b) gives results by loan purpose, and panel (c) gives results for loans with non-traditional amortization schedules.

Figure 6: Effect of CLTV on Default and Interest Rate



NOTE. Figure shows graphically the results of the models estimated in Table 3.

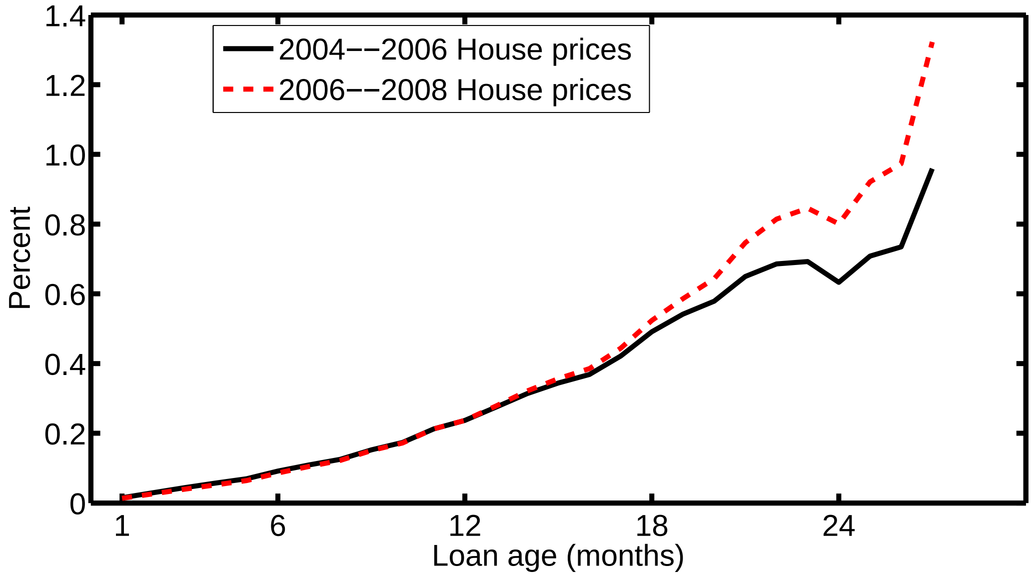
Figure 7: Vintage Simulations Using ABS Data



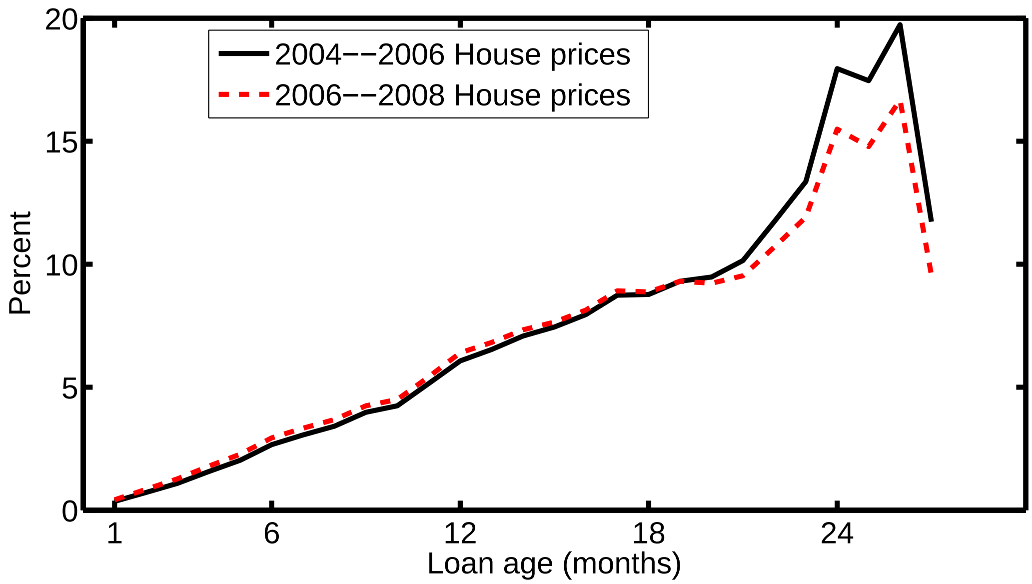
NOTE. Figures show actual and simulated cumulative defaults (top panel) and prepayments (bottom panel) for the 2004 and 2005 vintages of loans. The simulations assume perfect foresight about house prices, interest rates, oil prices, and unemployment rates.

