Modeling of Mortgage Defaults

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The growth in the nonagency housing market in recent years has fueled interest in mortgage credit analysis. The housing market's weakening over the last year and the subsequent turmoil in the subprime sector have emphasized the need for a solid foundation for evaluating credit-sensitive mortgage securities. This article describes a model for predicting defaults on residential mortgage loans. This model is a subset of our overall prepayment model, which projects both voluntary prepayments (resulting from housing turnover, refinancing, or curtailments), and involuntary prepayments (that is, defaults).[1]

For clarity, we start with some definitions. A mortgage loan is *current* when the borrower has made all of the contractually required monthly payments to date. It is *delinquent* when the borrower has missed one or more monthly payments. The mortgage is *30-day delinquent* when the borrower has missed one payment, it is *60-day delinquent* when the borrower has missed two payments, and it is *90-plus-day delinquent* when the borrower has missed three or more payments.[2] Loan servicers will typically start foreclosure proceedings after three missed payments.

Foreclosure is a legal process, the goal of which is to sell the collateral (the property) so that the proceeds can be used to meet the contractual obligations of the mortgage. The process is governed by state laws, and the time taken to foreclose on a property can vary from a few months to over a year, depending on the state; during this time the loan is said to be *in foreclosure.*[3] Before or during the foreclosure process, the servicer may encourage the borrower to sell the property, even if the selling price is less than the mortgage amount; this is called a *short sale.* If the servicer takes possession of the property, either at the end of the foreclosure process or earlier (if the borrower transfers the title to the servicer), the loan status is termed to be *real estate owned* (REO).

So what precisely is meant by a mortgage default? Surprisingly, there is no standard industry definition. We will use a definition we have found to produce default numbers that closely match deal remittance reports. We define a default to be a loan payoff (or prepayment) where the previous state was REO, or the previous state was delinquent or in foreclosure *and* there was a loss. In other words, a default only occurs when a loan is liquidated. If a loan becomes delinquent, or goes into foreclosure, but is cured (that is, becomes current again) or is prepaid without a loss to the servicer, there is no default.

Our definition also implies that a default occurs the month the loan is liquidated. If we assume the loss is taken the same month the loan is liquidated, then it follows there is no lag between a loan defaulting and the resulting loss to the servicer or investor.

The rest of this article is organized as follows. The next, or second, section discusses the main factors that affect mortgage default and provides a historical perspective on default behavior and trends. In the third section, we use the results of the second section to formulate an econometric model for mortgage defaults and show that this model predicts default levels quite well across time and for different mortgage types. In the fourth section, we use the model to examine likely defaults and losses on recent subprime deals, focusing in particular on the ABX indexes.

The current turmoil in the subprime market is leading to rapid changes in underwriting standards. The profile of subprime borrowers in the future, and the mix of mortgage products, will be quite different from that of the recent past. This presents a challenge to predictive models which tend to use the past as a guide to future behavior. These challenges, and possible ways to meet them, are discussed in the last section.

DETERMINANTS OF MORTGAGE DEFAULTS

For a default to occur, both of the following must occur:

- The homeowner is unable to make the monthly mortgage payments, typically because of the occurrence of some *trigger event* that impairs his ability to do so.
- There is a lack of equity in the home, so that the homeowner is unable to refinance or sell the home without a loss.

Traditionally, mortgage default rates have followed a pattern of being low initially, then increasing until they reach a plateau after a few years, and then beginning to decline once the loans are fairly seasoned. This pattern was captured by the Standard Default Assumption (SDA) curve, which was based on historical FHA default rates and was developed by the Bond Market Association as a guide to default seasoning curves.

Under the SDA curve, defaults increase linearly until Month 30, remain stable until Month 60, and then start declining. This seasoning pattern results from traditional underwriting practices. The borrower has to make a down payment, so that he has equity in the house, and he also has to satisfy the lender that he has the ability to make the monthly mortgage payments; this implies that there is unlikely to be a default soon after the mortgage is taken out.[4] After many years, it is likely that home prices have increased on average, so the borrower's equity in the home has thus increased, his financial situation is stable (since he has been making mortgage payments for many years), and a default again has a low probability.[5] Hence, the danger period is when the loans are moderately seasoned, when a downturn in the housing market and an adverse personal event for the mortgagor could lead to the loan becoming delinquent.

Factors that Affect Default Rates

Exhibit 1 provides data from Freddie Mac on why borrowers became delinquent on their mortgage payments.

The reasons cited in Exhibit 1 are those that one would expect. Job losses, illness or death, divorces, and excessive financial obligations tend to be the most common causes of mortgage delinquencies.[6] Although we cannot predict exactly when an individual will experience an adverse personal event such as a job loss, we can identify which known macroeconomic, borrower, property, and mortgage variables tend to be well correlated with trigger events, and hence express the likelihood of a trigger event as a function of these variables. We discuss these key variables next.

Loan-to-value ratio and HPA. The updated loan-to-value (LTV) ratio measures the amount of equity the borrower has in the home and thus determines how feasible it will be for the borrower to refinance or sell the

EXHIBIT 1

Trigger Events: Reasons for Mortgage Delinquencies (%)

Cause	2001–2005	2006
Unemployment or loss of income	42.8	36.3
Illness in the family	19.2	21.1
Excessive obligation	11.1	13.6
Marital difficulties	7.9	6
Death in the family	3.7	3.9
Property problems or casualty loss	1.7	2.8
Extreme hardship	2.8	0.9
Inability to sell or rent property	1.3	1.4
Employment transfer or military service	0.9	0.6
All other reasons	8.7	13.3

Numbers for 2006 exclude delinquent loans in Louisiana and Mississippi due to the effects of the 2005 hurricanes.

Source: Freddie Mac.

house if he can no longer make the monthly payments. Given the initial LTV, the current LTV is estimated using the cumulative home price appreciation (HPA) since the loan was originated, along with amortization. There are, however, complications.

Inflated appraisals. For refinanced loans, the initial LTV will be based on an appraisal of the property's value, rather than an actual sales price. Reports of inflated appraisals were widespread in the housing boom of recent years, especially for cash-out refinancings, and so the reported initial LTV may need to be adjusted upwards.

Silent 2nds. If the borrower has taken out a second mortgage on the property, then clearly the combined LTV should be used. In some cases, however, the existence of a second lien on the property may not be known. When analyzing a deal, an educated guess has to be made of the likely proportion of properties that have loans with second liens so that the LTV can be adjusted accordingly.

We have found that recent changes in home prices (*home price momentum*) have a strong effect on mortgage default rates, beyond the impact of HPA on LTV. For example, there was a sharp increase in default rates when the housing market slowed in 2006, even for older vintages. We suspect there are several reasons for this. First, the housing market may be a proxy for general economic conditions, so a weakening housing sector can mean a deteriorating situation for struggling borrowers. Second, servicers may decide to cut their losses when they think home prices are going to fall and provide incentives to a delinquent borrower to do a short sale (that is, sell the home for less than the mortgage balance) (*WSJ* [2007a]). Third, declining home prices may have a psychological impact on struggling homeowners who may decide that it is not worthwhile to try to hold on to the property.

Borrower and loan characteristics. The borrower's financial capabilities and general creditworthiness are key factors in assessing default risk.

Credit score. A borrower's FICO score is often used as an indicator of his creditworthiness.[7] Many large lenders have also developed proprietary credit scoring methods to screen borrowers.

There is a belief that FICO scores have lost some of their predictive power because of the housing boom of recent years that allowed many borrowers to refinance their way out of trouble. However, as we discuss in the next section, FICO scores still have a role to play in predicting the likelihood that a borrower will default.

Debt-to-income ratio. The debt-to-income (DTI) ratio is the ratio of the monthly mortgage payments and other debt payments to the monthly income of the borrower.[8] The higher the DTI ratio, the greater the proportion of the borrower's income that goes toward making debt payments, and hence the greater the strain a trigger event puts on the borrower's ability to continue making mortgage payments.

Loan documentation status. Traditional mortgage underwriting requires that the borrower's income is verified to ensure that he will have the ability to make the mortgage payments; this requires checking tax returns, pay stubs, and so on. In recent years, many lenders have developed "reduced" or even "no" documentation loans, where income verification is either cursory or nonexistent. The original intent behind these loans was to accommodate borrowers who had lumpy or irregular incomes, such as the self-employed, but who were otherwise considered to be good creditors. However, the concept has been abused in recent years, especially in the subprime sector, in order to qualify borrowers who probably would not qualify under more traditional underwriting criteria. For such loans, uncertainty about the borrower's true income translates into uncertainty about the stated DTI ratio and thus about the borrower's ability to handle mortgage payments.

Occupancy status. If the mortgaged property is the full-time residence of the borrower, then it is an owner-occupied property. If this is not the case, and the property was purchased as an investment (either to rent out or to "flip" for a profit), then it is an *investor* property. Mortgages on investor properties are considered riskier than those on owner-occupied ones for obvious reasons: Borrowers who live in a house will be more motivated to keep it than those who do not. Unfortunately, it can be a challenge to know whether a loan is truly owner-occupied due to fraud; for example, one report found that 66% of a sample of loan files reflected owner-occupancy fraud (Fitch [2007a]).

Loan purpose. We made the point earlier that there is greater certainty about the LTV ratio of a loan that was taken out to purchase a house compared to one that was a refinancing; in the former instance, we know the purchase price of the house, but in the latter the LTV is calculated using an appraisal. Balancing this risk, however, purchase loans—especially in subprime—are often taken out by first-time home buyers for whom there is typically greater uncertainty regarding their capability to keep up with the mortgage payments. In addition, anecdotally, cases of fraud often involve purchase loans.[9]

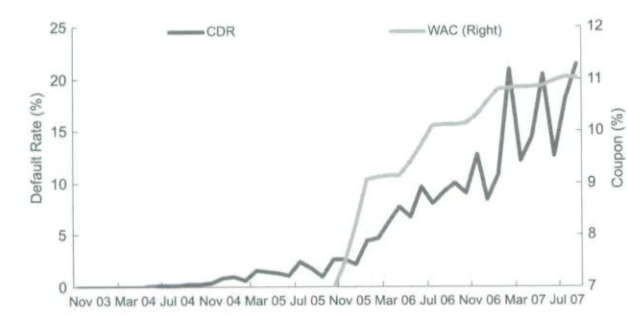
Payment shock. For a traditional fixed-rate mortgage, the monthly payments are fixed for the term of the loan. The majority of loans originated in the subprime market in recent years, however, have been adjustable rate mortgages (ARMs). The coupon on an ARM is fixed for a specified period of time and then resets periodically at a specified spread (or margin) over a reference index. In the subprime market, the most common loan has been a "2/28" on which the coupon is fixed for 2 years and then resets every 6 months for the remaining 28 years. In other sectors of the mortgage market, the most common ARM is a "5/1" on which the coupon is fixed for 5 years and then resets annually over an index. Note the difference in terminology between the subprime market and other sectors; for example, 5/25 versus 5/1, respectively.

The initial coupon on an ARM is typically set below the fully indexed rate (index + margin); hence, the coupon and monthly payment will typically increase at reset, often by substantial amounts. This payment reset acts as a trigger event after which many borrowers are unable to make the new higher monthly payment. The result is a spike in delinquencies and defaults after the coupon starts resetting. This is illustrated in Exhibit 2 which shows the coupon and default rate on a 2004 pool of loans.

For many recent loans, the payment shock at reset will be accentuated by an interest only (IO) period. For many 2/28s, for example, the monthly payment during the first two years consists of interest payments only; hence, the monthly payment after two years will increase because of a higher coupon and because the loan starts amortizing.[10] This double whammy of payment increases is

EXHIBIT 2

Coupon and Default Rates for 4Q 2003 Subprime 2/28s with Initial WAC of 7%



Sources: LoanPerformance and Citi.

likely to lead to sharply higher default rates after reset for recent vintage subprime ARMs.

Job losses. As indicated in Exhibit 1, job loss is a major trigger event for defaults. We use changes in unemployment rates to capture the likelihood of a job loss. While this seems straightforward, complications come from variation in unemployment rates from region to region, and even from city to city; a national unemployment rate may have little meaning for a group of loans from a specific geographical area. The most detailed unemployment data available should be used to most accurately capture the likelihood of this particular type of trigger event.

Risk-based pricing and SATO. The spread at origination (SATO) is the difference between the coupon on a loan and some measure of average prevailing mortgage rates (however defined). A high SATO means the loan was originated at well above prevailing rates, generally indicating that the lender perceived above-average risk in the borrower. The SATO is used in our prepayment model as a measure of the credit impairment of the borrower and of the resulting difficulty he may face in refinancing the loan.

In theory, the loan and borrower characteristics we have discussed, such as the FICO score, occupancy status, initial LTV, and so on, should capture the information provided by SATO. Even with these other variables, however, we have found SATO to be a critical element in projecting defaults. This is perhaps not surprising given the uncertainty surrounding variables such as the LTV and the DTI ratio. Additional risk factors about the borrower can be incorporated by the lender into the coupon rate, which, therefore, will be reflected in SATO.[11]

The 2006 Vintage and Implied Fraud Factors

Much has been written about subprime loans originated in 2006. With the possible exception of 2007, 2006 is easily the worst performing vintage to date, with delinquency rates well above those seen on earlier vintages at similar stages of seasoning. This poor performance is to some extent explained by the characteristics of the vintage, especially when one considers risk tiering or combinations of risk factors; for example, the percentage of loans that have both a high LTV and were originated with low or no documentation.

