Stability in Consumer Credit Scores:
Level and Direction of FICO Score Drift as a Precursor to Mortgage Default and Prepayment

Brent C Smith[1]

Abstract
This article represents an extension of the expansive credit risk and credit migration literature, prominent corporate bond and securities risk pricing, to an analysis of the drift of consumer credit scores. A rich data set of residential mortgages is used to observe credit score migration post loan origination and in a test of the ability of credit score transition to serve as a precursor to potential default and prepayment. The results indicate credit scores provide signals and information to investors and servicing agents in a fashion similar to credit ratings on commercial paper as to default potential.

JEL: G21, R11, R20, R21

Key Words: residential mortgage default, risk, lending, housing economics, mortgage underwriting, consumer credit

Draft
July 1, 2010

This paper has benefited from helpful conversations with Brent Ambrose, Allen Goodman, Kathleen Johnson, Edward Prescott, Anthony Sanders, and participants at the Housing and Financial Crunch Symposium May 26, 2010 at George Washington University. Mark Watson of the Federal Reserve Bank of Kansas City provided invaluable assistance with the data set. I am indebted to the Federal Reserve Bank of Richmond and LPS Applied Analytics for providing access to the data via a research affiliation. All views and errors, however, are the responsibility of the author and do not reflect those of the Federal Reserve Bank of Richmond or LPS Applied Analytics.
[1] Smith: Department of Finance Insurance and Real Estate, Snead School of Business, Virginia Commonwealth University; email: bcsmith@vcu.edu; phone 804.828.7161.

1. Introduction

Credit ratings published by agencies such as Moody's or Standard and Poor's play an increasingly important role in financial markets. This significance is highlighted by recently issued proposals by the Basel Committee that suggest ratings be used as a basis for calculating regulatory capital for financial institutions. A literature has developed around credit ratings and their utility as measures of default and business cycle events post issuance of debt (Bangia et al., 2002). In the construction of contemporary credit risk pricing models, analysis is employed in identifying relationships between credit rating transitions and overall credit quality (Hanson and Schuermann, 2006). Such analysis is dependent on calculating transition probabilities for different ratings classes. For example, given a matrix of rating classes what is the probability that an AAA bond downgrades to BBB, over a prescribed time horizon.

To date, however, there has been little effort to extend this literature to the consumer finance realm and the surrogate to corporate ratings, the consumer credit score. Just as changes in corporate ratings serve as leading indicators of default potential, analyzing consumer credit score drift can provide similar foresight to investors and servicing agents over the course of the loan as they seek to reduce risk and enhance the expected returns on mortgage portfolios. Both household and micro/macroeconomic factors can trigger changes in capacity to pay thereby increasing the probability of default or prepayment (Capozza and Thomon, 2006; Vandell, 1995). Trigger events that occur post origination are not readily observable by investors or servicing agents. Due to the moral hazard in the mortgage process the borrower is under no compulsion to report changes in financial status to the lender/servicing agent (Ashcraft and Schuermann, 2006). Trigger events that do impact credibility, though delayed, can be observed through the credit score providing a type of signal of potential change in status of mortgage (Harrison, Noordeweir and Yavas, 2004; Longhofer and Peters, 2005).

Such performance information can be applied as a means to head off and project potential early termination costs, and thus abate some of the systematic risk in mortgages from both default and prepayment. [i] One of the most important and accessible indicators of a borrower's credit quality and their ability/willingness to retire their indebtedness is the FICO score. In the United States the FICO score produced by the Fair Isaac Corporation is used by 90 of the top 100 financial institutions and over 75 percent of the mortgage companies in underwriting mortgage loans.[ii]

In 1958, Fair, Isaac introduced their first scoring system, called Credit Application Scoring Algorithms, touting that the results could accurately predict the payment behavior of revolving credit holders, including whether they would pay on time, pay late, or not pay at all. By the mid-1990s Fair, Isaac extended its business from credit card issues to the insurance industry, and small business. Meanwhile, Fannie Mae and Freddie Mac stepped up the use of the company's FICO scoring for home mortgages, despite criticism that credit scoring, which had helped overcome discrimination in the 1970s, now hampered implementation of Federal level affirmative action policies. Coupled with the credit collection agencies (e.g. Trans-Union, Equifax, and Experian) personal credit ratings have evolved into a mini-industry.

This article presents an investigation of FICO score changes (drift) over time for a sample of mortgage borrowers. The FICO score data is analyzed both as presented and grouped into categories referred to as grades. Allocating observed FICO scores into grades, similar to those of Moody’s and Standard & Poor's corporate bond ratings, the analysis attempts to answer the following related questions:

1) What is the FICO score experience of borrowers from origination of a mortgage through subsequent years following issuance?

2) Is there a tendency for borrowers of various initial FICO scores to be upgraded or downgraded over the observation period?

3) Is there temporal variation in score change over the period of observation?

4) Do credit score migrations provide signals to investors and servicing agents relative to potential default and prepayment risk?

These questions are addressed using a data set, from the state of Florida, of mortgages that includes information on origination and ongoing dynamic performance data, including the borrower FICO scores at periodic intervals over the observation period. Extending beyond the question of credit quality both static and dynamic obligor level factors are included in modeling credit score drift and default probability. For discussions on the links between credit ratings changes and bankruptcy / default modeling in a corporate setting, see for instance Altman (1968), Shumway (2001), and Hillegeist, Keating, Cram and Lundstedt (2004).

One of the objectives of this work is to provide a systematic review of the migration pattern in consumer credit scores, and to uncover the potential for ongoing observation of credit scores as a tool for predicting potential default in residential mortgages. The results suggest consumer credit scores have similar value to commercial debt ratings as signals of information on the future ability to pay of the obligor and his willingness to continue to pay under the current debt terms. The implications of these findings are significant as public and private sector risk management policies evolve in the mortgage industry post the 2008 credit collapse. The credit score is one of the few variables used by the underwriter that is not borrower provided (thus, outside the scope of borrower reporting bias), and also one of even fewer variables available to servicing agents and investors post origination (save for the payment history on the mortgage in question).

The remainder of the paper will proceed as follows. Section 2 presents consumer credit scores and illustrates the sample data organized into transition matrices with default probabilities. Section 3 presents the analysis of credit migration and a test of the relationship between credit score migration analysis and subsequent prepayment and default events. Section 4 provides final comments and suggestions for future work.

2. Consumer and Corporate Credit Similarities

The literature on mortgage credit risk emphasizes the important roles of equity in the home and vulnerability to so-called triggering events in determining the incidence of delinquency and default. Relevant data that contain information on trigger events in the borrower’s history are difficult to obtain and hard to quantify. The available evidence, however, indicates that loans made to borrowers with flawed credit histories (those who have had difficulties meeting scheduled payments on past loans) default or become delinquent more often than loans made to borrowers with good credit histories (Avery et al., 1996). Although a borrower’s credit history has been shown to play an important role in determining mortgage loan performance (Alexander et al, 2002; and Archer and Smith, forthcoming), only recently have researchers had access to sufficient information to begin analyzing the role that trigger events, or shocks have on the borrower’s ability to pay. Changes in the FICO score provide a hard data proxy for viewing the evolution in the borrower’s capacity to pay over the course of a mortgage, beyond the historical information obtained at origination.[iii]

Examination is initiated here with the unconditional transition matrices for the mortgage sample in whole and for various sub-samples. Credit migration or transition matrices characterize past changes in the credit quality of obligors (traditionally firms) using ratings migration histories. In commercial credit risk analysis it is customary to use a one year horizon. This one year standard is more a function of ratings evaluation patterns than a decision based on theory or statistical properties. In the case of consumer credit scores, information on credit capacity is continuously gathered and the credit score recalibrated frequently as information dictates changes in the score. Given the potential volatility and frequency of adjustment in credit scores there is no dictate on the "best" horizon. Lacking a directive the conditions will be reviewed at horizon intervals of 1, 2, and 3 years post origination.

The basic tenant behind this procedure is that, for a given sample, the probability of a transition from rating *i* to *j*, is a constant parameter, *pij*. This amounts to saying that, for a given initial rating, transitions to different possible future ratings follow a constant parameter, temporally independent multinomial process. Estimation may then be performed by taking the fraction of occasions in the sample (or sub-sample) on which an obligor starts the observation period in state *i* and ends in *j* (Nickell, Perraudin, and Varotto, 2001).

The data from the state of Florida includes a panel of nearly 7 million observations of roughly 270 thousand individual mortgage borrower's FICO scores issued over the 2001 – 2008 period. The loan level data is from a sample prepared by LPS Applied Analytics, Inc. (LPS), a data repository for the mortgage banking industry, representing the servicing reports on individual loans reported by participating lenders. Data from LPS is used by the Federal Reserve Board and member banks for analysis and forecasting of mortgage performance. Moreover, the data is considered among the most comprehensive data sets available on performance of loans over time. Observed loans have been issued between January, 2001 and December, 2008. FICO migration is observed through June, 2009. The sample is restricted to first lien mortgages used for the purpose of purchase or refinance of the owner occupied residence. Each observation includes the FICO score at origination and at different points into the horizon.[iv] In addition to using reported, raw scores for analysis, the observed scores are allocated into grades 1 through 8 in a similar fashion to the third party rankings on corporate debt.[v] This allows for the creation and comparison of credit score matrices and provides opportunities to test the many tools for credit migration analysis developed in corporate finance.[vi]

Obviously, the probability of a particular borrower in a specific FICO grade upgrading or downgrading is not equally likely for any one grade, nor would it be the same across the grades. For example, the probability of a grade 1 borrower's score being upgraded is zero, and the probability that same borrower' score downgrading is positive, while the probability of a grade 5 upgrading or downgrading is both positive. Further, there is no conditional restriction such that the probability of a downgrade is equal for a grade 1 or a grade 5 borrower. However, if the data is randomly divided across all borrowers in each rating category into three equal groups, then for a large sample and without any additional information it is anticipated that an equal number of borrowers will experience one of the three events, upgraded, downgraded or stay the same. Alternatively, if the risk neutral probability of default is used as the basis to allocate borrowers into three categories based on High, Medium, and low default probabilities, then one can expect more borrowers in the High (Low) group to be downgraded (upgraded) than in the Low (High) group. In the following discussion the data is sliced in a number of dimensions representing anticipated clusters of credit risk (e.g. temporal and purpose of borrowing). As previously noted, grade change tests that follow are conducted at 12, 24 and 36 month intervals from origination. The tables that follow will refer to the grades as running from 1 (800+) to 8 (<500). For reference purposes and external validity the population distribution according to Fair Corp. is also included in the first table. Examination of the migration patterns in the data set reveals a number of interesting patterns.