Figure 8: Effect of House Prices on a Generic 2/28 in the ABS Data

(a) Defaults

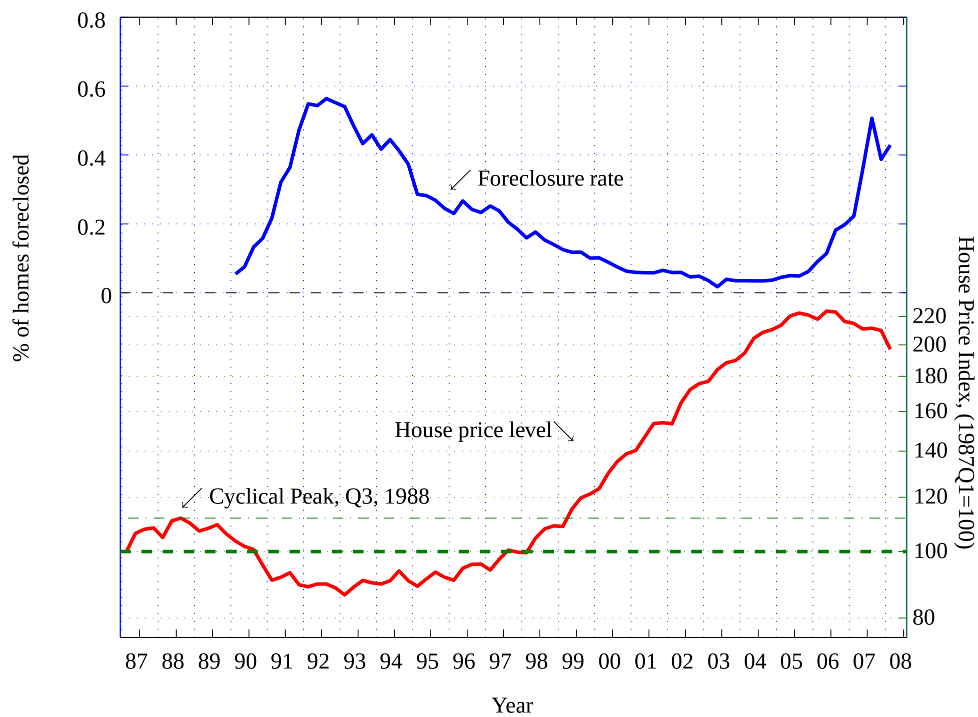


(b) Prepayments



NOTE. Figures show the probability in month t of default (top panel) and prepayments, conditional on surviving to month $t-1$ for a generic hybrid 2/28 subprime mortgage as described in Table 7; the dynamic variables follow their 2004 to 2006 trajectories, except for house prices, which are set either to their 2004 to 2006 trajectories or to their 2006 to 2008 trajectories. The model used to produce the estimates is described in the text.

Figure 9: Massachusetts House Prices and Foreclosure Rates, January 1990 to December 2007



The foreclosure rate is calculated at a quarterly frequency. The numerator is the total number of foreclosures in MA in a given quarter and is obtained directly from the Warren Group data. The denominator is the number of residential parcels in a given year, where a parcel is defined as a real unit of property used for the assessment of property taxes, and a typical parcel consists of a plot of land defined by a deed and any buildings located on the land. Information on parcel counts is obtained from the Massachusetts Department of Revenue. Finally, house prices are calculated using the Case-Shiller weighted, repeat-sales methodology, using data from the Warren Group.