However, even after accounting for these risk factors, the performance of the 2006 vintage is still worse than would be expected. In other words, a model that works well in predicting defaults on earlier vintages will not fully capture the poor performance of the 2006 vintage. This is consistent with widespread anecdotal stories of very lax and even fraudulent underwriting during the height of the recent housing boom. We have found that model differences between 2006 and earlier vintages can be captured by *implied fraud factors*; that is, by making time-dependent adjustments to loan and borrower characteristics. In fact, the differences can be mostly captured by adjusting the DTI ratio, which has been cited as a source of fraud.[12] Exhibit 3 shows the adjustment that needs to be added to the stated DTI to make the model perform well for all vintages.

Exhibit 3 is consistent with anecdotal evidence. The implied addition to the DTI ratio is zero prior to mid-2005 and then increases into 2006. One would expect that it will be zero in the future (at least until the next boom) given the current tightening in underwriting standards.

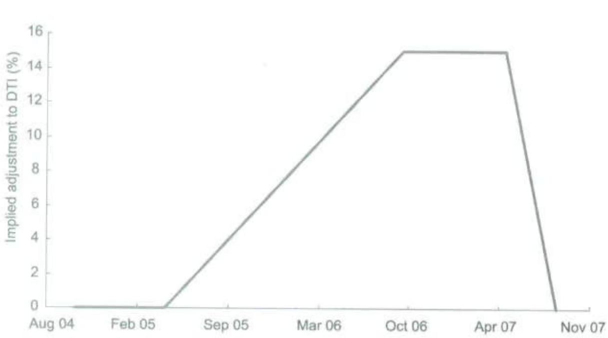
Time-dependent adjustments can also be used to capture the impact of a credit crunch in the future. We will discuss this in the last section.

DEVELOPING A DEFAULT MODEL

We have defined a default as an involuntary prepayment, a loan termination resulting from the inability of the borrower to continue making scheduled payments. Thus, we model defaults within the overall framework of our prepayment model.

Our prepayment model is modular, with four modules corresponding to prepayments resulting from 1) housing turnover, 2) refinancing, 3) curtailments, and 4) defaults. The first three components correspond to voluntary prepayments, while the last (defaults) constitutes involuntary prepayments. In the past, we have modeled defaults as a simple multiple of the SDA curve which we defined in the second section of this article.[13] For the new model, we have extended the default model to incorporate the loan, borrower, and economic factors previously discussed.

EXHIBIT 3
Implied Addition to the Stated DTI (%)



Source: Citi.

Parameter Estimation Methodology

Our parameter estimation process involves simultaneously fitting the default and total prepayment projections (inclusive of defaults). This process captures the interdependence of prepayments and defaults; for example, overall prepayment rates are a critical factor in determining cumulative default and loss rates on a deal.[14] While in theory we could fit at the loan level, we find it more practical and efficient to create *cohorts*, or pools of loans with similar characteristics, and use these to estimate the parameters of the model.

Our basic cohorts are created by pooling loans of the same type (fixed-rate, 2/28s, and so forth), same lien status, same prepayment penalty term, originated in the same quarter (so that they all have roughly the same seasoning), and with weighted average coupon (WAC) in a given range, typically 50 basis points (bps). The WAC bucketing is obviously critical for fitting prepayments because the WAC determines the refinancing incentive, which is a major driver of refinancings. However, the WAC bucketing is also important for defaults, as it ensures that the loans in a given cohort have similar SATOs, which, as discussed previously, is an important determinant of defaults. The cohorts thus created also tend to differ from each other in characteristics such as initial LTVs and FICO scores. The ability of the model to accurately predict defaults across such a diverse set of loans and across time is, we believe, a reliable validation of its soundness and predictive power.

In this section, we first show that our model fits well at the aggregate vintage level. The use of implied fraud factors captures the differences in underwriting standards between the 2006 and earlier vintages. We then show that the model also captures differences in collateral and borrower characteristics. We use state cohorts to demonstrate that the model accurately reflects differences in defaults caused by macroeconomic factors such as home price changes and unemployment rates.

In this section we focus on subprime loans, including fixed-rate, 2/28, and 3/27 first liens and fixed-rate second liens. In fact, for simplicity and because it has been the largest sector, most of our illustrations involve 2/28s. We will conclude this section, however, by demonstrating that the model fits fairly well not only for subprime products, but also for Alt-A fixed-rate and ARM loans.

There is one caveat. Almost all of the data for subprime and Alt-A loans is from the last 5 to 10 years, a period of positive home price changes in most regions of the United States. Hence, extrapolation is needed to project defaults for periods of negative HPA.

Aggregate Vintage Fits

Exhibit 4 shows actual and projected default rates for subprime 2/28 loans originated in periods ranging from 2002 to 2006. These are aggregate fits; for example, the fits for 2002 loans (the top left graph) are constructed by taking all 2002 cohorts (which are created by pooling loans originated in a given quarter and with a WAC in a specified range) and calculating balance-weighted actual and projected CDRs for each month. The model fits all vintages quite well with our implied fraud factor methodology accounting for underwriting differences over time.

We note two points about the results shown in Exhibit 4.

- The effect of coupon resets for 2005 and 2006 loans is apparent in the bottom four graphs in which data are grouped by quarter and the default rates start increasing after Month 24. For the earlier vintage graphs, the data are by year, so the effect of coupon resets is more dispersed. The effect of coupon resets is accentuated by sharp increases in overall prepayment rates that took place after the coupon reset upwards. These increases in prepayment rates reduced the balance outstanding, and because the default rate is expressed as a percentage of the remaining balance, this will cause default rates to increase.
- The default rates for the older vintages are still high and have not yet started to decline despite the booming housing market of recent years. Default rates are staying higher for longer than predicted by the old SDA curve, for two reasons. First, the strong housing market and high levels of prepayments have led to severe adverse selection on the remaining loans; these will tend to be on properties in areas that have not shared in the strong housing markets and/or are held by homeowners with financial or credit problems. Second, these loans are ARMs, so an increase in the coupon can lead to an uptick in defaults, even for seasoned loans.

Collateral Characteristics

We next examine model fits by specific collateral attributes and show that the model accurately predicts differences in default rates for loan groups that differ in these attributes.

Loan-to-value ratio. Exhibits 5 and 6 show actual and projected CDRs for two cohorts with differing initial LTVs. The model picks up the differences in CDRs quite well. Note that in the cases of an existing second lien on the property, a combined LTV (CLTV) is used, when available, in projecting default rates. Defaults for second liens use separate parameters, but the same CLTV. We discuss defaults on second liens in a later section.

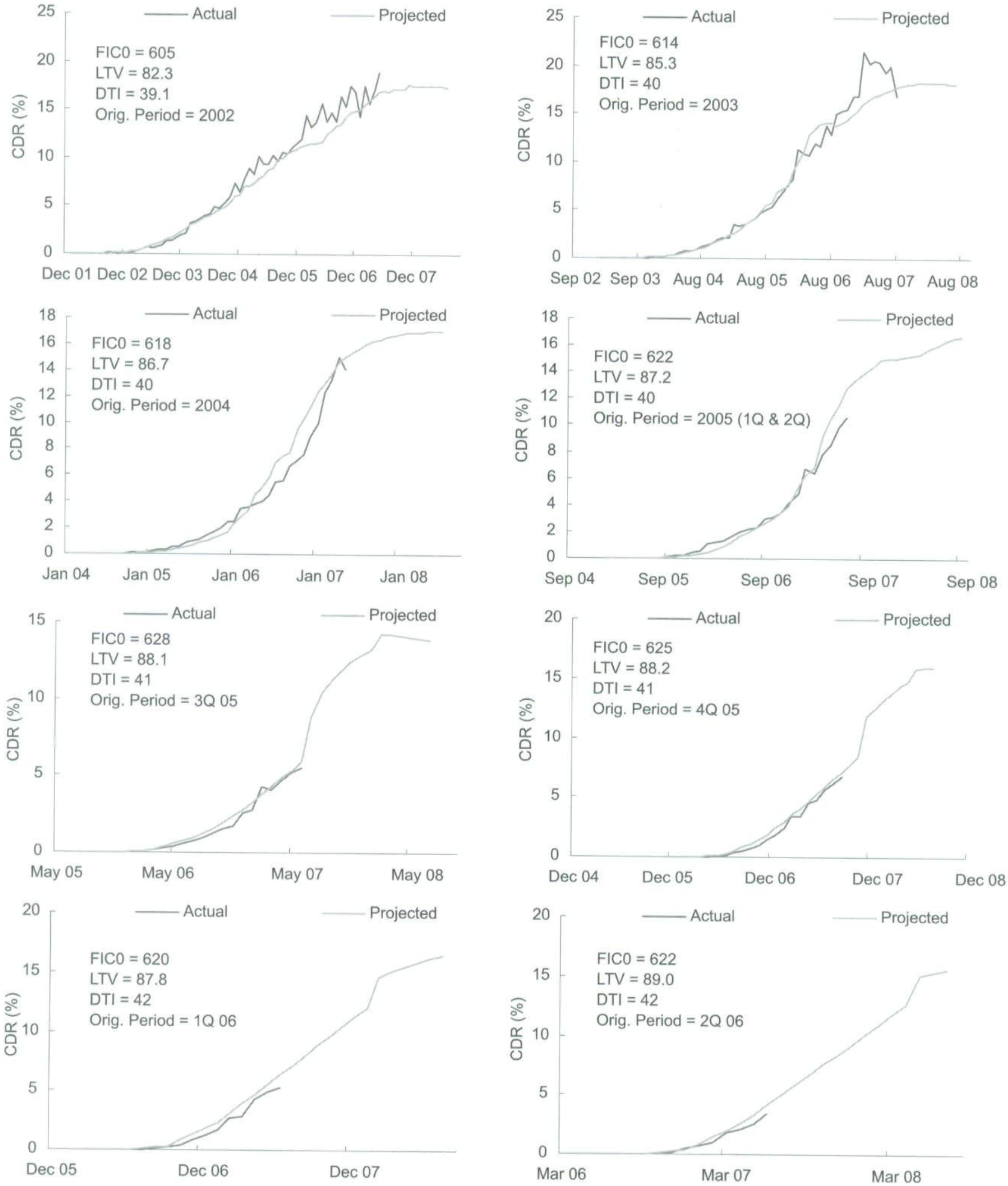
FICO scores. Exhibits 7 and 8 compare two cohorts with different FICO scores. Note that the CDRs are relatively similar for the two cohorts. This is because the higher FICO cohort has a significantly higher LTV. The combined interaction of two variables can be complex and nonlinear; in this case, the negative effect of a higher LTV almost exactly cancels the positive impact of a higher credit score. Our model captures the net effect of the two characteristics accurately, as the graphs show.

Loan purpose. Although inconspicuous, loan purpose is found to have an impact on default rates. As discussed earlier, purchase loans include a significant number of first-time inexperienced homebuyers who are more likely to default on their loans. Refinance loans are taken out by borrowers who already own a home and not only have a history of making their payments, but also have likely built significant equity in their home (this is particularly true for cash-out loans). This could also lead to a higher FICO on refinance loans. Since it is fairly difficult to isolate the interaction of other factors (such as LTV, FICO, and so forth), we simply compare the default rates on purchase and refinance loans in Exhibits 9 and 10 to highlight model fits against actual CDRs.

Debt-to-income ratio. Historically, the percentage of loans with a high DTI ratio (and low documentation) had been relatively small until 2004. There was, however, a significant increase in these loans under the deteriorating

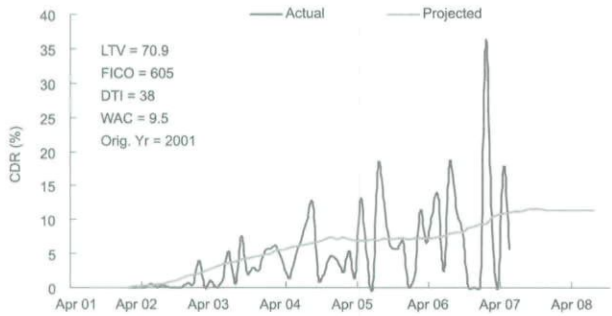
EXHIBIT 4

Actual versus Projected CDRs for Different Vintages



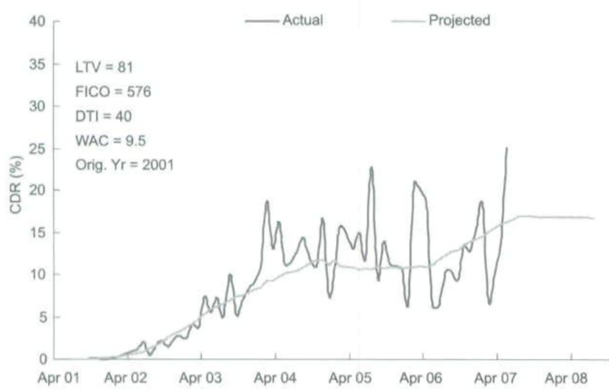
Sources: LoanPerformance and Citi.

