Draft: Not to be quoted without Permission of the author.

ROOTS of RESIDENTIAL MORTGAGE DELINQUENCIES in U.S.: 2000-2008

Gary Fissel*
Senior Financial Economist
Division of Research and Insurance
Federal Deposit Insurance Corporation
Washington, D.C.
gfissel@fdic.gov
and
Gerald A. Hanweck*
CONTACT AUTHOR
Professor of Finance
School of Management-5F5
George Mason University
4400 University Drive
Fairfax, VA 22030
703-993-1855
ghanweck@gmu.edu

October 13, 2010

* The views expressed are those of the authors and do not necessarily reflect the views of the FDIC or its staff. We would like to thank Jocelyn Grazal and Ahbinav Kapur for outstanding work in bringing together the price data.

Abstract

This study looks at the causes of the residential real estate and mortgage market collapse in terms of the delinquency and default movement of primarily subprime mortgages that were securitized in non-GSE securities. It examines the pool levels of these securities and their underlying mortgage contracts. In addition, this study analyzes the price behavior of the security pools relative to the underlying mortgages' performance to determine their coherence.

It is recognized that not all high risk loans move into some stage delinquency and/or default and so the study attempts to develop proxies of loan and borrower factors that indicate the profile of those mortgage loans and borrowers most likely to move into delinquency taking into consideration the economic and county-level mortgage markets. We also consider the prices of the pools' securities and interest rates paid by the mortgages that underlie the pool. This study analyzes the movements of borrowers into three separate areas of payment status changes – (1) more severe delinquency, (2) no change, or (3) recovery. Consideration of county level mortgage market characteristics is an attempt to address the question of why there occurred so many defaults during a period of no recession and a high rate of employment. To do this it is recognized that borrowers' willingness to pay depends largely on their desire to be a home owner rather than an investor in a residential property. To capture this desire, variables from the Loan Performance data base on loan and borrower characteristics at the time of loan origination are used. This study develops a cross-section analysis of delinquency status movements for different origination dates (vintages). The hypotheses tested represent the effects of loan and borrower level characteristics, pool factors and county mortgage factors, such as county employment growth, Case-Shiller house price index changes and their volatilities on the delinquency status changes for different origination dates. From a previous study (Hanweck 2008) that aggregated individual loan data to the MSA level, we found that loan and borrower level characteristics such as loan-to-value ratio weighted by original loan balances or the weighted proportion of loans that have no documentation, and MSA level economic factors such as employment growth are statistically significant and economically important in explaining MSA loan delinquency and default rates over the 359 MSAs for 2003 to 2008 vintage mortgages.

The uniqueness of this study is twofold. First, it develops estimates of individual loan level conditional probabilities of borrowers moving from one payment status to another – for example, current to 89-days or less delinquent would be a more severe delinquency event or any movement to a greater level of delinquency that may culminate in some foreclosure action, and vice versa would be a recovery. The results of this study can be used by investors to more efficiently value the conditional likelihood of borrowers' payment statuses on collateral that generates the revenue stream for these securities. These results can also be used for designing public policy regarding the housing market and locations and borrowers most likely to benefit from mortgage modifications such as for the Federal Government's HAMP Program. Secondly, the study statistically analyzes the relationship between the security pools' market prices and their underlying mortgage collateral performance. This would indicate the transparency of these securities to investors.

ROOTS of RESIDENTIAL MORTGAGE DELINQUENCIES in U.S.: 2000-2008

Draft October 13, 2010

I. Introduction

By mid-March 2007, the subprime mortgage market in the U.S. had virtually collapsed. Many subprime monoline firms had either been sold or were in bankruptcy. Further evidence of this collapse is that the ABX-HE-BBB index, an index represented by a basket of 20 credit default swaps (CDS) referencing U.S. subprime home equity securities of rating BBB, had declined from 100.1 on September 12, 2006 to 76.8 by mid-March 2007 and down to 26 by November 2007. This represents a 74 percent increase in the cost of a CDS, equivalently the cost of default insurance, on these securities. This study looks at the causes of this collapse in terms of the delinquency and default experience of subprime, Alt-A and Prime mortgages. It is recognized that not all high risk mortgage loans where property values have fallen below the outstanding balance of the mortgage will become delinquent and/or default. The study attempts to develop proxies of loan and borrower factors that indicate those loans most likely to move into some stage of delinquency taking into consideration the economic characteristics of the county-level housing markets, such as the typical borrowers' revenue status[1] and housing price changes represented by Case-Shiller house price index changes. Consideration of the local characteristics is an attempt to address the question of why there occurred so many defaults during a period of no recession and a high rate of employment. To do this it is recognized that borrowers' willingness to pay depends largely on their desire to be a home owner rather than an investor in a residential property. To capture this desire, variables from the Loan Performance data base on loan and borrower characteristics and local mortgage market conditions at the time of loan origination are used.

[1] Borrowers who are occupants of their properties represent 93 percent of the sample, and so, local employment growth will proxy for the borrowers' revenue status.

The study develops a model of individual mortgage debt valuation and uses this model as a guide for empirical estimation and choice of variables explaining delinquency and default with data based on borrowers and mortgages from the Loan Performance database. Since the value of any security – like a Collateralized Debt Obligation (CDO), Collateralized Mortgage Obligation (CMO), Mortgage-Backed Security (MBS) or Asset-Backed Security (ABS) – that depends on the value of the individual mortgage loans in the pool, valuing individual mortgages can provide investors with an estimate of the value of the security. Once these models are estimated, the implied likelihood of payment status changes to more severe delinquencies at various frequencies for mortgages in each security pool can be computed. Projections can be made of the rate that mortgages have more severe delinquencies or recoveries given the local economic and housing characteristics. As suggested by anecdotal information, the lax underwriting standards employed by originators over this 2000 to 2007 origination period would allow more borrowers with substandard credit histories and increase more severe delinquencies on their payment statuses. For example, the mean FICO score for all originations in this sample is 617 which is below the minimum level of a good FICO score, 620.

This study develops a cross-section and time-series analysis of payment status changes for residential subprime, Alt-A and Prime mortgages for 2000 to 2007 origination years where these mortgage contracts are followed on a monthly basis from their originations through 2008. As described more fully below, the hypotheses tested represent the effects of loan and borrower level characteristics and county-level mortgage market factors, such as employment growth, housing price changes and their volatilities, market level mortgage liquidity support and interest rate spreads, and security pool interest rates paid on its underlying mortgages and its market prices regressed on the payment status changes. In summary, we find that loan and borrower level characteristics such as loan-to-value ratio, the presence of no documentation for the borrower, and FICO score are highly statistically significant and

economically important in explaining the mortgage payment status through 2007 origination dates (vintages).

We next analyze the movement of pseudo-market prices that are constructed for each security pool and determine that these prices tend to not have any large quantitative relationship with the payment status changes of the underlying mortgages. This finding supports the view that possibly these securities were not transparent.

The paper proceeds with the development of a model of individual mortgage valuation to help to rigorously identify the factors that are the most likely to affect the decision by a borrower to default on a mortgage. The next section develops the empirical model and the estimation process. The fourth section discusses the results of the ordered logit models and the trends of these estimates from 2000 to 2008. The final section concludes with an analysis of the results from a policy perspective of mitigating mortgage defaults in the future which requires mortgage payments not to have delinquencies, identification of the most important factors that will need to change in order to currently reduce movements to more severe payment delinquencies and ultimately mortgage defaults, and a discussion about the lack of transparency in mortgage related securities.

II. Valuation of Default Risky Debt

The model that we use as a guide in valuing mortgage debt is that of Merton (1974) and Black and Cox (1973), MBC, to value corporate debt and its derived risk neutral probability of default. In our study this model is employed to value the mortgage debt, with the real estate property being the underlying asset in the option, and derive the risk neutral probability of insolvency or default. In this regard, we follow the application of the MBC model to residential mortgages as developed by

Hendershott and Van Order (1987) and Giliberto and Ling (1992), and a similar model for commercial mortgages by Titman and Torous (1989).

In general, the value of default risky debt can be thought of as the present value of the cash flow stream of the debt if it were default risk free less the value of an option held by the borrower to put the underlying asset to the lender if the borrower can not or is unwilling to continue paying on the debt. If this happens, the borrower defaults on the debt obligation. As developed, the likelihood of these occurring increases as the value of the underlying property falls toward or below the default free value of the debt owed by the borrower (the remaining balance of the mortgage).

Let L_t be the value of risky debt at time t and is defined for a zero coupon debt as:

$$L_t = B\exp(-R\tau) = B\exp(-R_f\tau) - p_t \tag{1}$$

where, $R(\tau)$ is the default risky discount rate, $R_f(\tau)$ is the risk free discount rate, $B\exp(-R\tau)$ is the present value of the default risky debt that is represented without any default risk, τ is the time to maturity, and p_t is the put option value that the lenders give the borrowers on the underlying asset at a strike price of the debt owed, B. In the MBC model the debt is considered to be zero coupon debt, an assumption that will be relaxed in applying the model to residential mortgages. In our case the underlying asset is the residential property placed as collateral on the loan and is valued at V_t.

The put option is the option held by the borrower to put the underlying property to the lender. In terms of the MBC continuous time model, the put option can be expressed as:

$$p_t = B\exp(-R_f\tau)N(-d_2) - V_t N(-d_1) \tag{2}$$

where:

$$d_1 = \left(\ln\left(V_t/B\right) + \left(R_f + 0.5\sigma_V^2\right)\tau\right) \Big/ \sigma_V\sqrt{\tau} \text{ and } d_2 = d_1 - \sigma_V\sqrt{\tau} \tag{3}$$

The value of the default risky mortgage debt can be restated by substitution of (2) into (1) and collecting terms:

$$L_t = B\exp(-R_f)N(d_2) + V_t N(-d_1) \tag{4}$$

From (4) and (3) the value of the default risky debt will increase as the value of the underlying property increases relative to the debt owed (V_t/B) and as the volatility of the underlying rate of change in the value of the property (σ_V) decreases (see (1) where the put option value will rise with the increase in property value volatility). In this model, borrower insolvency occurs when the value of the underlying asset falls below the promised value of the debt at any time. However, lesser housing price volatility can forestall this from occurring and can deter a borrower defaulting on the loan, i.e., giving over the property to the lender or entering into foreclosure.

II.A. Risk Neutral Probability of Default of Default Risky Borrowers

In the MBC model, the risk neutral probability of default is given by $N(-d_2)$.[2] More specifically from (3):

$$d_2 = \left(\ln(V_t) - \ln(B) + \left(R_f - 0.5\sigma_V^2\right)\tau\right) / \sigma_V\sqrt{\tau} \tag{5}$$

Hull (2007) points out that this value is also the number of standard deviations that the underlying asset value must change for it to fall below B and trigger a default.[3] The smaller is d_2, the more likely the borrower is to default. By assuming that the V is lognormally distributed, as above, the risk neutral probability of insolvency or, in the terminology of Moody's KMV, of default is:

[2] Hull (2007) p. 270-272 and Hull (2000) p. 630-632.
[3] This value is also known as the distance to default as used by Moody's KMV.

$$N(-d_2) = N\left[\left(\ln\left(B/V_t\right) - \left(R_f - 0.5\sigma_V{}^2\right)\tau\right) \Big/ \sigma_V\sqrt{\tau}\right] \tag{6}$$

This simple model identifies the principal factors in the valuation of default risky debt and the risk neutral likelihood of default. These are B/V_t (the loan-to-value ratio), σ_V, asset volatility, and τ, the time to expiration which could be considered the holding period of the borrower, the level of interest rates relative to the existing coupon rate on the mortgage, and/or time to interest rate reset for adjustable rate mortgages (ARMs). However some of these factors are not fully identified. For example, any impairment of the ability of the borrower to pay interest and principal can be considered to increase the uncertainty of the cash flow from the borrower and the asset value accordingly. However, if the market value of the real estate exceeds what is owed on the debt, the borrower can simply sell the property and payoff the loan. The borrower does not default and the lender is made whole just as in any mortgage prepayment. Thus, the inability of the borrower to pay on the mortgage is an important factor in possible default only when the value of the property falls to near or below the value of the outstanding debt (i.e., the optionality of the model). This suggests that loan defaults are going to be most affected by falling housing prices and rising loan-to-value ratios (falling V_t/B and rising $\ln(B)-\ln(V_t)$) than by factors that affect households' ability to repay, such as declining employment or rising unemployment. We will explore economic and demographic factors more when the empirical default model is specified.

II.B. Interpretation and Relaxation of the Assumptions of the MBC Model Parameters

1. The Value of Debt Owed, B

The value of the debt outstanding, B_t, needs a more precise definition in the application of the MBC model to value mortgages. In the MBC model as initially developed, debt was considered to be a zero coupon bond with a single maturity date with the option exercise only at the due date of the debt –

either it was repaid, renewed or defaulted with the asset put to the lenders. In contrast, a mortgage consists of a cash flow where, normally, principal and interest are paid monthly based on either a fixed or adjustable rate.[4] For fixed rate mortgages, the payments stream represents an annuity until the maturity of the mortgage, T, and with prepayment and default options. The certain payment value if the mortgage pays to maturity is the discounted values of these cash flows discounted by the risk-free rate for a term equal to the remaining maturity. However, if the house is sold or refinanced, the amount of the debt owed is the outstanding principle plus accrued interest. Thus if a borrower defaults, the value of the mortgage that is owed is the outstanding principal, the same as would be paid off if the borrower refinanced the mortgage. For the mortgage model, then, it is this value that we assign to B_t for each month, t, since payments of principal are made along with interest. An exception to this approach is for mortgages with an interest-only period. In this case B either remains constant over this period or increases if it is a negative amortization loan. In either case, B will change in a defined and systematic way with time.

