Federal Reserve System

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# *Making Sense of the Subprime Crisis*

**ABSTRACT** Should market participants have anticipated the large increase in home foreclosures in 2007 and 2008? Most of these foreclosures stemmed from mortgage loans originated in 2005 and 2006, raising suspicions that lenders originated many extremely risky loans during this period. We show that although these loans did carry extra risk factors, particularly increased leverage, reduced underwriting standards alone cannot explain the dramatic rise in foreclosures. We also investigate whether market participants underestimated the likelihood of a fall in home prices or the sensitivity of foreclosures to falling prices. We show that given available data, they should have understood that a significant price drop would raise foreclosures sharply, although loan-level (as opposed to ownership-level) models would have predicted a smaller rise than occurred. Analyst reports and other contemporary discussions reveal that analysts generally understood that falling prices would have disastrous consequences but assigned that outcome a low probability.

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 (MBSs) 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 those years. Rating agencies would have reacted similarly, rating a much smaller fraction of each deal investment grade. As a result, the subsequent increase in foreclosures would have been significantly smaller, with fewer attendant disruptions in the housing market, and 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 expectations about home prices. Had investors known the future trajectory of home prices, they would have predicted large increases in delinquency and default and losses on subprime MBSs roughly consistent with what has occurred. We show this by using two different methods to travel back to 2005, when the subprime market was still thriving, and look forward from there. The first method is to forecast performance using only data available in 2005, and the second is to look at what market participants wrote at the time. The latter, "narrative" analysis provides strong evidence against the claim that investors lost money because they purchased loans that, because they were originated by others, could not be evaluated properly.

Our first order of business, however, is to address the more basic question of whether the subprime mortgages that defaulted were themselves unreasonable ex ante—an explanation commonly offered for the crisis. We show that the problem loans, most of which were originated in 2005 and 2006, were not that different from loans made earlier, which had performed well despite carrying a variety of serious risk factors. That said, we document that loans in the 2005–06 cohort were riskier, and we 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 also find that the change in the mix of mortgages originated is too slight 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 turn to the role of the collapse in home price appreciation (HPA) that started in the spring of 2006.[1] To have invested large sums in subprime mortgages in 2005 and 2006, lenders must have expected either that HPA would remain high (or at least not collapse) or that subprime defaults would be insensitive to a big drop in HPA. More formally, letting

1. The relationship between foreclosures and HPA in the subprime crisis is well documented. See Gerardi, Shapiro, and Willen (2007), Mayer, Pence, and Sherlund (forthcoming), Demyanyk and van Hemert (2007), Doms, Furlong, and Krainer (2007), and Danis and Pennington-Cross (2005).

$f$ represent foreclosures, $p$ prices, and $t$ time, we can decompose the growth in foreclosures over time, d$f$/d$t$, into a part corresponding to the sensitivity of foreclosures to price changes and a part reflecting the change in prices over time:

$$\mathrm{d}f/\mathrm{d}t = \mathrm{d}f/\mathrm{d}p \times \mathrm{d}p/\mathrm{d}t.$$

Our goal is to determine whether market participants underestimated d$f$/d$p$, the sensitivity of foreclosures to price changes, or whether d$p$/d$t$, the trajectory of home prices, came out much worse than they expected.

Our first time-travel exercise, as mentioned, uses data that were available to investors ex ante on mortgage performance, to determine whether it was possible at the time to estimate d$f$/d$p$ on subprime mortgages accurately. Because severe home price declines are relatively rare and the subprime market is relatively new, one plausible theory is that the data lacked sufficient variation to allow d$f$/d$p$ to be estimated in scenarios in which d$p$/d$t$ 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 packaged in MBSs; it has sparse information on loans originated before 1999. The second is a dataset from the Warren Group, which has tracked the fates of homebuyers in Massachusetts since the late 1980s. These data are not loan-level but rather ownership-level data; that is, the unit of observation is a homeowner's tenure in a property, which may encompass more than one mortgage loan. The Warren Group data were not (so far as we can tell) widely used by the industry but were, at least in theory, available and, unlike the loan-level data, do contain information on the behavior of homeowners in an environment of falling prices.

We find that it was possible, although not necessarily easy, to measure d$f$/d$p$ with some degree 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 likely behavior of subprime borrowers in an environment of falling home prices. In effect, the out-of-sample (and out-of-support) performance of default models was sufficiently good to have predicted large losses in such an environment.

Although it was thus possible to estimate d*f*/d*p,* we also find that the relationship was less exact when using the data on *loans* rather than the data on *ownerships.* A given borrower might refinance his or her original loan several times before defaulting. Each of these successive loans except the final one would have been seen by lenders as successful. An ownership, in contrast, terminates only when the homeowner sells and moves, or is foreclosed upon and evicted. Thus, although the same foreclosure would appear as a default in both loan-level and ownership-level data, the intermediate refinancings between purchase and foreclosure—the "happy endings"—would not appear in an ownership-level database.

Our second time-travel exercise explores 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 d*f*/d*p* and understood, with remarkable accuracy, how falling d*p*/d*t* 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:[2] analyzing a representative deal composed of 2005 vintage loans, the report 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. That analysis was prescient: the ABX index, a widely used price index of asset-backed securities, currently implies that such a deal will actually face losses of 18.3 percent over its life. The problem was that the report assigned only a 5 percent probability to the meltdown scenario, where home prices fell 5 percent, whereas it assigned probabilities of 15 percent and 50 percent to scenarios in which home prices rose 11 percent and 5 percent, respectively, over the life of the deal.

We argue that the fall in home prices outweighs other changes in driving up foreclosures in the recent period. However, we do not take a position on why prices rose so rapidly, why they fell so fast, or why they peaked in mid-2006. Other researchers have examined whether factors such as lending standards can affect home prices.[3] Broadly speaking, we maintain the assumption that although, in the aggregate, lending standards may indeed have affected home price dynamics (we are agnostic on this

2. This is the bank designated Bank B in our discussion of analyst reports below, in a report dated August 15, 2005.

3. Examples include Pavlov and Wachter (2006), Coleman, LaCour-Little, and Vandell (2008), Wheaton and Lee (2008), Wheaton and Nechayev (2008), and Sanders and others (2008).

point), no individual market participant felt that his or her actions could affect prices. Nor do we analyze whether housing was overvalued in 2005 and 2006, such that a fall in prices was to some extent predictable. There was a lively debate during that period, with some arguing that housing was reasonably valued and others that it was overvalued.[4]

Our results suggest that some borrowers were more sensitive to a single macro risk factor, namely, home prices. This comports well with the findings of David Musto and Nicholas Souleles, who argue that average default rates are only half the story: correlations across borrowers, perhaps driven by macroeconomic forces, are also an important factor in valuing portfolios of consumer loans.[5]

In this paper we focus almost exclusively on subprime mortgages. However, many of the same arguments might also apply to prime mortgages. Deborah Lucas and Robert McDonald compute the price volatility of the assets underlying securities issued by the housing-related government-sponsored enterprises (GSEs).[6] Concentrating mainly on prime and near-prime mortgages and using information on the firms' leverage and their stock prices, these authors find that risk was quite high (and, as a result, that the value of the implicit government guarantee on GSE debt was quite high).

Many have argued that a major driver of the subprime crisis was the increased use of securitization.[7] 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. At the same time, information asymmetries, unfamiliarity with the market, or other factors prevented investors, who were accepting the credit risk, from putting in place effective controls on these incentives. Although this argument is intuitively persuasive, our results are not consistent with such an explanation. One of our key findings is that most of the uncertainty about losses stemmed from uncertainty about the future direction of home prices, not from uncertainty about the quality of the underwriting. All that said, our

4. Among the first group were Himmelberg, Mayer, and Sinai (2005) and McCarthy and Peach (2004); the pessimists included Gallin (2006, 2008) and Davis, Lehnert, and Martin (2008).

5. Musto and Souleles (2006).

6. Lucas and McDonald (2006).

7. See, for example, Keys and others (2008) and Calomiris (2008).

models do not perfectly predict the defaults that occurred, and they often underestimate the number of defaults. One possible explanation is that there was an unobservable deterioration of underwriting standards in 2005 and 2006.[8] But another is that our model of the highly nonlinear relationship between prices and foreclosures is wanting. No existing research has successfully distinguished between these two explanations.

The endogeneity of prices does present a problem for our estimation. One common theory is that foreclosures drive price declines by increasing the supply of homes for sale, in effect introducing a new term into the decomposition of $\mathrm{d}f/\mathrm{d}t$, namely, $\mathrm{d}p/\mathrm{d}f$. However, our estimation techniques are to a large extent robust to this issue. As discussed by Gerardi, Adam Shapiro, and Willen,[9] most of the variation in the key explanatory variable, homeowner's equity, is within-town (or, more precisely, within-metropolitan-statistical-area), within-quarter variation and thus could not be driven by differences in foreclosures over time or across towns. In fact, as we will show, one can estimate the effect of home prices on foreclosures even in periods when there were very few foreclosures, and in periods in which foreclosed properties sold quickly.

No discussion of the subprime crisis is complete without mention of the interest rate resets built into many subprime mortgages, which virtually guaranteed large increases in monthly payments. Many commentators have attributed the crisis to the payment shock associated with the first reset of subprime 2/28 adjustable-rate mortgages (these are 30-year ARMs with 2-year teaser rates). However, the evidence from loan-level data shows that resets cannot account for a significant portion of the increase in foreclosures. Christopher Mayer, Karen Pence, and Sherlund, as well as Christopher Foote and coauthors, show that the overwhelming majority of defaults on subprime ARMs occur long before the first reset.[10] In effect, many lenders would have been lucky had borrowers waited until the first reset to default.

The rest of the paper is organized as follows. We begin in the next section by documenting changes in underwriting standards on mortgages. The following section explores what researchers could have learned with the data they had in 2005. In the penultimate section we review contemporary analyst reports. The final section presents some conclusions.

8. This explanation is favored by Demyanyk and van Hemert (2007).
9. Gerardi, Shapiro, and Willen (2007).
10. Mayer, Pence, and Sherlund (forthcoming); Foote and others (2008a).

## Underwriting Standards in the Subprime Market

We begin with a brief background on subprime mortgages, including a discussion of the competing definitions of "subprime." We then discuss changes in the apparent credit risk of subprime mortgages originated from 1999 to 2007, and we link those changes to the actual performance of those loans. We argue that the increased number of subprime loans that were originated with high loan-to-value (LTV) ratios 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 MBSs. Loans originated with less than complete documentation of income or assets, and particularly loans originated with both high leverage and incomplete documentation, exhibited sharper subsequent rises in default rates than other loans. A more formal decomposition exercise, however, confirms that the rise in defaults can only partly be explained by observed changes in underwriting standards.

### *Some 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, and they charge higher fees to service these loans; thus, one definition of a subprime loan is one that is classified as subprime by the servicer. Second, some lenders specialize in loans to financially troubled borrowers, and the Department of Housing and Urban Development maintains a list of such lenders; loans originated by these "HUD list" lenders are often taken as a proxy for subprime loans. Third, "high-cost" loans are defined as loans that carry fees and interest rates significantly above those charged to typical borrowers. Fourth, a subprime loan is sometimes defined as any loan packaged into an MBS that is marketed as containing subprime loans.

Table 1 reports two measures of the importance of subprime lending in the United States. The first is the percent of loans in the Mortgage Bankers Association (MBA) delinquency survey that are classified as "subprime." Because the MBA surveys mortgage servicers, this measure is based on the first definition above. As the table shows, over the past few years, subprime mortgages by this definition have accounted for about 12 to

**Table 1. Subprime Share of the Mortgage Market, 2004–08[a]**
Percent

| | *Subprime loans as a share of* | | |
|---|---|---|---|
| | | *New originations[c]* | |
| *Period* | *Mortgage loans outstanding[b]* | *Home purchases* | *Refinancings* |
| 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 |
| 2008Q2 | 12.2 | n.a. | n.a. |

Sources: Mortgage Bankers Association; Avery, Canner, and Cook (2005); Avery, Brevoort, and Canner (2006, 2007, 2008).

a. Only first liens are counted; shares are not weighted by loan value.

b. From MBA national delinquency surveys; data are as of the end of the period (end of fourth quarter except for 2008).

c. Share of loans used for the indicated purpose that were classified as "high cost" (roughly speaking, those carrying annual percentage rates at least 3 percentage points above the yield on the 30-year Treasury bond).

14 percent of outstanding mortgages. The second and third columns show the percent of loans tracked by the Federal Financial Institutions Examination Council under the Home Mortgage Disclosure Act (HMDA) that are classified as "high cost"—the third definition. In 2005 and 2006 roughly 25 percent of loan originations were subprime by this measure.[11]

These two measures point to an important discrepancy between the *stock* and the *flow* of subprime mortgages (source data and definitions also account for some of the difference). Subprime mortgages were a growing part of the mortgage market during this period, and therefore the flow of new subprime mortgages will naturally exceed their presence in the stock of outstanding mortgages. In addition, subprime mortgages, for a variety of reasons, tend not to last as long as prime mortgages, and for this reason, too, they form a larger fraction of the flow of new mortgages than of the stock of outstanding mortgages. Furthermore, until the mid-2000s most subprime mortgages were used to refinance an existing loan and, simultaneously, to increase the principal balance (thus allowing the homeowner to borrow against accumulated equity), rather than to finance the purchase of a home.

11. The high-cost measure was introduced in the HMDA data only in 2004; for operational and technical reasons, the reported share of high-cost loans in 2004 may be depressed relative to later years.

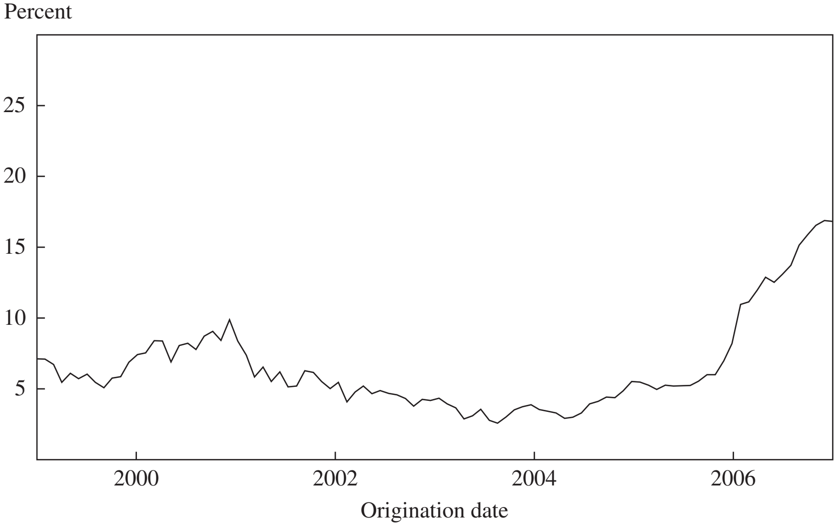
In this section we will focus on changes in the kinds of loans made over the period 1999–2007. We will use loan-level data on mortgages sold into private-label MBSs marketed as subprime. These data (known as the TrueStandings Securities ABS data) are provided by First American LoanPerformance and were widely used in the financial services industry before and during the subprime boom. We further limit the set of loans analyzed to the three most popular products: those carrying fixed interest rates to maturity and the so-called 2/28s and 3/27s. As alluded to above, a 2/28 is a 30-year mortgage in which the contract rate is fixed at an initial, teaser rate for two years; after that it adjusts to the six-month LIBOR (London interbank offer rate) plus a predetermined margin (often around 6 percentage points). A 3/27 is defined analogously. Together these three loan categories account for more than 98 percent of loans in the original data.

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 its 12th month of life, it had terminated following a foreclosure notice, or if the loan was listed as real estate owned by the servicer (indicating a transfer of title from the borrower), or if the loan was still active but foreclosure proceedings had been initiated, or if payments on the loan were 90 or more days past due. Note that some of the loans we count as defaults might subsequently have reverted 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 to have *not* defaulted.

Figure 1 tracks the default rate in the ABS data under this definition from 1999 through 2006. Conceptually, default rates differ from delinquency rates in that they track the fate of mortgages originated in a given month by their 12th 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 the fate of only those mortgages originated through December 2006. The continued steep increase in mortgage distress is not reflected in these data, 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 one to compare the ex ante credit risk of various underwriting terms. It is of limited

**Figure 1.** Twelve-Month Default Rate on Subprime Mortgages[a]




Sources: First American LoanPerformance; authors' calculations.
a. Share of all subprime mortgages originated in the indicated month that default within 12 months of origination.

usefulness as a predictor of defaults, because it considers only what happens by the 12th month of a mortgage, and it does not consider changes in the home prices, interest rates, or the overall economic environment faced by households. Further, this measure does not consider the changing incentives to refinance. The competing-risks duration models we estimate in a later section are, for these reasons, far better suited to determining the credit and prepayment outlook for a group of mortgages.

### *Changes in Underwriting Standards*

During the credit boom, lenders published daily "rate sheets" showing, for various combinations of loan risk characteristics, the interest rates they would charge to make such loans. A simple rate sheet, for example, might be a matrix of credit scores and LTV ratios; borrowers with lower credit scores or higher LTV ratios would be charged higher interest rates or be required to pay larger fees up front. Loans for certain cells of the matrix representing combinations of low credit scores and high LTV ratios might not be available at all.

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

We consider trends over time in borrower credit scores, loan documentation, leverage, and other factors associated with risk, such as the purpose of the loan, 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 refinancing an existing loan), and loans with nontraditional amortization schedules all grew. Borrower credit scores increased, while loans to non-owner-occupants remained essentially flat. Of these variables, 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.

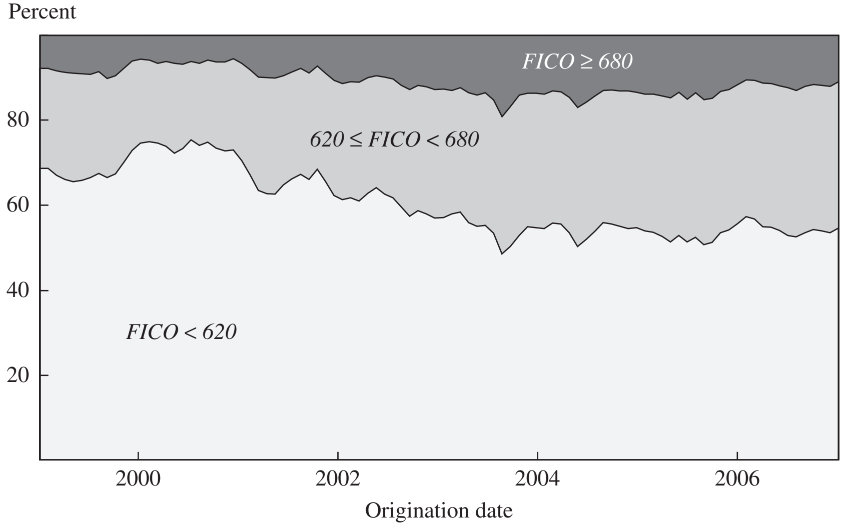
CREDIT SCORES. Credit scores, which essentially summarize a borrower's history of missing debt payments, are the most obvious indicator of prime or subprime status. The most commonly used scalar credit score is the FICO score originally developed by Fair, Isaac & Co. It is the only score contained in 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 some other accompanying risk factor, borrowers with credit scores between 620 and 680 may be considered subprime, and those with credit scores below 620 are rarely eligible for prime loans. 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 weight missed mortgage payments more than missed credit card payments.