Exhibit 5
Low LTV: Actual versus Projected CDRs



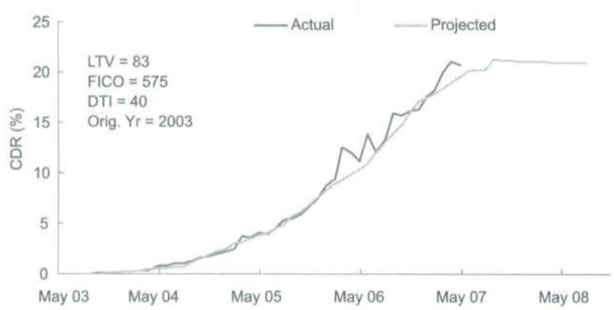
Sources: LoanPerformance and Citi.

Exhibit 6
High LTV: Actual versus Projected CDRs



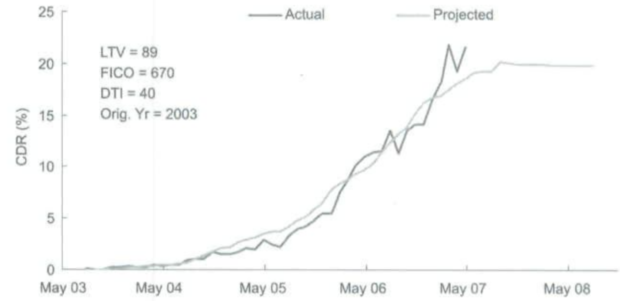
Sources: LoanPerformance and Citi.

Exhibit 7
Low FICO: Actual versus Projected CDRs



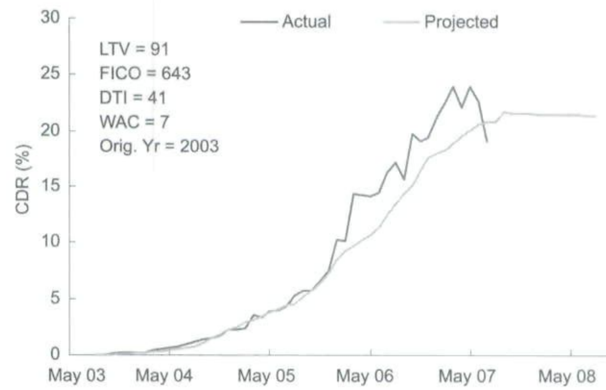
Sources: LoanPerformance and Citi.

Exhibit 8
High FICO: Actual versus Projected CDRs



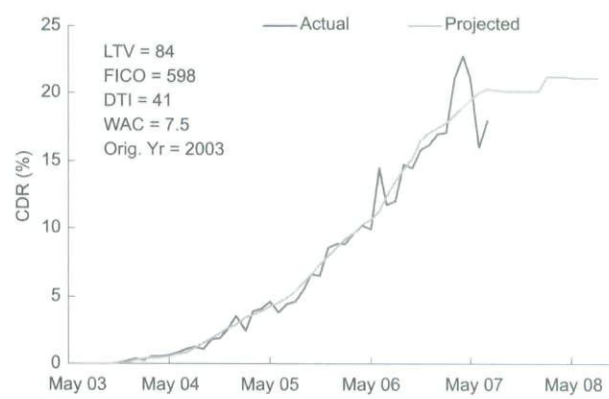
Sources: LoanPerformance and Citi.

Exhibit 9
Purchase Loans: Actual versus Projected CDRs



Sources: LoanPerformance and Citi.

Exhibit 10
Refinance Loans: Actual versus Projected CDRs



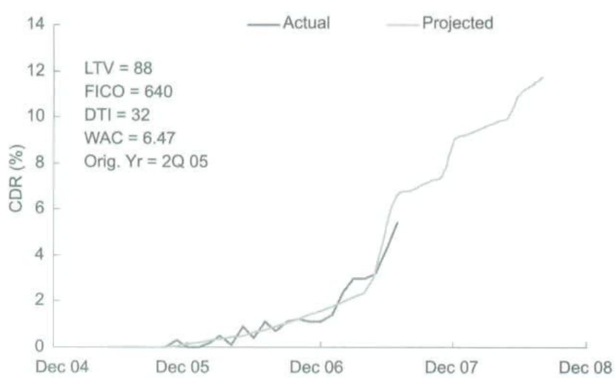
Sources: LoanPerformance and Citi.

underwriting standard beginning in 2005. We demonstrate the effect of high DTI by comparing default rates on two similar pools of loans which were originated in the second quarter of 2005, one with a much lower DTI than the other (see Exhibits 11 and 12). Note the greater impact of payment shock on the default rate for the high DTI group as indicated by the larger spike in default rates at reset.

Documentation Status. Low documentation (or no income verification) loans are often touted as tools for self-employed borrowers who are either too busy to meet the documentation requirement or have erratic income levels. However, absence of documentation provides the opportunity to exaggerate income levels or assets and form the source of most loan frauds. In the subprime market, the percentage of low documentation loans has increased from the high 30% range in 2001 to about 50% in 2006, reflecting the loose underwriting standards in the later stages of the recent housing boom. Exhibits 13 and 14, which contrast default rates for low/no documentation loans and full documentation loans, comparing them to the corresponding model projections, show clearly the higher defaults associated with low documentation loans.

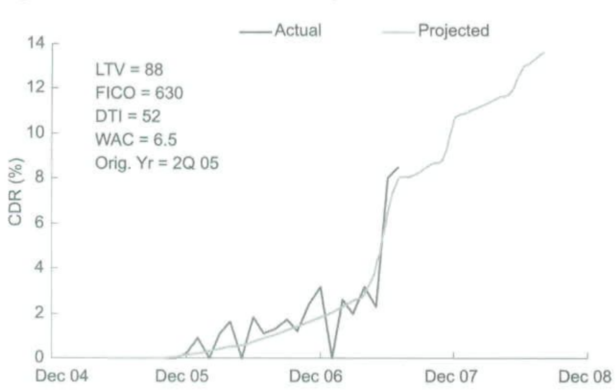
Coupon and spread at origination. We have noted that SATO (or, more or less equivalently, WAC on loans from the same origination period) provides important information about the risk of a borrower, beyond that provided by risk factors such as LTV, FICO, and so on. The main reason is that when default risks are higher (due to a high OLTV, low FICO, or so on) or when

EXHIBIT 11
Low DTI: Actual versus Projected CDRs



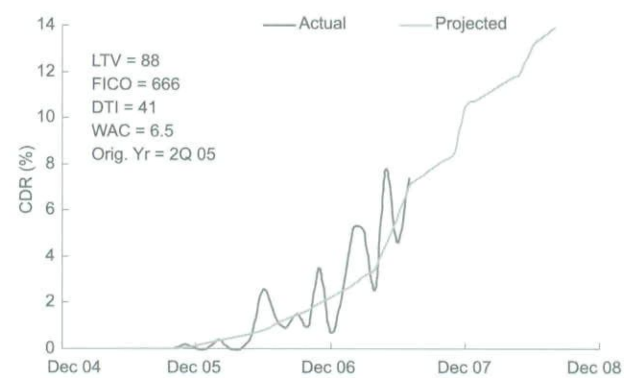
Sources: LoanPerformance and Citi.

EXHIBIT 12
High DTI: Actual versus Projected CDRs



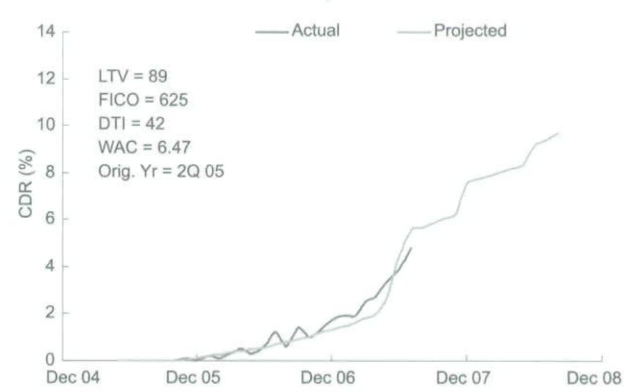
Sources: LoanPerformance and Citi.

EXHIBIT 13
Low Doc: Actual versus Projected CDRs



Sources: LoanPerformance and Citi.

EXHIBIT 14
Full Doc: Actual versus Projected CDRs



Sources: LoanPerformance and Citi.

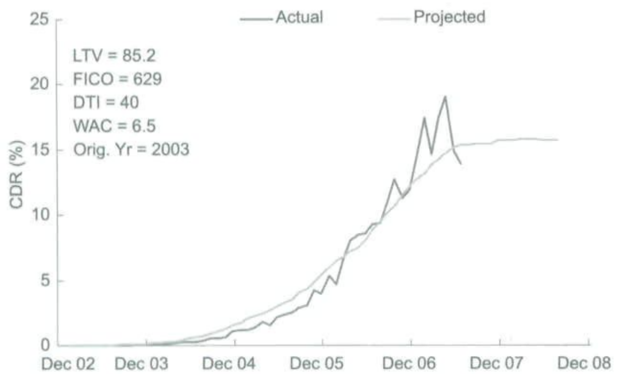
default risks are not properly understood, lenders charge mortgage interest rate premiums to compensate for the above-normal risk (what is often referred to as risk-based pricing). This is illustrated in Exhibits 15 and 16, which feature two cohorts from the same origination period which are similar with respect to OLTV, FICO, and DTI, but have differing WACs (and hence SATOs). The higher SATO cohort has markedly higher default rates.

Economic Factors

The key macroeconomic risk factors for mortgages are interest rates, HPA, and unemployment levels. Interest rates will determine the extent of a payment shock, as we have discussed, and also influence the ability to refinance. In this section we examine the combined impact of HPA and unemployment rates, as well as our model's ability to capture these effects, by looking at state-level fits. We have created state-level cohorts using the same criteria as for the general cohorts, but including loans just from a specific state—or in the case of Indiana, Michigan, and Ohio (aka IMO states), just loans from these three states. We also use unemployment and HPA rates specific to these states (see Exhibits 17 and 18). Exhibits 19 to 21 show actual and projected CDRs for these states in the context of the historical HPA and unemployment rates shown in Exhibits 17 and 18.

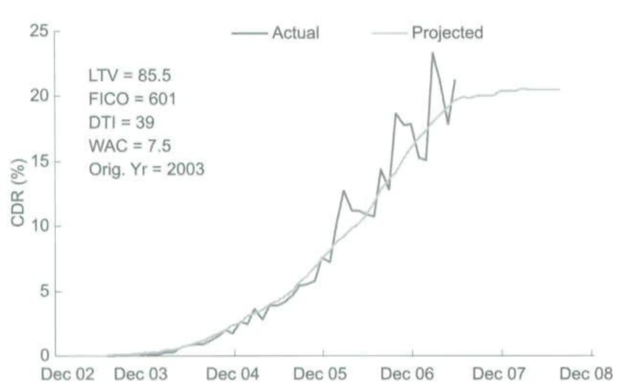
Note that while HPA flattened out for IMO starting in the last quarter of 2005, it has continued to increase for Texas. In addition, the unemployment rate has fallen

EXHIBIT 15
Low WAC (SATO): Actual versus Projected CDRs



Sources: LoanPerformance and Citi.

EXHIBIT 16
High WAC (SATO): Actual versus Projected CDRs

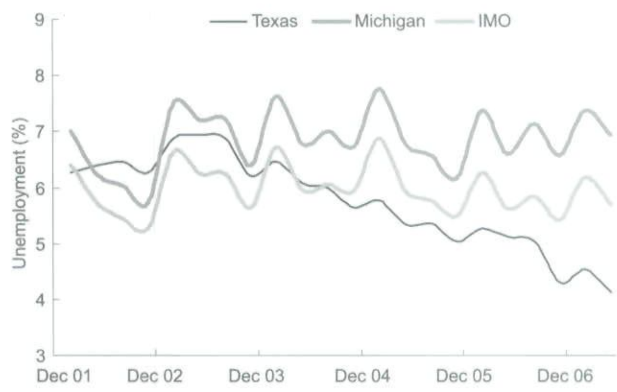


Sources: LoanPerformance and Citi.

EXHIBIT 17
Cumulative HPA since 2002 for TX, MI, and IMO

Source: OFHEO.

EXHIBIT 18
Historical Unemployment Rates for TX, MI, and IMO



Source: US Dept. of Labor.

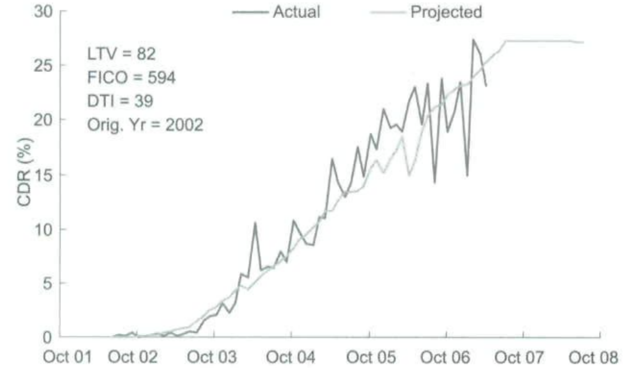
for Texas while it has remained relatively flat for IMO. These two effects have caused the CDR for Texas to flatten out after October 2005, but it continues to ramp up for IMO. The model fits reasonably well at the state level which gives us confidence that it is accurately capturing the effects of HPA and unemployment. One benefit of examining state-level fits is that it provides guidance on mortgage performance in the negative HPA environment widely expected in the next few years.