From a different perspective, the borrower is committed to paying each period a contracted amount of interest and principal. For most of the time to maturity, this amount is considerably less than the outstanding principal. If the borrower can not meet these obligations, the loan is considered delinquent and the lender can declare it in default (usually not sooner than 90 days into delinquency). At this stage, the lender can file to repossess the property and put it up for sale or hold in REO. So that the obligation committed to by the borrower to make monthly payments encourages them to evaluate the value of the property to them relative to what they owe on the mortgage, B_t, or the outstanding balance. So the value of the outstanding balance of the debt is considered as the strike price of the put option in (1) and (2) above.

[4] ARM contracts can be of an overwhelming variety with such features as interest only, negative amortization or teaser rates interest only. In the empirical estimation we will try to account for these differences with information about the payment type for the mortgages as reported in the Loan Performance data.

2. Home Owner's Housing Consumption Value and Psychic Income from Ownership

Influencing the choice of when to put the property back to the lender if the market value of the property is less than the debt value as defined above, is the willingness of the borrower to make the mortgage payments. A borrower has an incentive to pay the mortgage because the household receives a consumption value from residing in the house over and above the market value of the property. This periodic consumption value needs to be added to the market value of the house at each period in the life of the loan.[5] This adjustment has no effect on the likelihood of prepayment for refinancing or its timing, but does effect how far property values must decline to trigger default: asset values must fall below psychic value derived from home ownership plus the outstanding debt value. We treat this factor as more than simply an implied rental rate since it includes the value to the borrower of homeownership. In our empirical analysis, we will try to capture this psychic income from homeownership and the ability of the borrower to pay the mortgage by a variable that measures the presence (or absence) of loan documentation. The reasoning for this variable will be discussed more fully in the empirical section below.

The effect of including the psychic income from the ownership of the house is to account for the fact that many borrowers will continue to pay on a mortgage when the market value of the property is less that what is owed on the mortgage. In a reasonably competitive housing market, homeowners could give over their home to the lender when the market value is less than the debt owed and rent a similar property, allowing them to get the same consumption value. If they do not and assuming rationality on the part of homeowners, the psychic value from homeownership is positive. This means that the rational

[5] Hendershott and Van Order (1987, p.40) term the consumption value a service flow and treat it as a dividend in their mortgage default model. We will treat this consumption value as an addition to asset value when considering default.

mortgage borrower will be willing, if they have the sufficient resources, to continue in what would be an unfavorable out-of-the-money mortgage. It also helps explain those borrowers', with little or no homeownership pride, willingness to default as soon as the market value of the property can be reasonably expected to fall below the amount of the debt owed. The implication is that borrowers acquiring property for investment purposes would either try to sell the property quickly or default more often as property values fall. We will argue below that the absence of loan documentation, if the house is expected to be owner occupied, or whether the house is a single family detached or townhouse are important factors in helping to account for these types of borrowers.

Based on this discussion, we assume that borrowers will set a threshold on the market value of the property such that if it is less than the threshold the borrower will give over the property to the lender. The threshold property market value, V^*, will encompass the psychic income from ownership, PSI, and the value of the debt owed. The threshold can be stated as:

$$V_t^* = B_t - PSI_t \tag{7}$$

This suggests that mortgages that were originated say one year before a housing price peak, would have to experience greater declines in housing values from the peak before defaulting than for mortgages originated at or near the peak because for a similar property with the same LTV, since it has higher debt value, but the same PSI. This helps explain why mortgages originated at or near a housing peak may default more rapidly as housing prices fall than mortgages originated one year prior to the peak when housing prices were still rising. Explicit recognition of psychic income of home ownership also helps confirm that as a long as the borrower has sufficient cash flow, those with greater psychic income will be willing to withstand greater housing price declines than those with little or no attachment to the property except as an investment before defaulting.

3. Other Factors Influencing Mortgage Default

Other factors are thought to be important in determining default on a mortgage. Bartlett (1994) specifies the following list:

2. Borrower employment status,
2. Loan purpose such as a mortgage for purchase of the property of a refinance,
2. Property type such as single-family detached, townhouse or condominium,
2. Loan type such as a 30-year fixed rate mortgage or an ARM or reduced payment loan,
2. Loan seasoning,
2. Absolute loan size with large loans being associated with properties with greater value variability,
2. Loan documentation ranging from full documentation to no documentation indicates the quality of the underwriting, and
2. Presence of a second mortgage.

Empirical proxies for these factors in many cases are present in the Loan Performance database that we use and from other county-level data (Table 1 shows the variables used in the study).

Following Demyanyk and Van Hemert (2007), "there is a large literature studying the determinants of mortgage delinquencies and foreclosures, dating back to at least von Furstenberg and Green (1974)." Two of the more recent studies include Cutts and van Order (2005) and Pennington-Cross and Chomsisengphet (2007).[6] To the best of our knowledge, we are the first to study the effects of a number of determinants contributing to the changes in mortgage performance that lead to high delinquency and default rates or recoveries for 2000 to 2007 vintages of subprime, Alt-A and Prime mortgages by security pools. Preliminary analysis shows a trend in the delinquency and foreclosure rate from 2003 to 2008 vintage mortgages, after accounting for different loan characteristics, borrower characteristics, house price appreciation and employment growth. This is consistent with the trend found by Demyanyk and Van Hemert (2007) for 2001 to 2006 vintages using the Loan Performance data. They also found that 2006 vintage loans had the highest rate of delinquency and foreclosure of any other

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

vintage at ages up to 16 months with 2005 vintages in second place. Finally, we project payment status changes for each origination year with a random 25 percent of the sample not used for estimation (see Table 7). In this way we can assess the accuracy of this model for out-of-sample projections.

III. Data Sources, Variables and Empirical Estimation

A. Data

The residential real estate data used in this sample comes from LoanPerformance that was continuously collected monthly since 2000[7]. It has monthly mortgage loan data for subprime, Alt-A and some prime loans. The period that we investigate in this study is 2000 – 2008 with vintages of 2000-2007 and use data from the Asset-Backed Security portion of this data base. These origination dates were chosen because they constitute the period of the boom in originations and housing prices during 2005 and the fall in prices through 2008. We examine the factors that contribute to mortgage loan delinquencies and recoveries as well as how closely the market securities were related to their underlying mortgage loans. This data contains the mortgage loans that are the collateral base for one or multiple tranched Collateralized Debt Obligations (CDO) used in this study.[8] The sample has 393 separate deals, an average of 2.3 pools (or groups) per deal, and a mean of 3.5 separately traded securities per pool. The mortgage loans that serve as collateral for these CDO securities have origination dates from 2000 through 2007. The loan level data contains financial attributes of the mortgage loan as well as other attributes, such as the property geographic and pool (or group) information. We are also able to get other attribute data on the CDO deal from Intex at the pool level. For this sample, pools within a CDO are the groups of the underlying assets from which the security draws its revenue. The CDO deals can either contain pools or not, so in the latter case there is only one group within the whole

[7] This LoanPerformance data set contains non-Agency Mortgage- and Asset-backed securities, and the mortgage loans that support it. This data set is from First American CoreLogic.
[8] In this paper, we use Collateralized Debt Obligations (CDO) to refer to a number of different securities that are constructed into one or more tranches, such as collateralized mortgage obligations while excluding mortgage-backed securities.

deal whereas the former would contain separate pools of assets that generate revenue for the security. If a deal does have multiple pools, then they would typically have between two or three separate groups.

The prices for individual pieces of the CDO deal, via their CUSIP numbers, are from INTEX, as well as other attributes of this securitization deal including the pool for these assets. We created a price for each pool in our sample by weighting each market price by its outstanding principal balance at origination.[9]

The estimation sample period is from 2000 through 2008 and the securities within the pools had to be traded to be included in this sample. This extends from the mortgage loan originations through 2007, and the pools in this sample include pool 0 that exists for the 2000 and 2001 years, pools one and two are added in 2002 and pool three is added in 2003. The original sample contains six other smaller pools that were excluded because of their sizes. The lowest average number of securities in the pools for the estimation sample was slightly under 40, while the largest average number for the pools not in this sample was slightly under five securities.[10]

The data used here is at the individual mortgage level on a monthly basis from LoanPerformance, Intex and Bloomberg for the security prices. These data can be aligned directly to each pool. The other data, such as the Case-Shiller indexes and county employment are gotten from Moody's economy.com. These data are collected at the county level. Lastly, the net change in mortgage funding variable comes from Table F.217 in the Flow of Funds report by the Federal Reserve Board of Governors.

[9] Each pool (or group) within CDO deals have separate tranches that contain market prices and these tranches are appropriately weighted to form the pool price. For deals that do not contain tranches, then there is only one pool for that security. Each pool contains assets from the deal that are used to generate revenue for that security.
[10] There were a total of ten pools in the sample that exist over the 2000-2008 period.

We analyze this real estate data by mortgage vintages for separate CDO Pools (or Groups) to gain greater insight into the changing standards on mortgage originations. Every mortgage loan in a vintage is tracked through time until either its document payoff date or December 2008.

B. Empirical Model

1. Estimation Methodology

The model used for estimation relates mortgage payment status changes, as defined below, to concurrent characteristics of the loan, associated borrower, mortgage market, security pool, and market interest rate spread characteristics. Formally the model is:

Payment Status Change = f(*Loan and Borrower characteristics*, *Mortgage Market characteristics, Security Pool characteristics, Market Spread characteristics*) (8)

Since a borrower's payment status change is either one of three possibilities – more severe delinquency, recovery from a delinquent status or no change in a status, the estimating procedure should take this into account. To capture this, a borrower's transition through these status changes, this study uses a ordered logistic estimating procedure which assumes that the dependent variable belongs to any of the changes and that there is an index variable that is logistically distributed (see Curry, Fissel and Hanweck, 2008 for an example of this approach for bank holding company risk ratings). Estimating our model with ordered logistic regression procedure gives estimated parameters that can be used to predict the transition of a borrower through changes in the payments process and the probabilities associated with each transition. The estimating methodology will allow the estimation of the likelihood of a borrower moving to payment status change. For example, a borrower starting 30-days past-due within one month

can move to current or to 90-days past due where these hypothetical scenarios would result in recovery or more serious delinquency status changes.

2. Loan and Borrower Characteristics

The lagged delinquency status of the borrowers is the first set of variables that are used to predict their change in payment status. Identifying the previous payment status of borrowers is useful in determining their current status change. Given the three lagged status conditions used in the regression, the fourth excluded condition is the non-delinquent status.

The loan and borrower characteristic variables that we use attempt to follow those discussed above as likely indicators of default (see Table 1 for variable definitions). The Distance-to-Default measurement (Merton, 1974; Black and Cox, 1973) of the default likelihood by a risk-neutral borrower and it is designated as DEFAULT_DISTANCE. A smaller value for Distance-to-Default, then the larger is the likelihood of having more severe delinquency status changes. This variable, LTV ratios and FICO scores have been standard criteria used when evaluating the acceptability of mortgage loan applications.

The loan-to-value ratio at origination is reported at the loan level in the Loan Performance database and is estimated for each period using the current outstanding loan balance and an estimate of the property value from historical changes in MSA house prices. This variable is designated as COMB_LTV. For each loan at origination, the value of the original loan balance is divided by the appraised value or reported appraised value of the property on which the loan is made. The appraised value is as reported by the originator and may be subject to error. The loan balance that is used is the mortgage balance including any second mortgages or any take-downs on home equity lines of credit made at the time of origination and reported in each period. We expect that, following the model above in equation (8), a greater LTV will lead to a more severe delinquency status change indicating a greater likelihood of future default.

To capture the credit quality of the borrower, the FICO score at origination is used and reported by the lender. This variable is designated as FICO2 and is the individual borrower's FICO score at origination. We expect that the higher the FICO score, the better the credit quality of the borrower at origination and the less the likelihood of more severe delinquency payment status changes.

The structure of the mortgage is captured by the whether it is an ARM or not. Loans that are ARMs are designated as a dichotomous variable, flag_arm. Our hypothesis is that ARM mortgages are more likely to experience more severe delinquencies because the rates will usually reset much higher for subprime and Alt-A loans and the greater the servicing burden the borrower will have to bear.

The discussion above with regard to the psychic income from homeownership is proxied by the type of documentation the borrower was required to supply, flag_doc, and whether the house is intended to be owner occupied, flag_occupancy. Borrowers that supplied little documentation and did not intend to live in the house were likely those willing to sell the house as soon as it became profitable and had little attachment to the property or derived little psychic income. The hypothesis is that borrowers are more likely to have more severe delinquencies if they supplied little or no documentation and did not intend to be occupants. One other variable that may serve as a proxy for homeowner attachment to the property is whether the loan is for purchase of the house or a refinancing. This variable is designated as *purpose* and is expected to indicate lesser likelihood of default for loans that are for purchases. It was tried but found to be too unreliable and dropped.