2.1 FICO Score Distribution Matrix

Table 1 provides the distribution, by year, of the sample across the eight FICO score grades reported at the time of loan origination. The last line in the table is the population distribution according to the FAIR Corp. The FICO scores in Table 1 are clustered around the higher prime rate (i.e. 650 to 750), compared to the population. This is likely a function of the borrowing population from which the scores are drawn. The FAIR Corp. distribution is flatter than the sample due to the fact that it represents the population and the sample is restricted to those home buyers that possess a mortgage. Although 2.0 percent of the population according to FAIR Corp. has a credit score below 500 very few mortgage applicants will qualify for a loan at that low level. At the high end of the scale, many in the pool of FICO scores in excess of 800 will obtain funds and access to housing using nontraditional means that are not included in the dataset.

The data also indicates the distribution across FICO grades varies by time, particularly acute in 2006 and 2007. This is most easily observed in the bold cells. For example, between 2002 and 2005 grade 2 (750-799) averages roughly 29 percent of the sample distribution. In 2006 there is a substantial decline of borrowers at the upper end of the FICO categories (e.g. 2 & 3), substituted by equally significant increases at the lower end (5, 6, 7). In 2006 grade 2 drops to less than 24 percent. During the same period the percent of the sample in grades 6 (550-599) and 7 (500-549) nearly doubles from 3.5 and 1.0 to 6.5 and 2.5 percent respective. Post the subprime and broader mortgage market collapse this trend is reversed as lenders tighten underwriting standards in response to a near complete shut-down of secondary market activity. In 2008, when mortgage credit is tightened, the distribution returns to approximate a pre-2005 pattern, with the addition of high concentrations in the grade 1 (800+) tail. This is indicative of the period as lenders restricted access to those with the lowest perceived risk.

[Table 1 approximately here]

2.2 Unconditional Migration Matrices

Table 2 illustrates the unconditional transition matrices for the full sample over 1, 2 and 3 year post origination horizons. The cohort approach utilizes the observed proportions from the beginning of the observation period (in this case origination) to the end (typically on some annual basis) as the estimated migration probabilities. Conditional upon a given grade at time *T*, the transition, or migration matrix is a description of the probabilities of being in any of the various grades at *T+1*. It thus fully describes the probability distribution of grades at *T+1* given the grade at *T*. Assume for example that there are $N_i(t0)$ individuals of grade *i* at time *t*, and some level given as $N_{ij}(t1)$ had migrated to grade j at the end of the observation period. The migration probability for observation period $t=1$ is then given as:

$$P_{ij} = \frac{N_{ij}}{N_i} = \frac{\sum_{t=1}^{T} N_{ij}(t)}{\sum_{t=1}^{T} N_i(t)} \qquad [1].$$

Under the time homogeneity constraint the events in the period *t* are viewed as independent of events that occurred in prior any periods *t-n*. Time invariance translates into indifference between outcomes obtained from samples drawn on two different time periods (Schuermann, 2006).

Theoretically, transition matrices can be estimated for any desired transition horizon. As the ongoing coverage follows at least a quarterly review pattern, transition matrices estimated over short time periods best reflect the rating process. The shorter the measurement interval, the fewer rating changes are omitted. However, shorter duration also results in less extreme movements, as large movements are often achieved via some intermediary steps. The number of observations in each rating category naturally diminishes from year 1 as the horizon increases.[vii] The first panel presents the transition for all loans with a 12 month observation. The borrower's origination grade is presented in the first column and the direction of migration is projected on the lines. The observations in each grade remain consistent through the 24 month observation point then diminish significantly at the three year horizon. For example, 63,670 grade 3 observations have at least two years of experience; by the three year cut the number falls to 52,632. The proportion of the mortgages that retained their initial grade is listed on the diagonal in the table.

The results can be analyzed in several ways. First, as anticipated, all rating categories (save for category 1) show a continuously declining proportion of borrowers retaining their initial grade as the horizon lengthens. Also, grade 2 issues have the greatest stability, in terms of retaining their initial rating, up to three years after issuance. This is the core of the prime borrowing market, and as a group appear to retain sufficient ability to self-insure against negative trigger events post purchase. Nevertheless, grade 1 borrowers exhibited a sizable propensity to be downgraded; only 32 percent of those issues with a three-year or longer history retained their top rating. Equally surprising, of the remaining (those that have not defaulted or refinanced) grade 8 borrowers 62 percent had upgraded three years post origination. The low range and subprime borrowers 5, 6, and 7 represent the least stable categories.

The initial impact on the FICO score from the purchase appears different depending on the origination point. Within the first year the scores trend down for grades 1 through 3, but advance for those in grades 4 through 8. For grade 1 the wealth capacity allows for self correction via insurance against trigger events and the ability to refinance. In the first year only 24 percent of grade 1 borrowers remained at grade 1 and by year 3 the number approached 32 percent. Only 31 percent of grade 6 borrowers retained their initial rating just one year post origination, and the proportion fell to 19.6 percent in year 3. The entire transition matrix seems to indicate a somewhat symmetrical relation between the drop-off in stability as one moves both down and up the rating scale and converges on grades 2 through 4. As noted above, the grade 2 loans had the highest stability.

In addition to the level of migration or drift the degree of change is also of interest and provides yet another dimension for comparing stability. Of course this is where the nonlinear nature of the tables limits the direction and degree at each grade. For example, if relying on grades 4 and 5 as the separation between prime and subprime borrowers and given thirty-six months post origination roughly 2 percent of the grade 1 borrowers have migrated into a subprime status, and over 12 percent of grade 3 borrowers have fallen to high risk grades. At the same time roughly 20 percent of grade 6 and 25 percent of grade 7 borrowers have moved into prime (grade 4 and above) territory. The higher stability of the high grade borrowers is very likely a function of their increased flexibility and access to alternative financial resources that allow them to stave off the fiscal challenges from trigger events including refinancing the loan.

The ultimate interest is in the transition to default. It comes as no surprise that there is a strong indirect relationship between the FICO grade and the rate of default at all four time horizons, except for grade 8 at 36 months. The relatively small sample size for the lowest grade explains part of the difference. As the analysis will illustrate this particular anomaly is also due to the fact that many of those grade 8 borrowers in a tenuous financial state have already defaulted. Those that migrate up are quick to refinance out of the higher interest cost loans associated with subprime borrowers.

[Table 2 approximately here]

2.3 Extent of Migration and Performance Events

The study covers new mortgages from January 1, 2001 through 2008 and rating changes on those issues through November 2009. Figure (1) presents the mean and median FICO scores across the observation period by year of origination.[viii] Through the lens of household credit formation the observation period contains three distinct regimes. 2001 marks the *dotcom* recession with retraction in economic activity access to financial capital for mortgages. The second period beginning around 2003 represents the period when lenders expanded high risk mortgage offerings. The observed central measures of the originating FICO scores fall significantly during this period with an extensive drop in 2006 and 2007. In the third regime average FICO scores advance in 2008 with the restriction in credit as part of the implosion of the subprime market. It could be argued that the most recent regime reflects future FICO score requirements and the associated drift more accurately than do the results for the entire sample period (Altman, 1968). Alternatively, given the dramatic expansion in household debt over the last five years, one might expect an across the board decrease in the required FICO scores as financial institutions relax requirements to increase business. More likely new issues will be marketed to those with FICO scores somewhere near the apparent equilibrium exhibited in the 2002 to 2005 period. As the interest in this analysis is the propensity for an event in the future contingent on the present score, it is necessary to consider future changes first conditional on the base value at origination.

[Illustration 1 approximately here]

The mortgage market, like other financial systems, goes through distinct cycles of activity and performance, one of the most important of these is the housing cycle. It is reasonable to assume that aggregate economic activity will also be related to the incidence of FICO migration as households vary the degree of leverage they assume and, through changes in employment levels, may experience trigger events that influence their ability to pay. Upgrades can be expected to dominate when household payment histories suggest they are performing better as well as when there is evidence that performance will continue to improve.[ix] The opposite is likely with respect to downgrades. In some periods, however, counteracting forces can result in uncertainty about the direction of score changes. Economic activity may be strong while, at the same time, leverage is increasing. This is the case for many households over the recent housing market expansion (included in the period of observation) as incomes generally remained constant and debt burdens expanded. Coverage ratios are volatile and uncertain motivating the need to consider FICO migration as dynamic and a function of factors both endogenous and exogenous to the household.

To extend the analysis the following presents an examination of the overall variation in FICO migration with particular attention to those mortgages that terminate early in default or prepayment. The analysis moves to the serial correlation of future events with an analysis of the variations in volatility across the sample. For example, after a mortgager has experienced one downgrade/upgrade in the FICO grade, what is the probability that event will be followed by a default or prepayment? If this relationship is significant and tractable servicing agents and investors can take steps to initiate workout and reduce default risk or enhance the mortgage portfolio's expected performance.

In Table 3 the percent of all loans issued by year and positioned in one of eight FICO grades at origination that end in foreclosure is presented. It is important to note that the loan tenure for the observed loans varies across time. For example, loans originated in 2008 cannot be more than 23 months post origination since the last observation. Even with this limitation the loans issued later have higher overall probabilities of default than those issued in the early years of the period. As example, of the loans in the lowest FICO grade (grade 8) issued in 2008 nearly 17 percent are already in default by November of 2009. As Archer and Smith (2010) indicate this is likely the put option effect given LTVs for mortgages obtained in later years are more likely to be higher than the market value of the house when compared to first mortgage acquisitions in the earlier years of the observation period. The foreclosure rates for higher FICO grades (1-4) for loans originated in 2005 through 2007 suggest the potential for default is widespread across credit quality ranks. In the 2001 through 2003 period the distribution is clearly negatively skewed with the concentrations in the lower FICO grades. Although still skewed in the later periods, the distribution is much flatter during the "*halcyon years*" of high risk lending.

[Table 3 approximately here]

Table 4 presents the degree of migration across grades for the subsample of loans that ended in foreclosure during the observation period. For example 3,744 borrowers that were in grade 2 when their mortgage was originated enter into default during the period of observation. The third column reports those loans that remain in the origination grade at the point of default. Again for grade 2, 329 or less than 10 percent of the loans were still in grade 2 when default occurred. The last column indicates the mean degree of migration and direction for the defaulted loans from the point of origination to default. For example, the average total migration for the foreclosure subset, of the grade 2 group is 3.46 grades lower prior to entering default (between grade 5 & 6). The data indicates that as the initial grade deteriorates the average migration decreases except for the lowest grade 8 subgroup where the average actually increases slightly. This supports the view that the ability and willingness to pay of debtors increases as their respective FICO score increases (such willingness is exhibited in their history). Further, the costs of default are potentially higher for borrowers with higher FICO scores via the stigma effect (Quercia and Stegman, 2002). Capozza and Thomson (2005) suggest that high risk loans are more costly to administer and as such it is appropriate that they are priced higher. The authors posit that lender losses occur at the time of default and in a second stage during the remediation period. Although high risk borrowers default earlier than their prime counterparts, resulting in reduced loses, these borrowers impose greater realized losses on mortgage lenders (Capozza and Thomson, 2006).