Although even the weakest HPA states (including IMO) did not experience declines in home prices until recently, their HPA rates were so far below the highest HPA states (such as California) that a comparison of the two helps in extrapolation of the model to negative HPA scenarios and in making a judgment about whether the model captures well the effect of extreme HPA. We provide a comparison of average CDRs for IMO states and California along with 12-month HPA in Exhibits 22 and 23. Note that although the IMO HPA has not fallen severely, we still record a significant rise in default rates which is partly induced by HPA momentum (as explained earlier).

Deal Projections and Originator and Servicer Effects

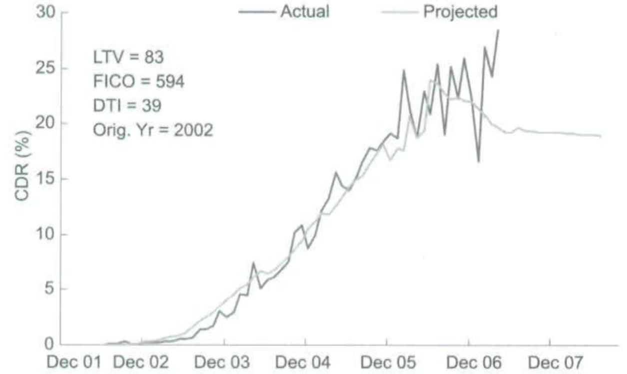
In the subprime market, collateral performance can be substantially affected by differences in originator underwriting policies and by servicer practices. These differences will be reflected in the prepayment and default rates on subprime deals. We use a dynamic adjustment methodology,

EXHIBIT 19
Actual and Projected CDRs: MI



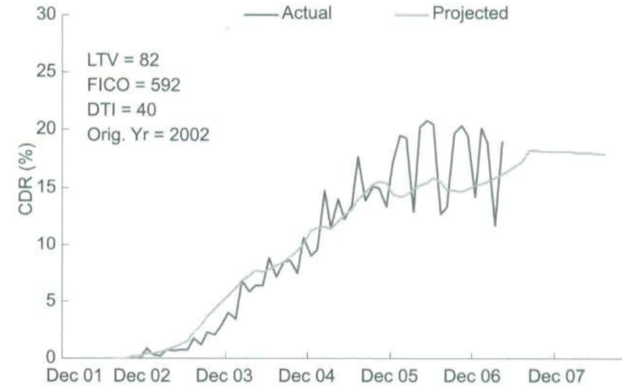
Sources: LoanPerformance and Citi.

EXHIBIT 20
Actual and Projected CDRs: IMO



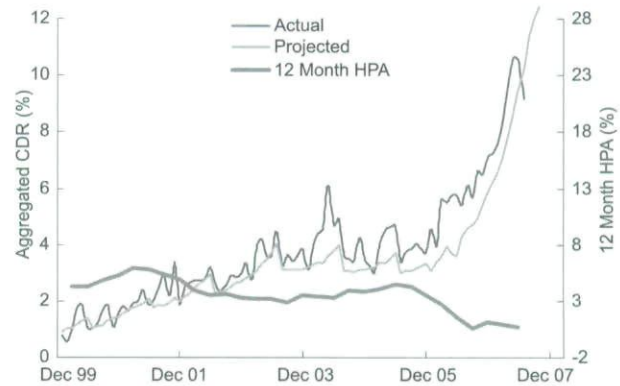
Sources: LoanPerformance and Citi.

EXHIBIT 21
Actual and Projected CDRs: TX



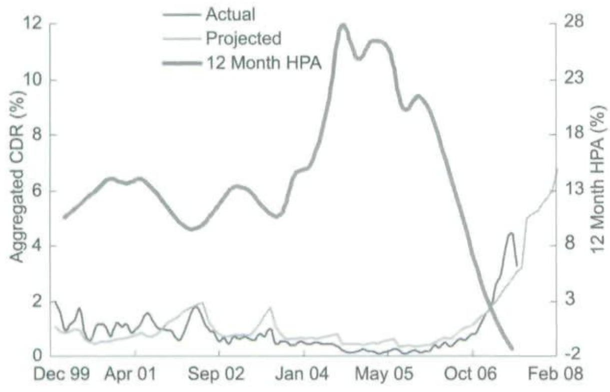
Sources: LoanPerformance and Citi.

EXHIBIT 22
IMO States: Aggregated CDR including All Vintages



Sources: OFHEO, LoanPerformance and Citi.

EXHIBIT 23
California: Aggregated CDR including All Vintages



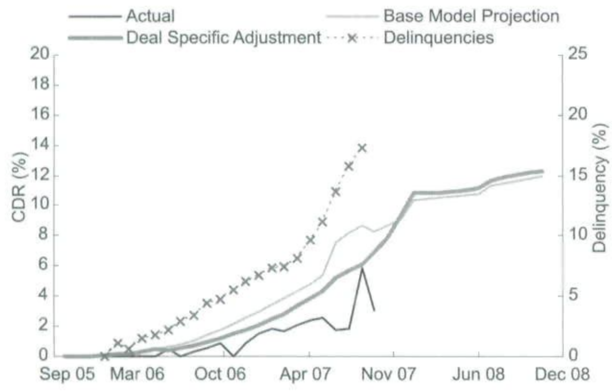
Sources: OFHEO, LoanPerformance and Citi.

based on deal delinquency and default data, to incorporate originator and servicer effects in our model.[15]

The adjustment is done in two ways. First, we compare actual and projected CDRs for the recent past. Second, we use current seriously delinquent levels to project CDR levels several months into the future and compare these with model projections. The two comparisons are then combined to adjust model projections in the future.

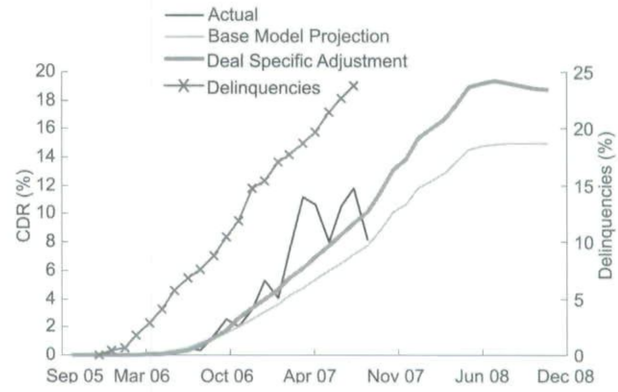
These adjustments are illustrated in Exhibits 24 and 25 which show base and adjusted projections—one for a deal where the model CDR projections are high and the second for a deal where model CDR projections are low. (We hasten to add that the model fits most deals quite well. These two deals were chosen because they illustrate the adjustments at work.) Most subprime deals contain a mix

EXHIBIT 24
Deal-Specific Adjustment for SABR 2006-OPT1



Sources: LoanPerformance and Citi.

EXHIBIT 25
Deal-Specific Adjustment for JPMorgan 2006-FRE1



Sources: LoanPerformance and Citi.

of loans—fixed-rate, 2/28s, different prepayment penalty terms, and so on—and the base projections shown in the graph are a balance-weighted average of the model projections for the various loan types in the deal. Note how the delinquency levels, particularly for the SABR 2006-OPT1 deal, adjust the short-term CDR. Initial delinquency levels were fairly low for this deal which lowered its CDR. However, the rapid increase in delinquency levels in the last few months has raised its future projected CDR.

Coupon Reset Adjustment Dials for Modeling Loan Modification

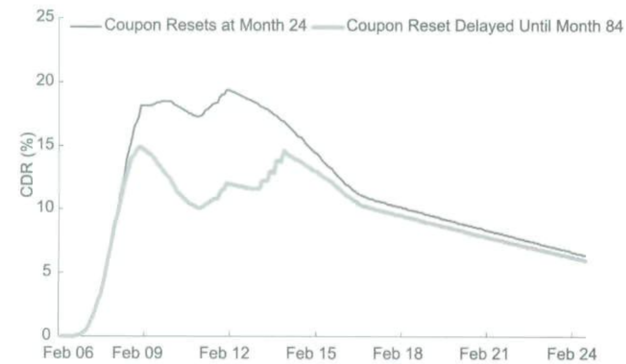
In early December 2007, mortgage industry members and Treasury officials proposed a standardized and streamlined plan to modify subprime loans.[16] We have discussed the potential impact of the plan in other publications[17]; in this article we indicate how the model can be modified to gauge the impact of the plan.

The proposed plan will allow the coupon rate on qualifying subprime 2/28 and 3/27 loans to be frozen for five years from the date of the first reset. The intent of the plan is to reduce default rates on subprime borrowers who have been current to date but may be unable to afford the higher monthly payment after the coupon reset.

Our default model captures the effect of the loan modification through dials that adjust the reset date by a specified number of months defined by the user. In Exhibit 26, we compare projected CDRs for 2/28 hybrid ARMs originated in 2006 when the coupon resets as scheduled at Month 24 (base case) and when loans are modified so that the coupon reset is delayed

EXHIBIT 26

Projected Default Rates on 2/28s in Base Case and if Coupon Reset is Delayed Until Month 84



Source: Citi.

until Month 84. The projected CDR for modified loans drops, as would be expected, but then increases again when the coupon resets in Month 84. (Note that the increase in CDR around February 2012 is due to IO loans that start amortizing and is not due to a rate reset.) The two CDR vectors in Exhibit 26 can be used to estimate the impact of loan modifications on collateral losses and bond valuations.

Defaults on Second Lien Mortgages

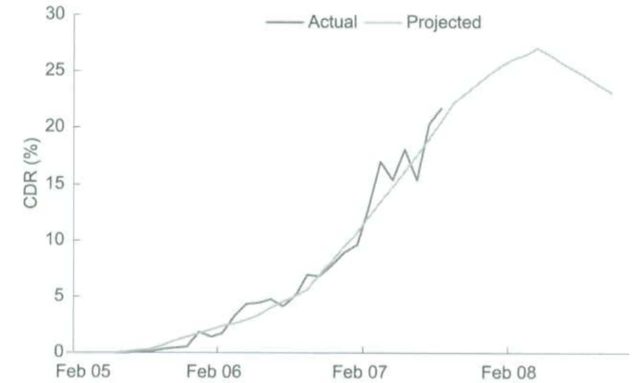
The loose underwriting standard in recent years has led to a large number of second lien originations that have turned out to be a bane on the mortgage industry. Many lenders were willing to extend loans to risky borrowers with a CLTV of, or even over, 100%. With no equity in their homes, these borrowers have little incentive to make their mortgage payments when home prices are falling. This is evident from the soaring default rates on the second liens. In general, the defaults on second liens tend to show up much earlier than the first-lien defaults, and the default rates are much steeper. In Exhibits 27 to 30, we compare actual default rates to model projections.

Vintage Fits for Alt-A

So far we have discussed defaults on subprime mortgages and shown that our model projections are fairly good. We now apply our model to Alt-A loans which have historically experienced much lower default rates. However, the effects of falling home prices as well as loose underwriting are showing up as higher (and steeper) CDRs

EXHIBIT 27

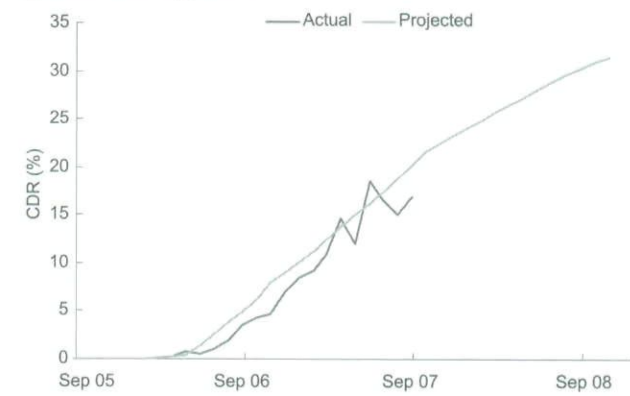
Actual and Projected CDRs for Second Liens, 1Q 2005 and 2Q 2005



Sources: LoanPerformance and Citi.

EXHIBIT 28

Actual and Projected CDRs for Second Liens, 3Q 2005 and 4Q 2005



Sources: LoanPerformance and Citi.

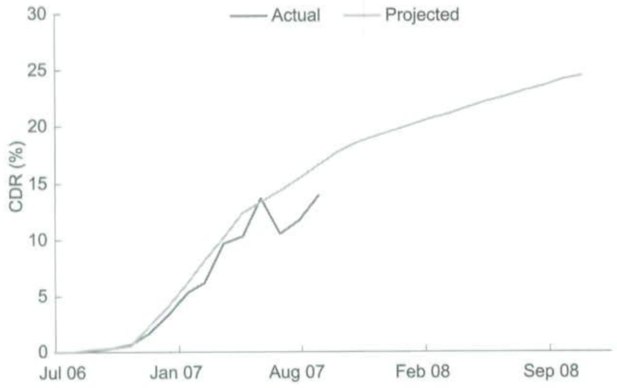
for Alt-A loans. We compare our model CDR projections against actual projections for fixed-rate as well as five-year adjustable rate Alt-A mortgages in Exhibits 31–36.