Figure 2 shows the proportions of newly originated subprime loans falling into each of these three categories. The proportion of such 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,

**Figure 2.** Distribution of Subprime Mortgages by FICO Score at Origination



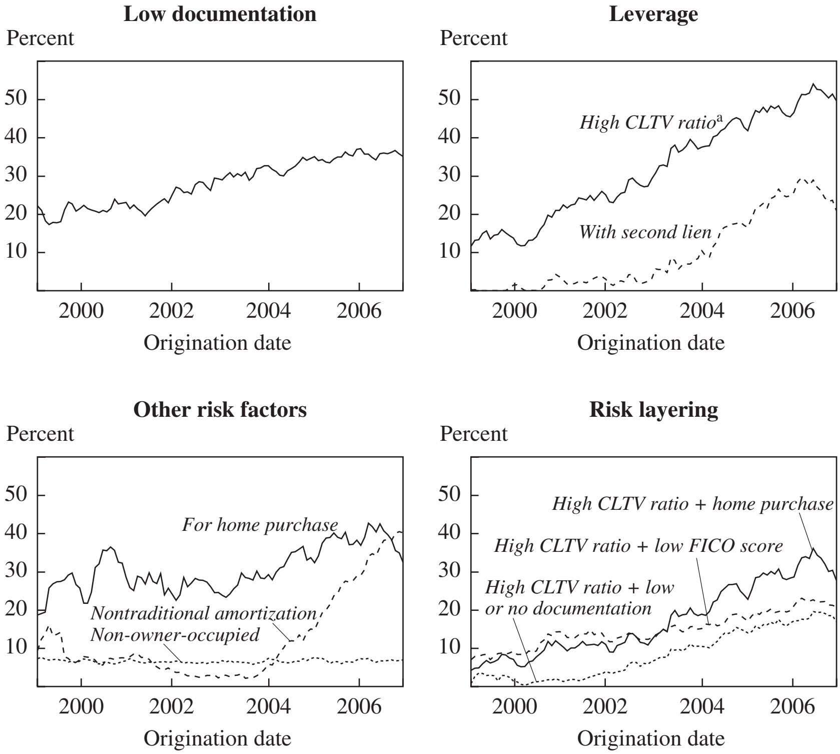

Sources: First American LoanPerformance; authors' calculations.

liquid assets, and 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, for which documentation of income or assets was incomplete. (These include the infamous "stated-income" loans.) The top left panel of figure 3 shows that the proportion of newly originated subprime loans carrying less than full documentation rose from around 20 percent in 1999 to a high of more than 35 percent by mid-2006. Thus, although reduced-documentation 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 on the property divided by its value. This is often referred to as the property's combined loan-to-value, or CLTV, ratio. Both the numerator and the denominator of the CLTV ratio will fluctuate over a borrower's tenure in the property: the borrower may amortize the original loan, refi-

**Figure 3.** Shares of Subprime Mortgages with Various Risk Factors




Sources: First American LoanPerformance; authors' calculations.
a. CLTV ratio ≥ 90 percent or including a junior lien.

nance, or take on junior liens, and the potential sale price of the home will change over time. However, the current values of 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 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 practice, high leverage during the boom 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 the 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 an AAA-rated piece and a below-investment-grade piece. Some investors might specialize in credit risk evaluation and hence prefer the riskier piece, while others might prefer to forgo credit analysis and purchase the less risky loan.

The reporting of these junior liens in the ABS data appears 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, and 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, 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 ratio. Although such borrowing should not affect the original lender's recovery, it does increase the probability of a default and thus lowers the value of the original loan.

The top right panel of figure 3 shows the growth in the number of loans originated with high CLTV ratios (defined as those with CLTV ratios of 90 percent or more or including a junior lien); the panel also shows the proportion of loans originated for which a junior lien was recorded.[12] Both measures of leverage rose sharply over the past decade. High-CLTV-ratio lending accounted 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 ratio of the first lien. As table 2 shows, loans without a second lien reported an average CLTV ratio of 79.9 percent, whereas those with a second lien reported an average CLTV ratio of 98.8 percent. Moreover, loans with reported CLTV ratios of 90 percent or above were much likelier to have associated junior liens, suggesting that lenders were leery of originating single mortgages with LTV ratios greater than 90 percent. We will discuss later 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 could have contributed to increased risk. The bottom left panel of

12. 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 the CLTV ratio and for other purposes, but the junior loan itself is not counted.

**Table 2. Distribution of New Originations by Combined Loan-to-Value Ratio, 2004–08**
Percent

| *CLTV ratio* | *Without second lien* | *With second lien* |
|---|---|---|
| Less than 80 percent | 35 | 1 |
| Exactly 80 percent | 18 | 0 |
| Between 80 and 90 percent | 18 | 1 |
| Exactly 90 percent | 15 | 1 |
| Between 90 and 100 percent | 8 | 16 |
| 100 percent or greater | 5 | 80 |
| Memorandum: average CLTV ratio | 79.92 | 98.84 |

Sources: First American LoanPeformance; authors' calculations.

figure 3 shows the proportions of subprime loans originated with a nontraditional amortization schedule, to non-owner-occupiers, 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. As the bottom left panel of figure 3 shows, nontraditional amortization schedules became increasingly popular among subprime loans. These were mainly loans that did not require sufficient principal payments (at least in the early years of the loan) to amortize the loan completely over its 30-year term. Thus, some loans had interest-only periods, and 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 the monthly payment, especially in the early years of the loan.

Subprime loans had traditionally been used to refinance an existing loan. As the bottom left panel of figure 3 also shows, subprime loans used to purchase homes also increased over the period, although not dramatically. Loans to non-owner-occupiers, which include loans backed by a property held for investment purposes, are, all else equal, riskier than loans to owner-occupiers because the borrower can default without facing eviction from his or her primary residence. As the figure shows, 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 was combined with other risk factors in a single loan; this practice was sometimes known as "risk layering." As the bottom right panel of figure 3 shows, risk layering grew over the sample period. Loans with incomplete documentation *and* high leverage had an especially notable rise, 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.

### *Effect on Default Rates*

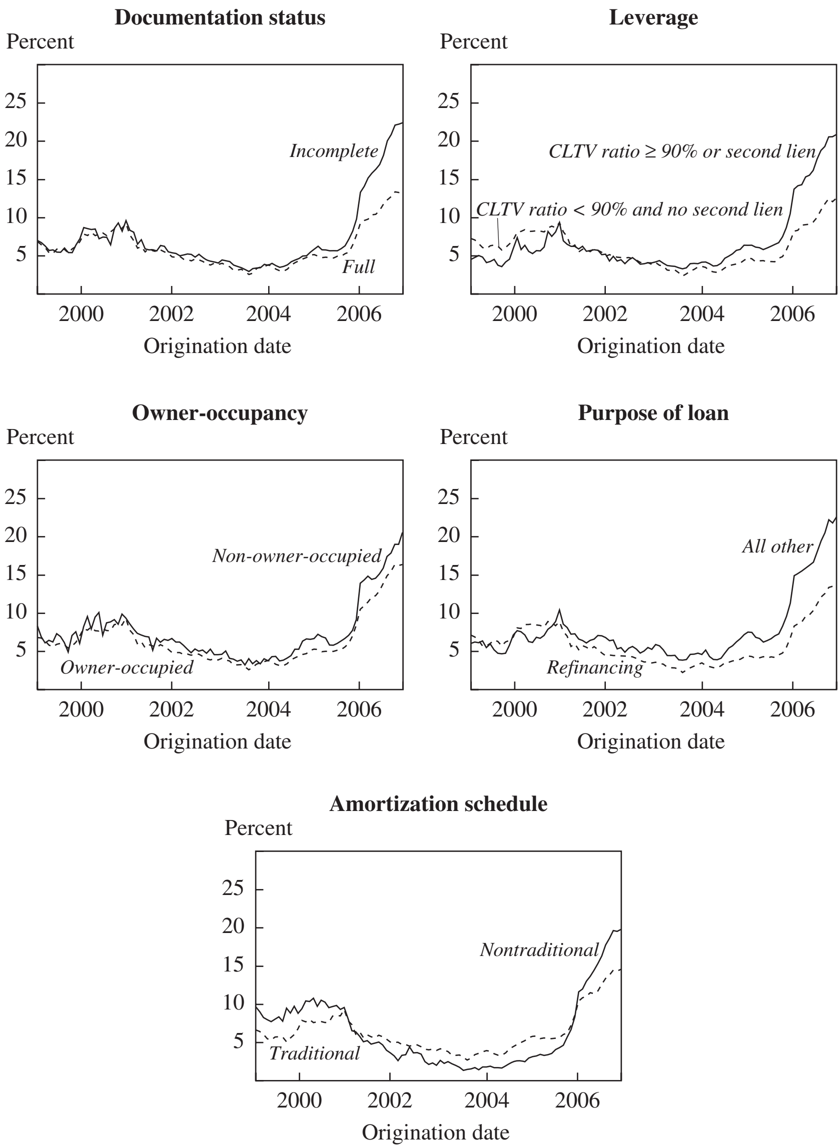
We now consider the performance of loans with the various risk factors just outlined. We start with simple univariate descriptions before turning to a more formal decomposition exercise. We continue here to focus on 12-month default rates as the outcome of interest. In the next section we present results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

DOCUMENTATION LEVEL. The top left panel of figure 4 shows default rates over time for loans with complete and those with incomplete documentation. 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 and without high CLTV ratios (defined, again, as those with a CLTV ratio of at least 90 percent *or* with 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 above, 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 the CLTV ratio at origination to the subsequent probability of default and to the initial contract interest rate charged to the borrower. For all loans in the sample, we estimated a probit model of default and an ordinary least squares (OLS) model of the initial contract rate. Explanatory variables were various measures of leverage, including indicator (dummy) variables for various ranges of the reported CLTV ratio (one of which is for a CLTV ratio of *exactly* 80 percent) as well as for the presence of a second lien. We estimated two versions of each model: version 1 contains only the CLTV ratio measures, the second-lien indicator, and (in the default regressions) the initial contract rate; version 2 adds state and origination date fixed effects. These regressions are designed purely to highlight the correlation among variables of interest and not as fully fledged risk models. Version 1 can be thought of as the simple multivariate correlation across the entire sample, whereas version 2 compares loans originated in the same state at the

**Figure 4.** Twelve-Month Default Rates of Mortgages with Selected Characteristics




Sources: First American LoanPerformance; authors' calculations.

**Table 3. Regressions Estimating the Effect of Leverage on Default Probability and Mortgage Interest Rates**

| | *Marginal effect on probability of default within 12 months of origination*[a] | | *Marginal effect on initial contract interest rate*[b] | | |
|---|---|---|---|---|---|
| *Independent variable* | *Version 1* | *Version 2* | *Version 1* | *Version 2* | *Variable mean*[c] |
| Constant | | | 7.9825 | 10.4713 | |
| CLTV ratio (percent) | 0.00219 | 0.00223 | 0.0093 | 0.0083 | 82.6929 |
| $CLTV^2/100$ | –0.00103 | –0.00103 | –0.0063 | –0.0082 | 70.3912 |
| Initial contract interest rate (percent a year) | 0.01940 | 0.02355 | | | 8.2037 |
| *Indicator variables* | | | | | |
| CLTV ratio = 80 percent | 0.00961 | 0.01036 | –0.0127 | –0.0817 | 15.72 |
| CLTV ratio between 80 and 90 percent | 0.00014 | –0.00302 | 0.0430 | 0.1106 | 15.56 |
| CLTV ratio = 90 percent | 0.00724 | –0.00041 | 0.1037 | 0.2266 | 12.86 |
| CLTV ratio between 90 and 100 percent | 0.00368 | –0.00734 | 0.0202 | 0.3258 | 9.68 |
| CLTV ratio 100 percent or greater | 0.00901 | –0.00740 | 0.0158 | 0.3777 | 16.20 |
| Second lien recorded | 0.05262 | 0.04500 | –0.8522 | –0.6491 | 14.52 |
| Regression includes origination date effects | No | Yes | No | Yes | |
| Regression includes state effects | No | Yes | No | Yes | |
| No. of observations[d] | 679,518 | 679,518 | 707,823 | 707,823 | |
| Memorandum: mean default rate (percent) | | | | | 6.55 |

Source: Authors' regressions.

a. Results are from a probit regression in which the dependent variable is an indicator equal to 1 when the mortgage has defaulted by its 12th month.

b. Results are from an ordinary least squares regression in which the dependent variable is the original contract interest rate on the mortgage.

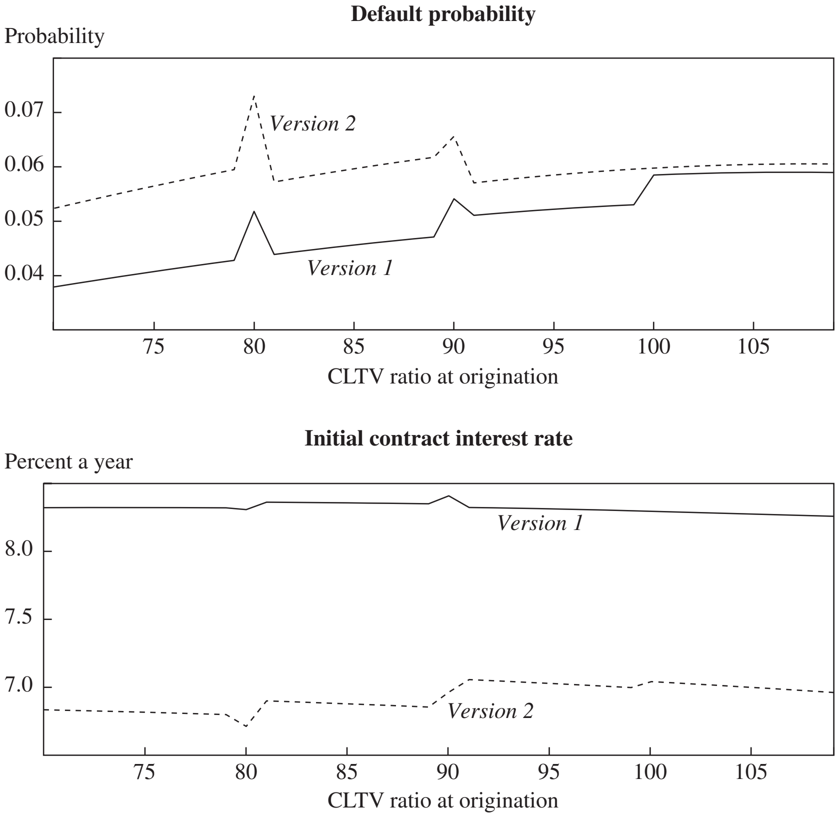
c. Values for indicator variables are percent of the total sample for which the variable equals 1.

d. Sample is a 10 percent random sample of the ABS data.

same time. The results are shown in table 3; using the results from version 2, figure 5 plots the expected default probability against the CLTV ratio for loans originated in California in June 2005.

As the figure shows, default probabilities generally increase with leverage. Note, however, that loans with reported CLTV ratios of exactly 80 percent, which account for 15.7 percent of subprime loans, have a sub-

**Figure 5.** Effect of CLTV Ratio on Default Probability and Initial Interest Rate[a]




Sources: First American LoanPerformance; authors' calculations.
a. Estimation results of model versions 1 and 2 are reported in table 3.

stantially higher default probability than loans with slightly higher or lower CLTV ratios. Indeed, under version 2 such loans are among the riskiest originated. As the bottom panel of figure 5 shows, however, there is no compensating increase in the initial contract rate charged to the borrower, although the lender may have charged points and fees up front (not measured in this dataset) to compensate for the increased risk. This evidence suggests that borrowers with apparently reasonable CLTV ratios were in fact using junior liens to increase their leverage in a way that was neither 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 described earlier: non-owner-occupancy, loan purpose, and nontraditional amortization schedules. Loans to non-owner-occupiers were not (in this sample) markedly riskier than loans to owner-occupiers. The 12-month default rates on loans originated from 1999 to 2004 varied little between those originated for home purchase and those originated for refinancing, and between those carrying traditional and nontraditional amortization schedules. However, among loans originated in 2005 and 2006, purchase loans and loans with nontraditional amortization schedules defaulted at much higher rates than did refinancings and traditionally amortizing loans, respectively.

RISK LAYERING. Figure 6 shows the default rates on loans carrying the multiple risk factors discussed earlier. As the top panel shows, loans with high CLTV ratios *and* low FICO scores have nearly always defaulted at higher rates than other loans. High-CLTV-ratio loans that were used to purchase homes also had a worse track record (middle panel). In both cases, default rates for high-CLTV-ratio loans climbed sharply over the last two years of the sample. Loans with high CLTV ratios and incomplete documentation (bottom panel), 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.

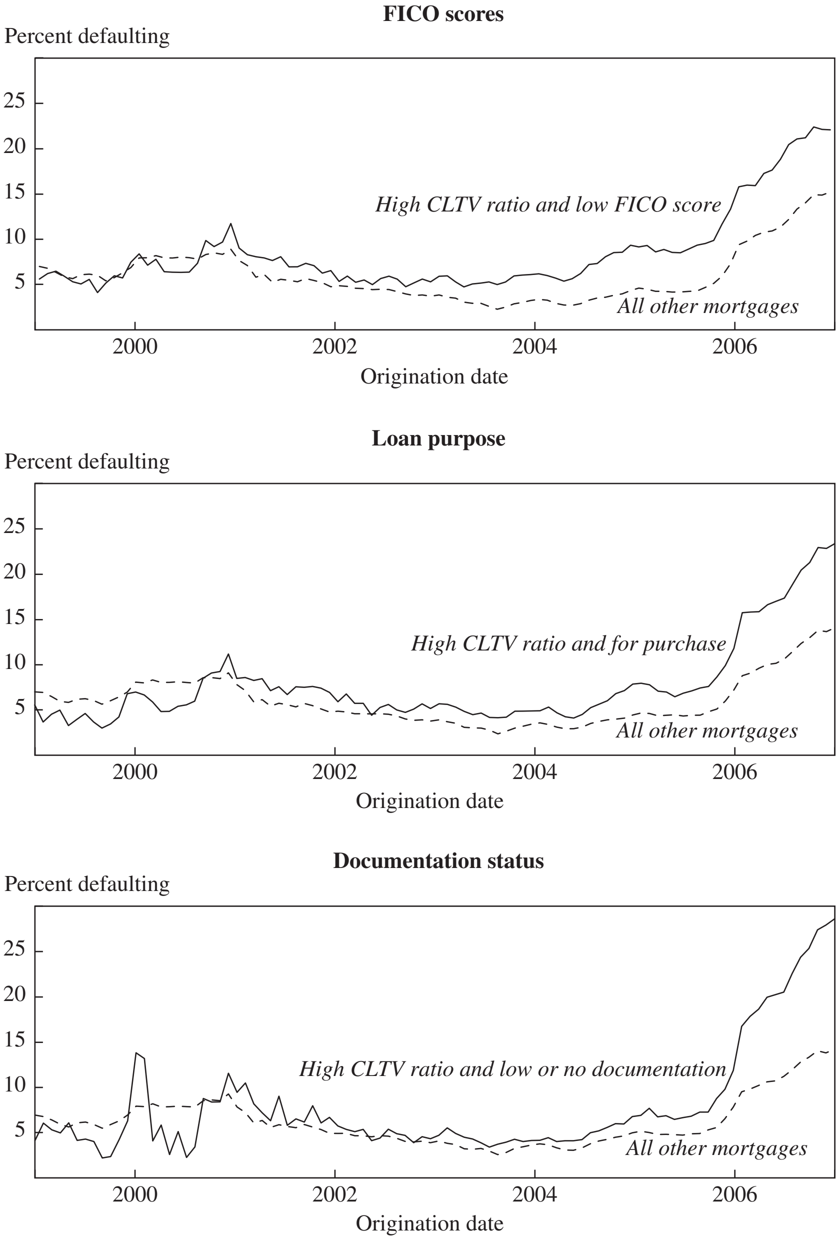
### *Decomposing the Increase in Defaults*

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

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

To test this idea more formally, we divide the sample into two groups: an "early" group of loans originated in 1999–2004, and a "late" group

**Figure 6.** Twelve-Month Default Rates on Mortgages with Risk Layering




Sources: First American LoanPerformance; authors' calculations.

originated in 2005 and 2006. We estimate default models separately on each group, and we track changes in risk factors over the entire period. We then 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 reports the means of the relevant variables for the two groups and for the entire sample. The table shows that a much larger fraction of loans originated in the late group defaulted: 9.28 percent as opposed to 4.60 percent in the early group. The differences between the two groups on other risk factors are in line with the earlier discussion: FICO scores, CLTV ratios, the incidence of 2/28s, low-documentation loans, and loans with nontraditional amortization all rose from the early group to the late group, while the share of loans for refinancing fell (implying that the share for home purchase rose).

