Quantitative Perspectives

# LOANDYNAMICS™: AD&CO'S APPROACH TO MODELING CREDIT RISK

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| October 2008

# Contents

*"The default risk of a loan depends largely on the state from which the loan is starting."*

The LoanDynamics™ Model (LDM) was developed to help investors better understand the inherent risks of credit-sensitive mortgages and related securities. It goes beyond the traditional two-state competing risk model, which focuses solely on prepayments and defaults. Instead it captures the behavior of a loan or portfolio of loans as it evolves from origination. LoanDynamics™ is based on a transition framework, in which the model makes predictions about the probability of a loan transitioning from one delinquency status to another. The default risk of a loan depends largely on the state from which the loan is starting. For example, the default risk is greater for a loan which is 90 days delinquent compared to a current loan. The behavioral equations behind LoanDynamics™ were based on strong economic rationale and were then parametrized using historical data.

LoanDynamics™ is unified across credit sector and product type and relies upon observed loan characteristics to make its projections. The benefit of this feature is that users do not have to make potentially arbitrary judgments about whether a loan falls into jumbo, Alt-A, high LTV, or subprime credit sectors. LDM was designed as a loan-level model, but can also operate on pool-level or repline data.

After a three-year development effort, the first version of LoanDynamics™ was released in January of 2007.

## The Data

The LoanDynamics™ Model was estimated from publicly available non-agency security data collected from the corporate trust department of Wells Fargo Bank, N.A. The database contains over 8 million loans from 144 different issuers covering the period from 1998 to 2006. This timeframe is characterized by mostly rising home prices. The database contains a robust cross-section of non-agency loan types including jumbo prime, Alt-A, subprime loans and second liens.

The composition of the database by credit sector and a list of top ten issuers (by # of loans) are contained in Tables 1 and 2. This database is updated monthly in order to monitor the accuracy of LDM forecasts. We used the OFHEO Total Transactions MSA-level indices to capture the monthly changes in loan-to-value (LTV) ratios for all loan-month records in the dataset.

**Table 1** Data Composition by Credit Sector

| | |
|---|---|
| Subprime | 39% |
| Alt-A | 22% |
| Jumbo Prime | 21% |
| Conforming Prime | 16% |
| Second Lien | 1% |

**Table 2** Top Ten Issuers in Database

| |
|---|
| Wells Fargo Mortgage-Backed Securities Trust |
| Structured Asset Securities Corp (SASCO) |
| GE Capital Mortgage Services Inc. |
| Structured Asset Investment Loan Trust (SAIL) |
| Banc of America Mortgage Securities |
| ACE Securites |
| Merrill Lynch Mortgage Loans Inc. |
| Park Place Securities |
| Norwest Asset Securities Corporation (NASCOR) |

## Model Structure

A traditional competing risk model views default as a one-step process. A loan starts out current and either prepays or defaults. In contrast, a roll-rate or transition framework dissects default into more granular pieces. In our approach, the LoanDynamics™ Model assumes that a loan can exist in one of four states: ***current (C), delinquent (D), seriously delinquent (S)*** and ***terminated (T)***. Current loans are at most one payment behind schedule or 0- 59 days delinquent. Delinquent loans are two to five payments past due or 60 – 179 days delinquent. Seriously delinquent loans are six months or more delinquent (180+ days delinquent), in foreclosure or real estate owned (REO). Loans can move among these three states and can also move to termination. Any loan whose balance drops to zero, whether by prepayment or foreclosure is considered a termination. These states were chosen for several reasons. First, they were aligned with cash flow delinquency triggers relevant to bond investors. Second, they best capture the distinct behavior patterns as borrowers cross these thresholds. Third, we wanted to minimize the modeling error that is introduced when transitions are broken into smaller segments.

In theory, there are 12 possible transitions among the four states. We explicitly model only seven transitions as shown in Figure 1 and Table 3.

Termination is an absorbing state, so terminated loans always remain terminated. By definition, the transition probabilities from the same starting status must all sum to one. Therefore, the transitions CtoC, DtoD and

StoS are residuals of loans transferring in and out of those states as shown in the following equations.

**Pr[CtoC] = 1 – Pr[CtoD] – Pr[C to S]– Pr[C to T]**

**Pr[DtoD] = 1 – Pr[DtoC] – Pr[DtoS] – Pr[DtoT]**

**Pr[StoS] = 1 – Pr[StoC] – Pr[StoD] – Pr[StoT]**

Also by definition, Pr[CtoS] = 0 since loans must become delinquent before migrating to seriously delinquent. We also explicitly set Pr[StoD] = 0 due to few observations of this transition.

Each transition equation was estimated separately and has a different functional form. Table 4 summarizes the principal drivers for each transition equation. We describe the economic rationale for each of the transitions below.