[Table 4 approximately here]

The next two Tables 5 and 6 use the same format for prepayments as Tables 3 & 4 for foreclosures. There is a direct relationship between age of issue and probability of prepayment (Table 5). The earlier loans have longer seasoning periods (due to observation), greater credit availability and rapidly increasing property values (translating into equity without additional leverage) in subsequent years (2004 through 2007), and thus higher prepayment ops. The middle and lower grade loans have the highest prepayment in early years especially 2003 through 2005. There is a pronounced drop in 2005 – 2006 likely due, among other factors, to increases in prepayment penalties with high risk loans (see Pennington Cross, 2006), and corresponding to the increase in LTV ratios as discussed above.

[Table 5 approximately here]

In Table 6 a very different trend emerges for the prepayment subset compared to that presented in the default data. The mean migration between origination and prepayment is limited and what little migration is exhibited is bi-directional. Higher FICO grade borrowers generally experience reductions in their grade, but again it is limited and largely a function of mathematics that limits the extent of upgrading possible. The more important observation may be that the lower FICO grades (4 through 8) have mean increases. This is likely tied to ability to refinance out of high interest costs associated with the low FICO scores at origination.

[Table 6 approximately here]

2.3 Identifying Risk in the Type of Loan

Although the intended use of purchase mortgage funds is self explanatory, the borrower's decision to refinance the house is subject to a broader set of use options. One directive has the borrower refinancing as an expression of the decision to smooth consumption over the life-cycle rather than save the equity in the housing asset.[x] Alternatively, refinancing could be a means of reducing borrowing costs in an attempt to time the present value of the transaction costs with their anticipated tenure in the residence. Households that experience a negative income shock and possess limited liquid assets to buffer the shock are more likely to refinance and access home equity. Furthermore, the propensity to refinance and remove equity for households that experience a negative income shock declines as access to liquid assets increases (Hurst and Stafford, 2004). This line of reasoning suggests that the pool of refinance mortgages should exhibit signs of both smoothed consumption on the basis of taste and equity stripping out of necessity.[xi] The two purposes for the loans represent to potentially different regimes and Table 7 presents the migration data divided into purchase and refinance. Three states are considered for both subsets, unchanged (rating unchanged from origination), prepayment and default. It should be noted the three states are not necessarily independent conditions. For example, it is possible that a borrower defaulted on the mortgage during the observation period and their FICO score did not change. Score stability is the first comparison considered.

The differences between purchase and refinance in percent of obligors whose FICO scores remain unchanged over the time horizon are minor across all grades. In nearly every case the two measures are within a few percentage points of one another. For the prepayment event there are two interesting observations. For purchase mortgages in this sample the decision to prepay the mortgage occurs early in the loan tenure. At the twelve month horizon roughly twenty percent of the loans have entered a prepayment status for all grades except 1 and 8. From that point forward the prepayment status remains consistent in a range of 18 to 25 percent of the remaining loans. For the refinance subset the prepayment status is not nearly as consistent. Prepayments appear to be concentrated in the 1-year and 2-year horizons for grades 1 through 5. For grades 6 and 7 prepayments fall as the observation period advances. For grade 8 borrowers the distribution of prepayments appears to be delayed as the percent does not reach twenty until the horizon is 36 months post origination. The differences across the grade spectrum are likely a function of both the ability to repay, and the purpose for the mortgage. High grade borrowers are more likely choosing present consumption of the equity over deferral. Their liquidity and wealth, reflected in their high FICO scores provide the ability to repay for short term use of the funds. Lower grade borrowers (e.g. grade 8) are more likely refinancing to respond to trigger events. While the decision is the same, current equity consumption, the ability to repay the funds is lower for the low grade group due to the lack of alternative resources. For this reason repayment is deferred resulting in higher interest costs over the total term of the loan.

There is a profound difference in the trends between purchase and refinance mortgages and the potential for the borrower to exercise the default option. Across the possible grade and horizon plane there are generally more purchase loans in default than refinance loans in nearly every instance. The gap between the two types of loans closes as time since origination passes, but only rarely. Among the possible interpretations for this result two are considered more likely. First, there is the possibility that purchase borrowers are more risky borrowers on average when compared to refinance borrowers. Second, the purchase borrowers may have entered the transaction with less equity than their refinance counterparts. The higher loan to value ratios for the purchasers create an additional inducement in falling property markets to default, while also creating enhanced moral hazard compared to refinance borrowers. This performance difference will be tested in the following nonparametric analysis.

[Table 7 approximately here]

The ultimate interest is in explaining the tendency for the FICO score of the obligor to migrate or drift post origination. Illustration 2 provides a simplified example of the process. Consider an issue at time *T*. At a point in the future *T+1* the FICO score is observed and the degree and direction of drift recorded. As illustrated, the obligor can remain unchanged over the time horizon (the diagonal) or drift to a new grade. Alternatively, the borrower can default or prepay, which is presented outside of the grade scale. Several approaches to estimating migration probability matrices are reviewed in Lando and Skodeberg (2002) and compared in Jafry and Schuermann (2004). In the following analysis I rely on the continuous nature of FICO credit scores in models designed to gain further information from the migration patterns of mortgage borrowers. The results from this model are then used in a model of default and prepayment.

[Illustration 2 approximately here]

3. Migration as a precursor to a change in loan status

The literature on mortgage default relies on two central theories. Option-based theories emphasize the role of equity in the home in determining loan performance. Theories of borrower capacity focus on the financial footing of borrowers and their corresponding vulnerability to events, (again triggering events), that can negatively impact a borrower's ability to pay. In this view, both negative equity and the event would be associated with most defaults. Under stable housing market conditions a triggering event alone is not considered sufficient to motivate default. Instead, the borrower would sell the property and repay the loan retaining the equity net of transaction costs (Avery et al. 2000). This raises a number of issues with regard to the present analysis.

First, it is necessary to control for the put-option by observing estimated equity for each mortgage at each observation period. Second, a shock to the borrower's ability to pay would be met with the borrower selling if possible. This assumes the market is healthy and there are active buyers and sellers. At the end of the observation period this becomes increasingly difficult to accomplish as the residential market collapses in Florida. Third, a priori one would expect that a negative trigger event to the individual borrower would increase the probability of foreclosure. This is not consistent with prior observations that suggest the borrower will sell. Furthermore, it is anticipated that borrowers with increased capacity, as measured by an increase in the FICO score, are more likely to prepay the loan and refinance into lower interest rates or into a loan that includes equity stripping options. Thus, at certain points during the observation period one might expect to see the probability of prepayment increase conditional on both increases and decreases in the FICO score.

3.1 Modeling Migration and Change in Loan Status

The following analysis begins with a model of FICO migration with the key variables of interest being the score at origination and the elements of the loan and local economy most likely to reflect potential for a change in the FICO score. The objective with this model is to extend the information from the previous tables to include both static and dynamic variables from the mortgage data that provide signals to the borrower's financial condition at origination, and ongoing over the term of the loan. Specifically, I estimate the following first-stage Tobit regression for censored panel data of the change in the FICO score:

$$\Delta FICO_{i,t-(t-1)} = \alpha + \beta_1 FICO_{i,t-1} + \eta J_{i,t-1} + \lambda X_{i,t-1} + \kappa Z_{i,t-1} + \psi Q_{i,t-1} + e_{i,t} \qquad [2],$$

where $\Delta FICO_{i,\, t-(t-1)}$ is the change in the FICO score for observation *i* between the origination period *($FICO_{i,\, t-1}$)* and the forward month observed *(t)*.[xii] The origination score is included as changes are not symmetric due in part again, to the censored distribution of potential values, and to the varying capacity to cure financial events for borrowers across the grade spectrum. $J_{i,t-1}$ is a vector of dummy variables for the FICO grades (1-8). $X_{j,t-1}$ represents a vector of observed static loan and location characteristics that proxy for the potential motivation by the servicer to obtain subsequent credit scores.[xiii] Z_{it} represents dynamic location and loan characteristics that serve to control temporal effects, such as the price index. The price index, for example, controls for the impact that a changing environment has on the borrower's decision set (continue, default, prepay). $Q_{i,t-1}$ represents a series of year dummy variables to capture any time-varying effects over the study period. This censored change model is run on the global data set and on the refinance and purchase regimes.

Although predicting migration patterns in FICO scores is interesting on its own the change in the credit score is hypothesized as providing signals of upcoming events. The interest is in extending the analysis to observe the link between FICO migration and loan performance through default or prepayment by the borrower. In this case I use a multinomial logit model of the following form:

$$P(D,P,C)_{i,t+n} = \alpha + \beta_1 \Delta FICO_{i,t} + \beta_3 J_{i,t-1} + \beta_4 X_{i,t-1} + \beta_5 Z_{it} + \beta_6 Q_t + e_{i,t} \qquad [3].$$

The response variable has three potential outcomes: default, prepayment and continuation recognizing the work of Ambrose and Buttimer (2000) that illustrate the borrower's decision is comprised of three options in a healthy credit market. This model is forward looking considering a change in the status of the mortgage (*D*=default, *P*=prepayment, *C*=continue) occurring at any point within 24 months of the observation point *t* of the $\Delta FICO$. For example, if the interval date $t = 12$, or twelve months post origination, status is observed from month 13 through month 36 post origination. This two year cutoff is arbitrary, and based on the notion that the effect of a financial trigger (whether negative or positive) will deteriorate, be cured, or progress into other factors that will call into question the merit of relying on the FICO score as an indicator of the event.[xiv] The independent variables are similar to those used in the model predicting credit score change, and will be discussed more fully in the presentation of the data that follows.