We also attempt to control for the type of property (PROP_SF_TH) – single family detached or townhouse compared to others such as condominiums – and the initial rate of interest, actually the coupon, on the mortgage (INIT_RATE). We expect that if the property is a single family detached or a townhouse that the likelihood of more severe delinquencies over the sample period is less because of the greater resources initially required to own one of these properties compared to a condominium. The initial interest rate variable may have two interpretations. The higher the initial rate

the greater the risk of more severe delinquencies expected by the lender. From this interpretation, high rates indicate riskier loans that should lead to higher delinquency severities. An alternative interpretation is that a higher initial rate means that the borrower is not getting a teaser that will adjust later on and the lender and borrower are more confident that the borrower can make the payments at the high rate. This interpretation implies that higher rates are associated with borrowers that are able to make payments and have a lesser likelihood of more severe delinquencies. We maintain the former interpretation.

5. Mortgage Market Characteristics

The mortgage market characteristics include four variables that cover the demand and supply sides of the housing market at the MSA level. The annual Case-Shiller residential house price index change is constructed to measure annual residential housing price changes at the county level. It is designated by CS_RESHPRC_LN12DIFF and it is negatively related to more severe delinquency status changes. The sigma in housing price changes, SIGMA_CS, over the sample period shows the actual volatility in house prices over the sample period using the Case-Shiller monthly price index values over the 1999-2008 period. From an investor's perspective, volatility brings uncertainty to an investment, and they prefer more certainty with their investments. These annual housing price volatilities are assumed to be positively related to mortgages that are likely to have more severe delinquencies, especially if the property is an investment.

The mortgage market flows as tracked by the Federal Reserve are the net movements of money in and out of the mortgage market, NETCHG_MTGQR. These market flows represent the funding that is potentially available for mortgages and we believe that it is negatively related to the likelihood of more severe delinquencies. The fourth mortgage market variable is the annual county level employment change, EMPLOYMENT_L12LNCHG. This employment change variable represents a major source of

income for homeowners to purchase their homes and service their mortgages. It is negatively related to the likelihood of having more severe delinquencies.

5. **Pool Characteristics**

The Pool characteristics of the CDO pools represent factors that typify the risk level of the pool and demonstrate the link between the pools' values and their underlying mortgage assets. These variables include the weighted average coupons or interest rates that are paid by the mortgages underlying the pools that are related to the risk level of the assets that underlie the pool. This variable is weighted by the mortgage volumes at origination and is positively related to the likelihood that borrowers would have more severe delinquencies. The other pool characteristic is the weighted average pool price, POOL_PRICE_WGTD, which is derived from the individual security market prices that are members of the pool. If investors know the assets in which they invest, then there should be a negative relationship between this pool price and the likelihood of more severe delinquencies.

5. **Market Interest Rate Spreads**

We use two variables to explain the interest rate spreads in the economy when the mortgage existed. The first is the difference between ten and one year constant maturity Treasury bonds, YLDDIFF10Y_1Y, to indicate yield curve movements in the economy. Since steeper yield curves are associated with healthier economic periods, this yield curve spread is assumed to be negatively related to the likelihood of borrowers have more severe delinquencies on their mortgage contracts. The second spread is the difference between AAA and BAA corporate bonds to indicate the economy's willingness to hold risk. We believe that a greater willingness to hold risk will mean that this spread is larger, and that there is a positive relationship between this spread and the likelihood of having a more severe delinquency.

The mortgage market traits include four variables that cover the demand and supply sides of the housing market at the MSA level. The Case-Shiller residential house price change represents the price movements in housing at the county level. The sigma in housing price changes over the sample period shows the actual volatility in house prices over the sample period. From an investor's perspective, volatility brings uncertainty to an investment, and they prefer more certainty with their investments. The sigma variable is indicating mortgage contract compliance from an investor's perspective. The mortgage market flows as tracked by the Federal Reserve are the net movements of money in and out of the mortgage market, and so, represent the funding that is potentially available for mortgages. The fourth mortgage market variable is the annual county level employment change that represents a major source of income for homeowners to purchase their homes and service their mortgages.

Pool traits represent unique characteristics of the CDO pools. These variables include the weighted average coupons or interest rates that are paid by the mortgages underlying the pools. This variable is weighted by the mortgage volumes at origination. The other pool trait variable is the weighted average pool price that is derived from the individual security market prices that are members of the pool.

C. RESULTS

1. Dependent Variable Sections

Table 1 shows the sample means and standard deviations broken down by pools for the explanatory variables in the model. Table 2 contains the mean values for each segment of the delinquency status change – (1) movement toward a more severe delinquency, (2) no delinquency status change, and (3) recovery from delinquency status. This table shows the sample characteristics and tests whether the group that has a recovery from delinquency is statistically different from the movement to a more severe delinquency group. We first note that the values for DF3_FLAGL1 and DF4_FLAGL1 are

zero because these dummy variables represent the extreme limits for lagged severe delinquencies and recoveries, respectively. All of the differences in the mean values between the recovery and more severe delinquency groups are statistically significant at the 1% level as shown by the t-statistic column on the far right side of the table. What characteristics do we see about this sample? Given that moving into the first stage of delinquency (DF1_FLAGL1) is the most common type of delinquency, recovery from that delinquency status is the most common. The change to the more severe delinquencies group has the highest proportion of lagged 90 days or more dummy variable (DF2_FLAGL1). Moreover, this group has most of the extreme values that tend to make more severe delinquency more likely throughout the list of independent variables. The ARM and no documentation flags, initial interest rates, risk sensitive interest rate spreads, LTVs and gross pool mortgage interest rates are maximum values for the more severe delinquency group. These expected signs are positive which increases the probability that borrowers with these characteristics of this group will have more severe delinquencies. In the same way, annual employment changes, distance-to-defaults, mortgage market funding flows, annual house price changes and weighted pool prices are minimum values. Since these variables' expected signs are negative, borrowers with these characteristics of this group would have a higher probability of worsening delinquency changes.

The recovery from delinquency group has the largest proportion of single family or townhouse properties and borrowers who occupy these mortgaged properties. The expected signs on these variables are negative and support the concept of psychic income from home ownership. Borrowers who recover from their delinquencies maintain home ownership. This is consistent with the psychic income from homeownership. That is, many homeowners have this psychic motivation to maintain their home ownership.

2. Ordered Logistic Regression Estimates

We look first at the mortgage data by vintages and security pools. We can see from Figure 2 that the mortgage loan originations for Pool 0 began in 2000 and that Pool 1 is was the largest pool with a maximum loan volume of approximately 3.8 million that were originated in 2005 and it is generally the largest for every origination year except 2006. The logistic regression results for each pool in its mortgage origination years are listed in Table 4, Panels A through D. In general, the model fits the data well with rescaled R^2 values ranging from 21.6 (Pool 3, 2003) to 3.0 (Pool 0, 2007) percent. The explanatory power of the model weakens as we move through the sample period for originations.

The explanatory variables in our model generally conform to the expected signs listed in Table 3. The lagged delinquency status variables identify the preceding status of the borrower and it shows in every pool and origination year that only the status of 90 days or more delinquent yields a greater effect on moving to a more severe delinquency relative to having no delinquencies.

Given the great volume of logistic regressions we have, twenty-two, that are shown in Table 4, Panels A through E, we summarize the consistency of the estimated coefficients using Table 3.[11] The mortgage loan and market variables tend to have appropriate estimated values except for a few variables that have unexpected fits. One of the variables that doesn't fit appropriately is the single family or townhouse property variable (PROP_SF_TH), which only agrees with the expected sign for 32 % of the regressions. In these cases, borrowers' ability to fulfill their mortgage contracts is not supported. A mortgage market variable, the Case-Shiller residential house price change standard deviation (SIGMA_CS), is consistent with the expected sign only for 45% of the regressions. The Merton model (equation 6) predicts that greater house price volatility (the volatility of the rate of change of the underlying assets' value) should increase the likelihood of default. This relative inconsistency occurs typically in the 2003-2005 origination years. For this period in the sample where house prices were

[11] The measurement of agreement with the expected sign is performed by testing whether the opposite sign is statistically supported at the 10% level or higher level of significance.

accelerating in most locations, an investor in mortgage properties would not optimally become delinquent on this contract. The interest rate difference variables do not yield consistent results. One of these variables is the U.S. Treasury constant maturity 10 year bond rates versus their 1 year rates conform to the expected sign half of the time. Since the steeper the yield curve is, it is typically related to periods of better economic conditions. As can be seen in Figure 3, this yield differential decreased by a large amount beginning in the mid-2004 period. Finally, both of the Pool variables only have sign agreements for approximately 70% of the regressions. The weighted pool price values conform to the expected sign for 67% of all regressions. We later perform an additional test on this relationship between the weighted pool prices and the performance of the underlying mortgages. The weighted average mortgage interest rates agree on 71% of the regressions. These results show that the mortgage collateral supporting the CDO deals was not followed closely.

The Estimated to Actual differences for the movements to a more severe delinquency in the sample are given in Table 5. The differences between the estimated and actual proportions of mortgages are small. These differences only range from approximately -17 to 8 basis points. The statistical significances are 10% and under for all of the pools, except for pool 3 that had no significant differences, for the 2004-2006 periods. However, the signs are predominantly negative indicating that the model tends to systematically under-estimate the movement to more severe delinquency. As previously noted, the differences are small, 17 basis points and less, for probabilities upwards of 10 percent, and the statistical significance is due to the extremely large sample size.

We now examine the in-sample predictions of our model that are shown in Table 6. The average correct delinquency movement predictions from all regressions are 63% with Type 1 and Type 2 errors of 37% and 57%, respectively. The average correct recovery movement predictions, Type 1 and Type 2 errors are 87.5%, 12.5% and 42.7%, respectively. Lastly, these values for the no delinquency category are 32%, 68% and 17.7%. In general, predicting movements in mortgage contract compliance entails a

variety of different factors and these results condition the model, but the in-sample predictions of delinquency and default movements are very close. These results provide support the reliability of the estimations.

The out-of-sample estimates are shown in Table 7. Each pool contains large correct prediction percentages. The Delinquency movement, No Change and Recovery movement categories have correct percentages of 54, 54 and 83, respectively. They far exceed the one-third ratio of a random selection. This out-of-sample analysis supports the explanatory power of this model and its ability to accurately predict the delinquency status movements of other mortgages.

We now perform explanatory variable effects from the mean values where the one independent variable is altered and the change in the probabilities of more severe delinquencies is simulated.[12] These simulations are carried out for two cases – (1) changes to make active the ARM, No documentation and occupancy dummy variables and (2) changes to the mortgage securities' pool prices by one standard deviation. It can be seen in Figure 4 that the security pools have a large amount of movement in their likelihood of having more severe delinquencies from making the ARM, No Documentation and occupancy flags active. The extreme case is shown by Pool 2 that reaches a maximum value of 17.2 percent in 2007 and a -4.7 percent minimum in 2008. Pool 0 initially hits the 10 percent mark in 2003 and 2007. Table 8 shows that an average total of approximately 20 thousand mortgages per month would have more severe delinquencies as a result of activating these flags, ceteris paribus. Figure 4 shows that 2007 is the year having the highest likelihood of more severe delinquencies for all of the pools simultaneously. Over all of the pools, the average value is 9.3 percent per month of the participating mortgages in all pools would have more severe delinquencies. The bottom row of Table 8 and Figure 5 show that the price of the security pools has relatively small effects on delinquency

[12] A dummy variable is changed from a 0 to 1 value making it active, and a continuous variable is changed by 1 standard deviation.

statuses. In other words, this supports the view that the price movements of the security pools and the payment status change of their underlying mortgages do not move together with expected consistency. Figure 5 illustrates that an increasing number of Pool 0 borrowers through mid-2003 move to higher likelihoods of having more severe delinquencies after increasing the pool price by 1 standard deviation. The estimated coefficients for the pool price variable are not consistently negative and large enough to provide any substantial effects in the expected direction.

3. Proportional Odds Ratio Sensitivity

The proportional odds ratio (odds ratio) estimates are exponents of the estimated coefficients. The odds ratios are the probability that an event will occur divided by the probability that it will not occur, ceteris paribus. They represent the estimated effect on this odds ratio from an increase of some desired magnitude in the specified independent variable for continuous variables and represent the effect from a switch to the alternative value of 0 for dummy variables. These estimates are useful to assess the practical and marginal effects of the independent variables on the odds that this event will occur.[13] Table 8 shows the odds ratio sensitivity estimates from a one standard deviation shock to each variable. Panels A and B show these sensitivities for the separate pools averaged over the 2000-2007 origination years and for the averaged pool values for each origination year, respectively.[14]

Let's look at the odds ratio sensitivities of a dummy and continuous variable. Table 9, Panel A contains the odds ratio sensitivity estimate for the dummy variable of Flag ARM in Pool 1 of 1.41. So, if a borrower for the next month's scheduled mortgage payment was changed to an ARM contract, then the odds of falling into a more severe delinquency relative to some other alternative would increase by 1.41. One hypothetical example of this change, assuming the initial odds ratio equals 1 where the

[13] See SAS, the Logistic Procedure: Odds Ratio Estimate. Suppose that the event is to have an ARM contract.
[14] Continuous independent variable estimates are computed for a one standard deviation change, and dummy variables have the binary change from 0 to 1.

probability of having a more severe delinquency is 50%, could be to increase the probability of getting a more severe delinquency to 58.5% and lower the alternative probability to 41.5%. As shown in Panel B of Table 9, these odds ratio sensitivities can change over the various mortgage origination periods. In Figure 7 we show the odds ratio estimates for a continuous variable, Case-Shiller House Price Change. The general effects prior to the 2006 origination years are that changes in house prices are inversely related to the likelihood of getting into more severe delinquencies. This trend either weakens or reverses for the 2006 and 2007 years.