**Figure 1** Principal Transitions

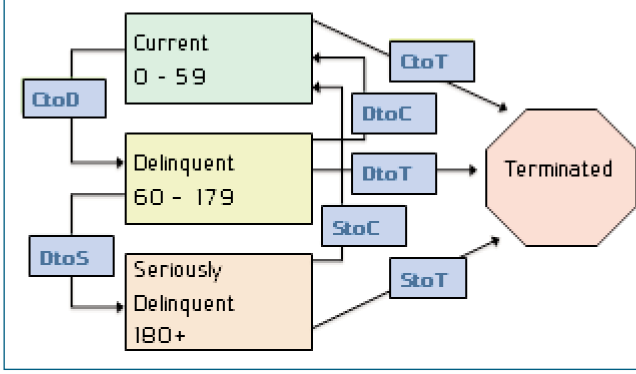



**Table 3** Principal Transitions

| TRANSITION | DESCRIPTION |
|---|---|
| C to T | Current to Terminated (voluntary prepayment) |
| C to D | Current to Delinquent (delinquency transition) |
| D to C | Delinquent to Current (cure transition) |
| D to T | Delinquent to Terminated (delinquent prepayment) |
| D to S | Delinquent to Seriously Delinquent |
| S to C | Seriously Delinquent to Current (Recovery) |
| S to T | Seriously Delinquent to Terminated (Liquidation) |

**Table 4** Principal Drivers of LoanDynamics™

| | TRANSITIONS | | | | | | LOSS SEVERITY | |
|---|---|---|---|---|---|---|---|---|
| | C to T | C to D | D to C | D to T | S to C | S to T | Loss Probability | Loss Magnitude |
| Turnover | X | | | | | | | |
| Refi | X | | | | | | | |
| Cashout | X | | | | | | | |
| Cure | X | | | | | | | |
| FICO | | X | X | | X | | X | |
| SatO Residual | | X | | | X | | | |
| Original LTV | X | | X | | | | X | |
| Change in LTV | X | | X | X | X | | | X |
| LTVAO * Change in LTV | | | | X | X | | | |
| Occupancy | | | | | | X | | |
| Original Balance | X | | | | X | | | |
| Current Balance | | | | | | | | X |
| Geography | | | | | | X | | |
| Documentation Type | | X | | | | | | |
| Change in Current Coupon | | | | X | | | | |

### DELINQUENCY TRANSITION (CtoD)

The principal factor that causes a borrower to miss one payment is generally triggered by a cash flow constraint. The propensity for borrowers to miss consecutive payments and become delinquent is captured by a borrower's initial credit score. For example, lower FICO borrowers have a greater likelihood to fall behind in payments than higher credit quality borrowers. The level of asset and income documentation also has a strong impact on delinquency rates in our model. Delinquency rates tend to be lower for borrowers who fully documented their income and assets across all FICO ranges.

Another important explanatory variable is a variable called SatO Residual. SatO Residual is a proxy for unobserved risk factors. SatO Residual is the difference between the actual spread at origination (SatO) and the expected spread at origination (SatOhat) given a set of loan characteristics. For example, a positive SatO Residual means that the actual coupon on the loan was higher than the predicted coupon based on the known characteristics of the borrower. The difference in actual and expected coupon rates suggests that the originator must have had additional information to charge the borrower a higher rate. SatO Residual attempts to capture, albeit imperfectly, information retained by originators but not revealed in the servicing files. For example, debt-to-income ratio and employment history are not readily available information in trustee reports. We found that SatO Residual has a high degree of explanatory power and is uncorrelated with other variables.

When we examine the model fit for C to D transition rates, the model does a good job of predicting delinquency rates across a range of FICO scores as shown in Figures 2 and 3. We present the model fits for both FRM and ARM loans. The solid lines represent actual transition rates, while the dotted-lines represent predicted transition rates. One notable feature about the graphs is the initial spike in C to D transition rates in the first few months, particularly for FICO scores 650 or less, which reflect early payment defaults (EPD).

**Figure 2** CtoD by FICO - FRM

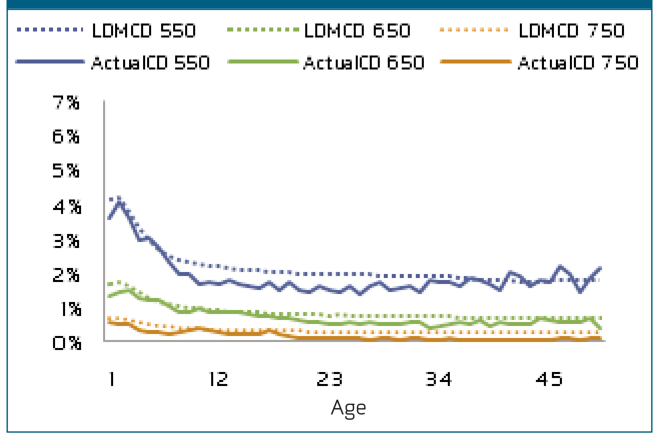



**Figure 3** CtoD by FICO - ARM

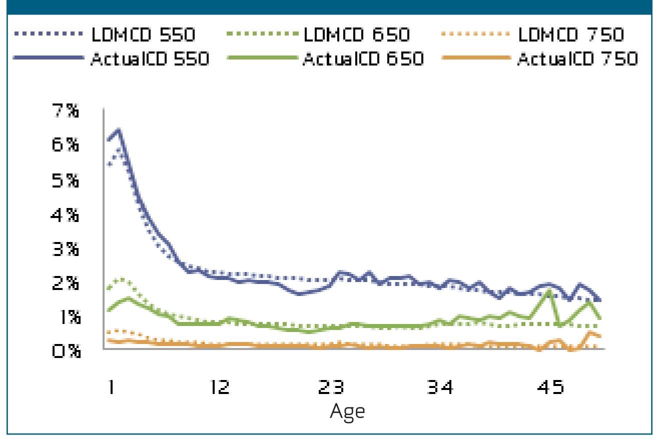



Figure 4.0 and 5.0 illustrate the actual and predicted C to D transition rates for SatO Residual. The model fits the actual data reasonably well as SatO Residual increases from 0.5 to 2.5.