One potential concern in designing this second test is that the pattern of migration is possibly endogenous to factors associated with decisions made by the obligor and ultimately performance of the loan. For example, the initial debt level provides signals of loan quality. Additionally, loan funds for marginal borrowers vary over the course of the observation such that access and default are potentially related (Dell'Ariccia, Igan, Laeven, 2009). For robustness and to test for the potential threat from endogeneity, I estimate model [2] a second time as a two-stage regression model that incorporates the residuals from the Tobit equation [1] into the multinomial logit model thereby focusing on those observations that have score changes that are anomalies to the sample. Again, the objective is to assess the potential for FICO score migration to signal impending default or prepayment. The residuals from the Tobit model are then used in the following model:

$$P(D,P,C)_{i,t+n} = \alpha + \beta_1 \overline{\Delta FICO_{i,t}} + \beta_2 FICO_{i,t-1} + \beta_3 J_{i,t-1} + \beta_4 X_{i,t-1} + \beta_5 Z_{it} + \beta_6 Q_t + e_{i,t} \qquad [4],$$

where $\overline{\Delta FICO_{i,t}}$ represents the change in the FICO score residuals from the estimation of equation [1] for the global data and both subsets. As modeled, $\overline{\Delta FICO_{i,t}}$ is the deviation in the borrower's score from the expected change in their score, given the conditions of the loan and local housing/employment markets observed over the interval. Thus, $\overline{\Delta FICO_{i,t}}$ corresponds to the unexpected drift in the FICO score between observation periods. Under the assumption that a falling FICO score signals a trigger event/shock (internal or external to the household) that effects the borrower's ability or desire to continue to pay on the mortgage, then a decrease in the score in excess of the predicted norm is expected to correspond to an increase in the probability of default or prepayment.

3.2 Data Description

This analysis requires data on house prices, local economic and fixed effects identifiers, the characteristics of the mortgage and borrower at origination, and the observable elements of the mortgage (asset and borrower capacity) as they evolve over time. County level quarterly price indices are created from a repeat sales model of transactions recorded with the Florida county property appraisers (assessors) over the observation period for the 20 most populous counties in the state (see Archer and Smith, forthcoming for details on the price index). The source for the local house price data is the State of Florida Department of Revenue data files on property tax assessments. These files contain data on assessed value and the last two sale prices for every property in the observed counties.

The LPS data, previously discussed, represents the servicing reports on individual loans. Mortgages are spatially identified by the five-digit zip code containing the asset (residence) and observed over the period 2001 through 2008. A number of filters are applied to the loan data to ensure a robust panel dataset over the observation period. In Table 8 summary statistics are provided for the variables used in both the Tobit and multinomial logit models. The mean, minimum and maximum are reported on the variable line. Immediately below the mean, in italics, is the standard deviation for each variable.

The static loan variables include: the FICO score at origination, the appraised value, the debt to income ratio (DTI), the loan to value ratio (LTV), and the interest rate charged. As previously noted the variable *ΔFICO* is the periodic change in the FICO score from the point of origination *t-1* to the observed point in the future *t+n*. The range of possible values for *ΔFICO* is -550 to + 550, but as the minimum and maximum indicate the limit is not met at either end (-404 and +449). The variable *seconds* is coded 1 if the LTV at origination is exactly 80 percent. Prior research with the LPS data indicates the 80 percent mark as a reasonably accurate proxy for borrowers with second loans (Ashcraft and Schuermann, 2006; Gerardi, Shapiro and Willen, 2007).

Variables controlling for temporal fixed effects include the current interest rate charged for the loan (*current rate*), the current status of the loan (*current)* and delinquency (*delinquency*), which indicates if the loan has been delinquent at any point in the twelve months prior to observation. For the purposes of this analysis a loan is considered to have been delinquent if at any time during the previous 12 months the loan was in arrears in excess of two months. On 93 percent of the observations the loans are in a current status, but 12 percent of observations were in a state of delinquency within 12 months preceding the observation date. Three price index variables are created from the assessor data. The variables *origin lag* and *as of lag* report the average change in the county house price index for the proceeding twelve months (at origination and at periodic observation). The twenty county study area experienced dramatic swings in appreciation/depreciation over the observation period with a range of -33% to +54% on an annual basis. The variable *as of index* is the total change in the median price of housing for each county. Additionally, a variable controlling for economic shocks at the county level is included and represents the average unemployment for the six months prior to the observation date.

Consistent with previous research, it is assumed that default is a rare event and in part driven by the put option effect (see, for example, Foote, Gerardi and Willen, 2008). Thus, it is necessary to control for the put option in order to allow the trigger events embedded in the FICO score change to be observed, albeit in a latent manner, through the default and prepayment decision of the borrower. As a proxy measure for the put option value I use a contemporary loan-to-value ratio at the time the loan is observed, expressed as:

$$asofLTV_t = \frac{W_t}{V_0(1+\Delta PI_{0t})} \qquad [5],$$

where W_t is the outstanding balance on the loan at time *t*, V_0 is the initial appraised value of the property at loan origination and ΔPI_{0t} is the percent change in the local house price index from the date of loan origination to the last date the loan is observed. Each *as of* LTV_t represents an estimate of the loan-to-value ratio at the time the loan is observed, incorporating both the change in the value of the property from appreciation and equity accumulation via mortgage payments.[xv] The mean of the variable *as of LTV* is significantly lower (64%) than the origination *LTV ratio* (77%) due in part to rapid appreciation during all but the last year of the observation period and the pay down in the principle.[xvi] Although the mean is lower the maximum is over 100 points higher at 250.

[Table 8 approximately here]

In Table 9 the data is divided into refinance and purchase loans for comparison. The variable *ΔFICO* indicates the average change for purchase loans between observations is -12.03 points and for refinance is -1.37, although the standard deviations are similar. Purchase loans have slightly higher origination FICO scores, on average, and 10 percent higher initial and "as of" LTVs. 80 percent of the refinance loans and 73 percent of the purchase loans are fixed rate. The proxy variable *seconds* indicates 14 percent of purchase loans and 11 percent of refinance loans have LTVs exactly equal to 80 percent. The slightly higher proportion of seconds for purchase loans is likely reflective of the use and application process between the two loans. This increase in unobserved leverage may be further expressed in the similarly higher delinquency level for purchase loans (again slightly higher). The remaining variables are similar in value, range and standard deviation across the subsets.

[Table 9 approximately here]

3.3 Results

Table 10 reports the estimation results for the panel Tobit regression of equation [1] on the full sample and the two regimes. Although the summary statistics presented in Table 8 do not suggest major differences between the sample subsets of purchase and refinance, a reasonable assertion could be made that the results above are not stable across both purchase and refinance loans as the motivations of the borrower's for acquiring the loans differs. The coefficients on the independent variables indicate the average change in the FICO score between observation points for a one unit change in the value of the independent variable. The static loan variables provide insight into the borrower's credit risk at the outset of the loan. Thus, a reasonable expectation is that higher risk loans at origination could have negative effects on the borrower's financial state as expressed in changes in the FICO score. The results of the model indicate borrowers with higher value houses, fixed rate loans, higher DTIs (excluding purchase) and second loans experience positive changes in their FICO score on average. For example, all else equal, fixed rate loans increase the change in FICO scores by approximately +5 points for all three models. The results for the proxy variable for second loans are potentially interesting suggesting that, on balance, borrowers in the dataset that qualify have 80 percent first loans experience relatively small but positive increases in FICO scores.

Borrowers with high initial LTVs and high interest rates experience significant decreases in their FICO scores over the observation period. For the temporal fixed effects both lag variables are negatively associated and the overall price level (*as of index*) is positively associated with changes in the FICO score. The results from the lag variables are consistent with the findings reported in Archer and Smith, (forthcoming) that illustrate greater risk taking by borrowers in areas with higher appreciation rates prior to loan origination. The current LTV is also negatively associated with the change in FICO, possibly indicating an increase in leveraging on the part of the borrower as the equity in the home falls.[xvii] This price level variable is consistent with the appraisal variable. Unemployment is negatively associated with changes in the FICO score. As expected, rising unemployment can impose downward pressure on the earning capacity of the borrower serving as a trigger that is exogenous to the household. The static location controls suggest borrowers in urban neighborhoods and neighborhoods with a high percent of white residents have increasing FICO scores, while the inverse is observed for Hispanic concentrated neighborhoods. The coefficient estimates for both the origination rank and year controls are consistent with previous migration tables. FICO scores deteriorate over the observation period and, the improvement is greatest for borrowers in the lower ranks where the ceiling created by censoring of the FICO scores is more distant.

[Table 10 approximately here]

Turning to the multinomial logit model [2] Table 11 reports the results for the estimation of equation [2]. All coefficients are presented as odds ratios; thus, interpretation is based on the change in the odds of the dependent variable event (e.g. default) for a one unit change in the independent variable. Estimated coefficients (*Cf*) less than 1 reduce the odds ratio for the dependent variable by *1-Cf*, and for those greater than 1 the increase in the odds ratio is *Cf-1*.

This set of models includes the variable *ΔFICO* to a test of the hypothesis that migration in the FICO score will signal changes in loan status within the next two years. It is thus assumed that changes in FICO scores will serve as a leading indicator of changes in loan status. An increase in the FICO score should correspond to a decrease in loan performance exemplified as an increase the odds of default or prepayment of the loan. Similarities in default and prepayment coefficients across all three models are evident in the variables *appraisal, LTV ratio* (current and origination), *fixed rate, current rate, Hispanic,* and *as of LTV*. Higher LTVs, interest rates, appraisal, and higher proportions of Hispanics in the neighborhood all increase the odds of both default and prepayment. The variable of interest, *ΔFICO*, along with fixed rate loans reduce the odds of both events over continuation of the loan.

Variables that influence default and prepayment in opposing directions include *DTI, seconds,* loan status (*current* and *delinquency*) and the location controls (the three index variables, *unemployment, white* and *urban*). The loan and borrower variables all have the expected signs for both default and prepayment. For example, DTI ratio, delinquency and seconds increase default and decrease prepayment risk. The inverse is the case if the loan is current as the odds of default decrease and prepayment increases. The results for the lag and index coefficients for default are again in keeping with the findings of Archer and Smith (forthcoming) in which forward pricing error increases default in areas with higher prices and higher price appreciation. For prepayment the results are inconsistent across the three models. The variables *unemployment* and *urban* increase default and decrease prepayment while the variable *white %* increases both default and prepayment in all cases except the default estimates for the purchase subset. The odds of purchase borrowers defaulting decrease as the percent of the white population in the zip code increases.

The year control variables indicate the odds of default increase through loans issued in 2006 then decrease, while prepayment decreases as the year of origination advances with a slight uptick in 2008 issues. The date prepayment relationship is likely a function of the data and the overall market. First, the censoring of the data dictates the time available for prepayment goes down over time. Second, options for the borrowers that desire to refinance are radically reduced after 2006 (Lehman Brothers). The increase in default is consistent with the findings from the subprime literature that illustrate higher risk lending in the later years of the observation period (Archer and Smith, forthcoming). As with the prepayment estimates, censoring post issue is likely the cause of default reductions. The coefficient estimates for the variable of interest $\Delta FICO$ are significant across the board and indicate that as the change in the credit score increases, positively, the odds of both default and prepayment decrease. This is a mean estimate for all initial ranks and through all years. One may argue that endogeneity is present in this set of models because both $\Delta FICO$ and the probability of default/prepayment post the change are functions of unobserved factors even though the default/prepayment is in the future of the credit score change.