IV. Summary and Conclusions

As indicated in the literature review and from studies by Hanweck (2008) and Demyanyk and Van Hemert (2007) these have only scratched the surface of the research potential that can be done with individual loan and borrower data from the Loan Performance database. This study relatively accurate estimates the borrowers' likelihoods of more severe delinquency payment status changes by using individual mortgage loan and other county-level risk factors as observations. Another use of this data is to determine the level of monitoring by securitizations of their underlying subprime, Alt A and prime loans that generate their revenues. We find that there were relatively weak links between the weighted pool prices and the underlying mortgage performance.

The data base is composed of data on individual loans that are in pools of securitizations. The valuation of a securitization pool of subprime, Alt-A mortgages or Prime mortgages and any of the tranches derived from it, depends on the underlying value of the component mortgages which in turn depends on the underlying value of the residential property. The projection of securitization value can be useful to better isolate the effect of regional economic factors on the valuation of the securitization and effect on investors holding these pools or tranches or the CDS written on these. As in the model presented above, the contingent claims approach to valuing debt and securitization value simultaneously

is the conceptual foundation to developing these empirical models with the added recognition that households may derive psychic income from home ownership. Investors attempting to buy and restructure loans need to be able to identify borrower factors important in potential defaults from that that are due to prior contractual arrangements (such as ARMs) and economic conditions of which borrowers and lenders do not have control. Future work will be measuring the interest sensitivity of the value from prepayments and default rates simultaneously, and that will yield better current valuations delinquency and default rates and the values of the pools and tranches.

References

Bangia, A. Diebold, F.X., Kronimus, A., Schagen, C., and Schuermann, T. (2002). "Ratings Migration and the Business Cycle with Application to Credit Portfolio Stress Testing". *Journal of Banking and Finance* 26, 445-474.

Bartlett, William W. (1994). *The Valuation of Mortgage-Backed Securities*, Irwin Professional Publishing, Burr Ridge, IL, p. 471- 482.

Bernanke, B. (2007). "Housing, Housing Finance, and Monetary Policy," Speech, Federal Reserve Bank of Kansas City's Economic Symposium, August 31, 2007.

Black, F. and J. Cox. (1973). "Valuing Corporate Securities: Some Effects of Bond Indentures". *Journal of Finance* 31(May) p. 1351-67.l

Campbell, J. Y., and J. F. Cocco (2003). "Household Risk Management and Optimal Mortgage Choice," *Quarterly Journal of Economics*, 118(4), 1449-1494.

Curry, Timothy, Gary Fissel and Gerald Hanweck (2008). "Equity Market Information, Bank Holding Company Risk and Market Discipline", *Journal of Banking and Finance*, 2008, 32(5), p. 807-819.

Cutts, A. C., and R. A. van Order (2005). "On the Economics of Subprime Lending," *The Journal of Real Estate Finance and Economics*, 30(2), 167-196.

Demyanyk, Y and O. Van Hemert (2007). "Understanding the Subprime Mortgage Crisis," Working Paper, *Federal Reserve Bank of St. Louis*, St. Louis, MO (October)

Deng, Y., J. M. Quigley, and R. A. Van Order (2000). "Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options," *Econometrica*, 68(2), 275-308.

Fama, E. (1986). "Term Premiums and Default Premiums in Money Markets". *Journal of Financial Economics* Vol.17, No. 1. 175-196.

Giliberto, S. Michael and David C. Ling (1992). "An Empirical Investigation of the Contingent-Claims Approach to Pricing Residential Mortgage Debt, *Journal of the American Real Estate and Urban Economic Association,* 20, p. 393-426.

Hanweck, Gerald A, (1971), *An Empirical Study Commercial Bank Pricing Behavior in Business Lending*, Ph.D. dissertation, Washington University in St. Louis, Department of Economics, St. Louis, MO.

Hanweck, Gerald A.(2001). "A Methodology for Using Market Information to Assess Banking Company Insolvency Risk: The Simultaneous Use of Subordinated Debt and Market Values", Working Paper, FDIC, October 2001.

Hanweck, Gerald A. and Lewis Spellman (2002). "Forbearance Expectations and the Subordinated Debt Signal of Bank Insolvency", presented at the joint FDIC and *Journal of Financial Services Research* Conference on "Pricing the Risks of Deposit Insurance". (September) 2002, FDIC, Washington, DC.

Hanweck, Gerald A. Sr. (2008). "Subprime Mortgage Delinquency and Default and Default Rates by Metropolitan Areas: An Analysis by Origination Vintages and Projections for 2007," presented at the *Western Economic Association International Meetings*, July 2008, Honolulu, Hawaii.

Hendershott, Patric H. and Robert Van Order (1987). "Pricing Mortgages: An Interpretation of the Models and Results," *Journal of Financial Services Research* 1, 77-111.

Hull, John C. (2000), *Options, Futures and Other Derivatives*, Prentice Hall, Inc., Upper Saddle River, NJ.

Hull, John C. (2007), *Risk Management and Financial Institutions*, Pearson Education, Inc., Upper Saddle River, NJ.

Koijen, R., O. Van Hemert, and S. Van Nieuwerburgh (2007). "Mortgage Timing," Working paper, New York University.

Koopman, S.J. and A. Lucas, (2003). "A Survey of Cyclical Affects in Credit Risk Measurement Models." *Tinbergen Institute Discussion Paper*, TI 2003 - 062/2, July.

Koopman, S.J. and A. Lucas, (2003). "Business and Default Cycles for Credit Risk." *Tinbergen Institute Discussion Paper*, TI 2003 - 062/2.

"TrueStandings Securities: Attributes Metrics and Filters," (2005). *Loan Performance*, 188 The Embarcadero, San Francisco, CA.

Merton, Robert C., (1974), "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance* 29 (May), 449-470.

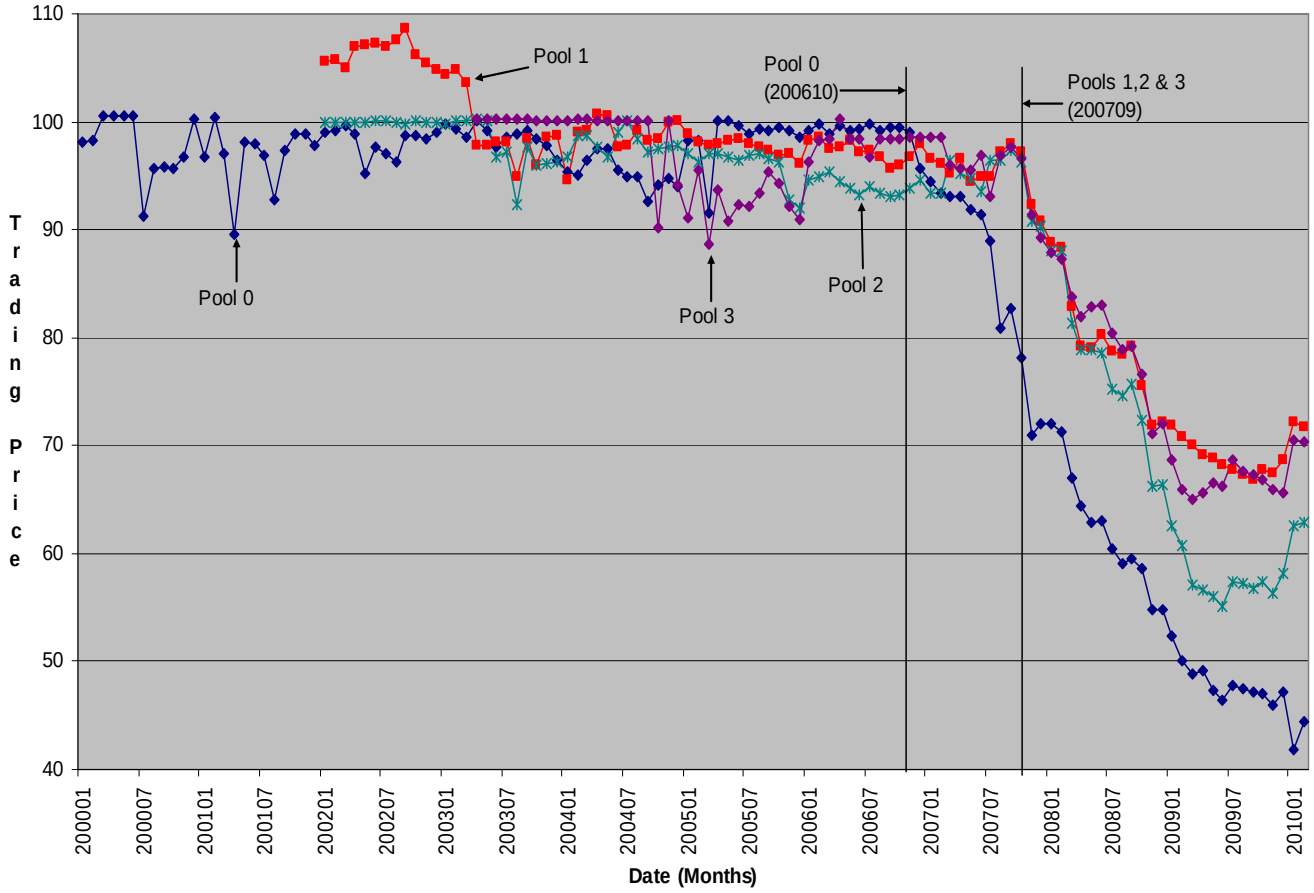
Pennington-Cross, A., and S. Chomsisengphet (2007). "Subprime Refinancing: Equity Extraction and Mortgage Termination," *Real Estate Economics*, 35(2), 233-263.

Titman, Sheridan and Walter Torous, (1989). "Valuing Commercial Mortgages: An Empirical Examination of the Contingent Claims Approach to Pricing Risky Debt," *Journal of Finance*, 44, p.345-373.

Van Hemert, O. (2007). "Household Interest Rate Risk Management," Working paper, New York University.

von Furstenberg, and R. J. Green (1974). "Home Mortgage Delinquencies: A Cohort Analysis," *Journal of Finance*, 29(5), 1545-1548.

Figure 1: CDO Mean Security Market Prices



Source: Intex

Figure 2: Sample Sizes of Pools

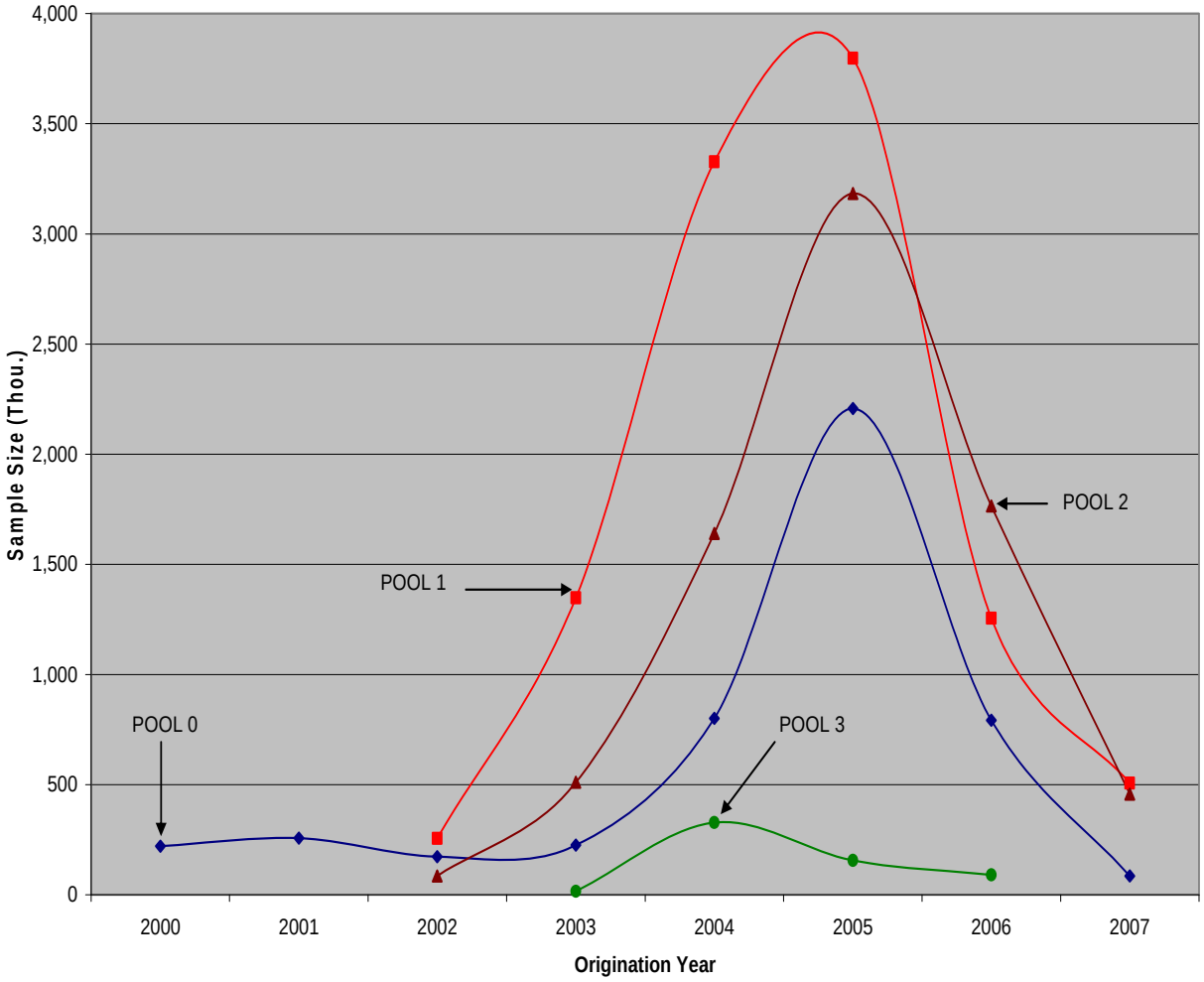


Figure 3: Interest Rate Differential (Constant Maturity 10 Year Treasury – 1 Year Treasury)