**Figure 4** CtoD by SatO R - FRM

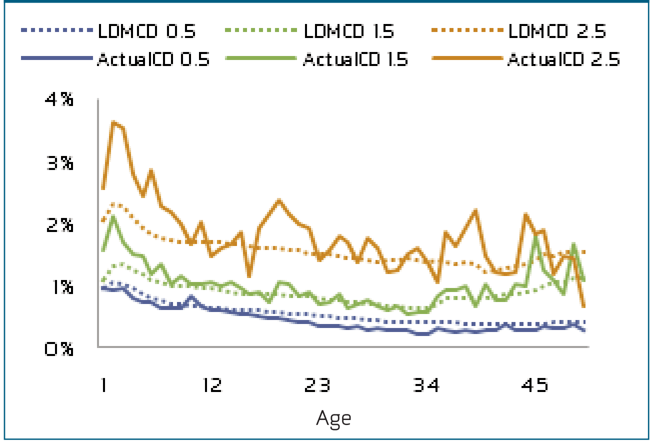
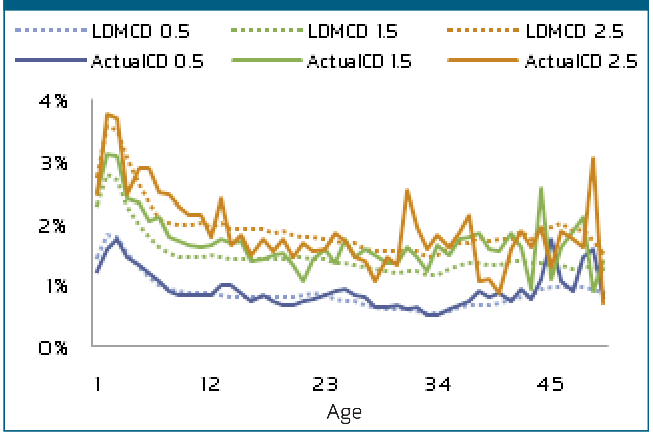



**Figure 5** CtoD by SatO R - ARM




### PREPAYMENT TRANSITION (CtoT)

The prepayment transition in LoanDynamics™ shares the same functional form as the AD&Co v5.2 FRM and ARM non-agency prepayment models. The AD&Co v5.2 non-agency prepayment models forecast total terminations, while LoanDynamics™ forecasts only voluntary terminations. In addition, the AD&Co v5.2 non-agency prepayment models were estimated using a different loan-level dataset.

Turnover, refinancing incentive, cashout and cure continue to be the main prepayment drivers in LoanDynamics™. For more detailed discussion about our prepayment modeling methodology, see Quantitative Perspectives: "Fixed-Rate Home Equity Loan Prepayment Model" by Sanjeeban Chatterjee at http://www.ad-co.com/qpsept05.pdf.

### CURE TRANSITION (DtoC)

A borrower's ability to cure depends greatly on whether equity exists in the property and whether the borrower can access that equity. Typically, a borrower would tap into the equity in his home by taking out a second lien mortgage or a home equity line of credit (HELOC). The main drivers in this transition are the original loan-to-value (LTV) and change in LTV. The original LTV captures the equity and the current LTV captures the change in equity due to change in house prices.

FICO also plays an important role in this transition. There is an inverse relationship between the ability to cure and FICO scores. The theory is that the circumstances that cause a creditworthy borrower to miss a few payments are materially different than the circumstances that cause a less creditworthy borrower to miss a few payments. High FICO borrowers get into trouble because of major life crises, such as life-threatening illness, death in the family, job loss or natural disaster. These borrowers rarely recover, because any financial cushion would have been depleted from the life-altering event. In contrast, low FICO borrowers who miss a few payments, do so because of temporary cash flow shortfalls. They have a history of missing payments, which accounts for a low FICO score in the first place. The cash flow constraints tend to be temporary in nature and not necessarily a sign of a serious problem. High FICO borrowers are generally immune to cash flow shortfalls because they tend to have more financial reserves on hand.

Figures 6 through 11 show actual and predicted D to C transition rates by original LTV for both FRM and ARM loans. The model does a reasonable job capturing cure rates across LTV ranges as shown below. The graphs illustrate how cure rates diminish as there is less equity in the property.