[Table 11 approximately here]

3.4 Robustness Test

As a test of this threat a two stage approach is taken where the predicted residual from the Tobit equations [1] is incorporated into the multinomial logit models [3] and interacted with the dummy variables for FICO origination rank. The residual serves as a measure of the impact of deviations from expected changes in the FICO score while controlling for the characteristics of the loan, the economic conditions at the observation point and the timing of the observation. Given the operating hypothesis that changes in FICO scores can serve as leading indicators of changes in loan status, a positive increase in the FICO score above the general trend in FICO score changes should correspond to positive loan performance exemplified as continuation or prepayment of the loan. The residuals measure the impact of deviations from expected changes in the FICO score given the characteristics of the loan, the economic conditions at the observation point and the timing of the observation.

The estimates from the three versions of this model are presented in Table 12. Substituting the FICO change variable with the interaction variables for origination rank and the residuals into equation [3], the results suggest that many of the coefficients are consistent with those reported in Table 11. The origination rank/residual interaction variables are statistically significant in most instances except for those borrowers with the lowest credit scores. The results for the model with the global data indicate that positive FICO score changes in excess of the norm, all else held constant, reduce the odds of default and increase the odds of prepayment. When the data is divided there is some loss of information in the prepayment response, particularly for the purchase group. This is again likely due to the duality of positive and negative changes in credit status as it relates to the prepayment decision. It appears, however, that the reported results are robust despite the potential endogeneity problem.

As for a material difference relative to the level of change in the FICO score, there is little difference in the coefficient estimates for the two models. The one area that does provide potential for extending the discussion is in the year variables for the *purchase* subset that end in default. There is a clear relationship between purchase loans in the data and time trends that lead to default and those trends are consistent with prior literature. The odds of default increase as the year increases, again until 2006 and in 2007 the odds drop off. A review of the results for refinance loans does not support this relationship. There has been far less performance research, of late, on refinance loans, and it appears that the distribution of defaults for those loans is fundamentally different when compared to purchase loans after controlling for the FICO change, etc.

[Table 12 approximately here]

4. Conclusions and Opportunities

Credit risk is a dominant source of risk for banks and the subject of strict regulatory oversight and policy debate (BCBS (2001a,b)).[xviii] Credit risk is commonly defined as the loss resulting from failure of obligors to honor their payments. Arguably a cornerstone of credit risk modeling is the probability of default. Two other components are loss-given-default or loss severity and exposure at default (Hanson and Schuermann, 2006). In fact these are three of the four key parameters that make up the internal ratings based (IRB) approach that is central to the New Basel Accord (BCBS (2003) Federal Reserve (2003)).[xix]

Relying on the vast literature in commercial credit risk analysis this paper has presented an investigation of FICO score changes (drift) over time for a sample of mortgage borrowers. The findings indicate there is potential information gain on mortgage performance by observing FICO score migrations over the life of the mortgage. As expected, those borrowers with higher initial FICO scores are more likely to refinance rather than default given their anticipated superior access to credit. Further, the high initial FICO borrowers that do end in default experience greater downward migrations in the FICO score prior to default. As exhibited in the migration matrices, those borrowers at the low range of the FICO distribution have the greatest volatility. The matrices and the models also reveal temporal trends that deserve further exploration.

Utilizing the FICO score as a periodic review of the capacity of all mortgage borrowers is likely a cost prohibitive proposal. However, through additional research it may be possible to identify efficient prescriptions for servicing agents acquiring subsequent scores. Work similar to that presented in this study with attention to the duration from a FICO score change to an event (e.g. default or prepayment) will aid in timing the signal to the outcome. Additional work in the volatility of FICO scores and forecasting has the potential to create additional signaling assistance. Given borrowers are not equal, and similarly the potential for their default is not equal, additional analysis with borrowers separated into capacity ranks will allow for examining more detail in the variations and direction of score migration while gauging the differential influence migration has on future performance given borrower capacity.

5. Bibliography

Alexander, William P., Scott D. Grimshaw, Grant R. McQueen and Barrett A. Slade. 2002. Some Loans Are More Equal than Others: Third-Party Originations and Defaults in the Subprime Mortgage Industry, *Real Estate Economics,* 30:4, 667-697.

Altman, Edward I. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance,* 23:4, 589-609.

Ambrose, Brent W., and Richard J. Buttimer. 2000. Embedded Options in the Mortgage Contract, *Journal of Real Estate Finance and Economics*, 21:2, 95-111.

Archer, Wayne R. and Brent C Smith. forthcoming. Residential Mortgage Default: The Roles of House Price Volatility, Euphoria and the Borrower's Put Option, *Journal of Real Estate Finance and Economics*.

Ashcraft, Adam B. and Til Schuermann. 2006. Understanding the Securitization of Subprime Mortgage Credit, Foundations and Trends in Finance, 2:3 191-309.

Avery, Robert B., Raphael W. Bostic, and Paul S. Calem. 2000. Credit Scoring: Statistical Issues from Credit Bureau Files, *Real Estate Economics*, 28:3, 523-47.

Avery, Robert B., Raphael W. Bostic, Paul S. Calem, and Glenn B. Canner. 1996. Credit Risk, Credit Scoring, and the Performance of Home Mortgages, *Federal Reserve Bulletin,* pp. 28.

Bangia, A., F.X. Diebold, A. Kronimus and C. Schagen and T. Schuermann. 2002. Ratings Migration and the Business Cycle, With Applications to Credit Portfolio Stress Testing, *Journal of Banking & Finance*, 26:2/3, 445-474.

Basel Committee on Banking Supervision, 2001a, *The New Basel Capital Accord*, <http://www.bis.org/publ/bcbsca.htm>, January.

Basel Committee on Banking Supervision, 2001b, *The Internal Ratings Based Approach*, <http://www.bis.org/publ/bcbsca.htm>, May.

Basel Committee on Banking Supervision, 2003, *Third Consultative Paper,* http://www.bis.org/bcbs/bcbscp3.htm, April.

Cantor, R. and E. Falkenstein. 2001. Testing for Rating Consistency in Annual Default Rates, *Journal of Fixed Income*, September, 36-51.

Capozza, Dennis R. and Thomas A. Thomson, 2005. Optimal Stopping and Losses on Subprime Mortgages, *Journal of Real Estate Finance and Economics*, 30:2, 115-131.

Capozza, Dennis R. and Thomas A. Thomson. 2006. Subprime Transitions: Lingering or Malingering in Default? *Journal of Real Estate Finance and Economics*, 33:3, 241-258.

Crouhy, Michael, Dan Galai, and Robert Mark. 2001. Prototype Risk Rating System, *Journal of Banking and Finance*, 25:1, 47-95.

Dell'Ariccia, Giovanni, Igan, Deniz and Laeven, Luc A. 2009. Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market, European Banking Center Discussion Paper No. 2009-46S, January.

Federal Reserve Board, 2003. Supervisory Guidance on Internal Ratings-Based Systems for Corporate Credit, Attachment 2 in http://www.federalreserve.gov/boarddocs/meetings/2003/20030711/attachment.pdf.

Gerardi, Kristopher, Adam Hale Shapiro and Paul S. Willen. 2007. Subprime Outcomes: Risky Mortgages, Homeownership Experiences and Foreclosure, Federal Reserve Bank working paper # 07-15.

Hamilton, D. and R. Cantor, 2004. Rating Transitions and Defaults Conditional on Watchlist, Outlook and Rating History, *Special Comment*, Moody's Investor Service, New York.

Harrison, David M., Thomas G. Noordeweir and Abdullah Yavas. 2004. Do Riskier Borrowers Borrow More? *Real Estate Economics*, 32:3, 385-411.

Hanson, Samual G. and Til Schuermann. 2006. Confidence intervals for probabilities of Default, *Journal of Banking & Finance*, 30:8, 2281–2301.

Hillegeist, Stephen A., Elizabeth K. Keating, Donald P. Cram and Kyle G. Lundsted, 2004. Assessing the Probability of Bankruptcy, *Review of Accounting Studies*, 9:1, 5-34.

Hurst, Erik and Frank Stafford. 2004. Home is Where the Equity is: Mortgage Refinancing and Housing Consumption, *Journal of Money Credit and Banking*, 36:6, 985-1014.

Jafry, Yafry and Til Schuermann. 2004. Measurement, Estimation and Comparison of Credit Migration Matrices, *Journal of Banking & Finance*, 28:11, 2603-39.

Lando, D. and T. Skodeberg, 2002. Analyzing Ratings Transitions and Rating Drift with Continuous Observations, *Journal of Banking & Finance*, 26:2/3, 423-444.

Longhofer, Stanley D. and Stephen R. Peters. 2005. Self-Selection and Discrimination in Credit Markets, *Real Estate Economics*, 33:2, 237-268.

Lopez, J.A. and M. Saidenberg. 2000. Evaluating Credit Risk Models, *Journal of Banking & Finance*, 24:1/2, 151-165.

Marrison, C. 2002. *The Fundamentals of Risk Management*, New York: McGraw Hill.

Nickell, P, W. Perraudin and S. Varotto. 2001. Stability of Rating Transitions, *Journal of Banking & Finance*, 24, 203-227.

Pennington-Cross, Anthony. 2006. The Value of Foreclosed Property, *Journal of Real Estate Research*, 28:2, 193-214.

Quercia, Robert and Michael Stegman. 2002. Residential Mortgage Default: A Review of the Literature, *Journal of Housing Research*, 3:2, 341-381.

Schuermann, Til. 2004. What Do We Know About Loss Given Default? ch. 9 in David Shimko (ed.) *Credit Risk: Models and Management*, *2nd Edition*, London, UK: Risk Books.

Shumway, Tyler. 2001. Forecasting Bankruptcy more Accurately: A Simple Hazard Model, *Journal of Business*, 74: 101-124.

Vandell, Kerry D. 1995. How Ruthless is Mortgage Default? A Review and Synthesis of the Evidence, *Journal of Housing Research*, 6:2, 245-264.

Von Furstenberg, George M. and R. Jeffery Green. 1974. Home Mortgage Delinquencies: A Cohort Analysis, *Journal of Finance*, 29:5, 1545-1548.