Figure 10: Estimate of Baseline Hazards

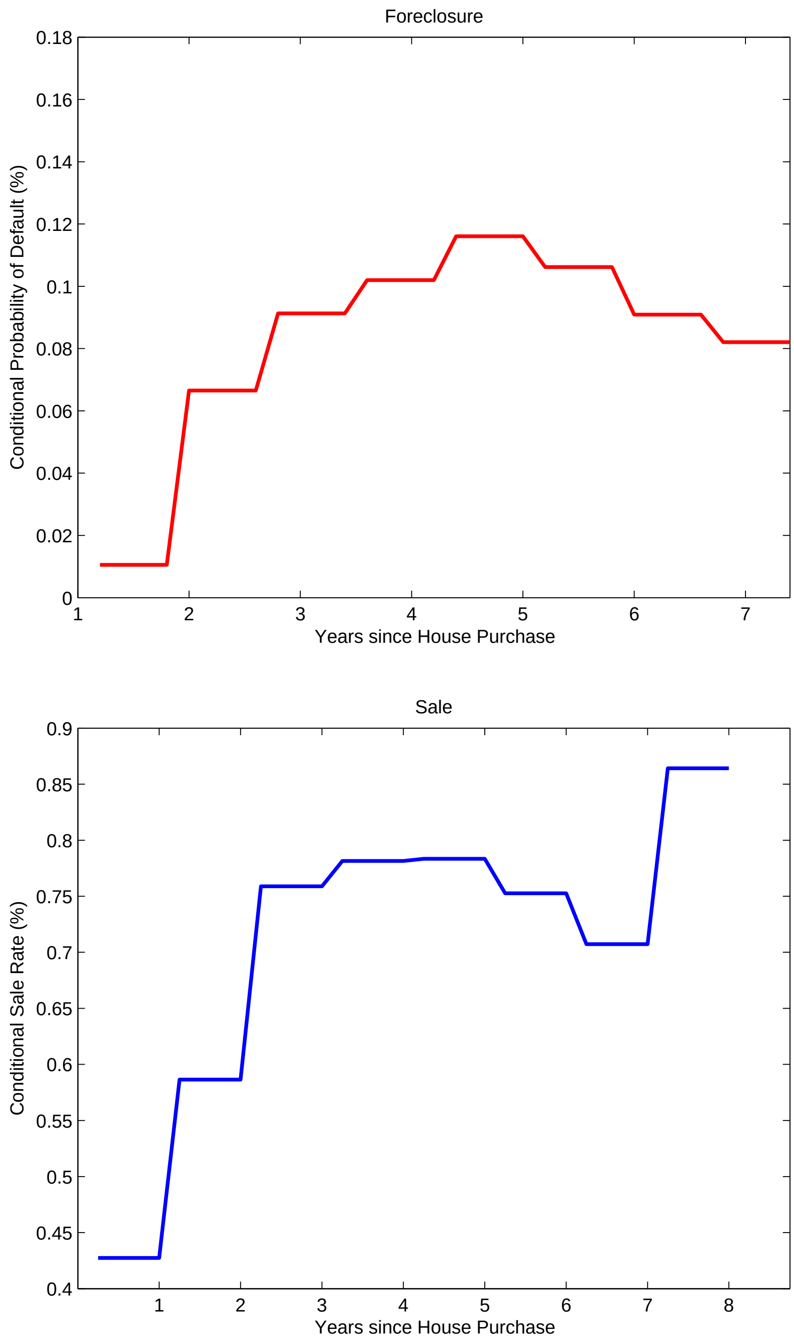


Figure 11: Estimated Effect of Equity on Foreclosure

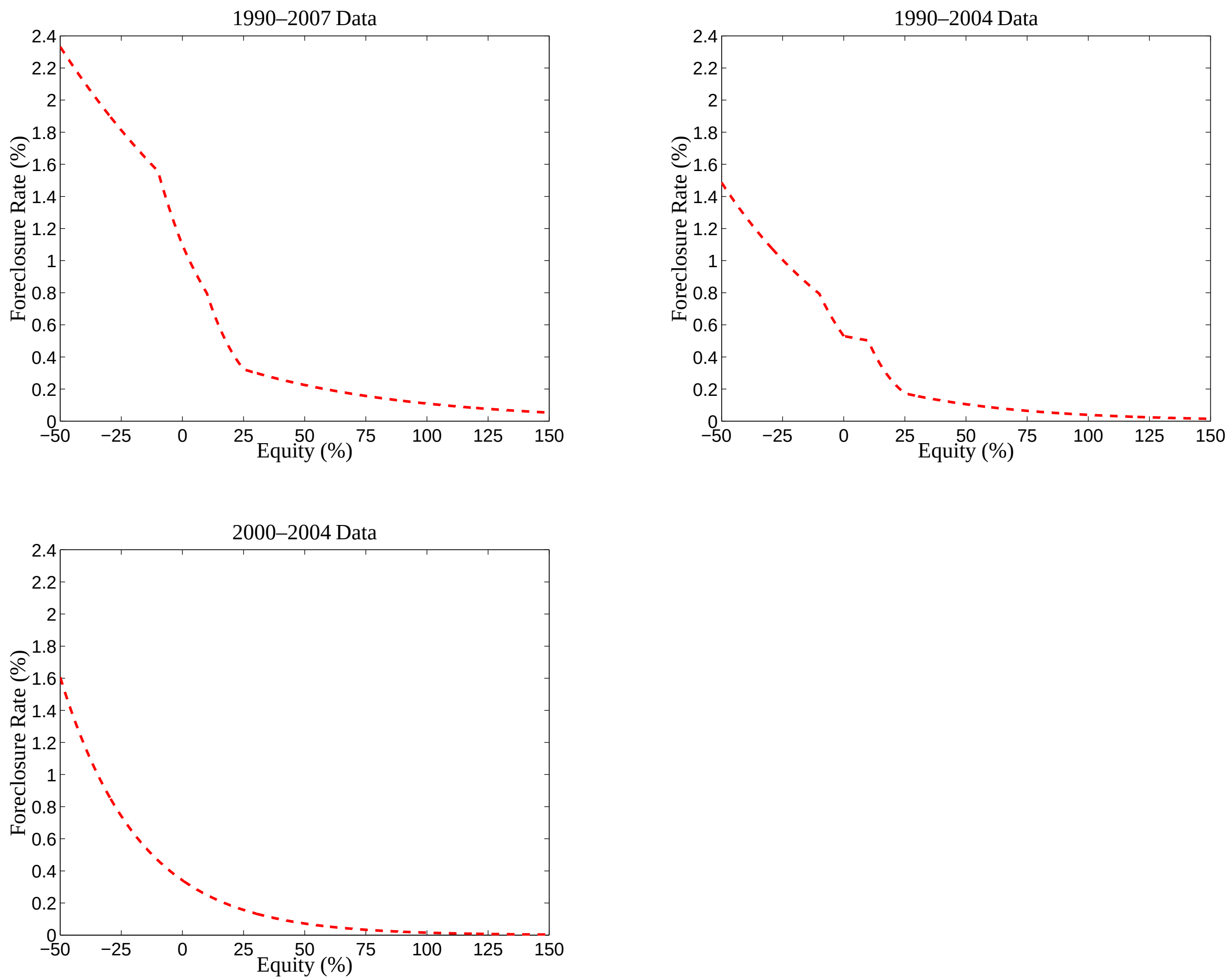