**Figure 6** DtoC by 55 LTV - FRM

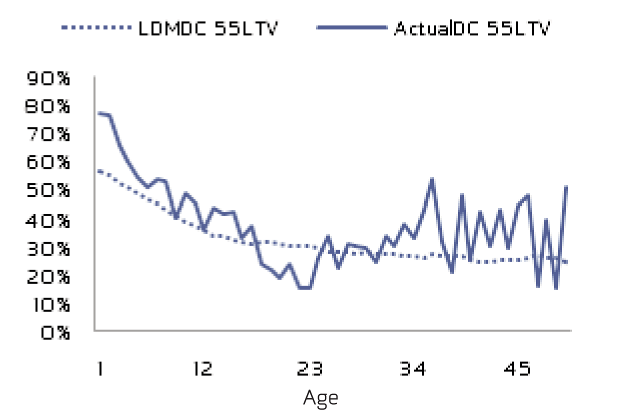



**Figure 7** DtoC by 55 LTV - ARM

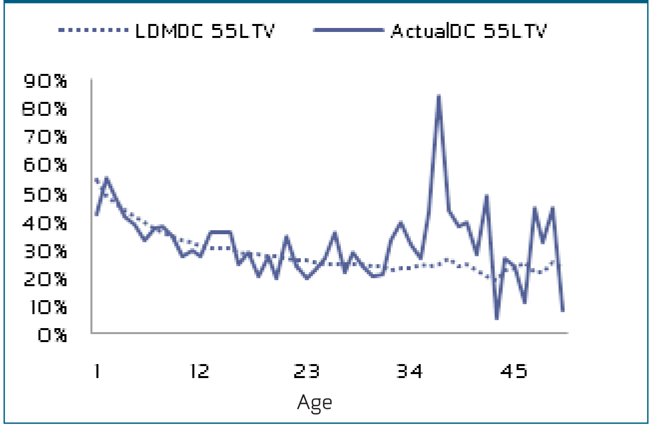



**Figure 8** DtoC by 70 LTV - FRM

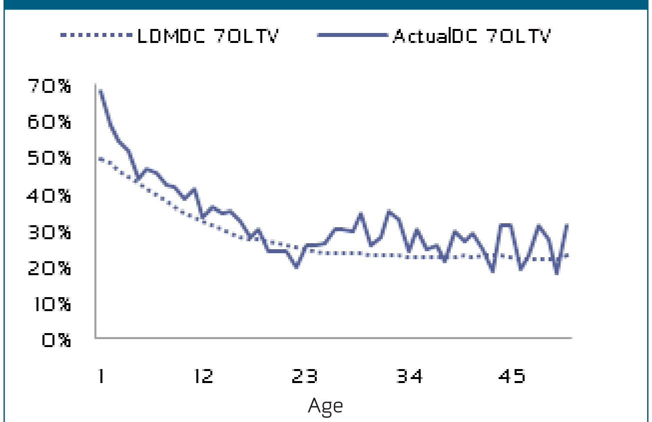



**Figure 9** DtoC by 70 LTV - ARM

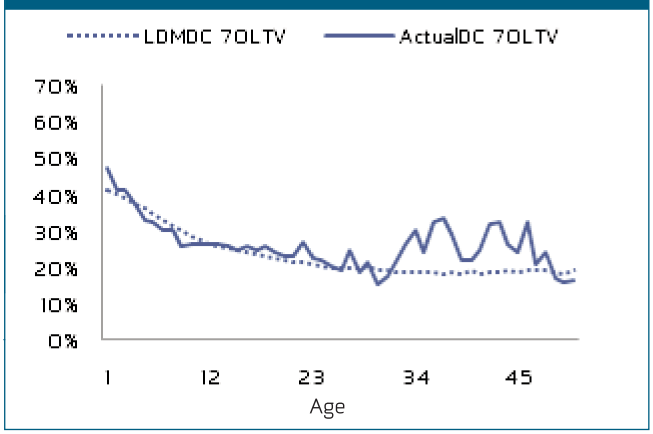



**Figure 10** DtoC by 90 LTV - FRM

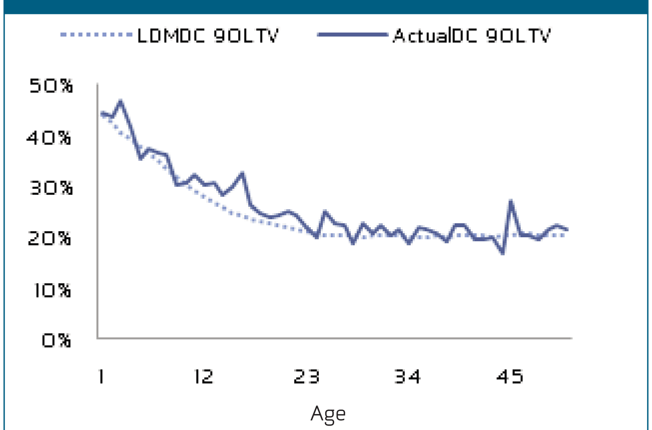
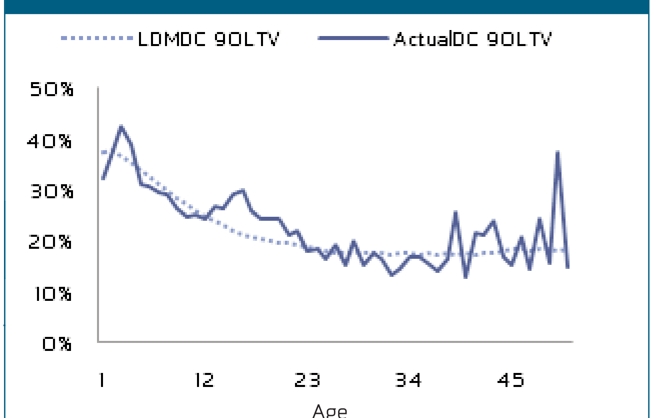



**Figure 11** DtoC by 90 LTV - ARM



Figures 12 and 13 depict the model fits for the D to C transition rates by FICO score for both FRM and ARM. These graphs also illustrate the point made earlier that lower FICO borrowers cure at higher rates than higher FICO borrowers.