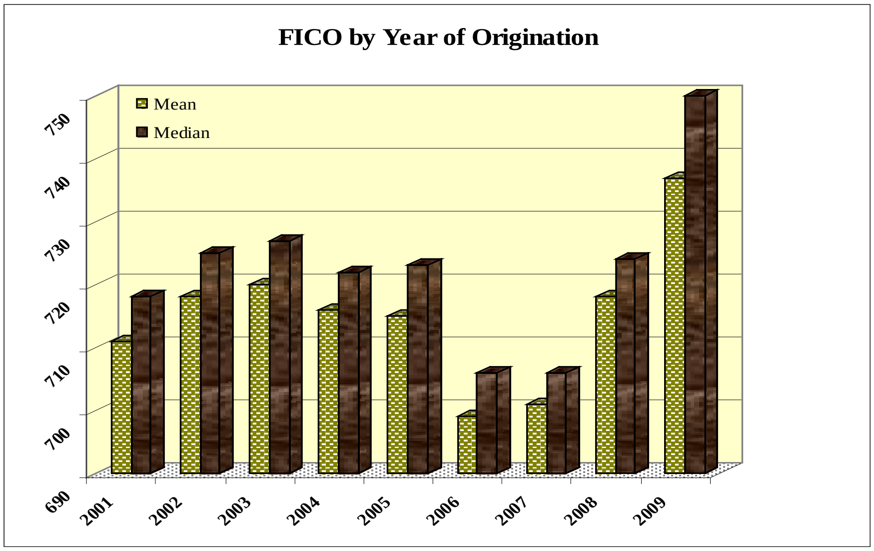
Williams, Alex O., William Beranek and James Kenkel 1974. Default Risk in Urban Mortgages: A Pittsburgh Prototype Analysis, *Real Estate Economics*, 2:2, 101-112.

Table 1: FICO Distribution of Sample at Origination

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Year	**800+**	**750 - 799**	**700 - 749**	**650 - 699**	**600 - 649**	**550 - 599**	**500 - 549**	**<500**
2001	2.9%	26.7%	28.2%	24.4%	13.1%	3.7%	0.9%	0.1%
2002	3.6%	29.0%	29.7%	22.7%	11.2%	3.1%	0.8%	0.1%
2003	3.7%	29.3%	30.1%	23.0%	10.7%	2.5%	0.6%	0.1%
2004	3.5%	28.6%	29.2%	22.9%	11.4%	3.4%	1.1%	0.1%
2005	4.4%	28.7%	28.6%	21.5%	11.7%	3.9%	1.2%	0.0%
2006	3.8%	**23.3%**	**25.4%**	23.0%	**15.5%**	**6.4%**	**2.5%**	0.1%
2007	4.5%	**23.5%**	**25.3%**	23.1%	**14.6%**	**6.5%**	**2.3%**	0.2%
2008	**7.1%**	**29.6%**	**27.2%**	**20.5%**	11.2%	3.8%	0.5%	0.1%
Population Distribution	13.0%	27.0%	18.0%	15.0%	12.0%	8.0%	5.0%	2.0%

The source for the annual grade data is the same provided by LPS Analytics Inc. For reference purposes the population distribution is take from the FICO.com, and represent all U.S. individuals with a FICO score. A direct comparison of the LPS sample and the FICO population would require recognizing the presence of selection bias. This is especially true in the case of the two tales (grade 1 and 8). Many in grade 1 do not acquire residential mortgage funds in the traditional market and many in grade 8 would not qualify for a mortgage with reasonable terms. Selection of the grades is based on FICO's distribution of the population data and is formatted as a best approximation to the grades employed on corporate debt.

Figure 1: FICO Score at Origination



The trends in the mean and median illustrate variations in the expansion and ultimate contraction in the mortgage market over the observation period. In 2006 and 2007, the height of the subprime market mean FICO scores for originated loans falls below 700. Although the analysis only includes originations through 2008 2009 is included to illustrate the dramatic change due to events in the credit markets. In 2009 during the period of contraction in credit the FICO score of originated loans is approximately 735 and the median is 750.

Table 2: Unconditional Migration Patterns

Panel A Twelve Months Post Origination

n	Grades	1	2	3	4	5	6	7	8	D
9,756	**1**	**24.16**	64.63	7.75	2.69	0.55	0.14	0.05	0.03	0.10
63,869	**2**	4.83	**62.79**	23.77	6.19	1.57	0.53	0.23	0.08	0.40
66,708	**3**	0.69	21.32	**47.39**	21.48	5.51	2.04	1.05	0.52	1.10
53,647	**4**	0.18	4.77	21.89	**46.54**	16.29	5.70	2.99	1.65	1.90
29,352	**5**	0.03	0.77	4.78	26.02	**38.11**	15.02	8.83	6.45	3.40
10,332	**6**	0.00	0.19	0.83	7.68	27.35	**31.37**	18.56	14.01	4.50
3,347	**7**	0.00	0.03	0.33	2.66	14.40	25.28	**32.57**	24.74	6.30
192	**8**	0.00	0.52	1.04	2.60	5.21	17.71	32.29	**40.62**	7.80

Panel B Twenty-four Months Post Origination

n	Grades	1	2	3	4	5	6	7	8	D
8,583	**1**	**30.46**	56.44	8.37	3.23	0.94	0.40	0.15	0.02	0.44
61,313	**2**	8.49	**60.97**	20.38	6.43	2.05	1.04	0.51	0.12	0.91
63,670	**3**	1.58	28.00	**41.36**	17.34	5.48	3.09	2.22	0.93	2.34
50,415	**4**	0.40	8.20	26.34	**36.69**	13.05	6.65	5.55	3.12	3.91
26,316	**5**	0.05	1.42	8.47	27.81	**24.77**	13.73	12.67	11.08	7.97
8,565	**6**	0.01	0.19	2.02	11.85	22.70	**21.84**	20.48	20.91	10.95
2,738	**7**	0.00	0.18	0.73	4.97	15.08	20.49	**29.95**	28.60	13.40
145	**8**	0.00	1.38	0.69	2.07	8.97	20.00	32.41	**34.48**	13.10

Panel C Thirty-six Months Post Origination

n	Grades	1	2	3	4	5	6	7	8	D
7,340	**1**	**31.63**	54.29	8.83	3.23	1.28	0.50	0.18	0.05	0.64
53,083	**2**	10.24	**59.73**	18.63	6.66	2.45	1.36	0.73	0.19	1.26
52,632	**3**	2.52	31.51	**37.80**	15.62	5.36	3.48	2.63	1.07	2.64
39,313	**4**	0.69	11.62	27.92	**31.95**	11.75	6.82	5.84	3.42	4.26
18,867	**5**	0.10	2.60	12.03	27.67	**21.60**	12.79	12.75	10.46	7.97
5,351	**6**	0.02	0.45	3.49	15.70	20.46	**19.60**	20.67	19.60	11.34
100	**7**	0.40	1.53	7.54	16.08	22.15	25.95	**26.35**	1.49	15.88
79	**8**	1.27	1.27	1.27	3.80	10.13	21.52	22.78	**37.97**	5.06

Table 3 Foreclosures by Grade by Year

% of observed by origination date

Year	1	2	3	4	5	6	7	8	n
2001	0.03%	0.12%	0.36%	0.90%	1.44%	2.04%	3.19%	1.96%	523,788
2002	0.08%	0.09%	0.23%	0.48%	1.04%	1.49%	3.31%	6.89%	1,316,843
2003	0.07%	0.12%	0.21%	0.47%	1.00%	2.15%	1.64%	1.06%	2,747,143
2004	0.09%	0.33%	0.74%	1.21%	2.15%	3.24%	4.61%	6.96%	1,803,906
2005	0.87%	1.47%	2.72%	3.94%	7.02%	7.20%	7.88%	8.56%	1,775,439
2006	0.88%	2.13%	4.84%	7.48%	12.93%	15.04%	17.98%	9.48%	1,500,955
2007	0.67%	1.85%	4.36%	6.17%	8.53%	8.66%	9.26%	9.60%	1,155,744
2008	0.31%	0.78%	2.52%	4.05%	4.65%	3.97%	5.81%	16.71%	420,336

Illustrates the percent of loans by year the loan is originated that end in foreclosure during the observation period. The data is further divided by the FICO score grade at the time of origination. High defaults are pronounced in years when high risk loans are most prevalent, and in grades comprising the lowest FICO scores.

Table 4: Mean Migration for Default Subset

Grade at Origination	FICO Origination	FICO Current	Mean Grade Migration
1	290	32	-3.93
2	3,744	329	-3.46
3	7,569	758	-3.04
4	9,059	1,600	-2.46
5	7,935	4,289	-1.93
6	3,420	8,057	-1.19
7	1,338	10,033	-0.33
8	67	8,324	0.45

Illustrates the degree of migration for those observed loans that end in default. For example, of the loans that end in default only 32 are in grade 1 at the time the default occurs. The censoring of the data, and the level of overall risk in the borrower's capacity to repay at onset are drivers in the general downward trend in total migration from grade 1 (averaging a 4 grade loss in FICO score) to grade 8 (increase in nearly one half).

Table 5: Prepayments by Grade by Year

% prepayments over observation period 01 to 09

Year	1	2	3	4	5	6	7	8	n
2001	24.71%	30.20%	33.72%	32.41%	33.39%	35.06%	32.94%	15.29%	523,788
2002	22.05%	26.91%	29.45%	30.52%	30.93%	29.21%	28.45%	21.64%	1,316,843
2003	18.34%	20.31%	22.77%	24.19%	25.72%	27.53%	33.53%	32.54%	2,747,143
2004	15.73%	17.66%	19.90%	20.70%	25.01%	29.15%	37.54%	17.84%	1,803,906
2005	9.03%	8.47%	8.45%	10.24%	13.54%	18.90%	20.47%	17.12%	1,775,439
2006	6.53%	5.29%	3.72%	3.30%	3.70%	4.73%	5.55%	5.94%	1,500,955
2007	4.67%	2.89%	1.68%	1.38%	1.47%	1.97%	2.17%	2.70%	1,155,744
2008	4.15%	2.71%	1.67%	1.49%	1.67%	1.65%	0.37%	0.00%	420,336

Illustrates the percent of loans by year the loan is originated that end in prepayment during the observation period. The data is further divided by the FICO score grade at the time of origination. The prepayment observation is clearly linked to loan seasoning and in part of function of the truncation in the observation period.

Table 6: Mean Migration for Prepayment Subset

Grade	FICO Origination	FICO Current	Mean Grade Migration
1	3,407	2,770	-0.87
2	24,406	26,525	-0.3
3	25,194	23,367	-0.05
4	20,464	19,353	0.11
5	11,413	10,709	0.21
6	3,800	4,535	0.31
7	1,260	2,189	0.51
8	61	557	1.3

Illustrates the degree of migration for those observed loans that end in prepayment during the observation period. For example, of the loans that end in prepayment only 61 originate in grade 8, but 557 terminate in grade 8. Though not as pronounced the direction of the trend in grade migration is similar.