Figure 12: 2004 Subprime Purchase Vintage Simulations

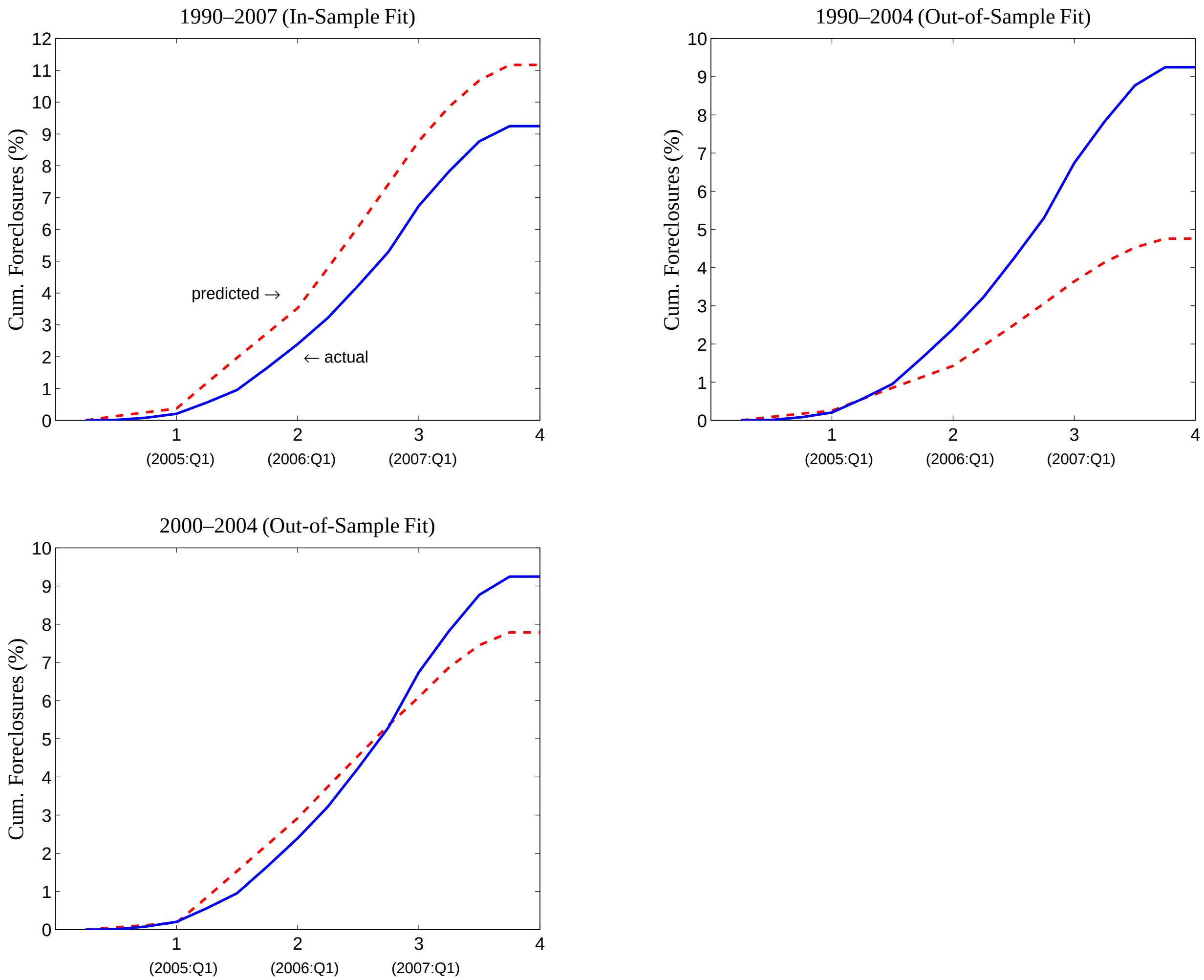


Figure 13: 2005 Subprime Purchase Vintage Simulations