**Figure 12** DtoC by FICO – FRM

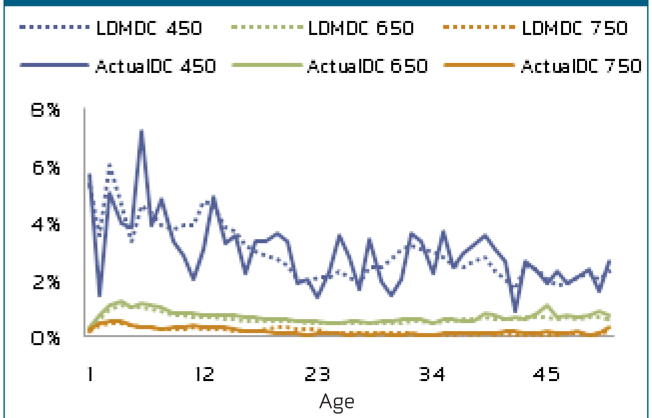
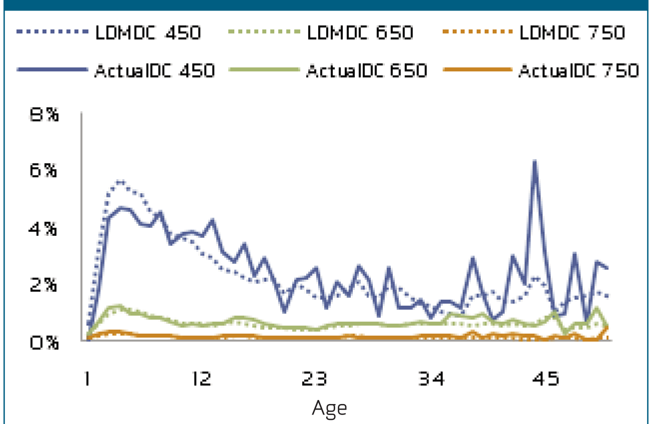



**Figure 13** DtoC by FICO – ARM




### DELINQUENT PREPAYMENT (DtoT)

Whether a borrower manages to prepay out of delinquency greatly depends on available equity in the property. If there is positive equity, a borrower can protect the equity by selling the home and paying off the outstanding loan balance. Original LTV, the change in LTV and the interaction between the two variables capture the equity effect in this transition. We see a strong relationship between D to T transition rates and current LTV ratios less than 80%. Delinquent prepayments are less sensitive for LTV ratios greater than 80% because refinancing options are limited for borrowers with less than 20% equity. The mortgage current coupon also plays a role in capturing refinancing opportunities available to the borrower. There are separate equations for ARMs and FRMs because of the impact of reset age for ARMs.

**Figure 14** DtoT by FICO – FRM

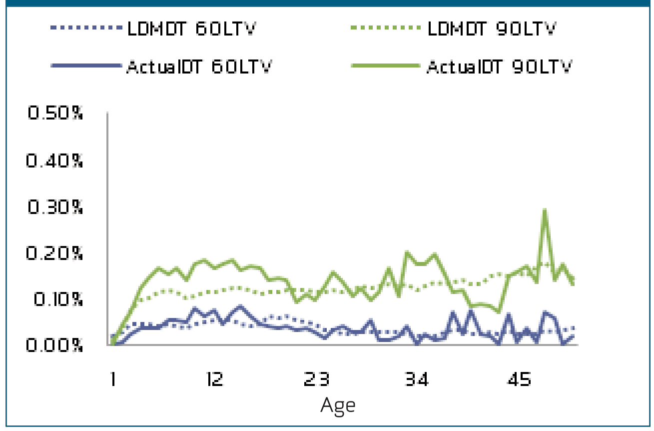
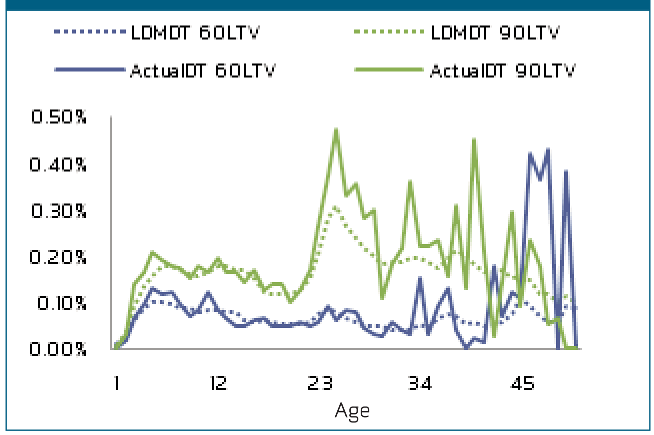



**Figure 15** DtoT by FICO – ARM



### RECOVERY TRANSITION (StoC)

The recovery transition is similar to the cure transition in that the ability of a borrower to become current again is principally a function of positive equity. If there is positive equity in the property, the borrower will make one last effort to save the property, most likely through a loan modification. Original LTV and change in LTV variables are the primary drivers of this transition. The occupancy type also is an important driver because there is a higher likelihood for owner-occupied properties to recover compared to investor properties.