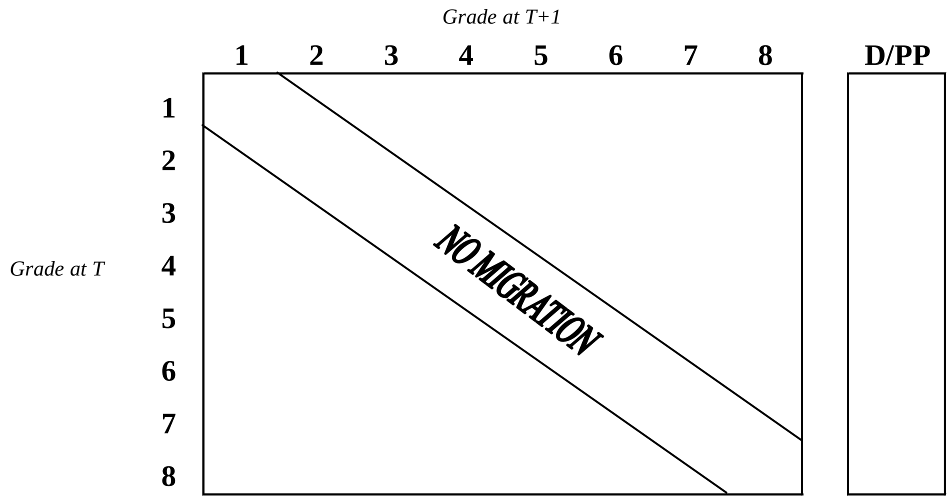
Table 7 Purchase v. Refinance

Comparison of Grade Stability

Grade	*Months Since Origination*	*Purchase % Unchanged*	*Purchase % Prepayment*	*Purchase % Default*	*Refinance % Unchanged*	*Refinance % Prepayment*	*Refinance % Default*
1	12	22.8	15.2	0.11	27.0	18.3	0.09
	24	30.8	14.1	0.44	29.9	20.2	0.45
	36	31.7	11.6	0.80	31.6	17.4	0.32
2	12	61.1	19.2	0.41	65.8	20.2	0.32
	24	60.8	18.2	0.91	61.2	21.6	0.90
	36	59.3	14.3	1.67	60.5	18.4	0.54
3	12	47.3	21.1	1.33	47.5	20.9	0.74
	24	41.6	19.4	2.52	41.1	21.7	2.10
	36	37.5	15.2	3.38	38.2	18.4	1.60
4	12	46.7	21.5	2.43	46.3	21.1	1.33
	24	36.8	19.9	4.36	36.5	20.8	3.39
	36	31.8	16.3	5.29	32.2	17.3	3.04
5	12	39.1	21.2	4.58	36.9	21.3	2.35
	24	24.9	19.9	9.76	24.6	18.9	5.90
	36	22.1	17.7	9.85	21.1	15.4	5.94
6	12	30.6	21.2	5.78	32.0	18.5	3.40
	24	20.6	19.2	11.72	23.0	13.7	10.26
	36	20.3	19.2	10.46	18.9	11.1	12.16
7	12	31.7	21.2	7.05	33.0	21.6	6.04
	24	29.5	18.9	12.23	30.2	12.9	14.04
	36	28.0	14.5	11.11	24.8	9.8	18.70
8	12	39.4	17.3	6.73	33.0	12.5	9.09
	24	41.4	18.4	13.79	24.0	15.5	12.07
	36	37.3	25.5	7.84	39.3	21.4	0.00

The selection of months post origination is somewhat arbitrary, but rooted in the literature on migration matrices for corporate debt. The mean reversion conclusion so often referenced to in corporate debt analysis is evident in the distribution of the mortgage data presented here (see Bangia et al. 2002 for example), but there is clearly more variation in the residential debt market than in the corporate debt markets. The periodic observations for both purchase and refinance do not sum to 100 percent as the reminder of the observations have not defaulted or prepaid, but have changed grades. For example, the six month snapshot for refinance loans originating in grade 1 indicates that 57.6 percent changed grades.

Illustration 2: The Migration Process to Default



The chart presents the flow of FICO scores across the matrix of possible grades with the addition of the default or prepayment termination of the mortgage.

Table 8 Summary Statistics Global Sample

Variable	Mean	Min	Max	Description
ΔFICO	-7.11	-404.00	449.00	FICO change from origination to current period
	58.87			
origin FICO	710.34	351.00	850.00	Reported FICO at origin
	61.74			
appraisal	250,529.60	16,500.00	18,500,000.00	Appraised value at origin
	234,135.00			
DTI ratio	26.92	1.00	99.00	Overall debt to income at origin
	12.55			
LTV ratio	77.20	50.00	148.08	Loan to value ratio at origin
	12.42			
fixed rate	0.76	0.00	1.00	Coded 1 if fixed rate loan else 0
	0.43			
current rate	6.09	1.00	13.75	Interest rate charged at time of observation
	0.89			
origin lag	0.14	-0.33	0.54	Change in county value index 12 mths prior to origin
	0.12			
as of lag	0.03	-0.33	0.54	Change in county value index 12 mths prior to current
	0.20			
as of index	263.53	129.77	444.97	Value of the county index with 1999=100
	54.66			
unemployment	5.02	2.70	10.20	6 months prior to observation
	1.52			
white%	0.81	0.01	0.99	By zip code
	0.17			
Hispanic%	0.18	0.01	0.93	By zip code
	0.21			
urban%	0.94	0.00	1.00	By zip code
	0.16			
seconds	0.13	0.00	1.00	First loans with LTV=80% precisely
	0.33			
as of LTV	63.71	0.00	249.77	Outstanding balance/current value
	26.11			
current	0.93	0.00	1.00	Coded 1 if loan status is currently, current
	0.26			
delinquency	0.12	0.00	1.00	Coded 1 if the loan has been delinquent in past year
	0.33			
n=			6,950,612	

The summary statistics for the global sample include a description of each of the variables utilized in the following models. The mean, minimum and maximum are reported on the variable line. Immediately below the mean, in italics, is the standard deviation for each variable.

Table 9 Summary Statistics by Regime

	Refinance			Purchase		
Variable	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
ΔFICO	-1.37	-383.00	449.00	-12.03	-404.00	309.00
	57.30			*59.75*		
origin FICO	706.33	351.00	842.00	713.77	422.00	850.00
	62.85			*60.56*		
appraisal	250,875.90	27,000.00	18,500,000.00	250,233.10	16,500.00	11,700,000.00
	221,822.70			*244,181.40*		
DTI ratio	26.95	1.00	99.00	26.90	1.00	99.00
	12.97			*12.18*		
LTV ratio	71.62	50.00	148.08	81.98	50.00	139.09
	10.58			*11.88*		
fixed rate	0.80	0.00	1.00	0.73	0.00	1.00
	0.40			*0.44*		
current rate	6.06	1.00	13.63	6.11	1.00	13.75
	0.90			*0.88*		
origin lag	0.13	-0.33	0.54	0.15	-0.33	0.54
	0.11			*0.12*		
as of lag	0.04	-0.33	0.54	0.03	-0.33	0.54
	0.20			*0.20*		
as of index	261.94	129.77	444.97	264.89	131.90	444.97
	55.25			*54.11*		
unemployment	5.01	2.70	10.20	5.04	2.70	10.20
	1.51			*1.54*		
white%	0.81	0.01	0.99	0.81	0.01	0.99
	0.17			*0.17*		
Hispanic%	0.18	0.01	0.93	0.19	0.01	0.93
	0.20			*0.21*		
urban%	0.94	0.00	1.00	0.94	0.00	1.00
	0.16			*0.16*		
seconds	0.11	0.00	1.00	0.14	0.00	1.00
	0.32			*0.34*		
as of LTV	58.21	0.00	249.77	68.42	0.00	220.27
	24.33			*26.66*		
current	0.93	0.00	1.00	0.92	0.00	1.00
	0.25			*0.27*		
delinquency	0.11	0.00	1.00	0.13	0.00	1.00
	0.32			*0.33*		
n=		3,193,789			3,756,823	

In this table the summary statistics are segregated between observed loans for purchase and refinance. The format is the same as that used in table 7.

Table 10 Tobit ΔFICO Global Sample

[redacted]

This table presents the results of estimating the Tobit model using panel estimation techniques. Yearly period fixed effects are included in the regression (year variables) with additional effects represented in the unemployment variable. The dependent variable is the change in the FICO score observed from month to month. Static borrower and location controls are represented by the loan and borrower variables, and the racial composition of the zip code in which the house is located. A set of dummy variables is also used to represent the rank at origination. Seconds is an attempt to control for borrowers that have second loans attached to the housing asset that increase the total LTV beyond that observed in this first loan dataset. Price index data at the county level is used to create price change lags prior to purchase and prior to each observation period. The index and the outstanding balance at the time of observation as used to create a variable representing the current ltv of the loan (as of ltv). * indicates coefficient estimates significant at a 99 percent confidence level.