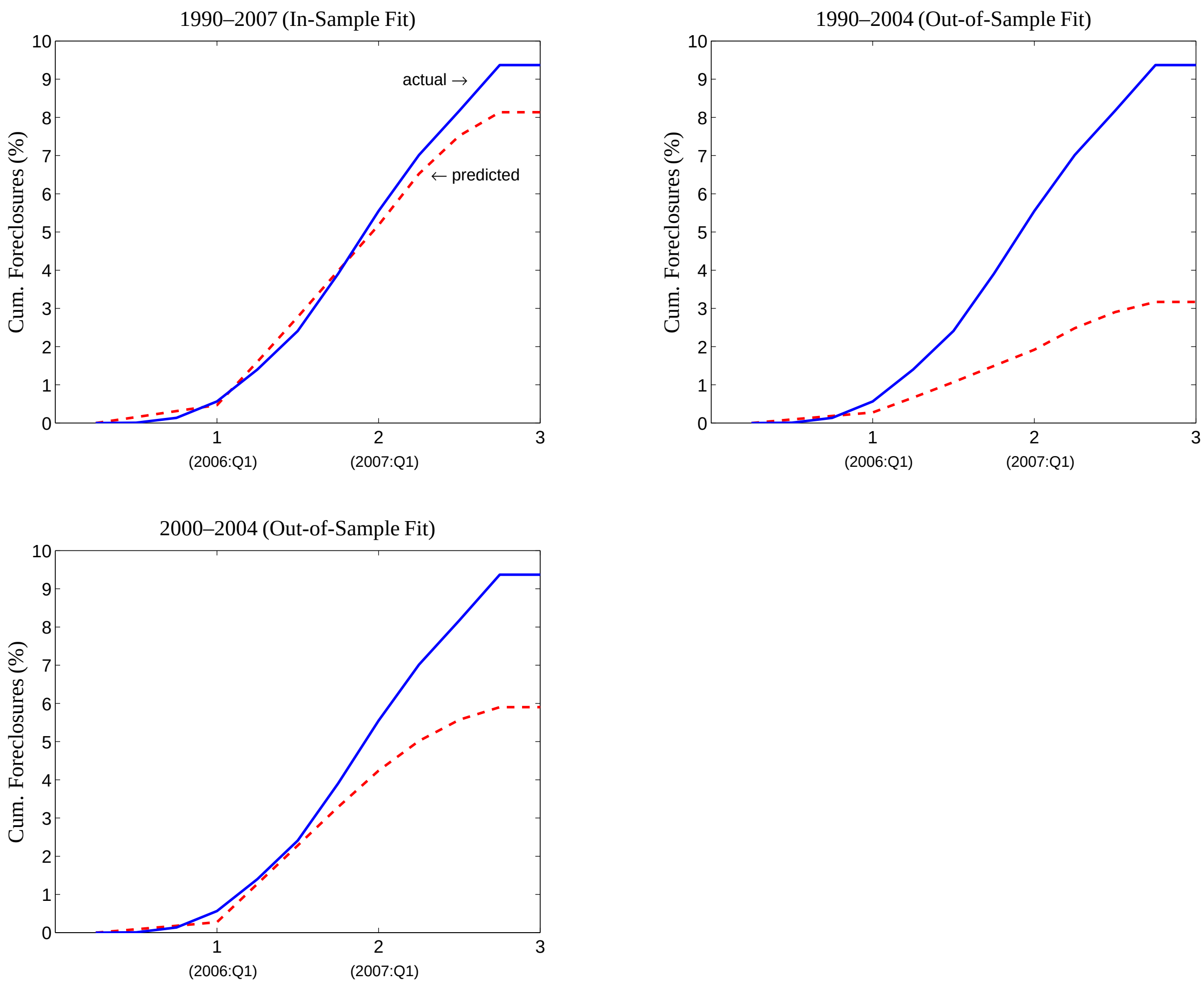


Figure 14: HPA and the Cost of Insuring Subprime-backed Securities. Source: Haver Analytics and Markit.