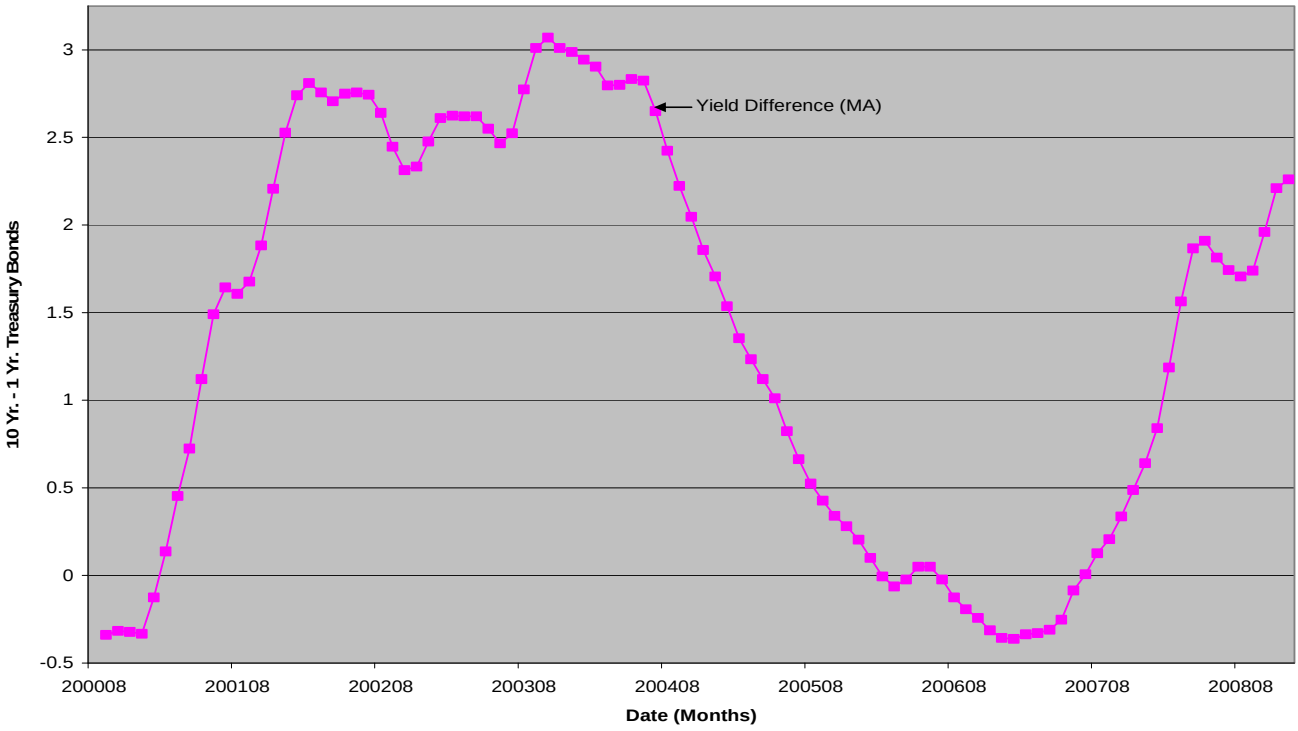


Figure 4: Borrower Effects of ARM, No Documentation & Occupancy Flag Changes

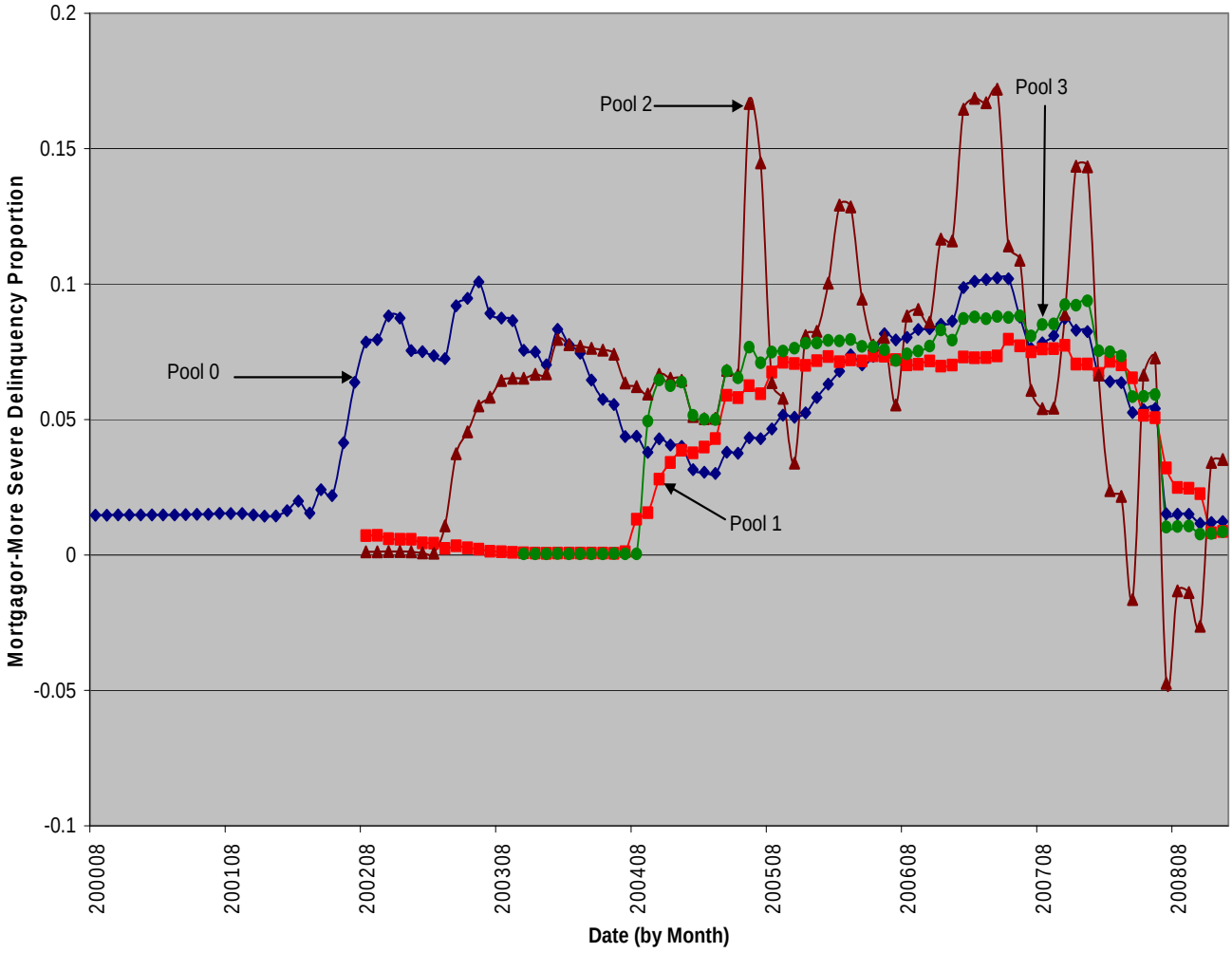


Figure 5: Borrower Effects (More Severe Delinquency) from Pool Price 1 Std. Change

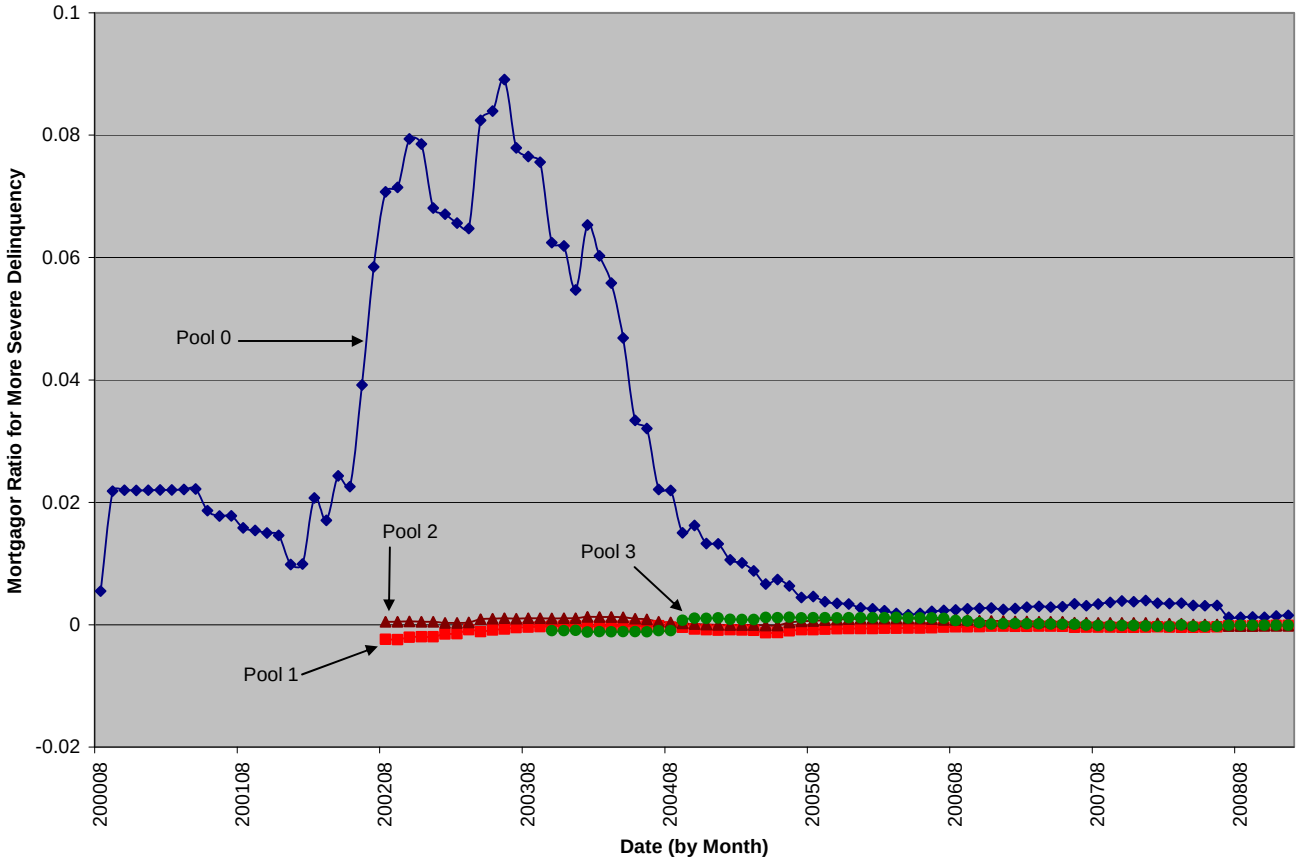


Figure 6: Odds Ratio Estimates for ARM Mortgages

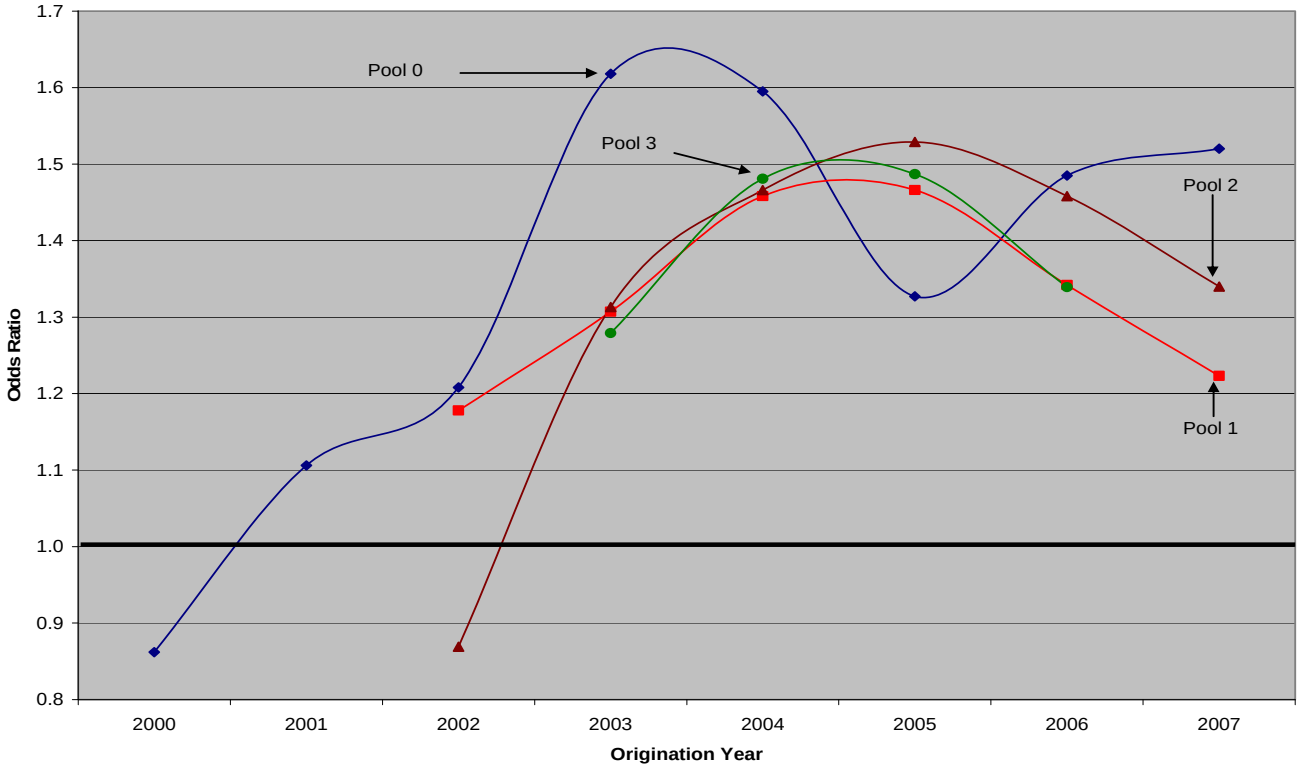


Figure 7: Odds Ratio Estimates for Case-Shiller Residential House Price Changes (1 STD.)