Table 5 reports the results of a loan-level probit model of the probability of default, estimated using data from the early group and the late group. The table shows marginal effects and standard errors for a number of loan and borrower characteristics; the model also includes a set of state fixed effects (results not reported). The differences in estimated marginal effects between the early and the late group are striking. Defaults are more sensitive in the late group to a variety of risk factors, such as leverage, credit score, loan purpose, and type of amortization schedule. The slopes in table 5 correspond roughly to the returns in a Blinder-Oaxaca decomposition, whereas the sample means in table 4 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 toward our decomposition, table 6 reports the predicted default rate in the late group using the model estimated on data from the early group, as well as other combinations. Using early-group coefficients on the early group of loans, the model predicts a 4.60 percent default rate. Using the same coefficients on the late-group data, the model predicts a 4.55 percent default rate. Thus, the early-group model does not predict a significant rise in defaults based on the observable characteristics for 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 changes in the distribution of risk factors between the two groups as well as changes in the riskiness of certain characteristics, it will be useful to consider the increase

**Table 4. Summary Statistics for Variables from the ABS Data**

Percent of total except where stated otherwise

| | All mortgages | | Early group[a] | | Late group[b] | |
|---|---|---|---|---|---|---|
| *Variable* | *Mean* | *Standard deviation* | *Mean* | *Standard deviation* | *Mean* | *Standard deviation* |
| *Outcome 12 months after origination* | | | | | | |
| Defaulted | 6.57 | 24.78 | 4.60 | 20.95 | 9.28 | 29.01 |
| Refinanced | 16.22 | 36.86 | 15.96 | 36.63 | 16.57 | 37.18 |
| *Mortgage characteristics* | | | | | | |
| Contract interest rate (percent a year) | 8.21 | 1.59 | 8.38 | 1.76 | 7.97 | 1.27 |
| Margin over LIBOR (percentage points) | 4.45 | 2.94 | 4.28 | 3.11 | 4.69 | 2.67 |
| FICO score | 610 | 60 | 607 | 61 | 615 | 58 |
| CLTV ratio (percent) | 83 | 14 | 81 | 14 | 85 | 15 |
| *Mortgage type* | | | | | | |
| Fixed rate | 28.14 | 44.97 | 32.30 | 46.76 | 22.43 | 41.71 |
| 2/28[c] | 58.54 | 49.27 | 53.40 | 49.88 | 65.58 | 47.51 |
| 3/27 | 13.33 | 33.99 | 14.30 | 35.01 | 11.99 | 32.48 |
| *Documentation status* | | | | | | |
| Complete | 68.28 | 46.54 | 70.62 | 45.55 | 65.07 | 47.68 |
| No documentation | 0.31 | 5.58 | 0.38 | 6.12 | 0.23 | 4.75 |
| Low documentation | 30.71 | 46.13 | 27.82 | 44.81 | 34.68 | 47.60 |

(*continued*)

**Table 4. Summary Statistics for Variables from the ABS Data (*Continued*)**

Percent of total except where stated otherwise

| | *All mortgages* | | *Early group*[a] | | *Late group*[b] | |
|---|---|---|---|---|---|---|
| *Variable* | *Mean* | *Standard deviation* | *Mean* | *Standard deviation* | *Mean* | *Standard deviation* |
| *Other* | | | | | | |
| Nontraditional amortization[d] | 16.04 | 36.69 | 6.93 | 25.40 | 28.53 | 45.15 |
| Non-owner-occupied | 6.57 | 24.78 | 6.51 | 24.68 | 6.66 | 24.93 |
| Refinancing | 67.00 | 47.02 | 70.95 | 45.40 | 61.58 | 48.64 |
| Second lien present | 14.59 | 35.30 | 7.50 | 26.34 | 24.32 | 42.90 |
| Prepayment penalty | 73.55 | 44.11 | 74.00 | 43.87 | 72.93 | 44.43 |
| No. of observations | 3,532,525 | | 2,043,354 | | 1,489,171 | |

Sources: First American LoanPeformance; authors' calculations.

a. Mortgages originated from 1999 to 2004.

b. Mortgages originated in 2005 and 2006.

c. A 30-year mortgage with a low initial ("teaser") rate in the first two years; a 3/27 is defined analogously.

d. Any mortgage that does not completely amortize or that does not amortize at a constant rate.

**Table 5. Probit Regressions Estimating the Effect of Loan and Other Characteristics on Default Probability[a]**

| Variable | Early group (1999–2004 originations) Marginal effect | Early group (1999–2004 originations) Standard error | Late group (2005–06 originations) Marginal effect | Late group (2005–06 originations) Standard error |
|---|---|---|---|---|
| Contract interest rate (percent a year) | 0.0097 | 0.0001 | 0.0328 | 0.0002 |
| Margin over LIBOR (percentage points) | 0.0013 | 0.0001 | 0.0016 | 0.0003 |
| Loan is a 2/28 | 0.0036 | 0.0009 | 0.0158 | 0.0016 |
| Loan is a 3/27 | 0.0030 | 0.0010 | 0.0105 | 0.0020 |
| CLTV ratio | 0.0007 | 0.0001 | 0.0037 | 0.0002 |
| $CLTV^2/100$ | –0.0002 | 0.0001 | –0.0018 | 0.0002 |
| CLTV ratio = 80 percent | 0.0035 | 0.0005 | 0.0225 | 0.0012 |
| 80 percent < CLTV ratio < 90 percent | –0.0017 | 0.0006 | 0.0119 | 0.0014 |
| 90 percent ≤ CLTV ratio < 100 percent | –0.0014 | 0.0008 | 0.0154 | 0.0022 |
| CLTV ratio ≥ 100 percent | –0.0000 | 0.0015 | 0.0229 | 0.0029 |
| Second lien present | 0.0165 | 0.0008 | 0.0391 | 0.0009 |
| FICO score | –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 |
| High CLTV ratio and low FICO | –0.0004 | 0.0006 | 0.0013 | 0.0010 |
| High CLTV ratio and purchase | 0.0053 | 0.0006 | –0.0143 | 0.0010 |
| High CLTV ratio and low documentation | 0.0059 | 0.0007 | 0.0129 | 0.0010 |
| Loan is a refinancing | –0.0064 | 0.0004 | –0.0223 | 0.0009 |
| Non-owner-occupied | 0.0113 | 0.0006 | 0.0158 | 0.0010 |
| Low documentation | 0.0127 | 0.0004 | 0.0160 | 0.0007 |
| No documentation | 0.0107 | 0.0027 | 0.0293 | 0.0059 |
| Prepayment penalty | 0.0012 | 0.0003 | 0.0087 | 0.0006 |
| Payment-to-income ratio 1[b] | 0.0003 | 0.0000 | 0.0008 | 0.0000 |
| Payment-to-income ratio 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 |
| Loan is from a retail lender | 0.0036 | 0.0005 | –0.0204 | 0.0012 |
| Loan is from a wholesale lender | 0.0050 | 0.0004 | 0.0044 | 0.0009 |
| Loan is from a mortgage broker | 0.0011 | 0.0011 | –0.0055 | 0.0019 |
| Nontraditional amortization | 0.0043 | 0.0005 | 0.0218 | 0.0006 |
| No. of observations | 2,043,354 | | 1,489,171 | |
| Pseudo-$R^2$ | 0.0929 | | 0.0971 | |

Source: Authors' regressions.

a. The dependent variable is the probability of default after 12 months. All regressions include a complete set of state fixed effects.

b. Ratios 1 and 2 are back- and front-end debt-to-income ratios, respectively.

**Table 6.** Predicted Default Rates
Percent

| | Default probability using model estimated on data from | |
|---|---|---|
| *Data used in estimation* | *Early period (1999–2004)* | *Late period (2005–06)* |
| Early period | 4.60 | 9.30 |
| Late period | 4.55 | 9.27 |
| *Origination year* | | |
| 1999 | 6.66 | 15.37 |
| 2000 | 8.67 | 20.00 |
| 2001 | 6.52 | 14.34 |
| 2002 | 4.83 | 9.86 |
| 2003 | 3.49 | 6.42 |
| 2004 | 3.44 | 6.05 |
| 2005 | 3.96 | 7.50 |
| 2006 | 5.31 | 11.55 |

Source: Authors' calculations.

in riskiness of a typical loan after varying a few characteristics in turn. Again, because of the nonlinearity of the underlying model, we have to consider just one set of observable characteristics at a time.

To this end, we consider a typical 2/28 loan 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 to a value suggested by the experience in the late period. Table 7 shows that even for loans with the worst combination of underwriting characteristics, the predicted default rate is less than half 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 ratio to exactly 80 percent increases the default probability, for reasons discussed earlier.)

## What Can We Learn from the 2005 Data?

In this section we focus on whether market participants could reasonably have estimated the sensitivity of foreclosures to home price decreases. We estimate standard competing-risks duration models using data on the performance of loans originated through the end of 2004—presumably 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 home price outcomes that the economy actually experienced. Later we address the question of what home price expecta-

**Table 7. Effects of Selected Mortgage Characteristics on Default Probability for a Generic 2/28 Mortgage**
Percent

| *Loan characteristics* | *Estimated 12-month default probability*[a] |
|---|---|
| Base case[b] | 1.96 |
| *Base case except:* | |
| CLTV ratio = 80 percent | 2.28 |
| High CLTV ratio (= 99.23 percent, with second lien) | 3.76 |
| Low FICO score (FICO = 573) | 2.47 |
| Low documentation | 2.88 |
| Nontraditional amortization | 1.96 |
| Home purchase | 2.41 |
| High CLTV ratio *and* low documentation | 6.17 |
| High CLTV ratio *and* low FICO score | 3.76 |
| High CLTV ratio *and* home purchase | 5.22 |

Source: Authors' calculations.
a. Calculated using the model estimated from early-period (1999–2004) data.
b. The base case is a 2/28 mortgage originated in California for the purpose of refinancing and carrying an initial annual interest rate of 8.22 percent (and a margin over LIBOR of 6.22 percent), with a CLTV ratio of 81.3, a FICO score of 600, complete documentation, no second lien, and traditional amortization. Mortgages with these characteristics experienced an actual default probability of 11.36 percent. Each of the remaining cases differs from the base case only with respect to the characteristic(s) indicated. Values chosen for these characteristics are late-period (2005–06) sample means or otherwise suggested by the experience in that period.

tions investors had, but here we assume that market participants had perfect foresight about future HPA.

In conducting our forecasts, we use two primary data sources. The first is the ABS data discussed 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, from county-level registry of deeds offices. Although these data are not national in scope and lack the level of detail on mortgage and borrower characteristics that the ABS data have, their historical coverage is far superior. 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 period covered by 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.

### *The Relationship between Housing Equity and Foreclosure*

For a homeowner with positive equity who needs to terminate his or her mortgage, a strategy of either refinancing the mortgage or selling the home dominates defaulting and allowing foreclosure to occur. However, for an "underwater" homeowner (that is, one with negative equity, where the mortgage balance exceeds the home's market value), default and foreclosure are sometimes the optimal economic decision.[13] 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. These observations imply that the relationship between housing prices and foreclosure is highly sensitive to the housing cycle. In a home price boom, even borrowers in extreme financial distress have more appealing options than foreclosure, because home price gains are expected to result in positive equity. However, when home prices are falling, highly leveraged borrowers will often find themselves in a position of negative equity, which implies fewer options for those experiencing financial distress.

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

Given that the ABS data do not contain a home 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 through 2004 have a harder time predicting foreclosures in 2007 and 2008.

### *Forecasts Using the ABS Data*

As described earlier, the ABS data are loan-level data that track mortgages held in securitized pools marketed as either 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 above is in the definitions of "default" and "pre-

13. See Foote and others (2008a) for a more detailed discussion.

payment." 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 different types of mortgage termination: by foreclosure or by prepayment without a notice of foreclosure. Here we define a default as a mortgage that terminates after a notice of foreclosure has been served, and a prepayment as a mortgage that terminates without such a notice (presumably through refinancing or sale of the home). Thus, loans can cycle through various delinquency stages and can even have a notice of default served, but whether they are classed as happy endings (prepayments) or unhappy endings (defaults) will depend on their status at termination.

To model default and prepayment behavior, we augment the ABS data with metropolitan-area-level home 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 home 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 Census Bureau.

EMPIRICAL MODEL. We now use the ABS data to estimate what an analyst with perfect foresight about home prices, interest rates, oil prices, and other variables would have predicted for prepayment and foreclosures in 2005–07, given information on mortgage performance available at the end of 2004. We estimate a competing-risks model over 2000–04 and simulate mortgage defaults and prepayments over 2005–07. The baseline hazard functions for prepayment and default are assumed to follow the Public Securities Association (PSA) guidelines, which are fairly standard in the mortgage industry.[14]

Factors that can affect prepayment and default include mortgage and borrower characteristics at loan origination, such as CLTV and payment-to-income ratios, the contractual mortgage interest rate, the borrower's credit score, the completeness of loan documentation, and occupancy status. We also include whether the loan has any prepayment penalties, interest-only features, or piggybacking; whether it is a refinancing or a purchase; and the type of property. Further, we include indicator variables to

14. For the specific forms of the PSA guidelines, see Sherlund (2008).

identify loans with risk layering of high leverage and poor documentation, loans to borrowers with credit scores below 600, and an interaction term between occupancy status and cumulative HPA over the life of the mortgage.

Similarly, we include dynamically updated mortgage and borrower characteristics that vary from month to month *after* loan origination. The most important of these is an estimate of the mark-to-market CLTV ratio; changes in home prices will primarily affect default and prepayment rates through this variable. In addition, we include the current contract interest rate, home price volatility, state-level unemployment rates, oil prices, and, for ARMs, the fully indexed mortgage interest rate (six-month LIBOR plus the loan margin).

Because of the focus on payment changes, we include three indicator variables to capture the effects of interest rate resets. The first is set to unity in the three months around (one month before, the month of, and the month after) the first reset. The second captures whether the loan has passed its first reset date. The third identifies changes in the monthly mortgage payment of more than 5 percent from the original monthly payment, to capture any large payment shocks. Variable names and definitions for our models using the ABS data are reported in table 8, and summary statistics in table 9.

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 and refinancings.

Table 10 reports the estimation results for the default hazard functions.[15] These results are similar to those previously reported by Sherlund.[16] As one would expect, home prices (acting through the mark-to-market CLTV ratio term) are extremely important. In addition, non-owner-occupiers are, all else equal, likelier 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.

SIMULATION RESULTS. With the estimated parameters in hand, we turn to the question of how well the model performs over the 2005–07 period.

15. For brevity we do not report the parameter estimates for the prepayment hazard functions. They are available upon request from the authors.

16. Sherlund (2008).

**Table 8. Variable Names and Definitions in the ABS Data**

| *Variable name* | *Definition* |
|---|---|
| cash | Indicator variable = 1 when mortgage is a refinancing with cash-out |
| cltvnow | Current mark-to-market CLTV ratio (percent) |
| cltvorig | CLTV ratio at origination (percent) |
| doc | Indicator variable = 1 when documentation is complete |
| educ | Share of population in zip code with high school education or less |
| ficoorig | FICO score at origination |
| frmnow | Current market interest rate on 30-year fixed-rate mortgages (percent a year) |
| frmorig | Market interest rate on 30-year fixed-rate mortgages at origination (percent a year) |
| hhincome | Average household income in zip code (dollars) |
| hpvol | Current home price volatility (2-year standard deviation of HPA, in percent) |
| hpvorig | Home price volatility at origination (2-year standard deviation of HPA, in percent) |
| indnow | Current fully indexed market interest rate on ARMs (6-month LIBOR plus margin, percent a year) |
| indorig | Fully indexed market interest rate on ARMs at origination (percent a year) |
| invhpa | Cumulative HPA if non-owner-occupied (percent) |
| kids | Share of population in zip code who are children |
| lngwind | Indicator variable = 1 when mortgage rate has previously reset |
| lofico | Indicator variable = 1 when FICO < 600 |
| loqual | Indicator variable = 1 when CLTV ratio > 95 and no documentation |
| mratenow | Current mortgage interest rate (percent a year) |
| mrateorig | Contract interest rate at origination (percent a year) |
| nonowner | Indicator variable = 1 when home is non-owner-occupied |
| oil | Change in oil price since origination (percent) |
| origamt | Loan amount at origination (dollars) |
| piggyback | Indicator variable = 1 when a second lien is recorded at origination |
| pmi | Indicator variable = 1 when there is private mortgage insurance |
| pmt | Indicator variable = 1 when current monthly payment is more than 5 percent higher than original payment |
| ppnow | Indicator variable = 1 when prepayment penalty is still in effect |
| pporig | Indicator variable = 1 when prepayment penalty was in effect at origination |
| proptype | Indicator variable = 1 when the home is a single-family home |
| pti | Payment-to-income ratio at origination (percent) |
| race | Minority share of population in zip code |
| refi | Indicator variable = 1 when the loan is a refinancing (with or without cash-out) |
| rstwind | Indicator variable = 1 when the mortgage is in the reset period |
| unempnow | Change in state-level unemployment rate since origination (percentage points) |
| unorig | State-level unemployment rate at origination (percent) |

**Table 9.** Sample Averages of Variables in the ABS Data[a]

| Variable name | *2000–04* At origination | *2000–04* Active mortgages | *2000–04* Mortgages in default | *2000–04* Mortgages prepaid | *2004* At origination | *2005* At 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 |
| 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 |
| pti | 38.99 | 38.87 | 39.09 | 39.18 | 39.41 | 40.07 |
| 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. of observations | 3,654,683 | 2,195,233 | 183,586 | 1,275,864 | 1,267,866 | 1,794,953 |

Source: Authors' calculations.

a. See table 8 for variable definitions.

**Table 10.** Default Hazard Function Estimates from the ABS Data, 2000–04[a]

| | *Subprime 2/28* | | *Subprime 3/27* | | *Subprime fixed-rate* | |
|---|---|---|---|---|---|---|
| *Variable name* | *Purchase* | *Refinancing* | *Purchase* | *Refinancing* | *Purchase* | *Refinancing* |
| Constant | 7.519* | 4.143* | 5.819* | –0.842 | 7.826* | 3.213* |
| cash | NA[b] | 0.016 | NA | 0.087 | NA | –0.110* |
| cltvnow | 0.030* | 0.008* | 0.019* | 0.025* | 0.036* | 0.028* |
| cltvorig | –0.032* | 0.002 | –0.010 | –0.008 | –0.027* | –0.011* |
| doc | –0.185* | –0.378* | –0.012 | –0.272* | –0.271* | –0.194* |
| educ | –0.439 | –0.125 | –1.401* | –0.376 | –0.075 | 0.227 |
| ficoorig | –4.388* | –4.881* | –4.084* | –2.321* | –4.874* | –4.386* |
| frmnow | –0.124* | –0.179* | 0.054 | 0.109 | 0.181* | 0.113* |
| frmorig | –0.105* | 0.105* | –0.310* | –0.025 | –0.209* | –0.198* |
| hhincome | –0.575* | –0.256* | –0.758* | –0.223 | –0.872* | –0.222* |
| hpvol | –0.034* | –0.038* | –0.046* | –0.029 | –0.064* | –0.037* |
| indnow | 0.291* | 0.369* | 0.217* | 0.234* | NA | NA |
| indorig | –0.270* | –0.358* | –0.136* | –0.145* | NA | NA |
| invhpa | –0.032* | –0.012* | –0.064* | –0.015 | –0.030* | –0.011* |
| kids | 0.317 | 0.249 | 1.304 | –0.635 | 0.521 | –0.695 |
| lngwind | 0.139 | 0.059 | 0.683* | –0.027 | NA | NA |
| lofico | –0.151* | –0.056 | –0.256* | 0.056 | –0.085 | 0.128* |
| loqual | –0.039 | –0.112 | 0.031 | –0.331 | –0.215 | 0.561* |
| mratenow | –0.031 | 0.044 | 1.071* | 0.376 | 0.468 | 0.109 |

| | | | | | | |
|---|---|---|---|---|---|---|
| mrateorig | 0.325* | 0.273* | –0.786 | –0.067 | –0.255 | 0.159 |
| nonowner | 0.557* | 0.281* | 0.883* | 0.351* | 0.540* | 0.431* |
| oil | 0.002 | 0.000 | 0.001 | –0.001 | 0.006* | 0.005* |
| origamt | 0.298* | 0.115* | 0.489* | 0.234* | 0.480* | 0.148* |
| piggyback | 0.287* | 0.286* | 0.300* | 0.287 | 0.133 | –0.329 |
| pmi | 0.075* | 0.174* | 0.212* | 0.074 | 0.311* | 0.160* |
| pmt | 0.525* | –0.149 | 1.478* | 0.707* | 1.144* | 0.393 |
| ppnow | –0.156* | –0.056 | 0.148 | –0.084 | –0.141 | –0.320* |
| pporig | 0.033 | 0.115 | –0.329 | 0.056 | 0.157 | 0.439* |
| proptype | 0.143* | 0.031 | 0.167 | 0.060 | –0.128 | –0.025 |
| pti | 0.005* | 0.009* | 0.009* | 0.007* | –0.002 | 0.006* |
| race | 0.690* | –0.302* | 0.182 | –0.082 | 0.593* | –0.324* |
| rstwind | –0.239* | –0.150* | 0.100 | 0.143 | NA | NA |
| unempnow | 0.007* | 0.009* | 0.005* | 0.004 | 0.000 | –0.003* |
| unorig | –0.023 | –0.040* | –0.028 | –0.043 | –0.080 | –0.091* |
| Log-likelihood | –140,135 | –297,352 | –30,071 | –50,544 | –36,574 | –170,927 |
| No. of observations | 1,095,227 | 2,015,104 | 241,511 | 373,976 | 324,431 | 1,582,146 |

Source: Authors' calculations.

a. Coefficient estimates are for the default hazard function from a competing-risks duration model. The model is estimated at a monthly frequency using the maximum likelihood method. Asterisks indicate statistical significance at the 5 percent level.

b. NA, not applicable.