VALUATION OF MORTGAGE CREDIT RISK

To value mortgage credit risk, we need to combine the default model we have described with a *prepayment model* and a *loss severity* model. The prepayment model projects the overall level of payoffs (including defaults). In fact, as we have discussed earlier, the default model is a subset of the overall prepayment model. The loss severity model predicts the loss when a mortgage defaults. It is an involved model that is described in detail in Hayre et al. [2008].

EXHIBIT 29

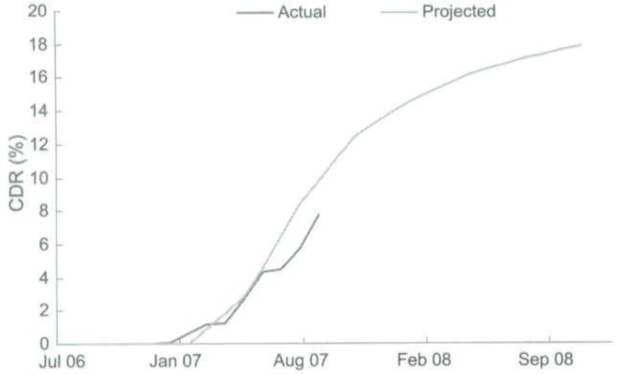
Actual and Projected CDRs for Second Liens, 1Q 2006 and 2Q 2006



Sources: LoanPerformance and Citi.

EXHIBIT 30

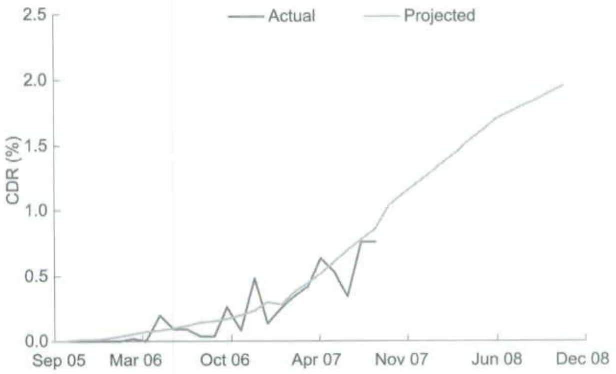
Actual and Projected CDRs for Second Liens, 3Q 2006 and 4Q 2006



Sources: LoanPerformance and Citi.

EXHIBIT 31

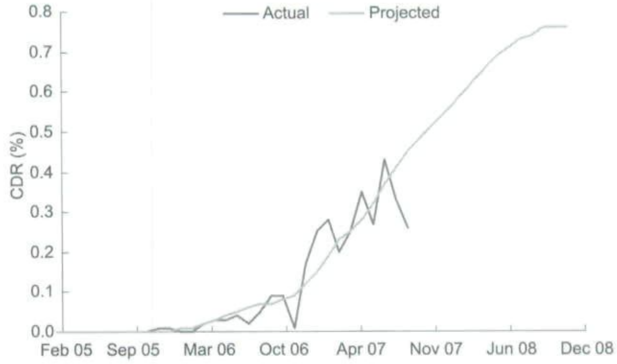
Actual and Projected CDRs for 5-Yr Adjustable-Rate Alt-A Mortgages Originated between 1Q 2005 and 2Q 2005



Sources: LoanPerformance and Citi.

EXHIBIT 32

Actual and Projected CDRs for Fixed-Rate Alt-A Mortgages Originated between 1Q 2005 and 2Q 2005



Sources: LoanPerformance and Citi.

As an example, we describe how the models are combined to obtain projected losses on a subprime asset-backed security (ABS) deal, ACE 2006-NC1. Exhibit 37 shows actual and projected CPRs (the total prepayment rate), Exhibit 38 shows CDRs (the involuntary portion of the overall prepayment rate), and Exhibit 39 shows actual and projected loss severities for this deal (first-lien and second-lien severities are shown separately).

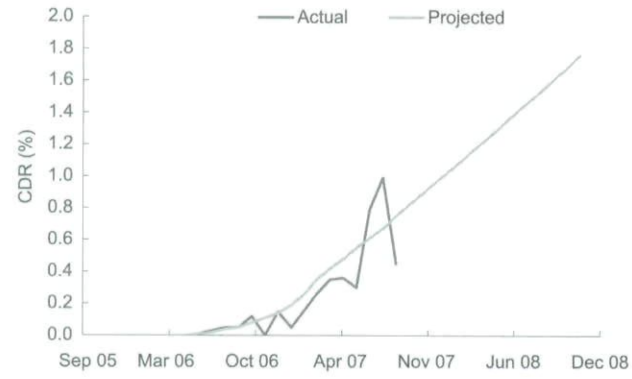
The projected CPRs, CDRs, and loss severities are combined to get projected cumulative losses, defined as the percentage of the initial balance that has been written down to date. Exhibit 40 shows actual and projected cumulative losses for ACE 2006-NC1.[18]

Importance of prepayments. While default projections clearly impact losses directly, prepayments can be just as important. Higher speeds reduce the overall balance and leave fewer borrowers who could potentially default.[19] This is illustrated in the cumulative loss percentage table shown in Exhibit 41, which shows losses by CDR and voluntary CPR (we assume a 50% loss severity).[20]

For example, at 15% CDR and 60% voluntary CPR, the cumulative loss is 7.7%. If the CDR doubles to 30%, then the cumulative loss increases to 14.2%. If, alternately, the voluntary prepayment speed is assumed to decline by 50%, losses increase even more, rising to a 15.5% cumulative loss.

EXHIBIT 33

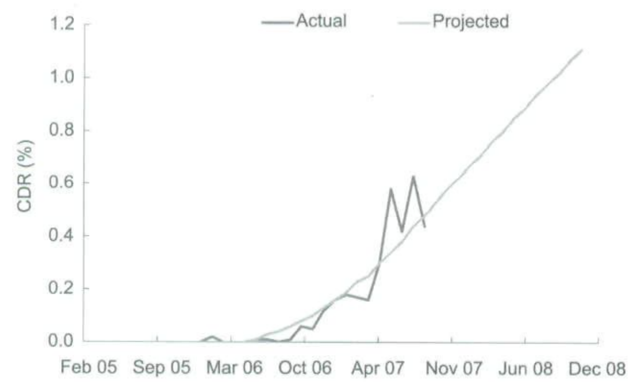
Actual and Projected CDRs for 5-Yr Adjustable-Rate Alt-A Mortgages Originated between 3Q 2005 and 4Q 2005



Sources: LoanPerformance and Citi.

EXHIBIT 34

Actual and Projected CDRs for Fixed-Rate Alt-A Mortgages Originated between 3Q 2005 and 4Q 2005



Sources: LoanPerformance and Citi.

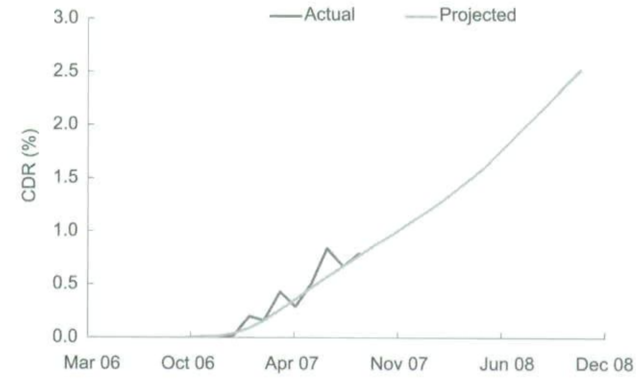
For bonds, the situation can be complicated by fast prepayments which reduce the amount of excess spread that is accumulated to provide additional credit enhancement; this can mitigate the benefits of the lower cumulative losses due to fast prepayments.

Cumulative Loss Projections by Vintage

Model projections for different vintages capture the effects of changing underwriting standards and different levels of HPA. Exhibit 42 shows projected losses for 2/28 subprime loans originated in 2003; the combination of decent underwriting standards and the strong housing markets experienced by these loans from 2003 to 2005

EXHIBIT 35

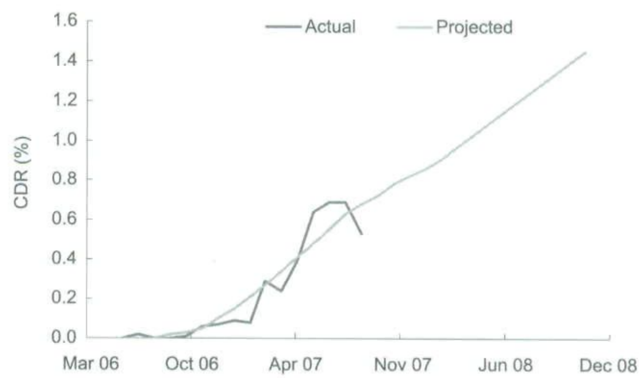
Actual and Projected CDRs for 5-Yr Adjustable-Rate Alt-A Mortgages Originated between 1Q 2006 and 2Q 2006



Sources: LoanPerformance and Citi.

EXHIBIT 36

Actual and Projected CDRs for Fixed-Rate Alt-A Mortgages Originated between 1Q 2006 and 2Q 2006



Sources: LoanPerformance and Citi.

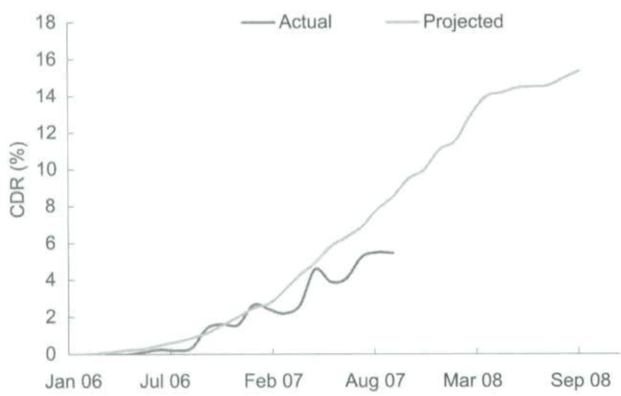
kept the losses to a fraction of what we project for more recent vintages.

Loss projections are much higher for recent originations. As discussed earlier, the model assumes that the degree of fraud and bad underwriting increased as the housing market slowed and interest rates rose. Exhibit 43 shows cumulative loss projections for 2/28s originated in the third quarter of 2005 versus those from the third quarter of 2006. The projected losses for the 3Q 2005 loans are initially higher, reflecting an extra year of seasoning. However, the losses for the 3Q 2006 loans soon rise, a result of their poorer risk characteristics and exposure to nothing but a weak housing market.

EXHIBIT 37
Actual versus Projected CPRs for ACE 2006-NC1

Sources: LoanPerformance and Citi.

EXHIBIT 38
Actual versus Projected CDRs for ACE 2006-NC1



Sources: LoanPerformance and Citi.

Actual cumulative losses for older subprime vintages, such as 2000 or 2001, are generally in the 3% to 5% range (consistent with the projections for the 2003 loans shown in Exhibit 42). The projected cumulative losses for the 2006 loans, by comparison, are north of 20%. Can the losses on the 2006 loans really be five or six times higher than those on older vintages? Unfortunately, the answer, in our opinion, is yes.

There are several points to note in assessing the projected losses in Exhibit 43:

- The shoddy underwriting and even outright fraud that was prevalent towards the latter stages of the housing boom have been well reported.[21] Serious delinquencies for 2006 loans are already very high, exceeding 20% on some deals, multiples above earlier vintages at the same stage of seasoning.[22] Performance for 2006 loans is likely to worsen as coupons on 2/28 ARMs reset upwards in 2008.
- The early 2000 vintages experienced a very strong housing market in their first several years. The buildup in equity allowed many people to refinance, shrinking the pool of potential defaulters.[23] In addition, a strong housing market will tend to reduce loss severities when there is a default.
- In contrast, the projected losses for the 2005 and 2006 loans in Exhibit 43 assume a housing recession, with prices dropping 15% over the next three years, mean reverting back to 3% over another year, and then increasing at 3% per year after that (equal to an assumed general inflation rate of 3%, although an HPA of 3% will seem anemic compared to recent years). This implies, for example, that it will be about 10 years before home prices return to current levels.

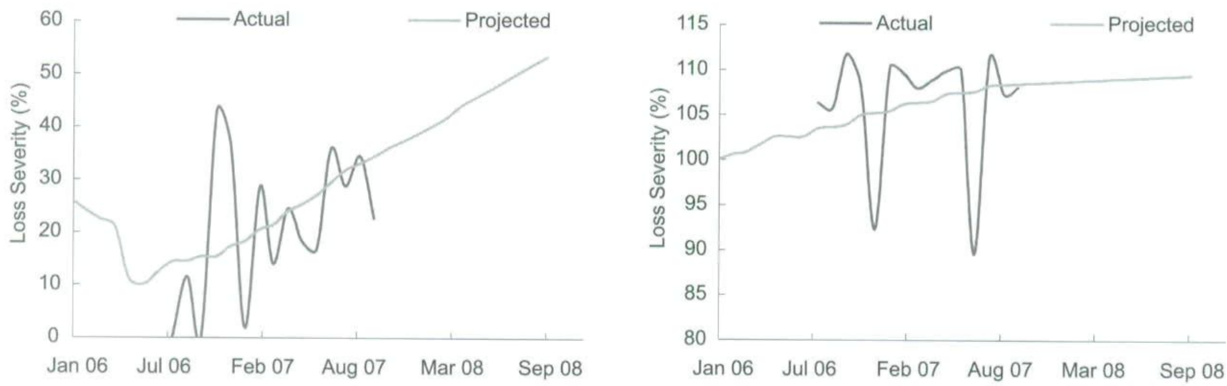
The impact of HPA on mortgage performance can be illustrated by a comparison of the Indiana/Michigan/Ohio (IMO) region, which has had weak housing markets in recent years, with the United States. Exhibit 44 shows actual and projected cumulative losses for the IMO states and for the nation as a whole. Cumulative losses for the IMO loans are several times higher than for the United States. As can be seen, the model captures the differences reasonably well. We further note that the IMO region had positive HPA until very recently (see Exhibit 17) in contrast to the 15% drop in home prices assumed in Exhibit 43.