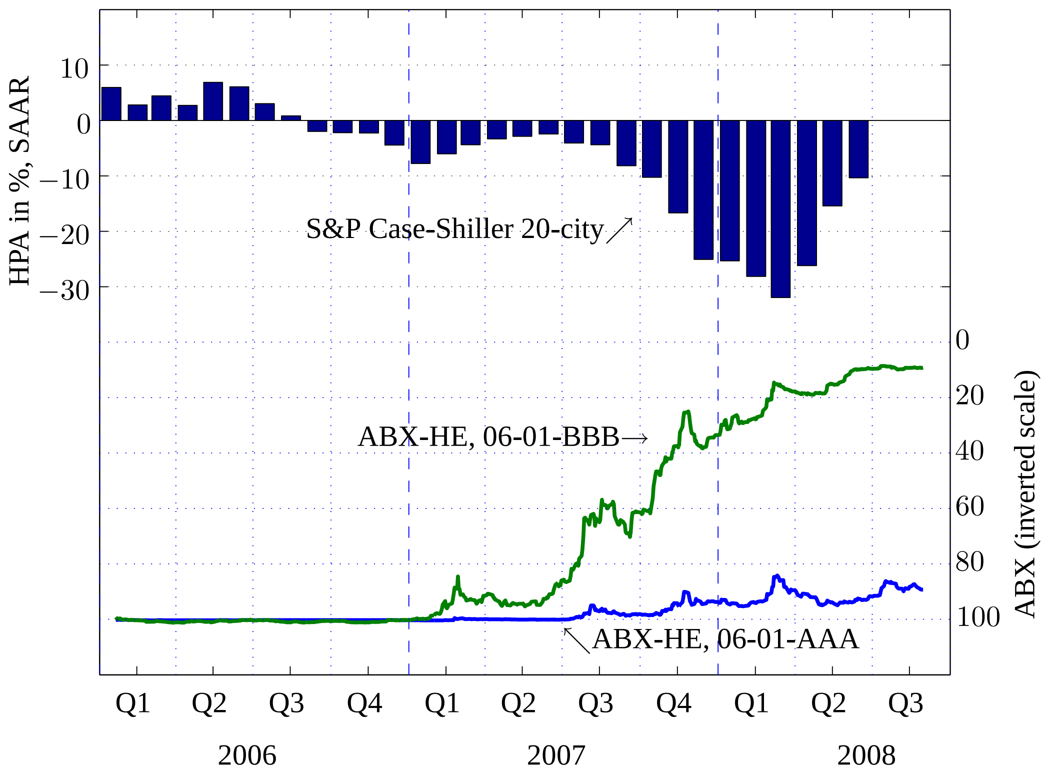


Figure 15: Bank C's 2006 Estimated Relationship between HPA and Delinquency and Cumulative Losses. Source: Bank C.