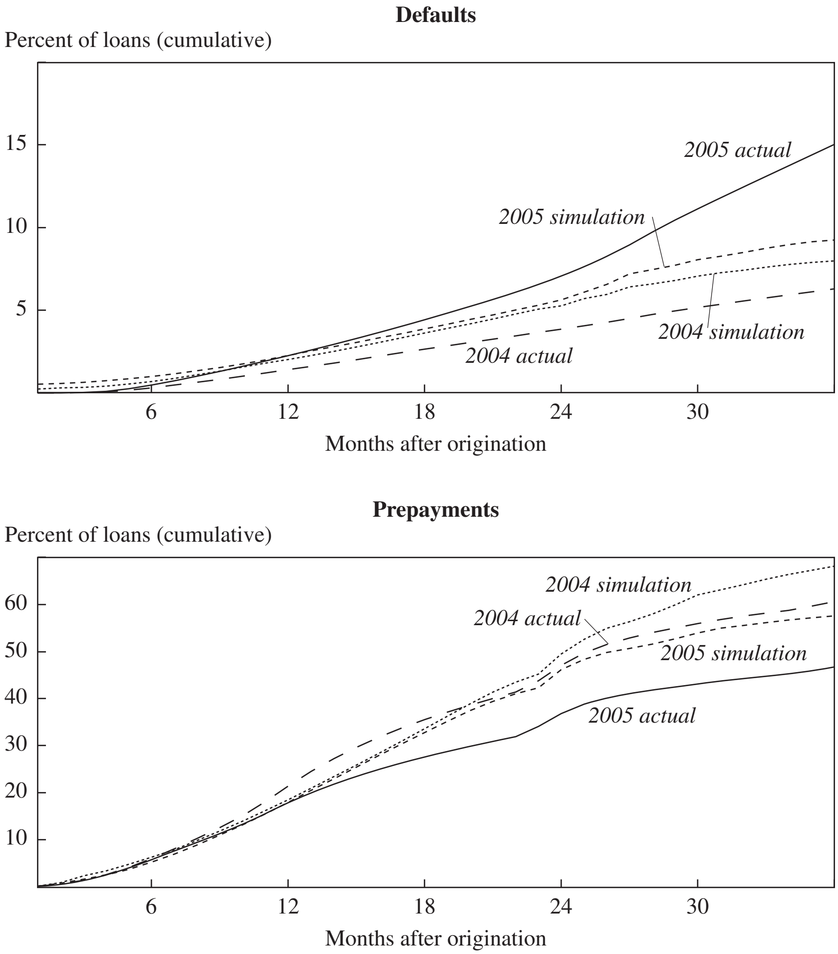
Here we focus on the 2004 and 2005 vintages of subprime mortgages contained in the ABS data. To construct the forecasts, we use the estimated model parameters to calculate predicted foreclosure (and prepayment) probabilities for each mortgage in each month during 2005–07. These simulations assume perfect foresight, in that the assumed paths for home 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 mortgages with the highest propensities defaulting first (and similarly for prepayments). We then compare the cumulative incidence of simulated defaults with the actual incidence of defaults using cumulative default functions (that is, the percent of original loans that default by loan age $t$).

The 2004 and 2005 vintages differ on many dimensions: underwriting standards, the geographic mix of loans originated, oil price shocks experienced, and so on. However, the key difference is in the fraction of active loans in each vintage that experienced the home 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, but those on the 2005 vintage skyrocketed. Thus, the comparison of the 2004 and 2005 vintages provides a tougher test of a model's ability to predict defaults. Any differences we find here would be larger when comparing vintages further apart; for example, the 2003 vintage experienced much greater and more sustained home price gains than did the 2006 vintage.

Figure 7 displays the results of this vintage simulation exercise. The model overpredicts defaults among the 2004 vintage and underpredicts defaults among the 2005 vintage. It estimates that after 36 months, 9.3 percent of the 2005 vintage would have defaulted, but only 7.9 percent of the 2004 vintage, an increase of 18 percent. Although 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.

Cash flows from a pool of mortgages are greatly affected by prepayments. Loans that are prepaid (because the underlying borrower refinanced or moved) deliver all unpaid principal to the lender, as well as, in some cases, prepayment penalties. Further, loans that are prepaid are not at risk for future defaults. As the bottom panel of figure 7 shows, predicted prepayment rates fell dramatically from the 2004 to the 2005 vintage. The model predicted that 68 percent of loans originated in 2004, but only

**Figure 7.** Default and Prepayment Simulations for the 2004 and 2005 Mortgage Vintages Using ABS Data[a]




Sources: First American LoanPerformance; authors' calculations.

a. Simulations assume perfect foresight about home prices, interest rates, oil prices, and unemployment rates.

57 percent of loans originated in 2005, would have prepaid by month 36, 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.

To further investigate the effect of home prices on the model estimated here, we compute the conditional default and prepayment rates for the generic hybrid 2/28 mortgage analyzed 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 home prices. We let home prices, oil prices, unemployment rates, and so on proceed as they did in 2004–06. We then keep everything else constant but replace 2004–06 home prices with their 2006–08 trajectories. The resulting conditional default and prepayment rates are shown in figure 8. For this type of mortgage at least, the sensitivity to home price changes is extreme. The gap between the default probabilities increases over time because, again, home prices operate through the mark-to-market CLTV ratio, and this particular loan started with a CLTV ratio at origination of just over 80 percent. The gyrations in default and prepayment probabilities around month 24 are associated with the loan's first interest rate reset.

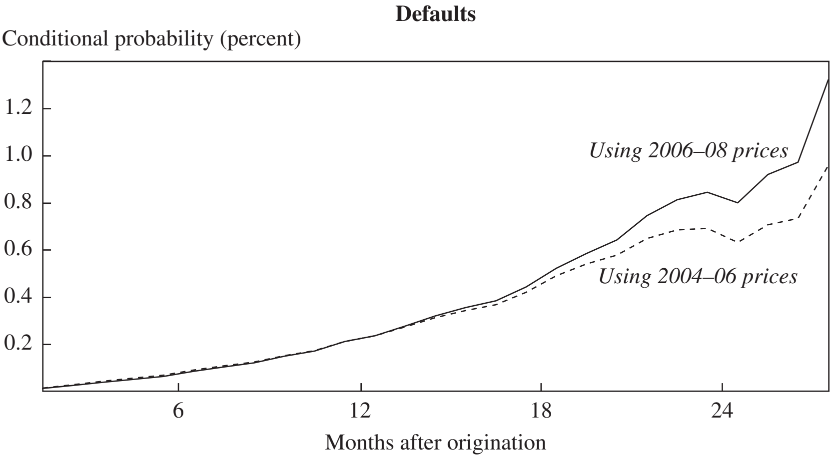
### *Forecasts Using the Registry of Deeds Data*

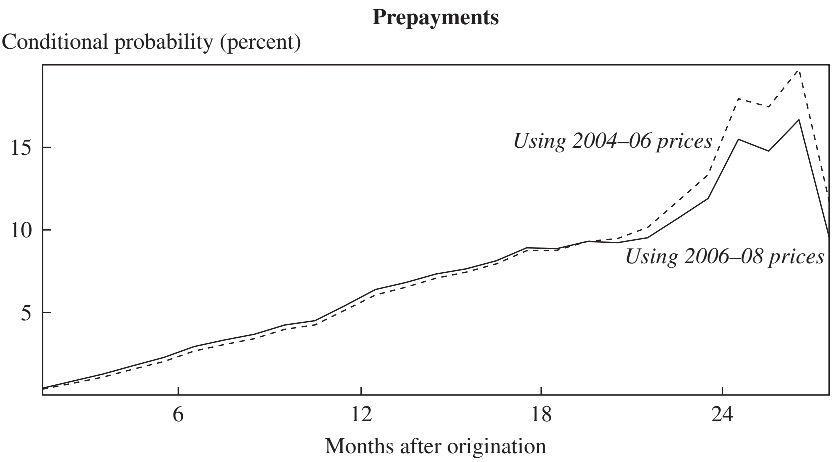
In this subsection we use data from the Warren Group, which collects mortgage and housing transaction data from Massachusetts registry of deeds offices, to analyze the foreclosure crisis in Massachusetts and to determine whether a researcher armed with these data at the end of 2004 could have successfully predicted the rapid rise in foreclosures that followed. We focus on the state of Massachusetts 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 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 not mortgage terms or borrower characteristics. The data do identify the mortgage lender, which enables us to construct indicators for mortgages originated by subprime lenders.

These data allow us to construct a panel dataset of homeowners, each of whom we can follow from the date when they purchase the home to the date when they either sell the home, experience a foreclosure, or reach the end

**Figure 8. Effect of Changing Home Prices on a Generic 2/28 Mortgage**[a]




Source: Authors' calculations using the model described in the text.

a. Probabilities are those in month *t* conditional on surviving to month *t* – 1, estimated for a generic 2/28 subprime mortgage with the characteristics described in the base case in table 7. It is assumed that all dynamic variables follow their 2004–06 trajectories except for home prices, which follow either their 2004–06 or their 2006–08 trajectories as indicated.

of our sample. We use the term "ownership experience" to refer to this time period.[17] Since the data include all residential sale transactions, we are also able to construct a collection of town-level, quarterly, weighted repeat-sales indexes using the methodology of Karl Case and Robert Shiller.[18]

We use a slightly different definition of foreclosure in the deed registry data than in the loan-level analysis above. Here we identify foreclosure through the existence of 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 state foreclosure laws vary greatly, resulting in significant heterogeneity in the time span between the beginning of the foreclosure process and the end.

COMPARISON WITH THE ABS DATA. The deed registry data differ significantly from the ABS data. Whereas the latter track individual mortgages over time, the deed registry data track homeowners in the same residence over time. Thus, with the deed registry data, the researcher can follow the same homeowner across different mortgages in the same residence and determine the eventual outcome of the ownership experience. In contrast, with the ABS data, if the mortgage terminated in a manner other than foreclosure, such as a refinancing 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 argue that analyzing ownership experiences rather than individual mortgages has certain advantages, depending on the question being addressed.[19]

As already noted, another major difference between the deed registry data and the ABS data is the period of coverage. The deed registry data encompass the housing bust of the early 1990s in the Northeast, in which there was a sharp decrease in nominal home prices as well as a significant foreclosure crisis. Figure 9 tracks HPA and the foreclosure rate in Massachusetts since 1987. Foreclosure deeds began to rise rapidly starting in 1991 and peaked in 1992 at approximately 9,300 statewide. The foreclosure rate remained high through the mid-1990s, until nominal HPA became positive in the late 1990s. The housing boom of the early 2000s is

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

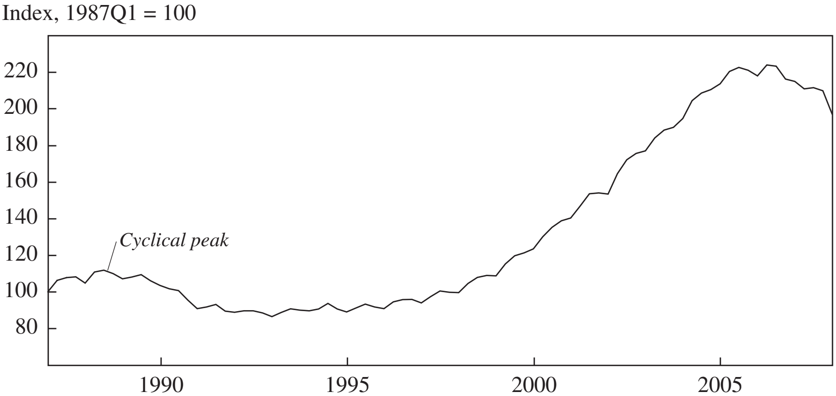
18. Many Massachusetts towns are too small to allow the construction of precise home price indexes. To deal with this issue, we group the smaller towns together based on both geographic and demographic criteria. Altogether, we are able to estimate just over 100 indexes for the state's 350 cities and towns.

19. Gerardi, Shapiro, and Willen (2007).

**Figure 9.** Massachusetts Foreclosure Rate and Home Prices, 1987–2007

**Foreclosure rate**[a]


**Home prices**[b]




Sources: Warren Group; Massachusetts Department of Revenue.

a. Total foreclosures in a given quarter divided by the total number of residential parcels that year, where a parcel is any real unit of property used for the assessment of property taxes, and typically consists of a plot of land defined by a deed and any buildings on that land.

b. Calculated using the Case-Shiller weighted, repeat-sales methodology.

evident, with double-digit annual HPA and extremely few foreclosures. We see evidence of the current foreclosure crisis at the very end of our sample: the number of foreclosure deeds begins rising in 2006 and by 2007 is approaching the levels witnessed in the early 1990s.

The final major difference between the two data sources is in their coverage of the subprime mortgage market. Since the ABS data encompass pools of nonagency MBSs, a subprime mortgage is defined simply as any mortgage contained in a pool of mortgages labeled "subprime." The deed registry data do not reveal whether a mortgage is securitized or not, and thus, we cannot use the same subprime definition. Instead, we match each lender against a list of lenders who originate mainly subprime mortgages; the list is constructed by the Department of Housing and Urban Development (HUD) on an annual basis. The two definitions are largely consistent with each other.[20] Table 11 shows the top ten Massachusetts subprime lenders for each year going back to 1999, as well as the number of subprime loans originated by each lender and by all lenders. The composition of the list does change 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 1999 to 2001 the subprime market consisted mostly of refinancings: in 1999 and 2000 home purchases with subprime mortgages made up only about 25 percent of the Massachusetts subprime market, and only about 30 percent in 2001. By 2004, however, purchases made up almost 78 percent of the subprime mortgage market, and in 2006 they accounted for 96 percent. 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.

EMPIRICAL MODEL. The empirical model we implement is drawn from Gerardi, Shapiro, and Willen and resembles previous models of mortgage termination.[21] 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 certain baseline hazards are 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 refinancings. In the loan-level analysis, a loan that is refinanced drops out of the dataset, because the

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

21. Gerardi, Shapiro, and Willen (2007). Previous models include those of Deng, Quigley, and van Order (2000), Deng and Gabriel (2006), and Pennington-Cross and Ho (2006).

mortgage is terminated. However, in the ownership experience analysis, a borrower who refinances remains in the data. Thus, a borrower who defaults on a refinanced mortgage will show up as a foreclosure in the deed registry dataset, but that borrower's first mortgage will show up in the ABS data as a prepayment, and the second mortgage may or may not show up in the data at all (depending on whether the mortgage was sold into a private-label MBS), but either way, the two mortgages will not be linked together. Thus, for a given number of eventual foreclosures, the ABS data will always show a lower apparent foreclosure rate.

Unlike for mortgage terminations, there is no generally accepted standard baseline hazard for ownership terminations. Thus, we specify both the foreclosure and the sale baseline hazards in a nonparametric manner, using an indicator variable for each year after the purchase of the home. In effect, we model the baseline hazards with a set of age dummies.[22]

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

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

where $CLTV_{i0}$ corresponds to household $i$'s initial CLTV ratio, and $C_{jt}^{HPA}$ corresponds to the cumulative amount of HPA experienced in town $j$ from the date of the home purchase through time $t$.[23] Based on our discussion above of the theory of default, an increase in equity for a borrower in a position of negative nominal home equity should have a significantly different effect from an increase in equity for a borrower with positive nominal equity. For this reason we assume a specification that allows the effect of equity on default to change depending on the borrower's equity. To do

22. Gerardi, Shapiro, and Willen (2007) and Foote, Gerardi, and Willen (2008) use a third-order polynomial in the age of the ownership. The nonparametric specification used here has the advantage of not being affected by the nonlinearities in the tails of the polynomials for old ownerships, but the results for both specifications are very similar.

23. This equity measure is somewhat crude as it does not take into account amortization, cash-out refinancings, or home improvements. See Foote and others (2008a) for a more detailed discussion of the implications of these omissions for the estimates.

**Table 11.** Top 10 Subprime Lenders in Massachusetts, 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[a] | 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 | 2,222 | Option One | 2,773 | 1,000 |
| Summit | 2,021 | 1,948 | New Century | 1,694 | 1,053 | Ameriquest | 2,047 | 287 |
| Freemont | 2,016 | 1,973 | Freemont | 1,519 | 1,089 | 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 | 1,502 | Option One | 2,828 | 1,013 |
| 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 Leader 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 |

Sources: Warren Group; authors' calculations.

a. Totals are for all lenders.

this we specify equity as a linear spline with six intervals: $(-\infty, -10\%)$, $[-10\%, 0\%)$, $[0\%, 10\%)$, $[10\%, 25\%)$, and $[25\%, \infty)$.[24]

Since detailed mortgage and borrower characteristics are not available in the deed registry data, we instead use zip code–level demographic information from the 2000 Census, including median household income and the percentage of minority households in the zip code, and town-level unemployment rates from the Bureau of Labor Statistics. We also include the six-month LIBOR in the list of explanatory variables, to capture the effects of nominal interest rates on sale and foreclosure.[25] Finally, we include an indicator variable for 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 from the prime mortgage market. We emphasize that we do not assign a causal interpretation to this variable. Rather we interpret the estimated coefficient as a correlation that simply reveals the relative frequency of foreclosure for a subprime purchase borrower compared with a borrower who has a prime mortgage.

Table 12 reports summary statistics for the number of new Massachusetts ownership experiences initiated, and the number of sales and foreclosures broken down by vintage. The two most recent housing cycles are clearly evident. Almost 5 percent of ownerships initiated in 1990, but fewer than 1 percent of those in vintages between 1996 and 2002, eventually experienced a foreclosure. Despite 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: between 80,000 and 100,000 ownerships were initiated each year between 1998 and 2006, almost double the number initiated each year in the early 1990s and 2007.

Table 13 reports summary statistics for the explanatory variables included in the model, also broken down by vintage. It is clear from the LTV ratio statistics that homeowners became more leveraged on average over the sample period: median initial CLTV ratios increased from 80 percent in 1990 to 90 percent in 2007. Even more striking, the percentage of CLTV ratios 90 percent or greater almost doubled, from approximately 22.5 percent in 1990 to 41.6 percent in 2007. The table also shows both

24. The intervals are chosen somewhat arbitrarily, but the results are not significantly affected by assuming different intervals.