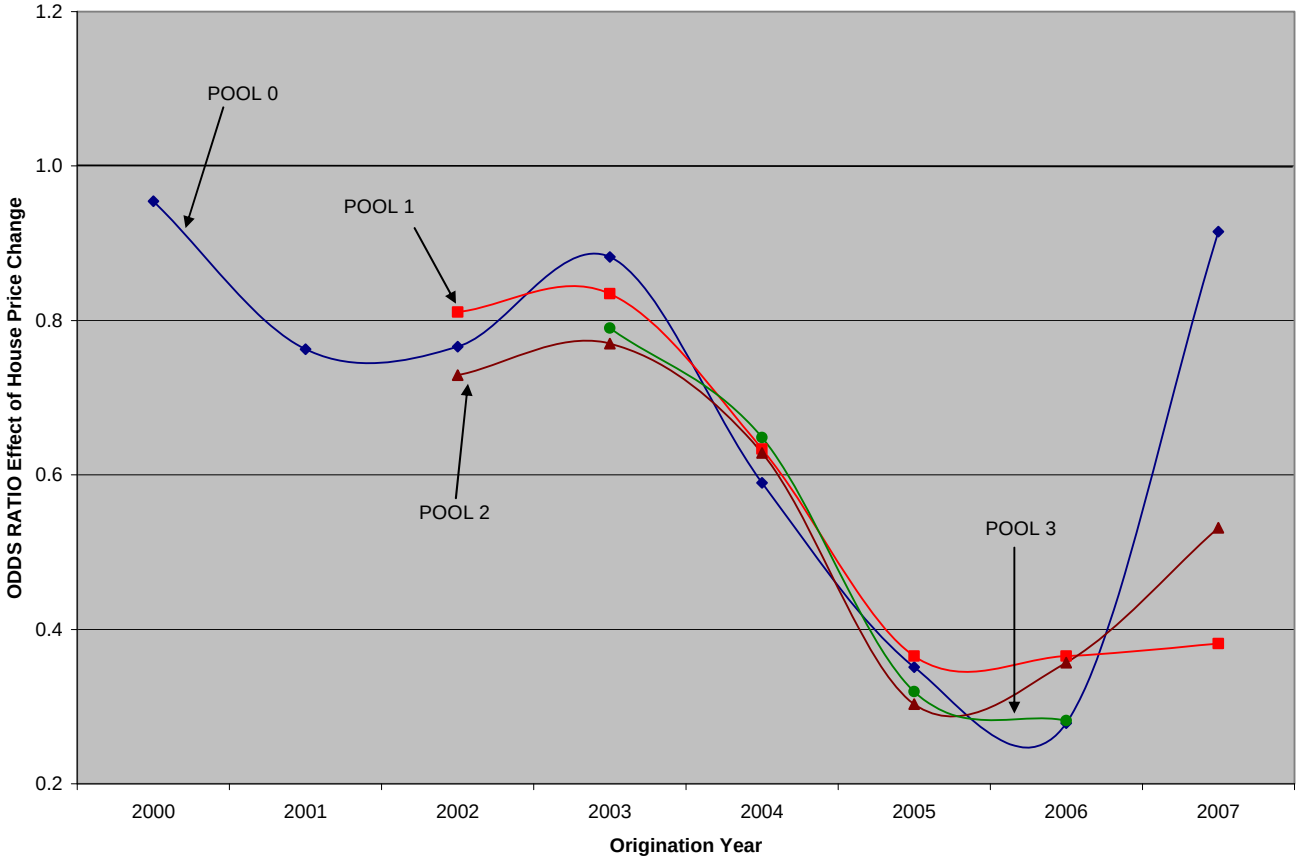


Table 1: Sample Means and Std. Deviations

VARIABLE		POOL 0 MEAN	POOL 0 STD.	POOL 1 MEAN	POOL 1 STD.	POOL 2 MEAN	POOL 2 STD.	POOL 3 MEAN	POOL 3 STD.
DF1_FLAGL1	Dummy -- Lagged Delinquent 89 days or less	0.113	22.00	0.108	38.58	0.114	35.08	0.106	11.56
DF2_FLAGL1	Dummy -- Lagged Delinquent 90 days or more	0.057	12.81	0.039	37.43	0.053	37.33	0.040	10.77
DF3_FLAGL1	Dummy -- Lagged Foreclosure, Bankruptcy, or REO	0.069	33.83	0.075	57.98	0.094	58.83	0.088	19.04
DF4_FLAGL1	Dummy -- Lagged Not Delinquent	0.777	34.69	0.790	64.87	0.751	58.67	0.778	18.81
FLAG_ARM	Dummy -- ARM Mortgage	0.414	13.09	0.706	15.58	0.664	12.10	0.703	10.22
FLAG_DOC	Dummy -- No Documentation Required for Mortgage	0.421	14.37	0.375	4.20	0.419	6.01	0.443	2.79
FLAG_OCCUPANCY	Dummy -- Mortgagee is Occupant of Home	0.922	17.33	0.902	12.33	0.934	17.40	0.933	10.44
PROP_SF_TH	Dummy -- Property is a Single Family home/TownHouse	0.744	14.72	0.747	7.70	0.738	10.29	0.747	5.06
INIT_RATE	Initial Interest Rate (%)	8.981	111.83	7.738	78.11	7.888	151.73	7.532	38.25
YLDDIFF10Y_1Y	10 Yr. & 1 Yr. Treasury Bond Interest Rate Spread	0.732	47.10	0.734	95.63	0.638	75.78	0.554	26.63
YLDDIFFBAA_AAA	BAA & AAA Bond Interest Rate Spread	1.074	48.33	0.995	90.97	1.059	86.45	0.983	27.33
EMPLOYMENT_L12LNCHG	Employment Change by Month from Prior Year	0.005	1.86	0.007	2.38	0.007	1.45	0.011	0.82
DEFAULT_DISTANCE	Distance-to-Default	4.290	193,399	9.204	337.92	6.834	383.66	8.127	128.14
NETCHG_MTGQR	Mortgage Market Liquidity	0.730	73.43	0.817	129.67	0.721	120.58	0.818	38.83
CS_RESHPRC_LN12DIFF	Case-Shiller Res. House Price Change from Prior 12 Months	0.003	11.13	0.047	14.74	0.005	12.80	0.048	4.10
SIGMA_CS	Case-Shiller Res. House Price Change Std. Deviation	0.110	1.13	0.110	0.98	0.121	0.53	0.123	0.24
FICO	FICO Score	638.560	2,520.15	619.922	2,252.02	630.546	2,143.91	625.680	489.99
COMB_LTV	Total Loans-to-Property Value	87.884	549.09	83.643	413.60	86.560	375.29	84.842	106.08
Gross_WAC	Weighted (by Loans) Average Annual Gross Interest Rate	7.987	396.93	7.260	87.78	7.181	87.43	6.843	18.90
POOL_PRICE_WGTD	Price of ABS/CDOs in Pool Weighted by Principle at Origination	90.605	2,470.75	93.813	2,860.46	90.444	2,349.49	92.387	911.89
Total Observations in Sample Period		4.8 million		10.5 million		7.6 million		589.2 thousand	

Table 2: Delinquency Status Change Components (Mean Values)

Model Variables	Dependent Variable Section: More Severe Delinquency (A)	No Delinquency (B)	Recovery from Delinquency (C)	Recovery from & More Severe Delinq. Difference (t-test)[2] (D)
DF1_FLAGL1	0.228	0.076	0.802	1036.820
DF2_FLAGL1	0.112	0.041	0.098	-34.409
DF3_FLAGL1	0.000	0.085	0.102	301.564
DF4_FLAGL1	0.660	0.812	0.000	-1779.867
flag_arm	0.707	0.626	0.683	-38.839
flag_doc	0.418	0.400	0.370	-72.442
flag_occupancy	0.927	0.916	0.936	25.861
PROP_SF_TH	0.763	0.741	0.781	30.920
INIT_RATE	8.384	7.996	8.323	-26.755
YLDDIFF10Y_1Y	0.711	0.698	0.677	-28.871
YLDDIFFBAA_AAA	1.093	1.026	1.053	-64.328
EMPLOYMENT_L12LNCHG	0.004	0.007	0.006	28.622
DEFAULT_DISTANCE	7.148	7.372	8.912	6.817
NETCHG_MTGQR	0.677	0.776	0.739	73.392
CS_RESHPRC_LN12DIFF	-0.016	0.028	0.016	178.603
SIGMA_CS	0.113	0.114	0.107	-74.086
FICO	611.337	629.424	603.203	-108.763
COMB_LTV	86.830	85.397	85.030	-97.395
Gross_WAC	7.430	7.366	7.387	-33.509
POOL_PRICE_WGTD	91.268	92.079	92.272	44.338

[1]This is the logistic regression sample.

[2] Mean value t-test hypothesis: (Recovery from Delinquency - More Severe Delinquency) = 0.

Table 3: Estimated Coefficient & Expected Sign Agreement (for 2000-2007 Origination Years)

Variable	Expected Sign	Sign Agree. (%)
DF1_FLAGL1		
DF2_FLAGL1		
DF3_FLAGL1		
Flag_ARM	+	92
Flag_DOC	+	100
Flag_OCCUPANCY	–	75
PROP_SF_TH	–	29
INIT_RATE	+	100
YLDDIFF10Y_1Y	–	50
YLDDIFFBAA_AAA	+	46
EMPLOYMENT_L12LNCHG	–	92
DEFAULT_DISTANCE	–	83
CS_RESHPRC_LN12DIFF	–	100
SIGMA_CS	+	46
NETCHG_MTGQR	–	92
FICO	–	100
COMB_LTV	+	100
Gross_WAC	+	71
POOL_PRICE_WGTD	–	67

Note: Sign Agreement ratios are calculated for all Pools in sample, and sign agreement occurs is when sign disagreement is not statistically verified.