Sensitivity to HPA and Other Economic Assumptions

As the comparison of the IMO region with the rest of the country indicates, HPA is generally the most important economic factor in determining subprime mortgage performance. This is illustrated in Exhibits 45 and 46. Exhibit 45 shows projected cumulative losses for 2006 2/28s for three HPA scenarios: 1) "benign" (HPA flat for a few years, then 3% per year after that); 2) moderate weakening (prices decline 5% over two years, stay flat for a year, then increase 3% per year); and 3) severe recession in housing (down 15% over three years, flat for two years, then increase 3% per year). Losses vary from about 13% of the initial balance in the benign scenario to about 22% for the more severe scenario.

EXHIBIT 39

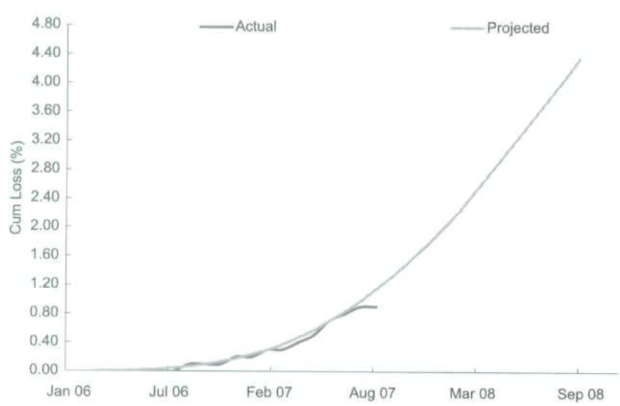
Actual versus Projected Loss Severities for ACE 2006-NC1 for First Liens (Left) and Second Liens (Right)



Sources: LoanPerformance and Citi.

EXHIBIT 40

Actual versus Projected Cumulative Losses for ACE 2006-NC1



Sources: LoanPerformance and Citi.

EXHIBIT 41

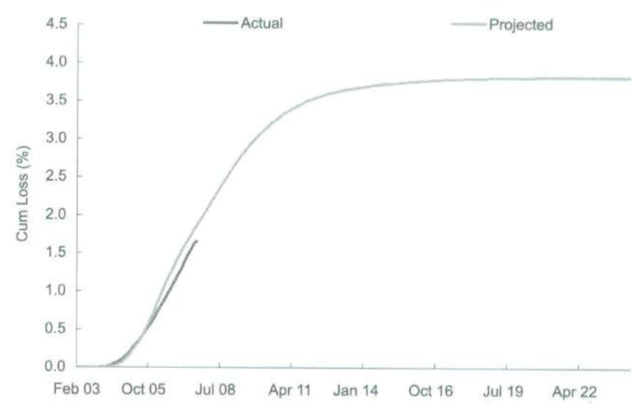
Cumulative Losses for ACE 2006-NC1 by Voluntary CPR and CDR (%)

	Voluntary CPR						
CDR	10	20	30	40	50	60	70
5	15	9.1	6.2	4.6	3.5	2.7	2.1
10	23.7	15.7	11.3	8.6	6.7	5.3	4.2
15	29.2	20.7	**15.5**	12.1	9.6	**7.7**	6.1
20	33	24.6	19.1	15.2	12.3	10	8.1
25	35.8	27.7	22.1	18	14.7	12.1	9.9
30	37.9	30.3	24.8	20.5	17	**14.2**	11.7

Source: Citi.

EXHIBIT 42

Actual versus Projected Losses—2003 Origination 2/28s



–5% HPA for 36 months, followed by HPA mean reverting to +3% over 12 Months; HPA is held constant at +3% thereafter.

Sources: LoanPerformance and Citi.

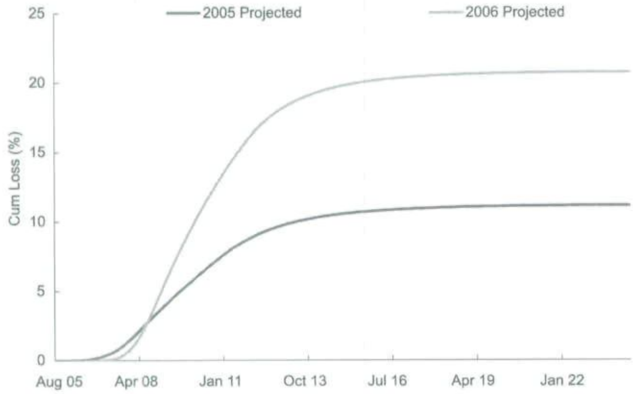
Exhibit 46 shows projected losses for different unemployment rate and interest rate scenarios (using the moderate weakening HPA scenario). The variation in losses is not as large as it is for changes in HPA. In the case of interest rates, this is partly because these are subprime ARMs so prepayments are relatively insensitive to rates.[24]

Analysis of the ABX Indexes

We have used cohorts, such as all 2006 2/28s, to illustrate applications of the model. Models are ultimately used for bond and portfolio analysis, however, so for this purpose we will use the ABX indexes as examples.

Exhibit 43

Actual versus Projected Losses—3Q 2005 versus 3Q 2006 Origination 2/28s

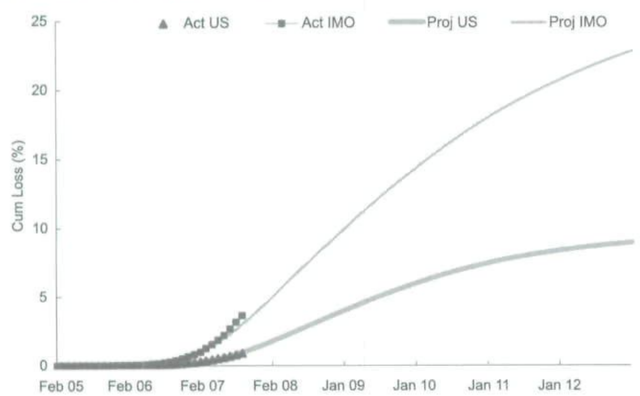


−5% HPA for 36 Months, followed by HPA mean reverting to +3% over 12 Months; HPA is held constant at +3% thereafter.

Sources: LoanPerformance and Citi.

Exhibit 44

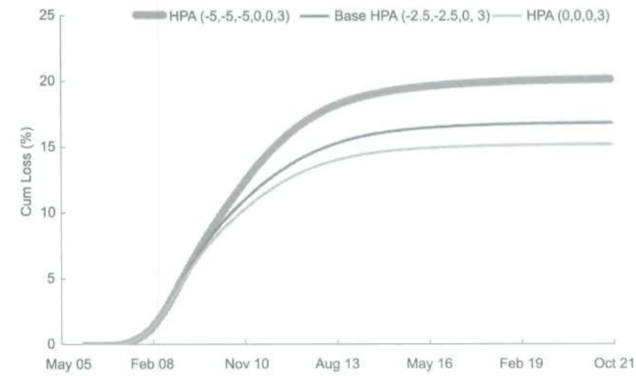
Actual and Projected 2/28s Cumulative Loss %—U.S. versus IMO 2005 2/28s



Sources: LoanPerformance and Citi.

Exhibit 45

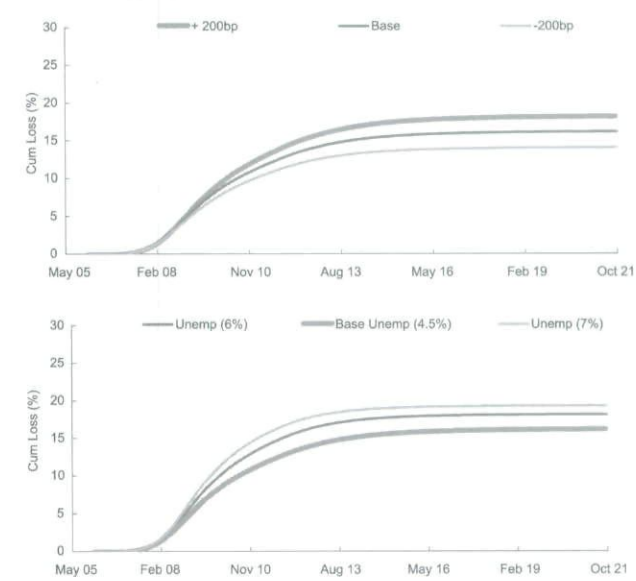
Projected Cumulative Losses on 2006 Subprime 2/28s under Different HPA Scenarios



Sources: LoanPerformance and Citi.

Exhibit 46

Projected Cumulative Losses on 2006 Subprime 2/28s under Different Interest Rate (Upper Panel) and Unemployment Scenarios (Lower Panel)



HPA assumed to be −2.5% for two years, zero for one year, and 3% thereafter.

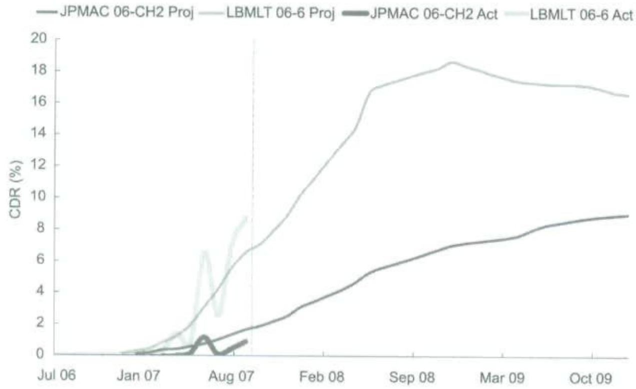
Sources: LoanPerformance and Citi.

We start with two of the underlying deals in ABX 2007-1—one performing worse than average and one performing better than average. The first deal, LBMLT 2006-6, has been performing poorly with serious delinquencies already at 28%. The second deal, JPMAC 2006-CH2, has been performing well with serious delinquencies at a relatively low 8% (the average for ABX07-1 is about 19% as of the November 2007 remittance reports). Exhibit 47 shows actual and projected CDRs for both deals, while Exhibit 48 shows collateral characteristics and projected lifetime cumulative losses.[25]

A comparison of the two deals illustrates the interplay of different collateral risk factors. The JPM deal has a larger fraction of low FICO borrowers, but this is offset by several other risk factors. The LB 06-6 deal has a higher SATO (as implied by the higher WAC), a higher LTV, a higher purchase percentage, and a higher second-lien percentage. These factors overwhelm the impact of a low

EXHIBIT 47

LBMLT 06-6 and JPMAC 06-CH2 Deal CDR Projections (Actual and Projected CDR Comparisons)



Sources: LoanPerformance and Citi.

FICO, which is consistent with the observation that FICO has become less predictive of credit performance because borrowers used previous equity gains to help pay bills and improve their credit records.

ABX indexes and bond analysis. While technical factors play a role in day-to-day changes of the ABX indexes, little doubt exists that the ABX indexes are one of the best leading indicators of the now well-documented problems of the subprime and housing markets.[26] In other words, the ABX indexes incorporate information about market expectations for home price appreciation and subprime credit performance in real time just as the yield curve incorporates market expectations for the economy and inflation.[27] As a result, it is only natural to use the ABX indexes to price mortgage credit, analogous to how the swap curve is used to determine discount rates to get present values of projected cash flows. Exhibit 49 shows the steps in this process.

Implied "HPA" risk. Taking the analogy a step further, just as forward rates are in some sense a probability-weighted average of possible rates, ABX index valuations can be thought of as an average over possible "HPA" scenarios. An "HPA" probability distribution that fits ABX index pricing can be used to price the credit risk of individual bonds. We put the term HPA in quotes because it refers to more than just traditional national HPA. We discuss this further shortly.

Our results from fitting the ABX index market prices in early January 2008 are shown in Exhibits 50 and 51. Exhibit 50 shows projected collateral losses and bond writedowns and Exhibit 51 shows model prices (along with the market price) for seven HPA scenarios. For each scenario, we assume that home prices fall by the stated amount over three years, then are flat for two years, then increase 3% per year after that (so, for example, the column labeled –15% assumes –5% HPA per year for three years followed by two years of zero HPA, and +3% thereafter).

A distribution with a mean cumulative drop of 30% in home prices over the next three years (a normal distribution with a volatility of 10% is assumed) best fits the market prices shown. This implied HPA distribution can then be used to price other ABS bonds.

Is the ABX market pricing to irrational levels of HPA? This is possible, since the mortgage credit market is clearly stressed, with even prime jumbo to conforming mortgage rate spreads about 75 bp wider than the spread has been traditionally.