25. We use the six-month LIBOR because 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.

**Table 12. Ownership Outcomes in the Massachusetts Deed Registry Data by Vintage**

| *Vintage* | *No. of new ownerships* | *Percent ending in foreclosure* | *Percent ending in 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 |

Sources: Warren Group; authors' calculations.

direct and indirect evidence of the increased importance of the subprime purchase mortgage market. The last column of the table reports the percentage of borrowers who financed a home purchase with a subprime mortgage in Massachusetts: fewer than 4 percent of new owners did so before 2003, but in that year the share increased to almost 7 percent, and in 2005, at the peak of the subprime market, it reached almost 15 percent. 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) has increased over time, as has the number of ownerships coming from lower-income zip codes.

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 predict foreclosure probabilities for the 2004 and 2005 vintages of subprime and prime borrowers, and we compare the predicted probabilities with the actual foreclosure outcomes of those vintages. The first sample encompasses the entire span of the data, from 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

**Table 13. Summary Statistics of the Massachusetts Deed Registry Data by Vintage[a]**

| Vintage | *Initial CLTV ratio* Median (percent) | *Initial CLTV ratio* Percent ≥ 90% | *Percent minority borrowers* Median | *Percent minority borrowers* Mean | *Median income of owner (dollars)* Median | *Median income of owner (dollars)* Mean | *Percent condos (mean)* | *Percent multifamily (mean)* | *Percent of subprime loans for purchase (mean)* |
|---|---|---|---|---|---|---|---|---|---|
| 1990 | 80.0 | 22.54 | 8.52 | 14.59 | 54,897 | 57,584 | 19.41 | 10.21 | 0.00 |
| 1991 | 80.0 | 24.20 | 7.98 | 13.39 | 56,563 | 59,784 | 17.08 | 7.69 | 0.00 |
| 1992 | 80.0 | 26.05 | 7.76 | 13.00 | 56,879 | 60,217 | 15.02 | 7.89 | 0.01 |
| 1993 | 84.9 | 30.47 | 7.77 | 13.33 | 56,605 | 59,714 | 14.77 | 8.86 | 0.10 |
| 1994 | 87.2 | 32.90 | 7.98 | 13.79 | 55,880 | 58,848 | 14.87 | 10.15 | 0.39 |
| 1995 | 87.4 | 35.29 | 8.26 | 14.49 | 55,364 | 58,089 | 16.01 | 10.97 | 0.43 |
| 1996 | 87.1 | 35.22 | 8.25 | 14.22 | 55,364 | 58,076 | 16.98 | 10.41 | 0.91 |
| 1997 | 85.0 | 33.87 | 8.26 | 14.39 | 55,358 | 57,864 | 17.64 | 10.59 | 1.92 |
| 1998 | 85.0 | 33.41 | 8.25 | 14.20 | 54,897 | 57,394 | 18.90 | 10.40 | 2.56 |
| 1999 | 85.0 | 33.28 | 8.63 | 14.88 | 54,677 | 56,742 | 20.15 | 11.11 | 2.43 |
| 2000 | 82.4 | 31.67 | 8.65 | 14.96 | 54,402 | 56,344 | 21.55 | 11.17 | 2.43 |
| 2001 | 85.0 | 34.42 | 8.63 | 14.98 | 53,294 | 55,524 | 21.34 | 11.46 | 2.89 |
| 2002 | 82.0 | 32.32 | 9.14 | 15.25 | 53,357 | 55,672 | 22.63 | 11.14 | 3.88 |
| 2003 | 85.0 | 34.47 | 9.14 | 15.51 | 53,122 | 55,337 | 22.68 | 11.20 | 6.86 |
| 2004 | 86.6 | 35.68 | 9.66 | 16.42 | 52,561 | 55,017 | 24.48 | 11.85 | 9.99 |
| 2005 | 89.9 | 39.40 | 10.19 | 17.07 | 52,030 | 54,231 | 28.29 | 11.83 | 14.81 |
| 2006 | 90.0 | 41.65 | 9.92 | 17.10 | 51,906 | 54,326 | 28.09 | 10.80 | 12.96 |
| 2007 | 90.0 | 41.62 | 9.92 | 16.64 | 53,122 | 55,917 | 29.95 | 8.54 | 3.95 |

Sources: Warren Group, U.S. Census Bureau, and authors' calculations.

a. All statistics except CLTV ratios are calculated from data at the zip code level. Medians and means reported are those of the median or the mean of all zip codes in the sample.

vintage ownerships were initiated. This period covers two housing downturns in the Northeast, and thus two periods in which many households found themselves with negative equity. From the peak of the market in 1988 to the trough in 1992, nominal housing prices (based on our index) fell by more than 20 percent statewide, implying that even some borrowers who put 20 percent down at the time of purchase found themselves with negative equity at some point in the early 1990s. For 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 using only data that would have been available to a researcher in 2004 to estimate the model. Thus, with this exercise we are asking 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.[26] However, it includes a relatively small number of ownerships involving the purchase of a home with a subprime mortgage. It is clear from table 11 that the peak of the subprime purchase mortgage market occurred in 2004 and 2005. Thus, although the 1990–2004 sample period does include a significant housing price decline, it does not include the peak of the subprime market. Furthermore, we presented evidence earlier 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 to have different characteristics than 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 HPA, as can clearly be seen in figure 9. Home 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.

ESTIMATION RESULTS. Unlike our loan-level analysis, which was estimated at a monthly frequency, our proportional hazard model is estimated at a quarterly frequency, because that is the frequency of the town-level

26. See Foote and others (2008a) for a more detailed analysis of Massachusetts homeowners with negative equity in the early 1990s.

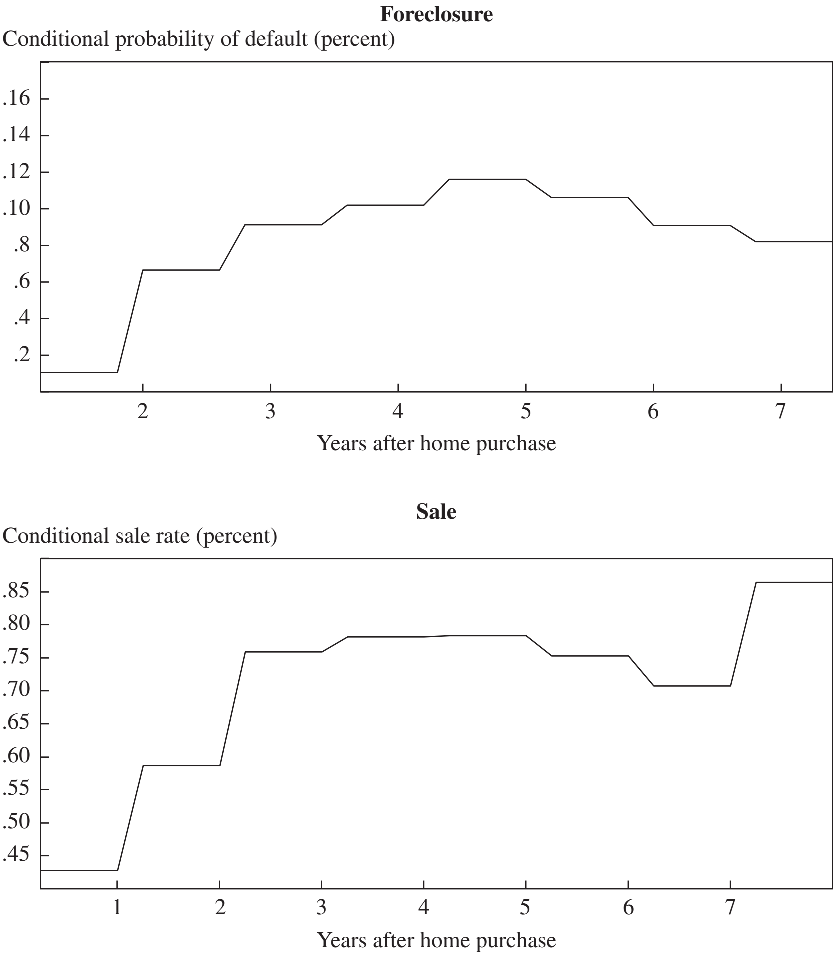
home price indexes. The model is estimated using the maximum likelihood method. Since we are basically working with a panel dataset containing the entire population of Massachusetts homeowners, the number of observations is too large to conduct the estimation. Thus, to facilitate computation, we use a random sample of ownerships for each sample (10 percent for the 1990–2007 sample, 10 percent for the 1990–2004 sample, and 25 percent for the 2000–04 sample). Finally, we truncate ownerships that last longer than eight years, for two reasons. First, there are relatively few of these long ownerships, which would result in imprecise estimates of the baseline hazard. Second, because information regarding equity withdrawal upon refinancing is unavailable, the equity measure becomes more biased as the length of the ownership experience increases.[27]

Figure 10 displays the estimates of the baseline hazards for both foreclosures and sales. The foreclosure baseline is hump-shaped, reaching 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, after which it resumes its rise. Table 14 reports the parameter estimates for the foreclosure hazard.[28] For the most part, the signs on the estimated coefficients are intuitive and consistent with economic theory. Higher interest and unemployment rates tend to raise foreclosures (the coefficients on these variables are positive), although the coefficient estimate associated with the LIBOR variable 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. In the full sample and in the 1990–2004 sample, borrowers who purchase a condominium or a multifamily property are more likely to experience a foreclosure than borrowers who purchase a single-family home. 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 housing stocks in many of the economically depressed cities in Massachusetts are disproportionately made up of multifamily properties. In the 2000–04 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 incomes are more likely to experience a foreclosure.

27. The estimation results are not very sensitive to this eight-year cutoff. A seven-year or a nine-year cutoff produces almost identical results.

28. For brevity we do not report the parameter estimates for the sale hazard. They are available upon request from the authors.

**Figure 10.** Estimates of Baseline Hazards




Source: Authors' calculations.

Table 15 explores the quantitative implications of the parameter estimates. The table reports the effect of a change in each of several selected variables (by one standard deviation for continuous variables, and from zero to one for dummies) on the probability of foreclosure. For example, the column for the 1990–2007 sample shows that a homeowner who purchased a home with a subprime mortgage is approximately 7.3 times as likely to default, all else equal, as a homeowner who purchased with a prime mortgage, and 1.1 times as likely to experience a foreclosure if the

**Table 14. Regressions Estimating Foreclosure Hazard Using Massachusetts Deed Registry Data[a]**

| | *1990–2007 sample* | | *1990–2004 sample* | | *2000–04 sample* | |
|---|---|---|---|---|---|---|
| *Independent variable* | *Coefficient* | *Standard error* | *Coefficient* | *Standard error* | *Coefficient* | *Standard error* |
| Initial LTV ratio | –0.27 | 0.19 | –1.40 | 0.22 | –0.82 | 1.71 |
| 6-month LIBOR | $1.96e^{-02}$ | $1.39e^{-02}$ | $-3.09e^{-02}$ | $1.52e^{-02}$ | 0.18 | 0.11 |
| Unemployment rate | $4.74e^{-02}$ | $6.00e^{-03}$ | $5.03e^{-02}$ | $6.14e^{-03}$ | $7.70e^{-02}$ | $5.24e^{-03}$ |
| Percent minority[b] | $9.23e^{-03}$ | $1.03e^{-03}$ | $1.09e^{-02}$ | $1.20e^{-03}$ | $6.30e^{-03}$ | $4.31e^{-.03}$ |
| Median income[b] | $-1.60e^{-05}$ | $1.82e^{-06}$ | $-1.71e^{-05}$ | $2.05e^{-06}$ | $-6.90e^{-05}$ | $1.03e^{-05}$ |
| *Indicator variables* | | | | | | |
| Condo | 0.33 | 0.05 | 0.44 | 0.05 | –1.19 | 0.35 |
| Multifamily property | 0.54 | 0.05 | 0.54 | 0.06 | –0.24 | 0.20 |
| Subprime purchase | 1.99 | 0.06 | 1.21 | 0.19 | 1.70 | 0.21 |
| No. of observations | 3,005,137 | | 2,365,999 | | 813,802 | |

Source: Authors' regressions.

a. Coefficient estimates are for the foreclosure hazard function from a competing-risks duration model. The model is estimated at a quarterly frequency using the maximum likelihood method.

b. From 2000 Census zip code–level data.

**Table 15. Standardized Elasticities Derived from Estimates Using Massachusetts Deed Registry Data**

| | | *Factor change in hazard* | | |
|---|---|---|---|---|
| *Variable* | *Change in the variable* | *1990–2007* | *1990–2004* | *2000–04* |
| Unemployment rate | + 1 SD[a] (2.06) | 1.10 | 1.12 | 1.17 |
| Percent minority[b] | + 1 SD (19.58) | 1.20 | 1.24 | 1.13 |
| Median income[b] | − 1 SD ($24,493) | 1.49 | 1.53 | 5.60 |
| *Indicator variables* | | | | |
| Multifamily | From 0 to 1 | 1.72 | 1.72 | 0.79 |
| Condo | From 0 to 1 | 1.39 | 1.55 | 0.30 |
| Subprime purchase | From 0 to 1 | 7.32 | 3.35 | 5.47 |

Source: Authors' calculations.
a. SD, standard deviation.
b. From 2000 Census zip code-level data.

unemployment rate is 1 standard deviation above the average. The functional form of the proportional hazard model implies that the effects of these different changes affect the hazard multiplicatively. For example, the combined effect of a subprime purchase ownership and 1-standard-deviation-higher unemployment is $7.3 \times 1.1 = 8.0$.

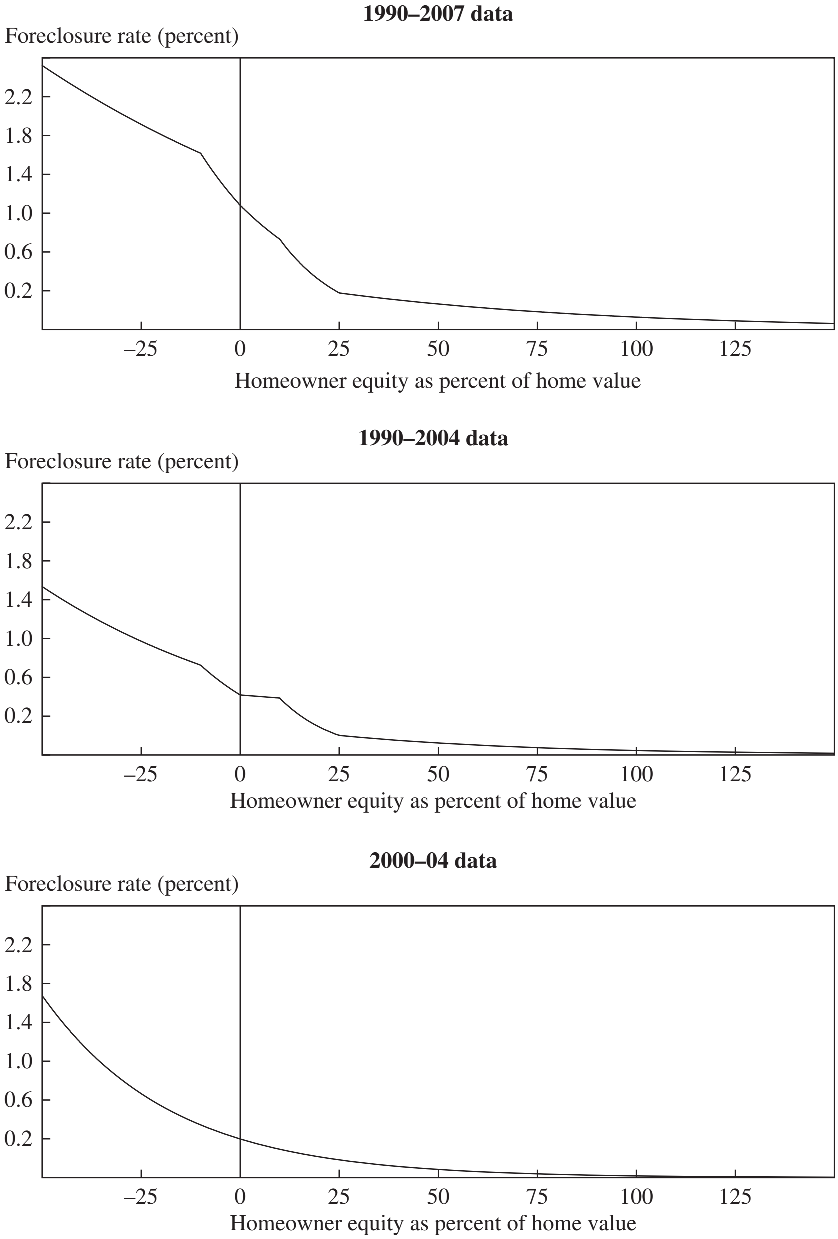
The results for the different sample periods in table 15 differ in interesting ways, most notably associated with the estimate of the subprime purchase indicator. As noted, for the full sample period, subprime purchase ownerships are more than seven times as likely to end in foreclosure, but in the earlier subsample period (1990–2004), they are only 3.4 times as likely. Our analysis above suggests that this difference likely reflects differences in mortgage and borrower characteristics between the two samples. For example, increases in debt-to-income ratios and in 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, other explanations are possible, such as a deterioration in unobservable, lender-specific underwriting characteristics. Another possibility is a higher sensitivity to declining home prices relative to prime purchase ownerships. Although the subprime market existed in the early 1990s, most of the activity, as noted above, came in the form of refinancings. Thus, few subprime purchase ownerships from the 1990–2004 sample actually experienced a significant decline in home prices, whereas the vast majority of subprime ownerships took place in 2004 and 2005, and many of these were exposed to large price declines. Subprime purchases in the 2000–04 sample perform better than the full sample but worse than the 1990–2004 sample: they are approximately 5.5 times as likely to experience a foreclosure.

Since housing equity $E_{it}$ is estimated with a spline, the estimates are not shown in table 15. Instead, figure 11 graphs the predicted foreclosure hazard as a function of equity relative to a baseline subprime purchase ownership. The covariates for the baseline ownership have been set to their full sample averages. There were virtually no equity values below zero in the 2000–04 sample from which to estimate the spline, so instead we were forced to use a single parameter.

What the figure reveals 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 either are in financial distress or need to move for another reason are not likely to default, since they are better off selling their home 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's commission (usually 6 percent of the sale price) and 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 nonlinear relationship is similar for the full sample and for the 1990–2004 sample. The scale is higher and the nonlinearity more pronounced in the full sample, which includes the recent foreclosure crisis. But perhaps the most surprising observation from figure 11 is the shape of the predicted hazard from the 2000–04 sample (bottom panel). Although the predicted hazard is necessarily smooth because of the single parameter that governs the relationship, its shape and scale are very similar to those of 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 the positive variation in equity, and then extrapolate to negative equity values and obtain findings that are similar to those obtained using a sample that includes housing price declines. This is, of course, in part due to the nonlinear functional form of

**Figure 11.** Estimated Effect of Equity Share on Foreclosure Rate




Source: Authors' calculations.

the proportional hazard model and would be impossible in a linear framework (for example, a linear probability model). The implications of this observation for forecasting ability are discussed below.