Table 4, Panel A – Pool 0: Regression Estimates (2000-2007) Origination Years

POOL 0	2000	2001	2002	2003	2004	2005	2006	2007
	ORIGINATION YEARS							
PARAMETER	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Intercept_1	-3.244 ***	-2.093 ***	-1.134 ***	-0.540 *	-0.076	-1.234 ***	-2.323 ***	-3.128 ***
	(20.74)	(13.44)	(5.73)	(1.88)	(0.83)	(30.60)	(29.50)	(8.66)
Intercept_2	3.605 ***	5.211 ***	5.814 ***	6.320 ***	6.707 ***	5.163 ***	3.784 ***	3.272 ***
	(22.97)	(33.12)	(29.11)	(21.92)	(72.63)	(126.62)	(47.91)	(9.06)
DF1_FLAGL1	-3.078 ***	-3.681 ***	-3.032 ***	-3.132 ***	-2.847 ***	-1.897 ***	-1.289 ***	0.286 ***
	(129.51)	(147.77)	(107.39)	(130.63)	(225.20)	(249.13)	(105.77)	(8.93)
DF2_FLAGL1	0.338 ***	0.436 ***	0.288 ***	0.104 ***	-0.372 ***	-0.301 ***	0.066 ***	-1.032 ***
	(10.35)	(10.86)	(7.22)	(2.83)	(18.55)	(31.31)	(4.81)	(20.76)
DF3_FLAGL1	-1.420 ***	-1.497 ***	-1.747 ***	-1.824 ***	-1.545 ***	-1.601 ***	-1.600 ***	-1.435 ***
	(54.83)	(50.18)	(50.36)	(54.36)	(81.25)	(152.97)	(110.94)	(13.36)
flag_arm	-0.148 ***	0.101 ***	0.189 ***	0.481 ***	0.467 ***	0.283 ***	0.396 ***	0.419 ***
	(6.59)	(4.52)	(7.47)	(23.25)	(33.72)	(51.62)	(41.82)	(8.06)
flag_doc	0.068 ***	0.108 ***	0.053 ***	0.146 ***	0.042 ***	0.162 ***	0.227 ***	0.157 ***
	(3.37)	(6.33)	(2.81)	(9.15)	(4.85)	(32.30)	(28.76)	(4.52)
flag_occupancy	0.141 ***	-0.082 ***	-0.052 *	0.043	0.061 ***	0.029 ***	-0.038 ***	-0.039
	(4.20)	(2.67)	(1.75)	(1.55)	(3.20)	(3.22)	(3.11)	(0.51)
PROP_SF_TH	0.027	0.051 ***	0.035	0.083 ***	0.048 ***	0.021 ***	0.031 ***	0.059 **
	(1.21)	(2.62)	(1.63)	(4.53)	(5.11)	(4.22)	(3.81)	(2.40)
INIT_RATE	0.116 ***	0.119 ***	0.088 ***	0.130 ***	0.084 ***	0.024 ***	0.043 ***	0.077 ***
	(19.78)	(21.29)	(11.72)	(26.37)	(27.74)	(17.61)	(17.40)	(7.15)
YLDDIFF10Y_1Y	0.108 ***	-0.032 ***	-0.083 ***	-0.172 ***	-0.149 ***	0.118 ***	0.064 ***	0.067 **
	(13.44)	(3.26)	(8.71)	(22.58)	(24.57)	(23.51)	(8.09)	(2.15)
YLDDIFFBAA_AAA	-0.319 ***	-0.270 ***	-0.549 ***	0.280 ***	0.100 ***	0.036 ***	0.011	0.026
	(9.41)	(8.30)	(13.87)	(6.62)	(4.60)	(3.72)	(0.91)	(0.78)
EMPLOYMENT_L12LNCHG	-0.245	0.566 ***	-0.404	-0.252	-0.358 ***	-0.309 ***	-1.214 ***	-0.739
	(1.55)	(3.13)	(1.56)	(1.37)	(3.24)	(5.16)	(10.28)	(1.50)
DEFAULT_DISTANCE	0.011 ***	0.004 ***	-0.001	2.19E-04	-0.012 ***	-2.37E-07	-0.003 ***	-0.023 ***
	(9.29)	(3.53)	(0.42)	(0.18)	(14.12)	(0.09)	(3.31)	(4.68)
CS_RESHPRC_LN12DIFF	-0.721 ***	-0.827 ***	-0.999 ***	-0.376 ***	-1.213 ***	-1.598 ***	-1.619 ***	-0.099
	(5.37)	(6.87)	(7.61)	(3.87)	(29.91)	(74.25)	(34.59)	(0.47)
SIGMA_CS	0.752 ***	-0.033	-0.670 ***	-0.855 ***	-0.704 ***	0.292 ***	0.211 **	3.046 ***
	(3.97)	(0.19)	(3.24)	(4.83)	(9.67)	(7.24)	(2.44)	(6.77)
NETCHG_MTGQR	-0.057 **	-0.227 ***	-0.245 ***	-0.038	-0.099 ***	0.068 ***	-0.046 ***	-0.116 ***
	(2.13)	(8.55)	(7.28)	(1.11)	(5.79)	(9.34)	(4.88)	(4.40)
FICO2	-0.003 ***	-0.003 ***	-0.004 ***	-0.004 ***	-0.004 ***	-0.004 ***	-0.002 ***	-0.001 **
	(21.35)	(21.96)	(22.63)	(27.29)	(47.59)	(81.99)	(32.28)	(2.17)
COMB_LTV	0.009 ***	0.007 ***	0.002 ***	0.004 ***	0.000	0.010 ***	0.009 ***	0.001
	(13.49)	(9.49)	(2.90)	(5.47)	(0.20)	(48.87)	(22.74)	(0.47)
Gross_WAC	0.023 ***	0.011 ***	0.083 ***	-0.074 ***	-0.031 ***	-0.033 ***	-0.032 ***	-0.064 ***
	(11.29)	(4.51)	(7.70)	(9.56)	(7.95)	(13.31)	(6.56)	(3.91)
POOL_PRICE_WGTD	0.002 ***	-0.001	0.001	-0.008 ***	-0.004 ***	1.787E-05	0.003 ***	0.004
	(3.96)	(1.50)	(1.18)	(3.26)	(11.43)	(0.17)	(12.86)	(1.52)
Max-rescaled R2	0.152	0.169	0.138	0.157	0.123	0.0672	0.0545	0.0304
Number of Observations	220,920	256,709	172,525	224,990	800,714	2,207,782	792,354	85,731

Table 4, Panel B – Pool 1: Regression Estimates (2002-2007 Origination Years)

	ORIGINATION YEARS					
POOL 1	2002	2003	2004	2005	2006	2007
PARAMETER	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Intercept_1	0.501	-3.680 ***	-1.603 ***	-1.733 ***	-2.278 ***	-2.579 ***
	(1.15)	(39.92)	(25.48)	(41.09)	(33.09)	(20.80)
Intercept_2	7.241 ***	3.943 ***	5.531 ***	4.782 ***	3.548 ***	3.505 ***
	(16.54)	(42.64)	(87.53)	(112.83)	(51.45)	(28.22)
DF1_FLAGL1	-3.276 ***	-3.710 ***	-3.306 ***	-2.372 ***	-1.343 ***	-0.939 ***
	(149.97)	(319.00)	(491.30)	(413.95)	(156.56)	(63.03)
DF2_FLAGL1	-0.072 *	0.437 ***	0.583 ***	0.267 ***	0.399 ***	1.059 ***
	(1.88)	(19.54)	(54.01)	(35.11)	(40.22)	(63.86)
DF3_FLAGL1	-1.728 ***	-2.088 ***	-2.022 ***	-1.669 ***	-1.413 ***	-1.660 ***
	(51.49)	(117.06)	(211.67)	(236.73)	(138.74)	(94.65)
flag_arm	0.164 ***	0.268 ***	0.377 ***	0.383 ***	0.294 ***	0.201 ***
	(8.08)	(26.59)	(65.17)	(78.10)	(37.16)	(16.81)
flag_doc	0.104 ***	0.088 ***	0.062 ***	0.097 ***	0.169 ***	0.166 ***
	(7.38)	(12.01)	(14.39)	(25.46)	(27.89)	(17.11)
flag_occupancy	0.003	0.120 ***	-0.038 ***	-0.072 ***	-0.115 ***	-0.137 ***
	(0.14)	(9.10)	(5.66)	(12.20)	(11.15)	(8.92)
PROP_SF_TH	0.044 ***	0.056 ***	0.079 ***	0.046 ***	0.026 ***	0.002
	(2.68)	(6.86)	(17.05)	(11.73)	(4.31)	(0.24)
INIT_RATE	0.070 ***	0.126 ***	0.093 ***	0.067 ***	0.040 ***	0.087 ***
	(11.44)	(36.22)	(53.26)	(43.37)	(16.91)	(21.36)
YLDDIFF10Y_1Y	-0.050 ***	-0.150 ***	-0.143 ***	0.082 ***	0.020 ***	0.043 ***
	(5.46)	(43.02)	(47.07)	(21.78)	(3.24)	(3.92)
YLDDIFFBAA_AAA	-0.380 ***	-0.011	0.197 ***	-0.044 ***	-0.079 ***	-0.014
	(11.00)	(0.52)	(16.89)	(5.45)	(6.89)	(1.16)
EMPLOYMENT_L12LNCHG	0.036	-0.840 ***	-0.226 ***	-0.317 ***	-0.850 ***	-1.654 ***
	(0.21)	(8.95)	(4.22)	(6.19)	(9.95)	(8.60)
DEFAULT_DISTANCE	0.001	-0.001	-0.007 ***	-0.005 ***	-0.002 ***	-0.004 ***
	(1.01)	(0.97)	(17.70)	(15.92)	(3.42)	(3.28)
CS_RESHPRC_LN12DIFF	-0.885 ***	-0.763 ***	-1.299 ***	-1.667 ***	-1.534 ***	-1.063 ***
	(7.82)	(16.28)	(60.03)	(116.90)	(42.14)	(13.28)
SIGMA_CS	-0.031	-0.550 ***	-0.753 ***	-0.457 ***	0.290 ***	0.685 ***
	(0.18)	(6.64)	(17.90)	(14.05)	(4.63)	(4.01)
NETCHG_MTGQR	-0.046	-0.177 ***	-0.046 ***	-0.009	-0.069 ***	-0.090 ***
	(1.19)	(11.70)	(5.04)	(1.44)	(8.19)	(9.35)
FICO2	-0.005 ***	-0.004 ***	-0.004 ***	-0.003 ***	-0.003 ***	-0.002 ***
	(37.28)	(55.25)	(97.35)	(91.55)	(44.86)	(21.03)
COMB_LTV	0.005 ***	0.004 ***	0.002 ***	0.006 ***	0.009 ***	0.010 ***
	(7.37)	(12.51)	(11.88)	(33.06)	(26.13)	(16.73)
Gross_WAC	0.086 ***	0.260 ***	0.085 ***	0.041 ***	0.078 ***	-0.005
	(6.04)	(30.19)	(11.96)	(9.91)	(16.25)	(0.84)
POOL_PRICE_WGTD	-0.013 ***	0.003 ***	-0.001 ***	-1.60E-04	1.61E-04	-0.001
	(3.05)	(12.63)	(8.04)	(1.62)	(1.03)	(1.39)
Max-rescaled R2	0.172	0.169	0.150	0.0964	0.0599	0.0649
Number of Observations	255,557	1,348,429	3,327,283	3,798,179	1,254,833	507,220

Table 4, Panel C – Pool 2: Regression Estimates (2002-2007 Origination Years)

	ORIGINATION YEARS					
POOL 2	2002	2003	2004	2005	2006	2007
PARAMETER	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Intercept_1	1.104 ***	-3.012 ***	-1.352 ***	-2.417 ***	-2.955 ***	-3.395 ***
	(3.43)	(22.56)	(17.48)	(51.81)	(52.25)	(28.57)
Intercept_2	8.360 ***	4.570 ***	5.677 ***	4.060 ***	2.831 ***	2.690 ***
	(25.60)	(34.08)	(72.97)	(86.79)	(50.05)	(22.64)
DF1_FLAGL1	-3.589 ***	-3.740 ***	-3.190 ***	-2.041 ***	-0.695 ***	-0.308 ***
	(84.16)	(200.72)	(341.06)	(315.19)	(98.09)	(21.06)
DF2_FLAGL1	0.285 ***	0.646 ***	0.346 ***	0.400 ***	0.179 ***	1.365 ***
	(4.27)	(19.11)	(22.75)	(52.34)	(23.40)	(87.38)
DF3_FLAGL1	-2.545 ***	-2.139 ***	-1.974 ***	-1.696 ***	-1.401 ***	-1.643 ***
	(35.96)	(76.45)	(148.75)	(226.47)	(177.42)	(98.12)
flag_arm	-0.141 ***	0.272 ***	0.383 ***	0.424 ***	0.377 ***	0.292 ***
	(3.70)	(17.98)	(49.42)	(77.32)	(56.86)	(23.31)
flag_doc	0.165 ***	0.084 ***	0.092 ***	0.132 ***	0.164 ***	0.196 ***
	(6.20)	(7.12)	(15.36)	(31.78)	(32.00)	(19.17)
flag_occupancy	0.022	0.051 **	-0.027 ***	0.011	-0.014	-0.097 ***
	(0.47)	(2.47)	(2.73)	(1.29)	(1.40)	(4.86)
PROP_SF_TH	-0.011	0.047 ***	0.061 ***	0.042 ***	0.019 ***	-0.005
	(0.36)	(3.42)	(9.12)	(9.92)	(3.76)	(0.47)
INIT_RATE	0.036 ***	0.103 ***	0.087 ***	0.066 ***	0.033 ***	0.061 ***
	(7.68)	(23.14)	(39.03)	(38.90)	(16.92)	(16.07)
YLDDIFF10Y_1Y	-0.084 ***	-0.143 ***	-0.114 ***	0.112 ***	0.054 ***	0.039 ***
	(4.53)	(25.67)	(26.69)	(26.71)	(10.49)	(3.61)
YLDDIFFBAA_AAA	-0.548 ***	-0.146 ***	0.142 ***	-0.018 **	-0.054 ***	-0.025 **
	(8.25)	(4.44)	(8.81)	(2.07)	(6.68)	(1.96)
EMPLOYMENT_L12LNCHG	-0.904 ***	-0.221	-0.236 ***	0.135 **	-0.128 **	-1.381 ***
	(2.72)	(1.43)	(2.83)	(2.39)	(1.98)	(7.99)
DEFAULT_DISTANCE	0.006 **	0.000	-0.006 ***	-0.004 ***	-0.003 ***	-0.003 ***
	(2.31)	(0.21)	(10.92)	(9.29)	(4.32)	(2.70)
CS_RESHPRC_LN12DIFF	-1.889 ***	-0.848 ***	-1.248 ***	-1.987 ***	-1.322 ***	-0.690 ***
	(8.47)	(11.19)	(41.61)	(126.46)	(44.43)	(8.77)
SIGMA_CS	0.924 ***	-0.463 ***	-0.938 ***	-0.074 **	0.655 ***	1.643 ***
	(2.73)	(3.61)	(15.98)	(2.05)	(12.03)	(10.17)
NETCHG_MTGQR	-0.038	-0.233 ***	-0.059 ***	0.076 ***	-0.041 ***	-0.053 ***
	(0.54)	(9.44)	(4.73)	(11.44)	(6.62)	(5.14)
FICO2	-0.006 ***	-0.004 ***	-0.004 ***	-0.003 ***	-0.002 ***	-0.002 ***
	(24.47)	(38.62)	(71.03)	(68.37)	(34.51)	(14.31)
COMB_LTV	0.008 ***	0.004 ***	0.003 ***	0.006 ***	0.008 ***	0.011 ***
	(6.09)	(7.63)	(10.88)	(29.46)	(25.97)	(16.04)
Gross_WAC	-0.078 ***	0.259 ***	0.040 ***	0.029 ***	0.076 ***	0.034 ***
	(3.16)	(22.04)	(4.59)	(6.32)	(21.46)	(5.52)
POOL_PRICE_WGTD	0.002 ***	0.001 **	0.000	0.001 ***	0.000	0.000
	(2.66)	(2.01)	(1.29)	(6.64)	(0.92)	(0.62)
Max-rescaled R2	0.183	0.177	0.144	0.082	0.045	0.078
Number of Observations	85,786	510,371	1,640,321	3,183,427	1,765,021	457,596