**Figure 16** StoC by 60 LTV - FRM

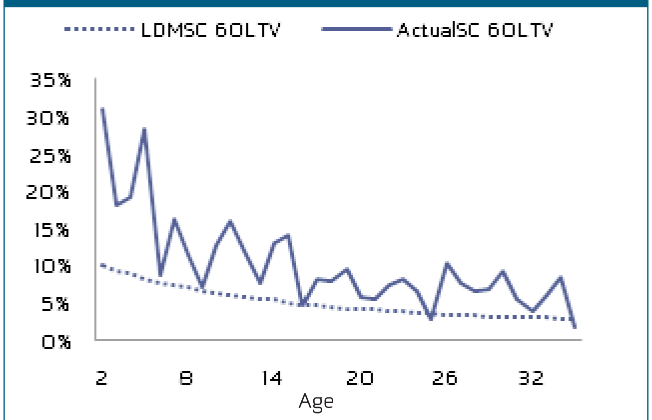



**Figure 17** StoC by 60 LTV - ARM

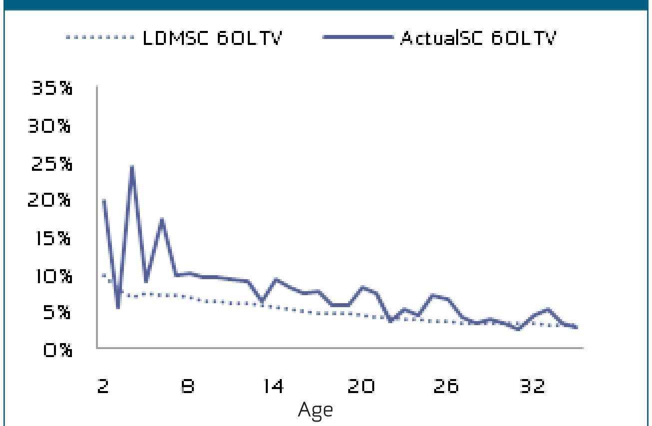



**Figure 18** StoC by 90 LTV - FRM

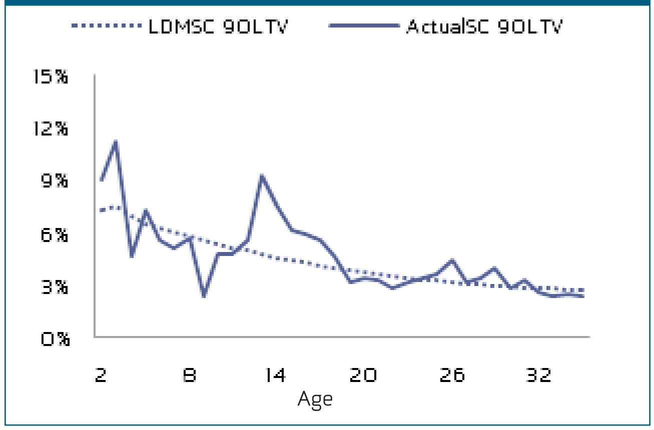
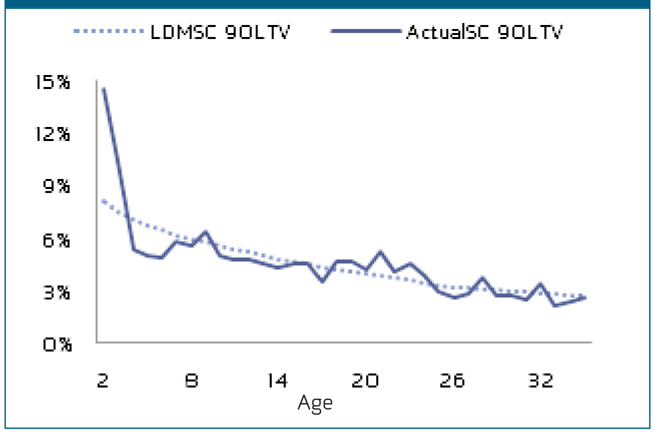



**Figure 19** StoC by 90 LTV - ARM




### LIQUIDATION (StoT)

Liquidation is a decision driven mainly by the servicer and the legal procedure for foreclosure. If the loan was made in a judicial state, the foreclosure process must proceed through the courts for a judgment, which can lead to a protracted liquidation process.

## Model Structure (CONTINUED)

### LOSS SEVERITY

There are two components in our loss severity model. We estimate both a probability of loss and a magnitude of loss (i.e. loss given default). The product of these components represents the loss severity generated by LoanDynamics™.