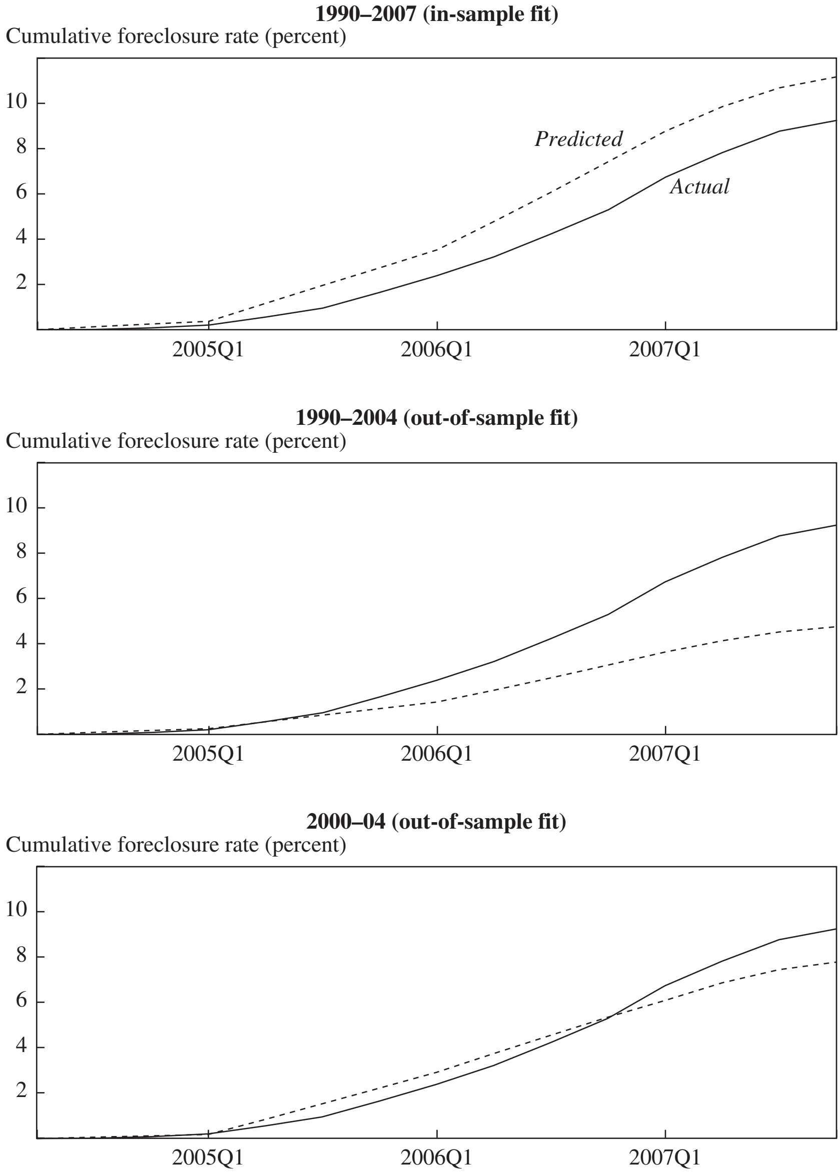
SIMULATION RESULTS. With the estimated parameters in hand, we turn to the question of how well the model performs, both in sample and out of sample. In this exercise we focus on the 2004 and 2005 vintages of subprime purchase borrowers—a choice motivated by performance as well as by data availability. The summary statistics in table 12 suggested that the 2004 vintage was the first to suffer elevated foreclosure levels in the current housing crisis, and the 2005 vintage is experiencing even higher foreclosure numbers. Unfortunately, we do not yet have enough data 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 2007Q4. We then aggregate the individual predicted probabilities to obtain cumulative foreclosure probabilities for each vintage, and we compare these with the probabilities that actually occurred.[29] Figures 12 and 13 display the results for the 2004 and 2005 subprime purchase vintages, respectively.

The model consistently overpredicts foreclosures for the 2004 subprime vintage (top panel in figure 12) in the full sample: approximately 9.2 percent of ownerships of that vintage had succumbed to foreclosure as of 2007Q4, whereas 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 sample periods. The model estimated using data from 1990 to 2004 (middle panel) is able to account for a little over half of the foreclosures experienced by the 2004 vintage, whereas the model estimated using data from 2000 to 2004 (bottom panel) accounts for almost 85 percent of the foreclosures. The better fit of the latter can likely be attributed to the larger coefficient estimate on the subprime purchase indicator variable for the 2000–04 sample than on that for the 1990–2004 sample (table 14). Figure 13 reveals 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

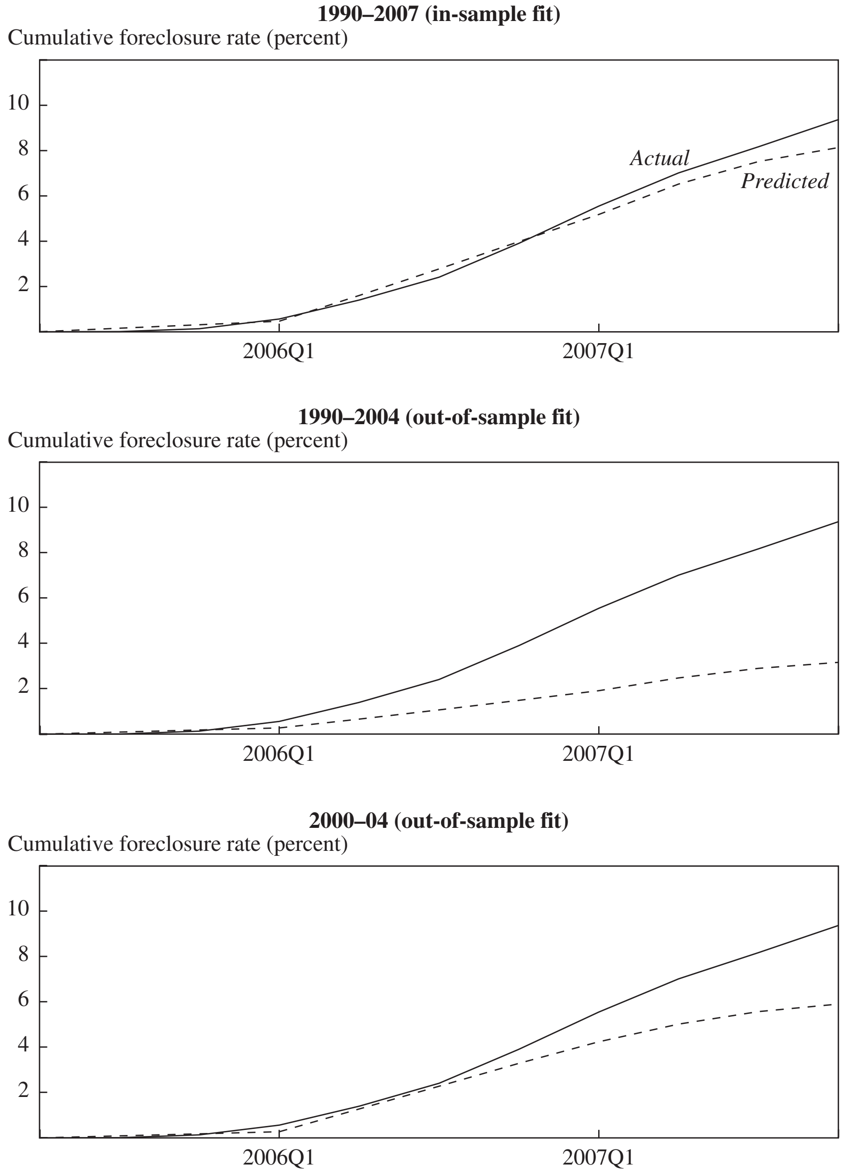
29. See Gerardi, Shapiro, and Willen (2007) for more details.

**Figure 12.** Foreclosure Simulations for the 2004 Subprime Purchase Vintage




Source: Authors' calculations.

**Figure 13.** Foreclosure Simulations for the 2005 Subprime Purchase Vintage




Source: Authors' calculations.

one-third of the foreclosures experienced by the 2005 subprime vintage; the 2000–04 forecast does better, accounting for more than 60 percent.

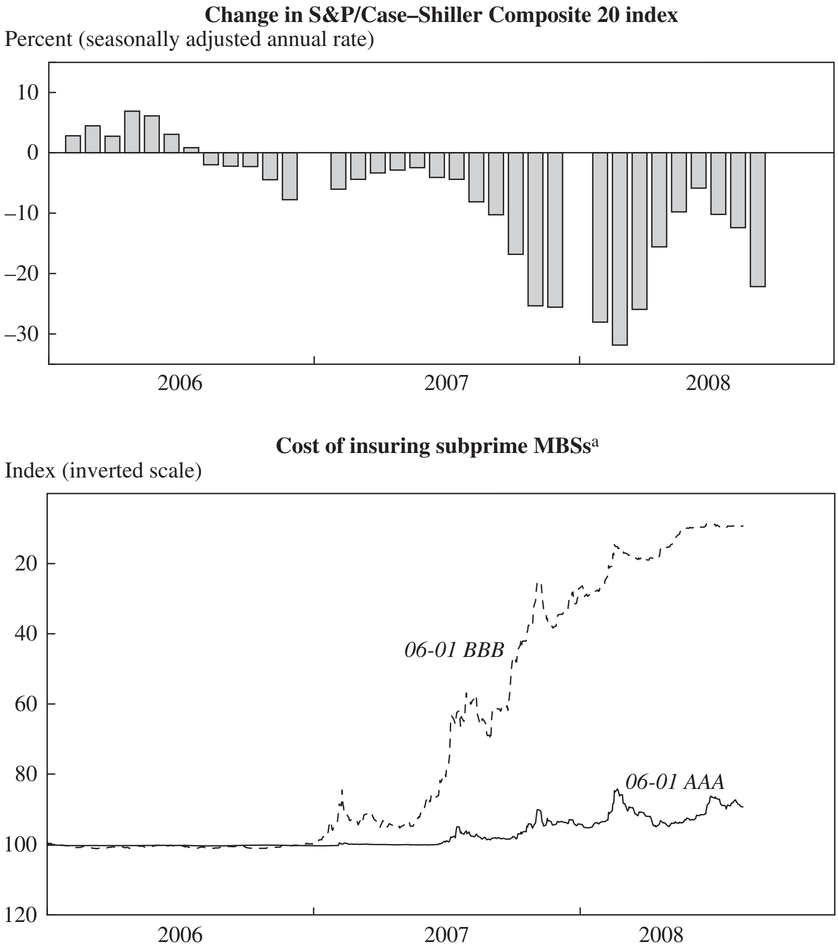
To summarize, the model estimated using data from the 2000–04 vintages does very well at predicting 2005–07 out-of-sample foreclosures for the 2004 vintage of subprime purchase borrowers, accounting for approximately 85 percent of cumulative foreclosures in 2007Q4. The model does not perform quite as well for the 2005 vintage, accounting for only 63 percent of cumulative foreclosures in 2007Q4. There are significant differences in the performance of the model estimated using data from different sample periods. The model estimated using the 2000–04 sample performs much better than the model estimated using the 1990–2004 sample, despite the fact that only the latter sample period includes a decline in housing prices. Figure 11 suggests that 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.

## What Were Market Participants Saying 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. Because we are interested in the behavior of the investment community as a whole more than of individual institutions, we have chosen not to identify the five major banks we discuss (J. P. Morgan, Citigroup, Morgan Stanley, UBS, and Lehman Brothers) individually, but rather by alias (Bank A, Bank B, and so on).[30] Five basic themes emerge. First, market insiders viewed the subprime market as a great success story in 2005. Second, subprime mortgages were viewed, in some sense correctly, as actually posing lower risk than prime mortgages because of their more stable prepayment behavior. Third, analysts used fairly sophisticated tools to evaluate these mortgages but were hampered by the absence of episodes of falling prices in their data. Fourth, many analysts anticipated the possibility of a crisis in a qualitative way, laying out in various ways a roadmap of what could happen, but never

30. Researchers interested in verifying the sources should contact the authors.

**Figure 14.** Home Price Appreciation and Cost of Insuring Subprime-Backed Securities, 2006–08




Sources: Haver Analytics; Markit.
a. ABX-HE indexes of AAA- and BBB-rated MBSs issued in late 2005.

fleshed out the quantitative implications. Finally, analysts were remarkably optimistic about HPA.

Figure 14 provides a timeline for this discussion. The top panel shows HPA during 2006–08 using the S&P/Case-Shiller Composite 20 index. In the first half of 2006, 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, however, HPA was negative, although given the reporting lag in the Case-Shiller numbers, market participants would not have had this data point until the end of the fourth quarter. The bottom panel tracks 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 MBSs issued in the second half of 2005 and containing mortgages originated throughout 2005. (The series are inverted so that a rise in the cost of insurance—a fall in the index—is plotted as a rise.) 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 2007, 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.

### *The 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 mortgage loan."[31] Analysts also noted that the credit quality of the typical subprime borrower had improved: the average FICO score of subprime borrowers had risen consistently from 2000 to 2005.[32] 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 borrower of the late-1990s has been replaced by the average American homeowner."[33]

Lenders had improved as well. Participants drew a distinction between the somewhat disreputable subprime lenders of the mid- to late 1990s and the new generation of lending institutions, which they saw as well capitalized and well run: "The issuer and servicer landscape in the [home

31. Bank A, October 20, 2005.
32. Bank A, October 20, 2005, and Bank E, February 15, 2005.
33. Bank A, October 20, 2005 (emphasis in original).

equity loan] 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."[34] The new lenders, analysts believed, could weather a storm: "Today's subprime issuers/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."[35] 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 of "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 risks."[36]

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 power to predict credit problems. In particular, statistical evidence showed that FICO scores, when combined with LTV ratios, could "explain a large part of the credit variation between deals and groups of sub-prime loans."[37] 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 sub-prime home equity security backed by 2001 and 2002 (or later vintage) loans is much more likely to get the advertised performance than via buying a deal from earlier years.*"[38] 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.[39] And as late as 1998, one observer points

34. Bank A, October 20, 2005. Here and elsewhere, "home equity loan" is the term typically used by market participants for either a junior lien to a prime borrower or a 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.

35. Bank E, January 31, 2006.

36. Bank A, October 20, 2005.

37. Bank E, February 15, 2005.

38. Bank E, February 15, 2005 (emphasis in original).

39. Mester (1997).

**Table 16. Outcomes of S&P Ratings of Mortgage-Backed Securities, 1978–2004**

| *Rating* | *No. rated* | *Percent subsequently upgraded* | *Percent subsequently downgraded* | *Percent defaulting* |
|---|---|---|---|---|
| AAA | 6,137 | NA | 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 |

Source: Standard & Poor's, "Rating Transitions 2004: U.S. RMBS Stellar Performance Continues to Set Records," January 21, 2005.

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.[40]

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."[41]

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. Standard & Poor's, for example, used a database "which compiles the loan level and performance characteristics for every RMBS [residential mortgage-backed securities] transaction that we have rated since 1998."[42] Market participants appeared to put a lot of weight on the historical stability of home equity loan credit ratings.[43] And indeed, through 2004 the record of the major rating agencies was solid. Table 16, which summarizes Standard & Poor's record from their first RMBS rating in 1978 to the end of 2004, shows that the probability of a downgrade was quite small and far smaller than the probability of an upgrade.

### *Prepayment Risk*

Many investors allocated appreciable fractions of their portfolios to the subprime market because, in one key sense, it was considered less risky

40. Bank E, February 15, 2005.
41. Bank A, December 16, 2003.
42. "A More Stressful Test of a Housing Market Decline on U.S. RMBS," Standard & Poor's, May 15, 2006, p. 3.
43. Bank A, October 20, 2005.

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-interest-rate loans. Thus, the sensitivity to interest rate changes of the income stream from a pool of subprime loans was lower than that of a pool of prime mortgages. According to classical finance theory, one could even argue that subprime loans were less risky in an absolute sense. Although 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 (as distinct from its sensitivity to interest rate changes) of subprime loans is quite high, reflecting the fact that borrowers with such loans often 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 behavior 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 highly correlated with interest rate shocks. Thus, Bank A analysts wrote in 2005 that "[subprime] prepayments are more stable than prepayments on prime mortgages, adding appeal to [subprime] securities."[44]

A simple way to see the difference in prepayment behavior between 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,[45] the minimum CPR they reported was 18 percent for subprime fixed-rate mortgages and 29 percent for subprime ARMs. By contrast, for Fannie Mae mortgages the minimums were 7 percent 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, however, the maximum CPRs for subprime fixed-rate and ARM borrowers were 41 percent and 54 percent, respectively, compared with 58 percent and 53 percent, respectively, for Fannie Mae borrowers. The lower CPR for subprime borrowers reflects, at least in part, the prevalence of prepayment penalties: more

44. Bank A, October 20, 2005.
45. Bank A, October 20, 2005.

than 66 percent of subprime borrowers face such penalties. Historically, the prepayment penalty period often lasted five years, but in most cases it had shortened to two for ARMs and three for fixed-rate mortgages by 2005.

### *Data*

Correctly modeling (and thus pricing) prepayment and default risk requires good underlying data. Thus, market participants have 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, but these data, for the most part, did not include any examples of sustained price declines. The databases relied on by the analysts in their reports have relatively short histories. And the problems were particularly severe for subprime loans, since there essentially were none before 1998. To add to the problems, analysts believed that the experiences 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 home 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 range of current LTV ratios examined was "> 70%."[46] The worst case examined in a Bank E analyst report in the fall of 2005 was one that assumed 0–5 percent annual HPA.[47]

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 2003: "Because of the strong home price appreciation over the past five years, high LTV buckets of loans thin out fast, limiting the history."[48] And they knew this was a problem. A Bank A analyst wrote in June 2005: "We do not project losses with home appreciation rates below –2.5%, because the data set on which the model was fitted contained no meaningful home price declines, and few loans with LTVs in the high-90%. Therefore, model projections for scenarios that take LTVs well above 100% are subject to significant uncertainty."[49]

46. Bank A, March 17, 2004.
47. Bank E, December 13, 2005.
48. Bank A, December 16, 2003.
49. Bank A, June 3, 2005.

However, at some point some analysts overcame these problems. In a debate that we discuss in more detail below, Standard & Poor's and Bank A analysts considered scenarios with significant declines in home prices. A Standard & Poor's report in September 2005 considered a scenario in which home prices fell on the coasts by 30 percent and in the interior of the country by 10 percent.[50] Bank A analysts examined the same scenario, illustrating that by December they were able to overcome the lack of meaningful price declines identified in June.[51]

### The Role of HPA

Market participants clearly understood that HPA played a central role in the dynamics of foreclosures. They identified at least four 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 refinancing activity and prepayment speeds for untroubled borrowers, which also reduced losses. Third, they knew that 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 greater losses.

The role of HPA in preventing defaults was thus 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: "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."[52] The "double-trigger" theory of default was the prevailing wisdom: "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 larger equity stakes."[53]

50. "Simulated Housing Market Decline Reveals Defaults Only in Lowest-Rated US RMBS Transactions," Standard & Poor's, September 13, 2005.

51. Bank A, December 2, 2005.

52. Bank A, October 20, 2005; see also Bank E, December 13, 2005.

53. Bank A, December 2, 2005.

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 home price appreciation. Slower prepayments extend the time a loan is outstanding and exposed to default risk."[54] The analyst claimed that a fall in HPA from 15 percent to −5 percent would reduce the CPR, the annualized prepayment rate of the loan pool, by 21 percentage points.

Analysts seem to have understood both that the high HPA of recent years accounted for the exceptionally strong performance of recent vintages, and that lower HPA represented a major risk going forward. As 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."[55] A Bank C analyst wrote, "The boom in housing translated to a buildup 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 [home equity loan] ABS vintages."[56] 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 [industry] conference would have removed all doubts. Virtually every speaker, whether talking about prepayments or mortgage credit, focused on the impact of home prices."[57]

Analysts did attempt to measure the quantitative implications of slower HPA. In August 2005, analysts at Bank B evaluated the performance of 2005 deals in five HPA scenarios. In their "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 index, which are 2005 deals, are between 17 and 22 percent, depending on the assumptions.[58]

The lack of examples of price declines in their data thus did not prevent analysts from appreciating the importance of HPA, consistent with the

54. Bank A, December 2, 2005.
55. Bank E, December 13, 2005.
56. Bank C, April 11, 2006.
57. Bank E, November 1, 2005.
58. See Bank B, August 15, 2005, and Bank C, August 21, 2008.