It is more likely, however, that the –30% cumulative HPA over the next three years, implied by ABX prices, represents more than just the risk of national home prices dropping by almost a third over the next three years—a scenario that seems highly unlikely. In other words, since the ABX indexes directly represent value in subprime bonds and are only indirectly related to national HPA, most of the stress implied by ABX pricing probably has more to do with subprime-specific factors than technical factors which may be depressing prices. A few examples follow:

EXHIBIT 48

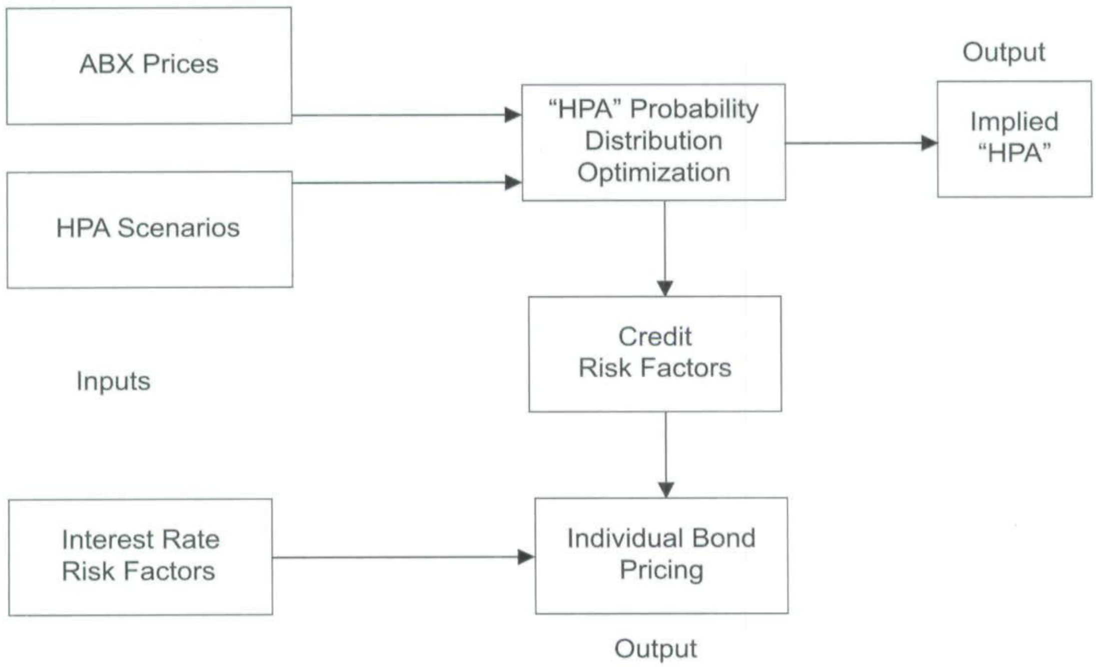
LBMLT 06-6 and JPMAC 06-CH2 Deal Collateral Characteristics

	WAC	FICO	FICO < 550	CLTV	LTV > 90	ARM	Prch	Cash	IMO	CA	Piggy Back	2nd Lien	Low Doc	D60 ++	Proj. Cum Losses
JPMAC 06-CH2 MV9	7.71	636	10.4	83	6.8	64.4	31.7	65.2	4.9	13.2	29.4	0	54.5	7.7	17.6
LBMLT 06-6 M9	8.24	638	5.7	90	9.5	84.3	56.4	39.3	2.6	41.8	48.9	4.8	49.6	28.0	29.0

Source: Citi.

EXHIBIT 49

ABX Implied "HPA" Probability Pricing System



Source: Citi.

- *Subprime specific HPA.* There have been numerous anecdotes suggesting that the hardest hit housing markets are often the ones with high concentrations of subprime mortgage borrowers. It is possible that the average HPA for subprime collateral turns out to be significantly worse than average.[28] For example, tiered home price data from S&P/Case-Shiller suggest that low- and mid-tier-priced homes have declined more than high-tier-priced homes in California.[29]
- *Data and model risk.* We have already discussed how some borrower data were fudged to help borrowers obtain loans. While one would hope that most of the loan application fraud surprises are behind us, we cannot rule out the possibility of further deception being discovered.
- *Servicer performance.* Unexpectedly poor default management, perhaps in part due to unprecedented volumes of delinquencies, could result in worse losses on corresponding subprime bonds. Thus, average losses per loan might increase as the volume of delinquent borrowers swells, perhaps overwhelming some servicers.

Our opinion is that the implied risk from ABX prices is equivalent to a 30% home price decline *assuming no other risk factors are present*. However, the market, for good reason, is likely pricing in subprime bond risk factors beyond just the risk of negative national HPA.

Application of the ABX Indexes to Bond Analysis

We can apply the implied "HPA" distribution from the previous section to individual bonds which provides a way to get a price consistent with ABX market pricing.[30] Exhibit 52 contains the information about the bonds in ABS deal Argent Securities Trust 2006-W4.

We can first price the bonds for each of the HPA scenarios that we used in pricing the ABX index. We then apply the implied "HPA" probability distribution (which fits ABX index market prices, shown at the bottom of Exhibit 51) to the Argent Securities Trust 2006-W4 bonds to get a weighted average price across scenarios for each bond (Exhibit 53). For simplicity we assume a zero discount margin.[31]

Justification of the lower-rated tranche prices. The models project cumulative losses of roughly 11.2% to 15.0% after two years, which seems reasonable given the bond's 29.3% D60++ percentage (in October 2007). Since the current

EXHIBIT 50

Projected Cumulative Collateral Losses (Shaded) and Bond Writedowns for the ABX Indexes

Index	Mkt Price	Collat. Cum. Losses and Bond Writedowns — Home Price Change in 3 Yrs (%) -5	-10	-15	-20	-25	-30	-35	Wgtd Avg
ABX 07-2 Collateral		20.5	22.6	24.8	27.2	29.7	32.4	35.2	30.5
AAA	69.8	0	0	0	0	0	1.6	4.8	1.5
AA	39.5	0	0	0.8	11	36.2	73.9	90	49.6
A	27.7	14.3	43.7	75.6	91.9	99.9	100	100	93.7
BBB	21.5	99.3	100	100	100	100	100	100	100
BBB-	20.3	100	100	100	100	100	100	100	100
ABX 07-1 Collateral		18.4	20.2	22	24	26.1	28.3	30.7	26.8
AAA	72	0	0	0	1	1.4	1.8	4.1	1.9
AA	40.2	3.5	5	6.1	14	37.2	53.4	72.6	41.7
A	22.7	38.5	52.4	60.5	70.8	85.1	95	98.8	84.8
BBB	16.5	74.4	80	90.8	98.1	100	100	100	97.9
BBB-	15.7	85.7	92.4	99.6	100	100	100	100	99.5
ABX 06-2 Collateral		16	17.3	18.8	20.3	22	23.8	25.7	22.6
AAA	83.9	0	0	0	0	0.5	2.2	4	1.6
AA	59.8	0	1	2.3	5.7	16.2	28.6	37.2	20.6
A	33.6	15.8	30.2	36.9	45.9	66.7	81.1	92.2	68.6
BBB	18	77.5	87.4	90.3	95	95	97.3	100	95.9
BBB-	17	90	90	95	95.8	98	100	100	98
ABX 06-1 Collateral		10.8	11.6	12.6	13.6	14.8	16	17.3	15.1
AAA	94.5	0	0	0	0	0	0	0	0
AA	83.6	0	0	0	0	2.5	5	7.2	3.5
A	57.4	2.7	8.6	10	10.6	13.8	32	55	26.7
BBB	30.1	26.2	41.4	62.2	79.1	86.3	90	90.6	82.8
BBB-	23	61.2	75.6	85.7	88.8	90.6	93.1	99.2	91.7
Implied Scenario Probabilities		1.10%	3.50%	8.40%	15.70%	22.80%	25.80%	22.80%	

Source: Citi.

credit enhancement of the M4 bond is 12.6%, it is not surprising that the tranches which are subordinate to M4 have prices in the single digits, basically reflecting one to two years of interest payments in most HPA scenarios.

ABX implied "HPA" is no-arbitrage pricing and not an HPA prediction. The "HPA" implied by ABX should not be viewed as a prediction of home prices, just as the forward yield curve is not a prediction of future interest rates. Some market observers contend that ABX prices are mainly a reflection of 1) pervasive negative sentiment and 2) the need to hedge CDO and other long positions. As a result, they do not represent fundamental value in subprime bonds.[32] We take an agnostic view on this—the ABX implied pricing system described is not so much a relative value tool as much as a no-arbitrage pricing method, just as the widely used option adjusted spread (OAS) is based upon no-arbitrage principles.

In the case of OAS, if volatility is priced at very high levels, the interest rate paths used to compute the OAS of a mortgage-backed security (MBS) will be calibrated to reflect the high implied volatilities so that the MBS is priced consistently with caps and swaptions. Similarly, the prices we have obtained in Exhibit 53 are calculated consistently with ABX. If a potential buyer were to price the bonds (Exhibit 53) to much more optimistic HPA scenarios (i.e., much higher prices), then one could take advantage by selling the bonds to this buyer at the higher prices and buying an appropriate ABX index (which is priced at the market-implied more pessimistic HPA scenarios) to replicate the bonds sold, with the difference in present values representing arbitrage profit.

Second Liens

The importance of second liens can be seen by breaking down actual losses on the 2006 vintage by product, shown in Exhibit 54.

EXHIBIT 51
Projected ABX Index Prices by HPA Scenario

		Model Prices							
	Mkt	Home Price Change in 3 Yrs (%)							Wgtd Avg
Index	Price-5	-5	-10	-15	-20	-25	-30	-35	Price
ABX 07-2 Collateral									
AAA	69.8	103.7	104.2	104.6	105.2	105.9	106.2	106	105.7
AA	39.5	114.7	116.7	117.9	110.1	85.4	50.3	33.2	72.5
A	27.7	127	95.2	59.5	36.4	27	24.4	22.6	33
BBB	21.5	37.7	30.6	26.5	24.1	22.4	21	19.9	22.5
BBB-	20.3	29.5	25.8	23.1	21.4	20	18.9	18	20.1
ABX 07-1 Collateral									
AAA	72	100.4	100.5	100.5	100.4	100.4	100.3	99.5	100.2
AA	40.2	98.2	97	96.2	88.5	68.7	53.1	36.7	64.1
A	22.7	72	60.6	49.9	37.6	24.9	16.5	13.6	26
BBB	16.5	40	28.5	19.3	14.7	13.1	12.3	11.7	14.2
BBB-	15.7	28.6	21.7	16.4	14.9	14	13.3	12.7	14.3
ABX 06-2 Collateral									
AAA	83.9	100.4	100.4	100.4	100.5	100.5	100.2	99.9	100.3
AA	59.8	101	100.3	99.4	96.7	87.8	77.3	69.7	83.9
A	33.6	89.8	77.6	71.8	61.7	42.9	30.8	20.9	41.9
BBB	18	37.7	28.4	24.3	18.7	16.7	12.9	11.1	16
BBB-	17	26.6	25.3	19.9	16.8	13.5	11.9	11.2	14.2
ABX 06-1 Collateral									
AAA	94.5	100.4	100.4	100.4	100.4	100.4	100.5	100.5	100.5
AA	83.6	101.3	101.5	101.6	101.8	100.1	98.2	96.5	99.2
A	57.4	101.7	97.1	95.9	95.7	92.8	77.2	58.6	82
BBB	30.1	90.2	77.3	58.5	41.2	32.2	26.9	22.5	34.5
BBB-	23	65.2	49.8	36.8	31.9	28.6	23	17.1	26.9
Implied Scenario Probabilities		1.10%	3.50%	8.40%	15.70%	22.80%	25.80%	22.80%	

Given that higher-rated tranches are more sensitive to factors such as ratings downgrade risk, we have placed most of the weight in the optimization/fitting to market prices on the lower-rated tranches.
Source: Citi.

Second-lien liquidations tend to be very quick with loss severities of 100% or more—lenders do not have many options as legal action may be dependent on the first-lien lender and may not be worthwhile in any case due to the small balances second-lien loans typically have.

Because of their unique loss curves, we model second liens separately from first-lien fixed-rate loans. As we see in Exhibit 54, model projected second-lien losses follow a pattern similar to that of actual losses.

SUMMARY

Subprime mortgage securities are challenging to model, as the market has learned to its detriment over the last year. One example is the problem of limited relevant data. Underwriting practices and standards change over time so that historical prepayment and performance data may be of limited use. Such practices and standards also vary widely among subprime originators because there are no equivalents of the GSEs imposing uniformity on the market. Beyond that, the data can be of questionable reliability. At the height of the housing boom in 2006, for example, the widespread presence of limited or no documentation loans and inflated appraisals created doubt surrounding reported risk factors such as DTIs and LTVs.

In this article, we have described a subprime default model that attempts to overcome these data issues in several ways. The model uses implied *fraud factors* to compensate for shoddy or even fraudulent underwriting. It uses dynamic deal-specific adjustments to incorporate originator- and servicer-specific effects. The result, as we have attempted to demonstrate in this article, is a model that has tracked actual prepayments and defaults quite well over time and that can be used for objective and rigorous analysis of subprime mortgage securities.