Table 4, Panel D – Pool 3: Regression Estimates (2003-2006 Origination Years)

POOL 3	ORIGINATION YEARS 2003	2004	2005	2006
PARAMETER	Estimate	Estimate	Estimate	Estimate
Intercept_1	1.025	-1.153 ***	-2.071 ***	-1.782
	(0.28)	(6.04)	(6.60)	(1.51)
Intercept_2	9.488 **	5.714 ***	4.372 ***	4.247 ***
	(2.56)	(29.78)	(13.90)	(3.60)
DF1_FLAGL1	-4.582 ***	-2.938 ***	-1.402 ***	-0.650 ***
	(34.98)	(143.69)	(44.47)	(19.02)
DF2_FLAGL1	0.461	0.589 ***	0.400 ***	0.353 ***
	(1.61)	(18.75)	(11.83)	(8.31)
DF3_FLAGL1	-1.537 ***	-2.035 ***	-1.656 ***	-1.447 ***
	(7.50)	(73.51)	(50.70)	(40.15)
flag_arm	0.246 **	0.393 ***	0.396 ***	0.292 ***
	(1.97)	(22.13)	(14.51)	(8.30)
flag_doc	0.223 **	0.048 ***	0.117 ***	0.208 ***
	(2.55)	(3.61)	(6.03)	(8.38)
flag_occupancy	-0.356	0.059 ***	-0.006	-0.102 **
	(1.50)	(2.64)	(0.13)	(2.14)
PROP_SF_TH	0.065	0.062 ***	0.026	0.022
	(0.71)	(4.19)	(1.38)	(0.92)
INIT_RATE	0.318 ***	0.121 ***	0.063 ***	0.039 ***
	(6.13)	(22.50)	(7.24)	(4.55)
YLDDIFF10Y_1Y	-0.137 ***	-0.122 ***	0.105 ***	0.045 *
	(3.38)	(11.43)	(5.27)	(1.65)
YLDDIFFBAA_AAA	-0.261	0.273 ***	-0.275 ***	-0.150 ***
	(1.16)	(7.91)	(6.58)	(4.29)
EMPLOYMENT_L12LNCHG	-0.815	0.329	-0.715 **	-0.176
	(1.10)	(1.46)	(2.30)	(0.54)
DEFAULT_DISTANCE	0.004	-0.010 ***	-0.006 ***	0.007 ***
	(0.46)	(7.17)	(2.93)	(2.62)
CS_RESHPRC_LN12DIFF	-0.624	-1.148 ***	-1.847 ***	-1.544 ***
	(1.49)	(18.34)	(26.78)	(10.23)
SIGMA_CS	-1.753 *	-0.963 ***	-0.377 **	1.434 ***
	(1.87)	(7.22)	(2.20)	(5.15)
NETCHG_MTGQR	-0.125	0.010	-0.060 **	-0.139 ***
	(0.73)	(0.38)	(1.99)	(5.14)
FICO2	-0.004 ***	-0.003 ***	-0.003 ***	-0.002 ***
	(5.05)	(27.28)	(14.27)	(8.91)
COMB_LTV	0.005	0.002 ***	0.006 ***	0.013 ***
	(1.21)	(3.16)	(6.02)	(8.84)
Gross_WAC	0.329	-0.127 ***	0.030	-0.099
	(0.71)	(5.30)	(0.73)	(0.57)
POOL_PRICE_WGTD	-0.055 **	0.002 ***	0.002 ***	-0.002
	(2.40)	(4.35)	(2.64)	(0.53)
Max-rescaled R2	0.216	0.131	0.060	0.043
Number of Observations	15,387	327,245	155,882	90,690

Table 5: Estimation Accuracy – Estimation to Actual Differences by Pool

		Movement to More Severe Delinquency				
Origination Year	**Pool**	**Estimated**	**Actual**	**Difference[1]**	**t-test[2]**	
2000	0	0.05650	0.05818	-0.00168	-2.445	**
2001	0	0.05011	0.05131	-0.00120	-1.985	**
2002	0	0.05540	0.05671	-0.00131	-1.683	*
2003	0	0.06178	0.06285	-0.00106	-1.481	
2004	0	0.05870	0.05991	-0.00121	-3.253	***
2005	0	0.06705	0.06832	-0.00127	-5.307	***
2006	0	0.07942	0.08052	-0.00111	-2.570	**
2007	0	0.08407	0.08356	0.00051	0.380	
2002	1	0.06573	0.06715	-0.00142	-2.051	**
2003	1	0.04544	0.04600	-0.00056	-2.195	**
2004	1	0.05456	0.05521	-0.00065	-3.697	***
2005	1	0.06633	0.06732	-0.00099	-5.467	***
2006	1	0.09083	0.09191	-0.00109	-2.990	***
2007	1	0.08923	0.08927	-0.00004	-0.068	
2002	2	0.05592	0.05665	-0.00073	-0.658	
2003	2	0.04672	0.04730	-0.00057	-1.374	
2004	2	0.05593	0.05673	-0.00080	-3.143	***
2005	2	0.06817	0.06904	-0.00087	-4.345	***
2006	2	0.09641	0.09731	-0.00090	-2.863	***
2007	2	0.09776	0.09700	0.00076	1.238	
2003	3	0.03522	0.03542	-0.00020	-0.094	
2004	3	0.05974	0.06052	-0.00078	-1.337	
2005	3	0.06784	0.06842	-0.00058	-0.645	
2006	3	0.08653	0.08709	-0.00056	-0.424	

1Differences are constructed as follows: Estimated -Actual value.

[2]This is a two-tailed t-test where ***, ** and * represent 1, 5 and 10% significance.

Table 6: IN-SAMPLE DELINQUENCY STATUS CHANGE PREDICTIONS (2000-2007 Origination Years)

POOL 0

		ACTUAL CHANGE		
		Delinquency Movement	No Delinquency Change	Recovery Movement
PREDICTED CHANGE	Delinquency Movement	61.02	48.34	8.20
	No Delinquency Change	14.47	31.21	4.32
	Recovery Movement	24.51	20.45	87.49

POOL 1

		ACTUAL CHANGE		
		Delinquency Movement	No Delinquency Change	Recovery Movement
PREDICTED CHANGE	Delinquency Movement	64.72	48.51	8.86
	No Delinquency Change	14.55	34.00	0.77
	Recovery Movement	20.73	17.49	90.37

POOL 2

		ACTUAL CHANGE		
		Delinquency Movement	No Delinquency Change	Recovery Movement
PREDICTED CHANGE	Delinquency Movement	62.01	46.88	11.21
	No Delinquency Change	15.93	30.52	3.80
	Recovery Movement	22.06	22.60	84.99

POOL 3

		ACTUAL CHANGE		
		Delinquency Movement	No Delinquency Change	Recovery Movement
PREDICTED CHANGE	Delinquency Movement	62.83	46.56	10.98
	No Delinquency Change	15.31	32.26	1.82
	Recovery Movement	21.85	21.18	87.20

Notes: (1) The values are percentages of the actual change category total volume; (2) The percentage values are weighted by the observation volumes.

Table 7: OUT-of-SAMPLE DELINQUENCY STATUS CHANGE PREDICTIONS (2000-2007 Origination Years)

POOL 0

		ACTUAL CHANGE		
		Delinquency Movement	No Delinquency Change	Recovery Movement
PREDICTED CHANGE	Delinquency Movement	51.98	37.40	14.84
	No Delinquency Change	27.85	52.65	12.51
	Recovery Movement	21.50	11.10	82.73

POOL 1

		ACTUAL CHANGE		
		Delinquency Movement	No Delinquency Change	Recovery Movement
PREDICTED CHANGE	Delinquency Movement	54.69	35.86	9.35
	No Delinquency Change	28.24	54.95	20.68
	Recovery Movement	19.32	11.41	85.29

POOL 2

		ACTUAL CHANGE		
		Delinquency Movement	No Delinquency Change	Recovery Movement
PREDICTED CHANGE	Delinquency Movement	53.55	36.58	11.69
	No Delinquency Change	35.78	53.45	54.48
	Recovery Movement	19.67	11.33	80.77

POOL 3

		ACTUAL CHANGE		
		Delinquency Movement	No Delinquency Change	Recovery Movement
PREDICTED CHANGE	Delinquency Movement	54.77	35.64	11.80
	No Delinquency Change	31.86	54.23	43.65
	Recovery Movement	17.97	11.54	82.92

Notes: (1) The values are percentages of the actual change category total volume; (2) The percentage values are weighted by the observation volumes.

Table 8: Variable Effects to More Severe Delinquencies (per Month)

Variable Effect	Pool 0		Pool 1		Pool 2		Pool 3	
	Number Affected	%	Number Affected	%	Number Affected	%	Number Affected	%
Make Active ARM, No Doc., Occupancy Flags	3,381	5.4209	7,905	4.0906	8,045	6.6306	652	5.5513
Increase Pool Price by 1 Standard Deviation	437	0.0227	-68	-0.0006	47	0.0005	6	0.0002

Table 9, Panel A: Odds Ratio Sensitivity

VARIABLE	POOL 0	POOL 1	POOL 2	POOL 3
DF1_FLAGL1	0.156	0.100	0.224	0.175
DF2_FLAGL1	0.892	1.580	1.578	1.656
DF3_FLAGL1	0.205	0.169	0.183	0.165
flag_arm	1.378	1.410	1.466	1.456
flag_doc	1.153	1.102	1.141	1.102
flag_occupancy	1.020	0.960	0.994	1.009
PROP_SF_TH	1.034	1.055	1.038	1.047
INIT_RATE	1.109	1.114	1.105	1.141
YLDDIFF10Y_1Y	1.034	0.978	1.022	0.980
YLDDIFFBAA_AAA	1.005	1.003	0.994	0.999
EMPLOYMENT_L12LNCHG	0.986	0.984	0.996	0.997
DEFAULT_DISTANCE	0.988	0.966	0.975	0.962
CS_RESHPRC_LN12DIFF	0.480	0.522	0.435	0.509
SIGMA_CS	1.016	0.952	1.008	0.947
NETCHG_MTGQR	0.999	0.997	0.999	0.998
FICO2	0.807	0.810	0.846	0.834
COMB_LTV	1.108	1.076	1.085	1.069
Gross_WAC	0.976	1.037	1.030	0.981
POOL_PRICE_WGTD	0.998	0.994	1.005	1.019

Note: The continuous numbers in this table are the product of the mean frequency-weighted estimated odds ratio to the power of each variable's standard deviation and the dummy variables have a binary change.

Table 9, Panel B: Frequency-Weighted Odds Ratio Sensitivity for 2000-2007 Origination Years

	Origination Year							
Variable	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
DF1_FLAGL1	0.046	0.025	0.040	0.026	0.042	0.122	0.378	0.617
DF2_FLAGL1	1.402	1.547	1.133	1.589	1.546	1.214	1.270	3.128
DF3_FLAGL1	0.242	0.224	0.160	0.127	0.145	0.187	0.236	0.195
flag_arm	0.862	1.106	1.137	1.342	1.479	1.430	1.424	1.298
flag_doc	1.070	1.114	1.103	1.099	1.069	1.114	1.197	1.195
flag_occupancy	1.151	0.922	0.989	1.097	0.984	0.966	0.949	0.895
PROP_SF_TH	1.028	1.052	1.033	1.058	1.071	1.022	1.024	1.004
INIT_RATE	1.182	1.192	1.127	1.163	1.146	1.072	1.066	1.115
YLDDIFF10Y_1Y	1.129	0.972	0.948	0.872	0.903	1.062	1.042	1.035
YLDDIFFBAA_AAA	0.911	0.928	0.898	0.998	1.047	0.977	0.974	0.989
EMPLOYMENT_L12LNCHG	0.988	1.024	0.990	0.977	0.992	0.978	0.982	0.964
DEFAULT_DISTANCE	1.111	1.043	1.012	0.997	0.945	0.958	0.984	0.970
CS_RESHPRC_LN12DIFF	0.954	0.763	0.782	0.824	0.627	0.335	0.342	0.490
SIGMA_CS	1.040	0.998	0.992	0.952	0.907	0.963	1.066	1.197
NETCHG_MTGQR	0.997	0.987	0.993	0.990	0.997	0.986	0.997	0.995
FICO2	0.810	0.820	0.755	0.785	0.784	0.809	0.880	0.908
COMB_LTV	1.144	1.105	1.062	1.056	1.033	1.085	1.125	1.135
Gross_WAC	1.111	1.037	1.032	1.114	1.009	0.986	1.031	1.001
POOL_PRICE_WGTD	1.033	0.988	0.994	0.992	0.985	0.987	1.013	0.996

Note: The Proportional Odds Ratio values are frequency-weighted mean values from all pools over the 2000-2008 period. The continuous numbers in this table are the product of the odds ratio estimates to the power of the change which is one are standard deviation, and the dummy variables the binary change.