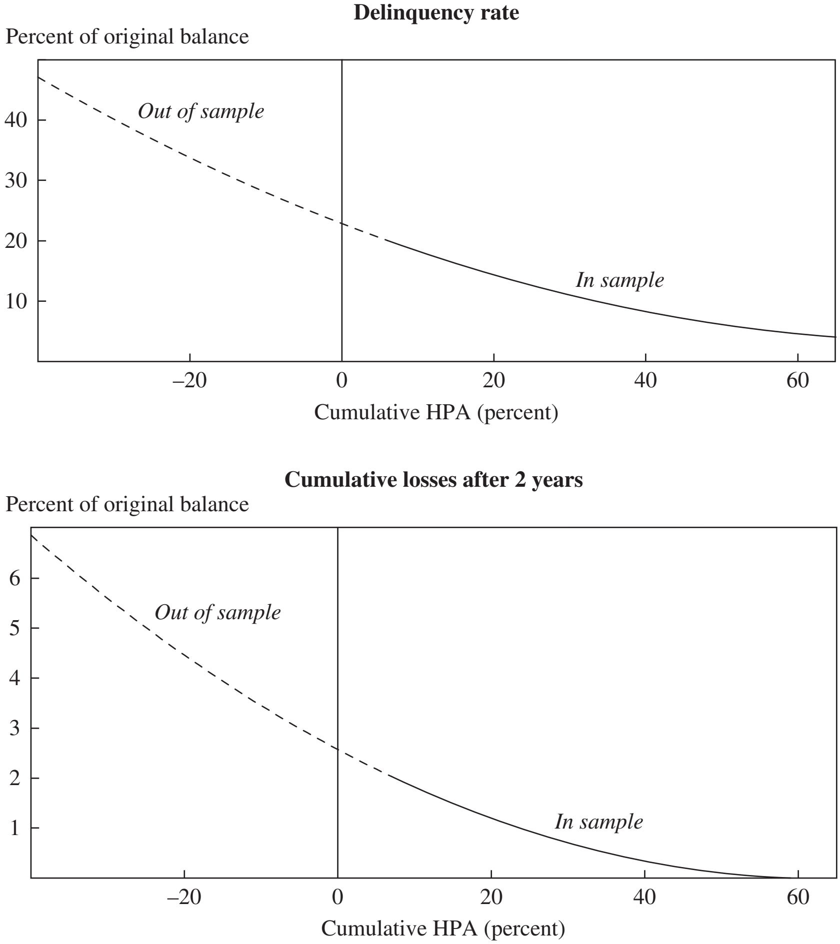
results of the previous section. In an April 2006 report, analysts at Bank C pointed out that the cross section of metropolitan areas illustrated the importance of HPA: "The areas with the hottest real estate markets experienced low single-digit delinquencies, minimal . . . losses, [and] low loss severity . . . a sharp contrast to performance in areas at the low end of HPA growth."[59] At that time Greeley, Colorado, had 6 percent HPA since origination and 20 percent delinquency. At the other extreme was Bakersfield, California, with 88 percent HPA and 2 percent delinquency. Bank C's estimated relationships between delinquency rates and cumulative loss rates, on the one hand, and cumulative HPA since origination, on the other, using the 2003 vintage, are plotted in figure 15. Even in their sample, there was a dramatic difference between low and high levels of cumulative HPA. But if the analysts had looked at predicted values, they would have predicted dramatic increases in both delinquencies. If they had used the tables to forecast delinquencies in May 2008 with a 20 percent fall in house prices (roughly what happened), they would have predicted a 35 percent delinquency rate and a 4 percent cumulative loss rate. The actual numbers for the 2006-1 ABX are a 39 percent delinquency rate and a 4.27 percent cumulative loss rate.[60]

What is in some ways most interesting is that some analysts seem to have understood that the problems might extend beyond greater losses on some subprime MBSs. In the fall of 2005, Bank A analysts mapped out almost exactly what would happen in the summer of 2007, but the analysis is brief and not the centerpiece of their report. They start by noting, "As of November 2004, only three AAA-rated RMBS classes have ever defaulted. . . ."[61] And, indeed, as of this writing almost no AAA-rated MBSs have defaulted. But the analysts 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."[62]

The only exception to the claim that analysts understood the magnitude of $\mathrm{d}f/\mathrm{d}p$ comes from the rating agencies. As a rating agency, Standard &

59. Bank C, April 11, 2006.
60. Citi, "ABX Monthly—September 2008 Remittance," October 1, 2008.
61. Bank A, October 20, 2005.
62. Bank A, October 20, 2005.

**Figure 15.** Bank C's Estimated Relationship between HPA and Delinquency Rates and Cumulative Losses, 2006




Source: Bank C.

Poor's 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 2005, they considered the following:[63]

—a 30 percent home price decline over two years for 50 percent of the pool

63. "Simulated Housing Market Decline Reveals Defaults Only in Lowest-Rated US RMBS Transactions," Standard & Poor's, September 13, 2005.

—a 10 percent home price decline over two years for 50 percent of the pool

—a "slowing but not recessionary economy"

—a cut in the federal funds rate to 2.75 percent, and

—a strong recovery in 2008.

In this scenario they concluded that cumulative losses would be 5.82 percent. Interestingly, their losses for the first three years are around 3.43 percent, which is in line with both of the estimates in figure 15 and the data from deals in the 2006-1 ABX. 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."[64]

Standard & Poor's concluded that none of the investment-grade tranches of MBSs would be affected at all—no defaults or downgrades. In May 2006 they updated their scenario to include a minor recession in 2007, and they eliminated both the rate cut and the strong recovery.[65] 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 Standard & Poor's does not provide detailed information on their model of credit losses, it is impossible not to conclude that their estimates of d$f$/d$p$ were way off. They obviously appreciated that d$f$/d$p$ was not zero, but their estimates were clearly too low.

The problems with the Standard & Poor's analysis did not go unnoticed; Bank A analysts disagreed sharply with it, saying, "Our loss projections in the S&P scenario are vastly different from S&P's projections under the same scenario. For 2005 subprime loans, S&P predicts lifetime cumulative losses of 5.8%, which is less than half our number. . . . We believe that the S&P numbers greatly understate the risk of HPA declines."[66] The irony in this is that both Standard & Poor's and Bank A ended up quite bullish on the subprime market, but for different reasons. The rating agency apparently believed that d$f$/d$p$ was low, whereas most analysts appear to have believed that d$p$/d$t$ was unlikely to fall substantially.

### *Home Price Appreciation*

Virtually everyone agreed in 2005 that the record HPA pace of the immediately preceding years was unlikely to be repeated. However,

64. Bank C, September 2, 2008.

65. "A More Stressful Test of a Housing Market Decline on U.S. RMBS," Standard & Poor's, May 15, 2006.

66. Bank A, December 2, 2005.

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 2005 expressed the prevailing view on home prices: "A slowdown of HPA seems assured."[67] The question was by how much. In that report, the Bank A analysts stated that "the risk of a national decline of home prices appears remote. The annual HPA has never been negative in the United States going back to at least 1972." The authors acknowledge that there had been regional falls but noted, "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 followed from the fact that "few economists predict a near-term recession in the United States"[68] An analyst at Bank D described the future as a scenario in which house prices would "rust but not bust."[69]

In August 2005 Bank B analysts actually assigned probabilities to various home price outcomes.[70] They considered five scenarios:

—an *aggressive* scenario, in which HPA is 11 percent over the life of the pool (with an assigned probability of 15 percent)

—a *modestly aggressive* scenario, with 8 percent HPA over the life of the pool (15 percent)

—a *base* scenario, in which HPA slows to 5 percent by the end of 2005 (50 percent)

—a *pessimistic* scenario, with 0 percent HPA for the next three years and 5 percent HPA thereafter (15 percent), and

—a *meltdown* scenario, with −5 percent HPA for the next three years and 5 percent HPA thereafter (5 percent).

HPA over the relevant period (the three years after Bank B's report) actually came in a little below the −5 percent of the meltdown scenario, according to the S&P/Case-Shiller index. Reinforcing the idea that they viewed the meltdown scenario as implausible, the analysts devoted no time to discussing its consequences, 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 MBSs.

67. Bank A, December 2, 2005.
68. Bank A, December 2, 2005.
69. Bank D, November 27, 2006.
70. Bank B, August 15, 2005.

The belief that home prices could not decline that much 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:[71]

—"More widespread declines with early stabilization signs" (December 8, 2006, reporting data from October 2006)

—"Continuing declines with stronger stabilization signs" (January 10, 2007, data from November 2006)

—"Tentative stabilization in HPA" (February 6, 2007, data from December 2006)

—"Continued stabilization in HPA" (March 12, 2007, data from January 2007)

—"Near the bottom on HPA" (September 20, 2007, data from July 2007)

—"UGLY! Double digit declines in August and September" (November 2, 2007, data from September 2007).

By 2008 Bank C analysts had swung to the opposite extreme, arguing in May, "We expect another 15% drop in home prices over the next 12 months."[72]

However, not everyone shared the belief that a national decline was unlikely. Bank E analysts took issue with the views expressed above, writing, "Those bullish on the housing market often cite the historic data . . . to make the point that only in three quarters since 1975 have U.S. home prices (on a national basis) turned negative, and for no individual year period have prices turned negative,"[73] and pointing out, correctly, that those claims are only true in nominal terms; home prices in real terms had fallen on many occasions.

### *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 $\mathrm{d}f/\mathrm{d}p$ does not appear to have been a problem. In a sense, that more or less implies that failure to accurately predict $\mathrm{d}p/\mathrm{d}t$ 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 since observed in certain states—Arizona, California, Florida, and Nevada—that accounted for a disproportionate share of subprime lending.

71. Bank C, "HPA Update," dates as noted.
72. Bank C, May 16, 2008.
73. Bank E, November 1, 2005.

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

## Conclusion

The subprime mortgage crisis leads one naturally to wonder how important and sophisticated market participants so badly underestimated the credit risk of heterodox mortgages. As we have shown, subprime lending added risk features only incrementally, and the underlying leverage of loans was, at least in some data sources, somewhat obscure. Thus, far from plunging them into uncharted waters, investors may have felt that each successive round of weaker underwriting standards was bringing them increasing comfort.

The buoyant home price environment that prevailed through mid-2006 certainly held down losses on subprime mortgages. Nonetheless, as we have also shown, 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 home 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 in the past by a major price drop, such as Massachusetts in the early 1990s, would have allowed market participants to derive significantly more precise estimates of the likely increase in foreclosures following a drop in home 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 such a decline. However, the results of these models are sensitive to the specification and to the assumptions chosen 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 home price collapse or misunderstood the consequences of such a collapse. Here our reading of the mountain of research reports, media commentary, and other written records left by market participants of the era sheds some light. Analysts were focused on issues such as small differences in prepayment speeds that, in hindsight, appear of secondary importance to the potential credit losses stemming from a home price downturn. When they did consider scenarios with home price declines, market participants, as a whole, appear to have correctly gauged the losses to be expected. 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 home prices, with analysts disagreeing over valuation metrics and even the correct index with which to measure home prices. Thus, at the start of 2005, it was genuinely possible to be convinced that nominal U.S. home prices would not fall substantially.

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# Comments and Discussion

**COMMENT BY**

**DEBORAH LUCAS** In the wake of falling home prices and skyrocketing default rates, seemingly sophisticated investors have lost hundreds of billions of dollars on subprime mortgages. This paper by Kristopher Gerardi, Andreas Lehnert, Shane Sherlund, and Paul Willen provides new evidence on to what extent investors could have anticipated such severe losses, and whether they assigned a reasonable probability ex ante to the events that occurred. The authors also offer an interesting interpretation of their evidence, which is that investors probably understood the sensitivity of foreclosure rates to home price declines but placed a very low probability on a severe, marketwide decline.

What investors believed ex ante has been the subject of considerable debate. Some commentators have argued that it would have been very difficult to foresee the possibility of such large losses. They point to the short time series of available data on subprime performance and the benign default rates over the preceding period. Others claim that investors were poorly informed or even duped about the risk of what they were buying. Investors may not have realized the increased prevalence of highly leveraged properties and low-documentation loans. Further, complex securitization structures may have made the risks opaque to the ultimate investors, who were inclined to rely on credit ratings rather than a careful analysis of the underlying collateral. Reliance on securitization and complicated mechanisms to transfer risk also created agency problems by rewarding originators for increasing loan volumes rather than for prudently screening borrowers. A dissenting point of view, however, is that although investors in the triple-A-rated tranches of subprime mortgage-backed securities (MBSs) may have been genuinely surprised to be hit with losses, the risktolerant investors who bought the junior tranches were making a calculated bet that they understood to be quite risky.

These different viewpoints can be evaluated against the evidence provided in the paper's analysis. Such an evaluation is important because the appropriate policy response depends on whether the subprime losses were primarily attributable to unforeseeable circumstances, to bad information, or to purposeful risk taking. If the ex ante probability of a meltdown was objectively extremely low, then perhaps few fundamental regulatory changes are called for. If, on the other hand, a lack of transparency was the root of the collapse, the remedy likely rests on stronger disclosure requirements and greater regulatory oversight of the mortgage origination and securities markets. Finally, if the cause was deliberate risk taking that had systemic consequences, then enhanced controls, such as more stringent capital requirements and greater oversight of the over-the-counter market, are likely to be the most appropriate response.

In this discussion I briefly review the main findings of this analysis and consider whether the authors' conclusions are convincing in light of the data presented. I also consider some broader evidence about what investors were aware of before the crisis. To summarize, I am persuaded by the authors' argument that even in an environment of rising home prices, the sensitivity of foreclosures to home equity can be identified in publicly available cross-sectional data, and that this sensitivity was likely understood by many market participants. I also agree that the evidence points to weaker lending standards exacerbating the problems, but probably to a lesser extent than some observers have claimed. In fact, the authors make a plausible case that the riskier loans could have been expected to perform reasonably well had home prices not fallen. What is less convincing is their more speculative conclusion, based on investment analysts' published reports, that investors underappreciated the risk of a significant decline in home prices. Drawing on a variety of financial indicators, I argue that many investors must have recognized the possibility of large losses, but that apparently they did not have an incentive to avoid the risk. Thus I conclude that the evidence points more toward deliberate risk taking than to a lack of warning signs about the risks. Notwithstanding these differences in interpretation, this paper is the most substantive analysis of the subprime crisis that I have seen, and I think it will have a significant influence on how the crisis is understood.

EVALUATING THE FINDINGS. The central question addressed in this paper is to what extent investors could have anticipated the increase in foreclosure rates that occurred. The authors break the change in the foreclosure rate into two pieces: the sensitivity of the foreclosure rate to changes in home prices, $\mathrm{d}f/\mathrm{d}p$, and the change in home prices over time, $\mathrm{d}p/\mathrm{d}t$. Combining the two components, the change in the foreclosure rate over time is given by $\mathrm{d}f/\mathrm{d}t = (\mathrm{d}f/\mathrm{d}p) \times (\mathrm{d}p/\mathrm{d}t)$.

This decomposition is useful empirically because better information is available for evaluating each component separately than for trying to explain changes in foreclosure rates directly. Nevertheless, investors and analysts may not have conceptualized risk in exactly this way, and so their statements may not map smoothly into this framework. This is an issue for how the authors interpret what the rating agencies were saying at the time, as discussed below.

Using publicly available data—both a nationwide sample and one that has a longer time series but is specific to Massachusetts—the authors are able to estimate the sensitivity of foreclosure rates to changing home prices. An important insight is that although the era of subprime lending coincides with a period of overall home price appreciation, it is possible to exploit regional variation in price changes to study the sensitivity of foreclosure rates to price declines. The authors make a convincing case, first, that this sensitivity is high, and second, that the relationship is nonlinear.

To see whether the historical sensitivity of foreclosure rates to price changes carries over to the environment of falling prices after 2005, the authors predict foreclosure rates for that period using models estimated with data from 2000 to 2004, but calibrated with the actual price changes for the later period. They find that had investors been endowed with perfect foresight about actual home price changes, they could have predicted a significant portion of the increase in foreclosure rates that ensued, although not all of it. This finding is particularly interesting because the incentive to default could have been significantly affected by whether price declines are local or broadly based, for instance because prices may be perceived as less likely to recover quickly when declines are more widespread.

Given the public availability of these data and the robustness of their results to different specifications, the authors conclude that investors were likely to have been aware of these historical relationships. Their extrapolations also suggest that historical experience was predictive of foreclosure sensitivity to home price changes during the crisis. I would emphasize that a further reason to believe that investors were aware of the nonlinear sensitivity of foreclosures to home prices is that it is consistent with basic economic theory—and with common sense. The right to default is a type of put option, and it is only worth exercising when the price of the home, plus various costs associated with defaulting such as loss of access to credit, falls below the principal balance on the mortgage. Further, whether or not market participants studied the same data that the authors use, it is likely that they observed a very similar pattern in any local data with which they were familiar.

The analysis also provides evidence about the extent to which underwriting standards had declined and how much that decline contributed to the increase in foreclosure rates. Consistent with most accounts of the crisis, the authors find increases over time in risk factors such as high loan-to-value ratios, the presence of second liens, low- or no-documentation loans, and loans with a combination of these risk factors, or "risk layering." Interestingly, they find that the increase in foreclosure rates during the crisis for riskier loans that had been originated several years before the crisis was not much above that for more tightly underwritten loans originated around the same time. Loans originated shortly before the crisis, however, had much higher overall foreclosure rates, and for this later group lower underwriting standards are more important. The authors conclude that weaker underwriting standards can account for only a portion of the increase in foreclosure rates.

Although this part of the authors' analysis provides very useful information that helps put the role of underwriting standards into perspective, it does not resolve the question of to what extent declining underwriting standards caused the crisis. Since the information provided is based on public data, it suggests that sophisticated investors should have known that standards were deteriorating, but it is not established that they did know. More critically, the data do not reveal whether the decline in standards was due to an increasing appetite for risk among investors, or instead to agency problems associated with the opaque nature of MBSs.

On the question of what investors perceived about the likely direction of home prices in the period leading up to the crisis, much less concrete information is available. The authors have chosen to examine the published reports of financial analysts, and they conclude that analysts assigned a small probability to a home price meltdown of the magnitude that occurred. I suspect that these reports are unreliable indicators of what market participants believed. After all, research reports are a sales tool, and it seems unlikely that investors view these reports as providing unbiased information. For instance, it is well known that the frequency of sell recommendations in stock analysts' reports is much lower than the fraction of stocks that subsequently fall in value. Reporting a high probability of a crash in the housing market would be tantamount to a sell recommendation on mortgage securities, so it is not surprising that such forecasts were difficult to find. Nor is it surprising that these same banks now support the idea that a price decline would have been extremely difficult to predict, since the alternative, which is that they were marketing as good investments securities that they perceived to be extremely risky, would be an invitation to litigation. A final point is that the occurrence of a crisis is not in itself evidence that analysts should have assigned any particular ex ante probability to its occurrence. The conclusion that the probabilities reported by analysts were unrealistically small can be established only if there is other evidence of greater risk, which, as I argue below, there appears to be.

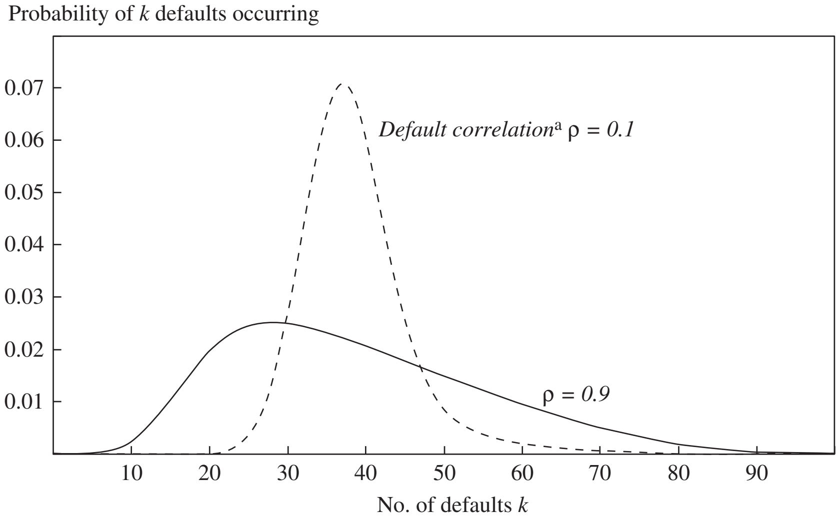
Finally, the authors suggest that unlike the investment banks, the rating agency Standard & Poor's (S&P) did not understand the sensitivity of foreclosure rates to home price declines. This inference is based on their analytical framework, $df/dt = (df/dp) \times (dp/dt)$; on the fact that S&P used a scenario in its worst-case analysis that resembled the home price decline that actually occurred; and on the observation that S&P estimated the probability of losses in the senior tranches of MBSs to be close to zero. The reasoning is that if $df/dt$ is reported to be close to zero and $dp/dt$ is highly negative, then $df/dp$ must have been thought to be close to zero. However, given the rest of the evidence in this paper, it seems quite unlikely that S&P was unaware that $df/dp$ is significantly negative. A more plausible explanation, which has been suggested elsewhere,[1] is that the rating agencies understood the effect of home price risk on the performance of individual mortgages, but failed to properly model the effect of correlation between mortgages in a pool and how it would affect the losses on different tranches of MBSs. Figure 1, taken from a case study by Darrell Duffie and Erin Yurday,[2] shows that when the probability of default on each individual mortgage is held fixed, increasing the assumed default correlation in a portfolio changes the shape of the distribution of portfolio default rates in a way that increases expected losses on triple-A-rated tranches. Hence this could explain why S&P reported a low probability of losses on highly rated securities despite understanding that foreclosures are sensitive to home prices.