EXHIBIT 52

Overview of Bonds in ABS Deal Argent Securities Trust 2006–W4

Tranche	Type	Coupon (%)	Float Formula	Moody's/S&P/Fitch Original	Moody's/S&P/Fitch Current	Factor
A1	Sen Flt	5.04	1 Mo. LIBOR + 0.175	Aaa/AAA/AAA	Aaa/NA/AAA	0.5051
A2A	Sen Flt	4.925	1 Mo. LIBOR + 0.06	Aaa/AAA/AAA	Aaa/NA/AAA	0.0823
A2B	Sen Flt	4.975	1-Mo. LIBOR + 0.11	Aaa/AAA/AAA	Aaa/NA/AAA	1
A2C	Sen Flt	5.025	1-Mo. LIBOR + 0.16	Aaa/AAA/AAA	Aaa/NA/AAA	1
A2D	Sen Flt	5.135	1-Mo. LIBOR + 0.27	Aaa/AAA/AAA	Aaa/NA/AAA	1
M1	Mez Flt	5.175	1-Mo. LIBOR + 0.31	Aa1/AA+/AA+	Aa1/NA/AA	1
M2	Mez Flt	5.185	1-Mo. LIBOR + 0.32	Aa2/AA/AA	Aa2/NA/AA	1
M3	Mez Flt	5.205	1-Mo. LIBOR + 0.34	Aa3/AA-/AA	Aa3/NA/AA	1
M4	Mez Flt	5.295	1-Mo. LIBOR + 0.43	A1/AA-/AA-	Baa2/NA/A	1
M5	Mez Flt	5.325	1-Mo. LIBOR + 0.46	A2/A+/A+	Ba1/NA/A-	1
M6	Mez Flt	5.405	1-Mo. LIBOR + 0.54	A3/A/A	B1/NA/BBB	1
M7	Mez Flt	5.915	1-Mo. LIBOR + 1.05	Baa1/A-/BBB+	Ca/NA/BBB-	1
M8	Mez Flt	6.115	1-Mo. LIBOR + 1.25	Baa2/BBB+/BBB	C/NA/BB	1
M9	Mez Flt	6.965	1-Mo. LIBOR + 2.10	Baa3/BBB/BBB	C/NA/B	1
M10	Mez Flt	7.365	1-Mo. LIBOR + 2.50	Ba1/BBB-/BBB-	C/NA/CCC	1

Source: Intex.

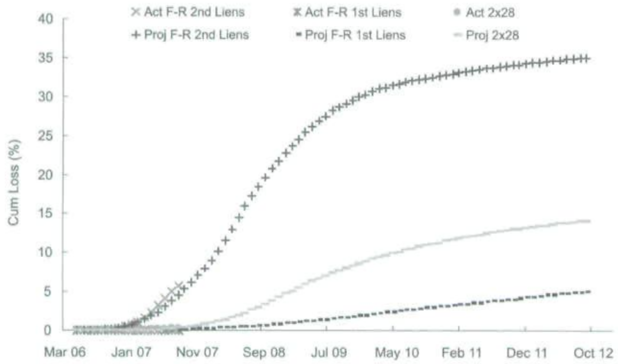
EXHIBIT 53

Pricing Bonds in Argent Securities Trust 2006–W4 Deal

Tranche	CUSIP	Home Price Changes in 3 Yrs: -5	-10	-15	-20	-25	-30	-35	Wgtd Avg Price
A1	040104TU5	100.31	100.35	100.4	100.46	100.55	100.61	97.62	99.86
A2A	040104TE1	100	100	100	100	100	100	100	100
A2B	040104TF8	100.08	100.08	100.08	100.08	100.08	100.08	100.08	100.08
A2C	040104TG6	100.29	100.3	100.32	100.33	100.36	99.41	94.68	98.81
A2D	040104TH4	101.11	101.33	101.65	102.14	102.95	87.54	77.07	92.76
M1	040104TJ0	102.33	102.89	103.71	85.86	38.96	19.19	16.46	44.45
M2	040104TK7	103.56	96.28	50.41	19.65	16.34	14.45	13.23	22.3
M3	040104TL5	71.74	22.59	17.25	14.67	13.18	12.08	11.21	14.01
M4	040104TM3	20.5	16.56	13.98	12.5	11.41	10.56	9.89	11.51
M5	040104TN1	15.03	12.96	11.42	10.43	9.7	9.07	8.56	9.71
M6	040104TP6	11.44	10.26	9.36	8.73	8.21	7.76	7.38	8.19
M7	040104TQ4	9.53	8.81	8.23	7.78	7.41	7.06	6.78	7.38
M8	040104TR2	7.29	6.9	6.57	6.3	6.09	5.88	5.7	6.06
M9	040104TS0	6.39	6.12	5.94	5.77	5.62	5.49	5.37	5.61
M10	040104TT8	5.04	4.93	4.84	4.72	4.66	4.6	4.54	4.65

Source: Citi.

EXHIBIT 54
Actual and Projected Cumulative Losses for 1Q 2006 Subprime Originations by Lien



Sources: LoanPerformance and Citi.

Nevertheless, there are challenges in trying to model subprime prepayment and default behavior in the future. First, subprime mortgage performance is critically dependent on home price changes. Home prices are dropping nationally by significant amounts for the first time since the Great Depression, and seem likely to keep dropping for the next year or two. We have almost no data on subprime performance in a severe housing market downturn.[33] We have compared low- and high-HPA regions to extrapolate to a negative HPA regime, but the inherent uncertainty in such projections should be recognized.

Second, the subprime market has undergone a dramatic change since mid-2007. Underwriting standards have gone from being very loose to extremely tight, and there has been a shift from adjustable- to fixed-rate mortgages. The tightening in underwriting standards is modeled in several ways. The implied fraud factors can be set back to zero if the DTI and LTV data for new originations are deemed reliable. A general tightening in the availability of mortgage credit can be modeled by time-dependent costs of refinancing. As long as the data are reliable, the model, with these time-dependent features, should be able to provide useful projections regardless of the loan composition in new originations.

ENDNOTES

The authors wish to thank Lawrence Jin for his immense help with the analysis for this article, Janice London for her careful preparation of the manuscript, and Andrew Weissman, Judith Antelman, Louise Bylicki, and Norma Lana for their fine editorial assistance.

[1]A general description of Citi's overall prepayment model is given in Hayre et al. [2004].

[2]The percentage of loans that are delinquent in a pool can be measured using either the Mortgage Bankers Association (MBA) or the Office of Thrift Supervision (OTS) convention. The two methods differ in how missed payments are counted with the MBA counting the missed payment at the end of the same month and the OTS counting it at the beginning of the following month, but only if the borrower has not caught up all missing payments. Hence, if, for example, a borrower misses the August 1 payment, the MBA method will say the borrower is 30-day delinquent as of the end of August. If the borrower becomes current in September (that is, makes both the August and September payments on September 1), the OTS method will count him as current for both August and September; if he misses his September 1 payment, the OTS will say that he is 30-day delinquent in September. The OTS method is more widely used in the industry, and unless otherwise stated we will use the OTS convention.

[3]A more detailed discussion of the foreclosure process is given in Hayre et al. [2008], a companion paper describing our loss severity model.

[4]The lax and sometimes fraudulent underwriting in recent years has led to some borrowers becoming delinquent soon after the loan is taken out, a phenomenon often labeled *early payment defaults*, or EPDs.

[5]This also follows from basic statistical theory. Under very reasonable probabilistic assumptions about changes in home prices (and assuming that the long-term trend is upward), it can be shown that the average increase in home prices grows linearly with time, while the dispersion of possible home prices around the mean increases proportionally to the square root of time. Hence, after a long time, the probability that the home price is less than its initial value is very low.

[6]Note that even though the data in Exhibit 1 is for prime conforming mortgages, there has been an increase in the proportion of delinquencies caused by excessive obligations. Clearly, the trend will be much more pronounced for subprime loans.

[7]The FICO (Fair Isaacs & Co.) score is based on an algorithm which uses a borrower's past debt history along with estimated current obligations and other related information to assign a score of between 300 (lowest) and 850 (highest) to a borrower. Most prime borrowers will have a score above 700, while most subprime borrowers will have a score below 700. Newer credit scores have been developed, such as the VantageScore created by the three major credit bureaus, to compete with the FICO score.

[8]Lenders often use two DTI ratios, one based on just the mortgage payments including property tax and insurance (sometimes called the front-end ratio) and one based on all of the borrower's monthly loan payments (sometimes called the back-end or total ratio). The latter, which includes other debt such as car loans, is the one we refer to in the article and the one most commonly referred to. In Loan Performance's MarketPulse publication (March 2007 Data), "The Impact of Underwriting Subprime ARMs at the Fully Indexed Rate: An Analysis of Debt-to-Income Ratios," explains that "in LP's database, only about 4% of the loans included both front-end ratios and back-end ratios, while 88% had only a back-end ratio, and the balance, about 7%, had neither reported."

[9]"Overstated property values" were among the problems cited for loans of one subprime lender as stated in *The New York Times* [2007]: "One loan involved a property in Ohio bought for $20,000 in August 2002 and sold two months later...[to] borrowers for $77,500. The average sales price in the neighborhood was $31,685 at the time."

[10]Many fixed-rate loans also have an IO period, and hence are also subject to payment shock.

[11]The SATO is calculated based on the initial coupon which could suggest some type of modification would be needed when it could be applied to ARMs. We have found, however, that the SATO works quite well for subprime ARMs without any type of modification, perhaps because few of these loans survive much past the first coupon reset.

[12]Vintage defaults in 2006 were related to the incorrect calculation of DTI ratios (Fitch [2007b]).

[13]A detailed description of our prepayment modeling framework is in Hayre [2004] which is available on FI Direct.

[14]By definition, the default and loss severity rates are applied to the remaining balance to get losses, so slower overall speeds imply a greater balance outstanding and, hence, greater losses.

[15]We prefer to make these adjustments at the deal level rather than at the originator and servicer level since this will incorporate the combined effect of both, and also reflects changes in originator and servicer practices over time.

[16]For a detailed description of the plan refer to American Securitization Forum [2007].

[17]See the strategy note in Hayre et al. [2007].

[18]Exhibits assume –3% HPA for projections.

[19]The projected CDR also depends on voluntary speeds to date. Higher voluntary speeds are assumed to leave more credit-impaired borrowers in the pool, and hence lead to higher defaults.

[20]Zero lag is assumed.

[21]In addition to the 66% of a sample of loan files showing owner-occupancy fraud mentioned earlier, another 16% of the sample indicated that a straw-buyer/flip scheme was involved. See Fitch [2007a].

[22]"Seriously delinquent" refers to loans that are delinquent by 60 days or more or are in foreclosure, REO, or bankruptcy.

[23]The rally in interest rates starting in 2001 also boosted refinancings on subprime loans.

[24]We also assume that HPA does not change with interest rates; if HPA declined as rates increased, for example, losses would be higher.

[25]For both Exhibits 47 and 48, we assume that HPA is –5% for the next 36 months, then moving over 12 months to a long term +3% where HPA remains for the rest of the life of the collateral.

[26]See *WSJ* [2007b] which illustrates how some doubted the implications of the deterioration in ABX prices.

[27]CME Housing Futures are a more direct measure of HPA expectations, but small trading volumes limit their usefulness. See Parulekar et al. [2006].

[28]We have previously indicated that nonagency products are located in areas that have suffered greater home price drops than agency collateral based on geographical concentrations. See *Speed Talk* [2007].

[29]About –3.6% HPA for low- and mid-tier-priced California homes versus –2% for high-tier-priced California homes from 1Q 2006 to 1Q 2007.

[30]Although not completely consistent (because the market and model prices are not exactly the same in Exhibit 51), market prices could be more closely matched by additionally adjusting the model (for example, by applying a multiplier to the default model) for that purpose.

[31]For a thorough discussion of discount margins, see Parulekar et al. [2007].

[32]We discussed earlier how the market is likely pricing in subprime bond risk factors beyond just the risk of negative national HPA.

[33]Although home prices have dropped by significant amounts in certain regions in the past, such as the oil patch states in the mid-1980s and California in the early 1990s, data on subprimes are limited. In addition, because the data are from such different housing and mortgage origination markets, they are of limited use.

REFERENCES

American Securitization Forum. "Streamlined Foreclosure and Loss Avoidance Framework for Securitized Subprime Adjustable Rate Mortgage Loans," December 6, 2007.

Fitch Ratings. "Drivers of 2006 Subprime Vintage Performance," November 13, 2007a.

——. "Fitch: Underwriting & Fraud Significant Drivers of Subprime Defaults: New Originator Reviews." November 28, 2007b.

Hayre, Lakhbir, et al. "Anatomy of Prepayments." Citi, March 2004.

——. "Streamlined Loan Modification Plan—Impact and Commentary," Citi, December 11, 2007

——. "A Loss Severity Model for Residential Mortgages." Citi, January 22, 2008.

New York Times. "Borrowing Trouble—A Class-Action Suit Tests a Home Lender's Practices," April 1, 2007.

Parulekar, R., et al. "CME Housing Futures—Hedges for Houses." *Real Estate ABS and Mortgage Credit*, Citi, June, 16, 2006.

——. "Relative Value in ABX Tranches—HPA Scenario-Based Approach versus Risk Premium Approach." *MBS and Real Estate ABS*, November 30, 2007.

Speed Talk. "First Quarter HPA—Still Positive or Negative," Citi, June 2007.

Wall Street Journal. "Banks Move Earlier to Curb Foreclosures," January 24, 2007a.

——. "Does Subprime Index Amplify Risk?" February 27, 2007b.