There are three separate loss probability equations depending on the state (C, D, S) from which the loan was terminated. The probability of loss differs materially for loans terminated from the different states. FICO, current loan balance and LTV are the primary explanatory variables. There is a strong correlation between FICO and the probability of loss for loans terminating from C and D. FICO has less impact on loans 6 months or more delinquent because the original FICO score is no longer relevant for loans 6 months behind in payments. There is also a strong correlation between LTV and probability of loss. The higher the LTV or the lower the equity, the more likely a loss is to occur in the future.

There are three separate equations for the magnitude of loss, which distinguish between the different states from which the loan was terminated. The magnitude of loss is strongly correlated with the change in LTV and the current loan balance. The change in LTV captures whether any equity is left in the property. The greater the equity, the smaller the loss or vice versa. Current loan balance is also strongly correlated with the magnitude of loss particularly for small loan balances less than $100,000. The size of the loss is magnified for small balance loans because the fixed costs associated with a foreclosure process have to be distributed over a smaller base amount. The presence of mortgage insurance is also an important determinant of the loss magnitude. However, the mortgage insurance variable is only a flag that indicates whether a loan is covered by mortgage insurance. The loss reported in the data represents the loss after accounting for any mortgage insurance payments.

## Model Inputs

### LOAN INPUTS

Table 5 on the following page summarizes the model inputs required to run LoanDynamics™. The model requires users to provide a set of loan, borrower and property characteristics. At a minimum, users must provide the data fields denoted with an asterisk for the model to run. Model accuracy will improve by including the optional data fields. For loans with missing values for lien position, the model will assume they are first liens. If current LTV is not provided, the model will compute the value by using OFHEO's Total Transactions State-Level Home Price Index. If geographic location is not provided, the model will default to the OFHEO's National-level Home Price Index.

**Table 5** LoanDynamics™ Model Inputs

| Loan Inputs | | | ARM Characteristics | Option ARM Loans |
|---|---|---|---|---|
| *--Loan Characteristics* | Original Term* | Original LTV* | Gross Margin* | Payment Cap Change* |
| | Age* | Current LTV | First Reset Age* | Payment Reset Period* |
| | Remaining Term* | Original Total LTV | Subsequent Reset* | Payment Recast Period* |
| | Original Coupon* | Current Total LTV | ARM Index Type* | Current Minimum Payment* |
| | Current Coupon* | Lien Position | Life Cap | Max Negam Limit* |
| | Coupon Type* | Mortgage Insurance | Life Floor | |
| | Original Loan Balance* | MI Coverage | Periodic Caps & Floors | |
| | Current Loan Balance* | | Prepayment Penalty | |
| | | | IO Period | |
| *--Borrower Characteristics* | Original FICO* | Delinquency Status* | | |
| | Loan Purpose | Documentation Type | | |
| *--Property Characteristics* | Geographic Location | Occupancy Type | | |
| | Number of Units | Property Type | | |
| *Denotes Required Data Field | | | | |
| **Tuning Parameters** | | | | |
| *--Prepayment Transition* | Scale | Cashout | Slide | Burnout |
| | Refi | Cure | SatO | Lag |
| | Turnover | Age | Curve Spread | |
| *-- Default Transitions* | CD | DT | SC | |
| | DC | DS | ST | |
| *--Loss Severity* | Loss Probability TC | Loss Probability TS | Loss Magnitude TD | |
| | Loss Probability TD | Loss Magnitude TC | Loss Magnitude TS | |
| *--Loan Characteristics* | FICO Slide | SatO Residual | | |
| | LTV Slide | | | |
| *--Home Price Sensitivity* | HPI Slide | | | |
| **Economic Drivers** | | | | |
| | Interest Rate Forecast | | | |
| | Home Price Index Forecast | | | |

### TUNING PARAMETERS

The model architecture allows users to tune model parameters in order to express their views about collateral performance or market conditions. The tuning parameters also allow users to perform sensitivity analysis. This feature is particularly valuable for periods when market conditions deviate drastically from historical averages.

The model exposes all of the transitions to scale up or down, including the loss severity components (probability of loss and loss magnitude). It is important to note that the scalar applied does not result in a directly proportional increase (decrease) in SMM, CDR, delinquency or loss output. In the case of the default transition tuning parameters, a multiplier of 1.5 for the C to D tuning parameter will increase the monthly CtoD transition rates by 50%. However, monthly MDRs will increase by slightly less than 50%.

## Model Inputs (CONTINUED)

In addition, users can scale *Slide* variables in order to perform sensitivity analysis. LDM allows users to increase or decrease the original LTV, FICO or HPI inputs globally for all loans rather than having to change these collateral characteristics individually. For example, if a user would like to see the impact of reducing all FICO scores in a given pool by 20 points, he would enter in "-20" for this tuning parameter. The HPI slide variable allows users to easily shift the HPI scenarios up or down from a base scenario.

The model also allows users to reduce or magnify the SatO Residual effect. Users can turn off the SatO Residual effect by setting the tuning factor to zero, which effectively sets the coefficient of the SatO Residual variable to zero. This can be problematic when comparing loans with identical characteristics except for original coupon. A SatO Residual tuning factor of zero will ignore the behavioral differences between these loans even though the coupon differences reveal different levels of risk. Therefore, we recommend that users who want to do this kind of sensitivity analysis, leave the SatO Residual tuning factor at "1" and adjust coupons manually in order to produce SatO Residual values equal to zero.