OTHER EVIDENCE. Although there is little direct evidence that investors understood the risk of a sharp decline in aggregate home prices before the subprime crisis, I believe that there were many indicators of heightened risk; I will describe these briefly here.

1. See, for example, Darrell Duffie and Erin Yurday, "Structured Credit Index Products and Default Correlation," case study no. F269 (Harvard Business School, 2004); Joshua D. Coval, Jakub W. Jurek, and Erik Stafford, "Economic Catastrophe Bonds," *American Economic Review* (forthcoming).

2. Duffie and Yurday, "Structured Credit Index Products and Default Correlation."

**Figure 1. Distribution of Portfolio Default Rates under Different Assumed Default Correlations**



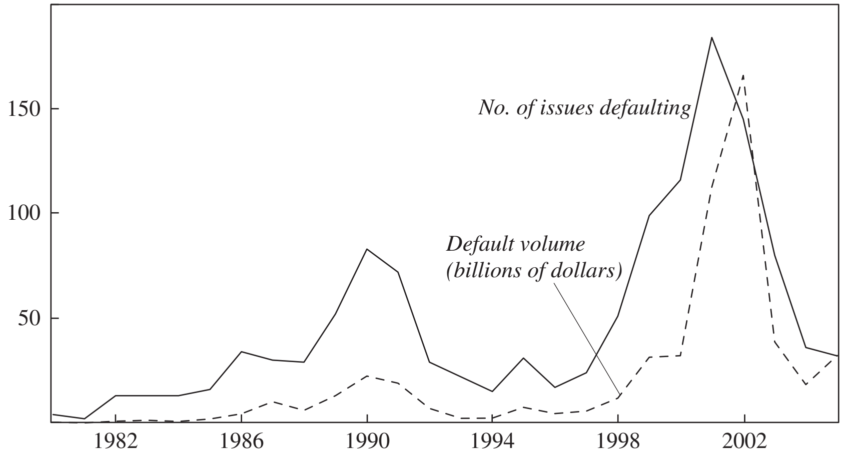

Source: Darrell Duffie and Erin Yurday, "Structured Credit Index Products and Default Correlation," case study F269 (Harvard Business School, 2004).

a. Pairwise correlation between firms in the portfolio of default events. The probability of an individual firm defaulting is held constant across the two cases.

It is important to realize that investors do not need to see a high frequency of defaults or home price declines to understand that there is a significant risk of such occurrences. Credit losses, because they arise from what are in effect written put options, should be expected to be low most of the time but on occasion to be very large. The historical pattern of default rates on corporate bonds is consistent with this prediction. Most years see very few defaults, but occasionally, and as recently as in 2001, default rates have been very high (see my figure 2). Although aggregate home price declines are very rare events in U.S. history, the rapid rate of home price appreciation that started in the late 1990s was also unprecedented. It seems reasonable to expect that a period of unprecedented price increases could be followed by one of unprecedented price declines (see figures 1 and 2 in the paper by Karl Case in this volume). The NASDAQ bubble of the late 1990s also should have served as a recent reminder to investors that rapid price increases can be quickly reversed.

An examination of credit spreads also reveals much about the degree of risk tolerance in credit markets before the crisis. The spread over Treasury rates on speculative-grade investments had fallen to less than half of its

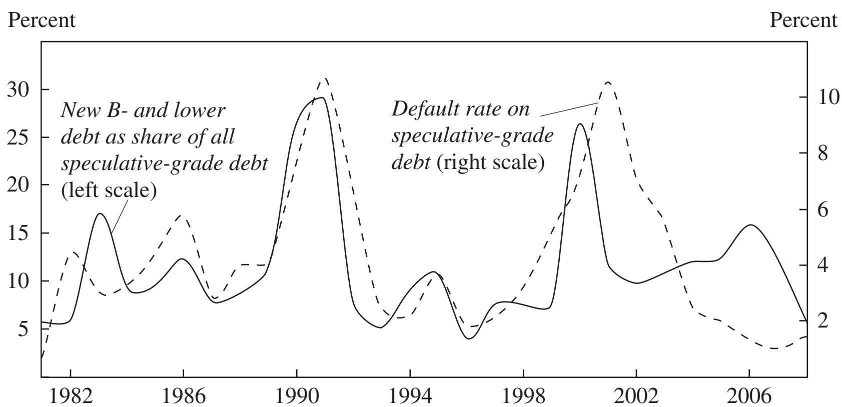
**Figure 2. Defaults on Corporate Bonds, 1980–2005**




Source: Moody's.

historical average by 2004, and the narrow spreads persisted through the first half of 2007. This could be interpreted as indicating either low expectations of default or unusually high risk tolerance. A factor that points to the latter is the sharp increase in speculative-grade debt outstanding over the same period, suggesting that rating agencies expected higher default rates. As my figure 3 shows, speculative-grade corporate debt issuance is a lead-

**Figure 3. Originations of and Default Rates on Speculative-Grade Debt, 1981–2008**




Sources: Standard & Poor's Global Fixed Income Research; Standard & Poor's CreditPro.

ing indicator of default rates on speculative debt generally. By analogy, investors should have been able to infer that the sharp increase in subprime originations would have a similar effect on defaults in the mortgage market. In fact, the emergence of a fully private subprime lending market can itself be interpreted as arising from increased risk tolerance, since before 2000 most subprime loans carried Federal Housing Administration guarantees.

This body of evidence, together with the findings in this paper, leads me to conclude that unusually high risk tolerance was likely to have been more important than a misperception of risk to the rapid growth in subprime lending and to the crisis that followed.

## COMMENT BY

**NICHOLAS S. SOULELES** Kristopher Gerardi, Andreas Lehnert, Shane Sherlund, and Paul Willen have assembled a number of rich mortgage datasets and carefully analyzed them to address some important issues at the center of the current financial crisis. In particular, could (and should) analysts have predicted the recent surge in home foreclosures? The paper's answer to this question has three main parts. First, the declines in home prices and housing equity were the key drivers of the foreclosures; other factors such as underwriting standards did not deteriorate enough to explain them. Second, the strong sensitivity of foreclosures to home prices was predictable in advance. Third, analysts must therefore have believed that there was little chance of a large decline in home prices. I will start by discussing the first two arguments and the paper's empirical analysis of mortgage defaults. To summarize, although it is not necessary to run a "horserace" between home prices and underwriting standards, the empirical analysis provides compelling evidence that one could have predicted that a large decline in home prices would lead to a significant increase in defaults. This is an important result. But what the result implies for home price expectations is a more subtle issue.

THE ANALYSIS OF MORTGAGE DEFAULTS. First, underwriting standards could potentially have played a larger role than implied by the paper's results. Figure 3 of their paper shows that underwriting standards declined along numerous margins, and there could be important interactions across those and other margins. To illustrate, the top left panel of figure 4 shows that through 2005 the probability of default for low-documentation (low-doc) loans was similar to that for full-documentation loans, but after 2005 the probability of default rose much more for the low-doc loans. This suggests that some other factor that interacts with low-doc loans deteriorated after 2005. The key question is whether this factor is (mainly) the decrease in home prices. There are other, not mutually exclusive, possibilities. Suppose that before the housing boom, lenders were more likely to offset the risk associated with low documentation by reducing risk along other margins; for instance, by relying more on lower loan-to-value (LTV) ratios, or on higher credit scores, traditional amortization, or other positive risk factors. This would have reduced the overall risk of low-doc loans in the past. Conversely, there might have been more observations of bad combinations of risk factors (for example, low documentation and low scores) in recent years. The point is that underwriting standards have many components, and they can endogenously interact. In that case one cannot simply introduce the individual components separately into an empirical model. The paper recognizes this point and includes some interaction terms ("risk layering"), but only a few; these are mostly interactions with LTV and are mostly limited to the first default model, the probit model reported in their table 5. In this sense the results provide a lower bound on the importance of underwriting standards. It would be interesting to know what greater proportion of defaults could be explained by including more interaction terms—indeed, as saturated a set as possible.

Further, although the paper's datasets are rich in information about borrowers and their mortgages, this is still only a subset of the information available to lenders for assessing their loans. For instance, the datasets lack information on some contract terms, such as points and fees; some application data, such as the borrowers' financial wealth; and some credit bureau data, such as past mortgage payment problems. Such information, which is known by lenders, could potentially have been used to predict even more of the increase in defaults.[1]

Second, it is not necessary to think of the paper's exercise as a horserace between underwriting standards and home prices. To begin with, in nonlinear models generally there is no unique decomposition of the importance of individual explanatory variables. More substantively, if home prices interact with underwriting standards and other factors, it is inherently difficult to quantify the relative importance of home prices per se. For example, a number of studies have found that low equity interacts with

1. For example, David Gross and Nicholas Souleles, "An Empirical Analysis of Personal Bankruptcy and Delinquency," *Review of Financial Studies* 15, no. 1 (2002): 319–47, using an administrative dataset containing all the key variables tracked by credit card lenders, analyze the increase in consumer bankruptcy and credit card default in the late 1990s.

"triggers" such as unemployment spells.[2] Such triggers can also be correlated with underwriting standards; for example, unemployment risk could be correlated with a low credit score.

A larger role for declines in underwriting standards (or for other factors) can still be consistent with the overall argument of the paper, so long as these declines were largely observable or predictable, and so long as home prices were a predictably significant factor in generating default. If recent subprime mortgages were even more risky, and predictably so, the argument would be that this implied even more optimism about future home prices. Pushing the argument further, many of the subprime mortgages might have been unviable unless the borrowers could eventually refinance out of them, which presumes positive-enough net equity and high-enough home prices.[3]

The paper does provide compelling evidence about the predictable significance of housing equity for mortgage default. (One small quibble: The paper contends that analysts could have used the results for low-but-positive equity in 2000–04 to quantitatively extrapolate the effects of negative equity after 2004. This extrapolation depends, of course, on the assumed functional form, and analysts could not have known ex ante which functional form would have worked well.) As for the effects of underwriting standards, to the extent that there were few observations in the early data of some of the bad combinations of risk factors that became salient later (perhaps, for example, low documentation combined with low credit scores), it would have been more difficult to forecast future default rates with precision. In fact, the main default model applied to the ABS data (the competing-risks model reported in table 10) could not include some salient mortgage characteristics—not even the uninteracted effects of nontraditional amortization, or of negative equity (that is, a nonlinear

2. See, for example, Christopher Foote, Kristopher Gerardi, and Paul Willen, "Negative Equity and Foreclosure: Theory and Evidence," *Journal of Urban Economics* 64, no. 2(2008): 234–45. To illustrate, consider the polar case in which default occurs if and only if the borrower both has negative equity and becomes unemployed. Foote and his coauthors find that borrowers with negative equity in recent years are more likely to default than borrowers with negative equity were in 1991 (before the growth in subprime loans), ceteris paribus. Using the ABS data in this paper, but without ending the sample in 2004, Shane M. Sherlund, "The Past, Present, and Future of Subprime Mortgages," Staff Paper 2008-63 (Washington: Federal Reserve Board of Governors, 2008), finds that borrowers with fixed-rate mortgages were less significantly sensitive to negative equity than were borrowers with adjustable-rate mortgages, ceteris paribus. Such results suggest that net equity might interact with other factors, such as the characteristics of borrowers or their mortgage terms.

3. See, for example, Gary Gorton, "The Panic of 2007," working paper (Yale University, 2008).

effect for low equity, in addition to the included linear equity variables)—since there were too few observations of mortgages with those characteristics in the ABS data before 2004.

IMPLICATIONS FOR HOME PRICE EXPECTATIONS. Supposing it was predictable that large declines in home prices would lead to large increases in default rates, can one therefore conclude that lenders and other analysts must not have been expecting large declines in home prices? There are again alternative, not mutually exclusive, possibilities.

First, without complete information on the terms of the mortgage contracts, it remains possible that lenders thought they were offsetting somewhat more of the mortgage risk than implied by the analysis. Second, lenders and investors might have been willing to tolerate some nonnegligible risk of a large decline in home prices, if their risk aversion was low enough and they considered alternative outcomes (such as a period of stagnant home prices) sufficiently likely. Third, insofar as agency problems were important, some lenders might have thought that they would not fully bear the costs of the increased defaults, even if they could have predicted them.[4] To investigate this possibility, one would ideally like to distinguish the information set of the mortgage originators from the information sets of investors and other agents, which presumably are subsets of the former, to see whether the additional information available to the originators would have predicted significantly more of the defaults.

Finally, even if analysts should have been able to predict much of the increase in mortgage defaults, it would have been more difficult to forecast their spillover onto the rest of the financial system and the extent of the resulting crisis, and moreover to forecast how the crisis in turn would spill back into the mortgage market, further increasing defaults through even lower home prices and other mechanisms (such as higher unemployment).

Although the paper's competing-risks models explain much of the increase in defaults, in the end they still generally underpredict them, especially for the 2005 vintage of mortgages. The paper suggests that this could reflect the fact that the 2005 vintage was more exposed than the 2004 vintage to home price declines. However, the competing-risks models are

4. On this topic, see, for example, Adam Ashcraft and Til Schuermann, "Understanding the Securitization of Subprime Mortgage Credit," Staff Report 318 (Federal Reserve Bank of New York, 2008); Charles Calomiris, "The Subprime Turmoil: What's Old, What's New, and What's Next," working paper (Columbia University, 2008); Benjamin Keys and others, "Securitization and Screening: Evidence from Subprime Mortgage Backed Securities," working paper (University of Michigan, 2008); and Atif Mian and Amir Sufi, "The Consequences of Mortgage Credit Expansion: Evidence from the 2007 Mortgage Default Crisis," working paper (University of Chicago, 2008).

supposed to control for the effects of lower home prices through lower housing equity (and for the resulting decline in the borrower's ability to refinance the mortgage or sell the home instead of defaulting). How much larger a share of the observed defaults could be explained through improved measurement and modeling of housing equity remains an open question. Perhaps other relevant risk factors are still missing from the model, or perhaps the increase in defaults was to some degree inherently difficult to predict in advance, even given the path of home prices. Nonetheless, the paper has made a valuable contribution in showing that home prices were in any case a predictably significant contributor to the defaults.

**GENERAL DISCUSSION** Jan Hatzius remarked that the idea that people incorrectly guessed the direction of home prices but not the relationship between home prices and defaults was consistent with his impression from discussions he had had with market analysts over the past few years. Most refused to believe, despite a history of large regional declines in home prices, and of nationwide declines in other countries, that home prices in the United States could decline in nominal terms. This denial, he believed, was the essential problem that led to the crisis.

Karl Case stressed the importance of examining the data at the regional level. What was happening in Florida, Nevada, and Arizona, for example, was very different from what was occurring in the Midwest and the Northeast. California's situation was particularly notable since that state accounts for 25 percent of the nation's housing value and experienced a steep decline in prices. He added that the laws relevant to housing differ in important ways from state to state, and that markets clear at different rates in different areas.

Austan Goolsbee offered an airline analogy to illustrate how the crisis arose largely from the interaction of declining home prices and deteriorating lending standards, with the latter playing the lead role. To enable people with bad credit to buy homes, the financial markets had created subprime mortgages and other products that translated home price appreciation into broader home ownership. Just as flying on a budget airline is fine until something goes wrong, so these subprime mortgages were fine until prices started to fall. Goolsbee added that the securitization of those mortgages was much more complicated than what the paper portrayed, and that lending standards deteriorated not only through the relaxation of lending criteria but also through outright fraud: people were allowed to lie about the owner-occupier status of the home they purchased. This matters because people are more likely to walk away from a second home than from a primary residence as soon as they fall into negative equity. Lenders should have assumed that the market would go bad at some point and priced their loans accordingly.

Frederic Mishkin noted that the adjustable subprime contracts inherently assumed a rise in asset prices, because otherwise the loans would not continue to be serviced when the interest rate was reset. Lenders assumed that prices would continue to rise, turning subprime borrowers into prime borrowers, who could then refinance the loan on better terms. He indicated that loans made with the expectation that they would be refinanced may have been prompted by underlying principal-agent issues.

Robert Hall mentioned the work of John Campbell and Robert Shiller showing that overvaluation in a stock market can be detected by looking at the price-dividend ratio: the higher the ratio, the higher the likelihood of a price decline. He suggested incorporating this type of analysis into the paper by looking at price-rent or price-income ratios, noting that their unprecedentedly high levels in the mid-2000s signaled a high probability of future decline.

Martin Baily directed the Panel's attention to the prices of ABX securities—the collateralized debt obligations built on the mortgage-backed securities—and to delinquency rates, which, he argued, revealed a likely change in underwriting standards in the years before the crisis. ABX securities declined significantly in price between the first and the second quarters of 2006, too short an interval to be explained by a drastic change in the underlying mortgages. Delinquency rates, in contrast, increased sharply in the fourth quarter of 2005 and continued to rise in subsequent quarters. The dissimilarity between these two data series seems to indicate a change in something other than housing prices, such as underwriting standards.

Charles Schultze summarized the paper as saying that analysts did understand the nonlinear dependence of foreclosures on changes in home prices but were shocked by the idea that home prices would fall as much as they did. He attributed the unusual size of the price drop to the fact that there had not been an upward movement in home prices this large in the previous forty years. He blamed the incentive structure facing the managers and employees of financial firms: one's approach to risk management changes if one can expect bonuses for four or five years on the upside and only miss one or two on the inevitable downside. He cited a UBS report written after the bank lost the first $19 billion of $42 billion in eventual losses, in which the downplaying of risk management is noted. In addition, the lack of attention to risk evaluation by investors generated a surge in demand for subprime mortgage-backed securities that put pressure on mortgage originators for a substantial erosion of underwriting standards.

Lawrence Summers noted the long tradition of financial messes made because people observed that over a long period the strategy of writing out-of-the-money puts had proved consistently profitable, and so continued the strategy until inevitably a problem occurred. He seconded Goolsbee's comment on the interaction of factors deepening the crisis and asked the authors to try to tease out these different factors. He also suggested that the authors examine the strategies pursued by major builders, the stock prices of those builders, and the implied volatility in puts on their stocks, since builders are essentially betting their franchises on the housing business remaining strong. He guessed that such an examination of these factors would show that the builders shared in the euphoria of rising home prices yet did not share in the ignorance—an idea at odds with Schultze's emphasis on Wall Street's compensation structures.

Bradford DeLong came to the defense of those who had bought homes in California, Florida, and Boston, arguing that long-term interest rates will eventually decline, leading to an increase in home price–rent ratios. Also, rising population in the United States will eventually lead to increased congestion, so land will essentially become a Hotelling good with prices rising over time.

Richard Cooper remarked that one should not limit one's analysis of home price–income ratios to a period of worldwide decline in real long-term interest rates, because housing is a long-term asset. He also pointed out that, at least in the United States, the income elasticity of demand for housing is significantly greater than one, so that rising incomes would eventually lead to an increase in home price–income ratios. But it would be too simplistic to make an evaluation from this ratio alone.