Tuning parameters for transitions are set for the entire life of the loan. Tuning of selected outputs, CDR, CPR and Loss Severity are available on a vector basis.

### ECONOMIC DRIVERS

There are two main economic drivers necessary to run LoanDynamics™. The model requires that users provide both a path of interest rates and home price index. The results generated are conditional upon the interest rate and home price assumptions. Users have the option of running static scenarios, running simple scenario shifts, or providing a monthly vector of interest rates and home price indices.

For seasoned loans, the model computes Current LTV by using the OFHEO's Total Transaction State-Level Home Price Index. It is possible for users to provide state-level HPI forecasts and to map these forecasts to individual loans. Although LoanDynamics™ does not generate random home price scenarios, it can accept home price vectors generated by AD&Co's stochastic HPI Generator.

## Definitions of Default

LoanDynamics™ allows users to choose from four definitions of default: **Basic, Bank, Implied** and **Loss Termination**. The choice of definition does not alter the cash flows, thus losses remain internally consistent across all definitions. The distinction lies in how defaults and prepayments are distributed across definitions. Table 6 summarizes the portion of terminated loans that are included in the calculation of prepayments, defaults and losses.

## Definitions of Default (CONTINUED)

**Table 6** LoanDynamics™ Output Definitions

| | *Basic* | *Bank* | *Implied* | *Loss Termination* |
|---|---|---|---|---|
| **Prepayments** | Terminations from C & D without losses | Terminations from C & D without losses | Terminations from C without losses | Terminations from C, D, & S without losses |
| **Defaults** | Terminations from C & D with a loss; Loans Terminated from S | Terminations from C & D with a loss All loans in S | Terminations from C with loss All terminations from D & S | All terminations from C , D, S with losses |
| **Losses** | Terminations from C, D, S with losses | Terminations from C, D, S with losses | Terminations from C, D, S with losses | Terminations from C, D, S with losses |
| **Severity** | Losses/Default | Losses/Default | Losses/Default | Losses/Default |

## Model Performance and Validation

As part of monitoring the performance of LoanDynamics™, we continue to examine the model forecasts against actual performance of mortgage loans to date. We have tested the model performance with an out of sample mortgage loan portfolio. The portfolio consisted of 750,000 unique loans and 22 million loan-month records. The portfolio contains loans originated between 2002 and 2008 and represents 115 issuers.

We look at model fits by collateral characteristics (FICO, LTV, Documentation Type, etc.) and by credit sector (jumbo prime, subprime, Alt-A, etc.). The loan-level results were weighted by original loan balance. We also compare the actual monthly transition rates and loan statuses against predicted transition rates and loan statuses over time. We are not able to compare forecasts with actual losses because newer vintages have yet to experience losses.

Given the recent mortgage crisis, model forecasts have started to deviate from actual performance for 2007 and forward, particularly when analyzing model fits by credit sector. For a complete set of model fits, please see http://www.ad-co.com/support/user/release_notes/LDMv1.7.1b_tuning2.htm.

We have developed new tuning recommendations by credit sector in response to the recent market turbulence. These tunings were not designed to match perfectly the historical experience prior to 2007 or the current market environment, but to balance both periods and reflect longer-term market trends. The new recommended tunings are presented in Table 7.0.

**Table 7**

| Collateral Type | LDM Transition Tunings | | | | | | LDM Underwriting | | Prepayment (CT) tunings | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CD | DC | DS | DT | SC | ST | LTV Slide | FICO Slide | Turnover SMM | Refinance SMM | Slide (BP) | Aging Curve |
| Jumbo Prime FRM | 0.5 | | | 1 | | 0.75 | | | 0.85 | 0.75 | 25 | |
| Jumbo Prime ARM | 0.9 | 0.85 | 1.4 | 1 | 0.7 | 0.75 | | | 0.85 | 0.50 | 100 | 0.6 |
| Alt-A FRM | 0.8 | 0.85 | 1.5 | 1 | 0.7 | 0.75 | | | 0.85 | 0.75 | 25 | |
| Alt-A ARM | 1.45 | 0.85 | 1.5 | 1 | 0.7 | 0.75 | | | 0.85 | 0.50 | 100 | 0.6 |
| Subprime ARM | | 0.5 | 1.2 | 0.8 | 0.5 | 0.75 | 7 | -40 | 0.85 | 0.50 | 100 | 0.6 |
| Subprime FRM | 1.25 | 0.5 | 1.25 | 0.5 | | 0.75 | | | 0.85 | 0.75 | 25 | |

## Conclusion

We believe that LoanDynamics™ embodies a valuable framework for understanding and analyzing the credit risk of individual mortgage loans or entire portfolios. This approach allows investors to develop insights about what drives a borrower to migrate in and out of key delinquency statuses. LoanDynamics™ is an attractive alternative to full-blown roll rate models because the condensed number of transitions facilitates a better understanding of key performance measures like 60+ delinquencies, defaults and losses. By developing a deeper and more intuitive understanding of what transitions are likely to drive future losses, investors are better equipped to make informed decisions.

Quantitative Perspectives

**Quantitative Perspectives** is available via www.ad-co.com

*We welcome your comments and suggestions.*



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