Table 11 MNL With ΔFICO

MNLw/	Global						Purchase						Refinance					
ΔFICO	*Default*			*Prepayment*			*Default*			*Prepayment*			*Default*			*Prepayment*		
Variables	**Coef**	**Standard Error**		**Coef**	**Standard Error**		**Coef**	**Standard Error**		**Coef**	**Standard Error**		**Coef**	**Standard Error**		**Coef**	**Standard Error**	
FICO change	0.991	0.000	*	0.999	0.000	*	0.991	0.000	*	0.999	0.000	*	0.991	0.000	*	0.999	0.000	*
appraisal	1.000	0.000	*	1.000	0.000	*	1.000	0.000	*	1.000	0.000	*	1.000	0.000	*	1.000	0.000	*
DTI ratio	1.004	0.000	*	0.995	0.000	*	1.003	0.000	*	0.996	0.000	*	1.004	0.001	*	0.995	0.000	*
LTV ratio	1.017	0.000	*	1.005	0.000	*	1.017	0.001	*	1.005	0.000	*	1.011	0.001	*	1.006	0.000	*
fixed rate	0.677	0.009	*	0.407	0.003	*	0.749	0.012	*	0.432	0.005	*	0.615	0.015	*	0.374	0.005	*
current rate	1.256	0.004	*	1.278	0.002	*	1.329	0.005	*	1.310	0.003	*	1.195	0.007	*	1.244	0.003	*
origin lag	1.273	0.033	*	0.903	0.024	*	1.255	0.043	*	0.854	0.032	*	1.272	0.053	*	1.059	0.037	
as of lag	0.365	0.037	*	8.706	0.009	*	0.376	0.045	*	10.283	0.012	*	0.359	0.066	*	7.098	0.013	*
as of index	1.004	0.000	*	0.998	0.000	*	1.003	0.000	*	0.997	0.000	*	1.004	0.000	*	0.998	0.000	*
unemploymen t	1.271	0.003	*	0.706	0.001	*	1.268	0.004	*	0.727	0.002	*	1.298	0.006	*	0.678	0.002	*
white%	1.019	0.020		1.174	0.008	*	0.944	0.024	&	1.249	0.011	*	1.192	0.034	*	1.085	0.012	*
Hispanic%	1.312	0.017	*	1.422	0.006	*	1.283	0.022	*	1.498	0.008	*	1.277	0.029	*	1.306	0.010	*
urban%	1.137	0.024	*	0.848	0.008	*	1.318	0.031	*	0.858	0.011	*	0.920	0.036	&	0.835	0.012	*
year02	0.843	0.033	*	0.973	0.005	*	0.945	0.039		1.018	0.007	*	0.628	0.062	*	0.897	0.008	*
year03	1.164	0.030	*	0.890	0.005	*	1.292	0.036	*	0.999	0.007		0.887	0.055	&	0.772	0.008	*
year04	1.492	0.029	*	0.789	0.006	*	1.823	0.035	*	0.859	0.007	*	0.982	0.056		0.708	0.009	*
year05	1.417	0.029	*	0.390	0.007	*	1.780	0.035	*	0.410	0.009	*	0.873	0.055	*	0.384	0.012	*
year06	1.432	0.030	*	0.207	0.009	*	1.707	0.036	*	0.212	0.011	*	0.984	0.055		0.201	0.013	*
year07	1.296	0.030	*	0.133	0.011	*	1.599	0.036	*	0.147	0.015	*	0.874	0.056	&	0.115	0.018	*
year08	1.129	0.033	*	0.206	0.019	*	1.396	0.040	*	0.257	0.023	*	0.743	0.061	*	0.140	0.033	*
seconds	1.122	0.010	*	0.885	0.004	*	1.176	0.014	*	0.834	0.005	*	1.092	0.016	*	0.947	0.006	*
as of LTV	1.004	0.000	*	1.005	0.000	*	1.004	0.000	*	1.004	0.000	*	1.003	0.000	*	1.006	0.000	*
current	0.029	0.027	*	1.244	0.009	*	0.027	0.036	*	1.286	0.012	*	0.033	0.042	*	1.173	0.014	*
delinquency	44.701	0.083	*	0.915	0.006	*	17.288	0.107	*	0.910	0.008	*	19.886	0.142	*	0.924	0.009	*
orig_rank2	1.114	0.050	&	1.066	0.007	*	1.224	0.060	*	1.016	0.010		0.855	0.090		1.112	0.011	*
orig_rank3	1.498	0.049	*	1.206	0.007	*	1.687	0.059	*	1.122	0.010	*	1.135	0.088		1.278	0.011	*
orig_rank4	1.663	0.049	*	1.335	0.007	*	1.789	0.059	*	1.222	0.010	*	1.388	0.087	*	1.430	0.011	*
orig_rank5	1.763	0.049	*	1.516	0.008	*	1.894	0.059	*	1.379	0.011	*	1.502	0.088	*	1.626	0.012	*
orig_rank6	1.969	0.050	*	1.659	0.010	*	2.234	0.061	*	1.543	0.013	*	1.656	0.089	*	1.730	0.015	*
orig_rank7	2.460	0.053	*	1.802	0.015	*	2.812	0.066	*	1.546	0.021	*	2.168	0.092	*	2.069	0.022	*
orig_rank8	3.578	0.086	*	1.499	0.045	*	4.327	0.109	*	1.080	0.058	&	2.871	0.143	*	2.554	0.072	*

constant	0.086	0.040	*	0.287	0.024	*	0.082	0.045	*	0.210	0.033	*	0.078	0.050	*	0.431	0.037	*
n=	6,950,612						3,756,823						3,193,789					
LR c2	1,506,367						901,514						604,583					
Prob> c2	0.000						0.000						0.000					
Pseudo R2	0.231						0.246						0.211					

This table presents the results of estimating equation multinomial logit model using panel estimation techniques. The dependent variable in this model is coded 1 if the loan ended in default during the observation period, 2 if the loan was prepaid and 3 if the loan was continued during one of the observation periods. The interest is in the potential for a change in the FICO score to be used as an early warning sign of potential change in status of a mortgage loan. This is accomplished with the inclusion of the variable ∆FICO as an independent variable with other established controls for modeling default . These differences are established via the matrices previously presented. The value of this variable is the difference between the observed change in the FICO score from period to period and the predicted value from the Tobit model. Coefficients that are statistically at the 99 percent level are identified by * and those with 95 percent significance are identified by &.

Table 12 MNL with FICO Change Residual

MNLw/	**Global**						**Purchase**						**Refinance**					
Residual	*Default*			*Prepayment*			*Default*			*Prepayment*			*Default*			*Prepayment*		
Variables	**Coefficient**	**Standard Error**		**Coefficient**	**Standard Error**		**Coefficient**	**Standard Error**		**Coefficient**	**Standard Error**		**Coefficient**	**Standard Error**		**Coefficient**	**Standard Error**	
FICO_orig	0.99957	0.000	*	1.00002	0.000	*	0.99930	0.000	*	0.99820	0.000	*	0.99918	0.000	*	0.99767	0.000	*
appraisal	1.00000	0.000	*	1.00000	0.000	*	1.00000	0.000	*	1.00000	0.000	*	1.00000	0.000	*	1.00000	0.000	*
DTI ratio	1.00389	0.000	*	1.00010	0.000	*	1.00299	0.000	*	0.99594	0.000	*	1.00370	0.001	*	0.99442	0.000	*
LTV ratio	1.02089	0.000	*	1.00012	0.000	*	1.01946	0.001	*	1.00472	0.000	*	1.01453	0.001	*	1.00611	0.000	*
fixed rate	0.64295	0.009	*	1.00340	0.003	*	0.71179	0.012	*	0.43174	0.005	*	0.58846	0.015	*	0.37494	0.005	*
current rate	1.32685	0.004	*	1.00209	0.002	*	1.42171	0.005	*	1.31064	0.003	*	1.24348	0.006	*	1.24056	0.003	*
origin lag	1.32270	0.033	*	1.02476	0.024	*	1.30296	0.043	*	0.78365	0.033	*	1.32622	0.053	*	0.99847	0.037	
as of lag	0.42071	0.037	*	1.00892	0.009	*	0.44580	0.045	*	10.37225	0.012	*	0.40126	0.066	*	7.16830	0.013	*
as of index	1.00325	0.000	*	1.00003	0.000	*	1.00304	0.000	*	0.99718	0.000	*	1.00342	0.000	*	0.99819	0.000	*
unemployment	1.28974	0.003	*	1.00148	0.001	*	1.28110	0.004	*	0.72915	0.002	*	1.32328	0.006	*	0.68051	0.002	*
white%	0.92945	0.020	*	1.00801	0.008	*	0.86145	0.024	*	1.24179	0.011	*	1.08492	0.034	&	1.07486	0.012	*
Hispanic%	1.44255	0.017	*	1.00628	0.006	*	1.43102	0.021	*	1.50247	0.008	*	1.35213	0.029	*	1.30911	0.010	*
urban%	1.10631	0.024	*	1.00807	0.008	*	1.27650	0.031	*	0.85473	0.011	*	0.90310	0.036	*	0.83223	0.012	*
year02	0.82489	0.033	*	1.00511	0.005	*	0.91740	0.039		1.00446	0.007		0.62679	0.062	*	0.88820	0.008	*
year03	1.17473	0.030	*	1.00531	0.005	*	1.30810	0.036	*	0.98672	0.007	&	0.90427	0.055	&	0.76312	0.008	*
year04	1.52247	0.030	*	1.00583	0.006	*	1.86003	0.035	*	0.85109	0.007	*	1.00918	0.056		0.70055	0.009	*
year05	1.53443	0.029	*	1.00728	0.007	*	1.90859	0.035	*	0.41052	0.009	*	0.97427	0.055		0.38492	0.012	*
year06	1.60016	0.030	*	1.00872	0.009	*	1.88767	0.036	*	0.21271	0.011	*	1.12714	0.055	&	0.20114	0.013	*
year07	1.46181	0.030	*	1.01161	0.012	*	1.81179	0.037	*	0.14445	0.015	*	1.00338	0.056		0.11377	0.018	*
year08	1.31586	0.033	*	1.01881	0.019	*	1.66458	0.040	*	0.25056	0.023	*	0.85215	0.061	*	0.13721	0.033	*
seconds	1.12184	0.010	*	1.00376	0.004	*	1.17983	0.014	*	0.83478	0.005	*	1.09037	0.016	*	0.94798	0.006	*
as of LTV	1.00389	0.000	*	1.00009	0.000	*	1.00408	0.000	*	1.00460	0.000	*	1.00322	0.000	*	1.00604	0.000	*
current	0.02933	0.027	*	1.00905	0.009	*	0.02730	0.036	*	1.29157	0.012	*	0.03288	0.042	*	1.17671	0.014	*
delinquency	45.65640	0.087	*	1.00574	0.006	*	15.78500	0.115	*	0.95925	0.008	*	9.78500	0.143	*	0.97426	0.009	*
rank1_residual	0.98922	0.001	*	1.00020	0.000	*	0.98917	0.001	*	1.00132	0.000	*	0.98921	0.001	*	1.00146	0.000	*
rank2_residual	0.99032	0.000	*	1.00006	0.000	*	0.99001	0.000	*	0.99941	0.000	*	0.99099	0.000	*	0.99837	0.000	*
rank3_residual	0.98985	0.000	*	1.00005	0.000	*	0.98969	0.000	*	0.99892	0.000	*	0.99000	0.000	*	0.99905	0.000	*
rank4_residual	0.99029	0.000	*	1.00004	0.000	*	0.99034	0.000	*	0.99896	0.000	*	0.99025	0.000	*	0.99924	0.000	*
rank5_residual	0.99163	0.000	*	1.00006	0.000	&	0.99217	0.000	*	0.99988	0.000		0.99084	0.000	*	0.99985	0.000	
rank6_residual	0.99224	0.000	*	1.00011	0.000	*	0.99244	0.000	*	0.99989	0.000		0.99247	0.000	*	0.99925	0.000	*
rank7_residual	0.99349	0.000	*	1.00022	0.000	&	0.99283	0.001	*	0.99971	0.000		0.99460	0.001	*	0.99940	0.000	&
rank8_residual	0.99765	0.001		1.00054	0.001	*	0.99762	0.002		0.99976	0.001		0.99925	0.002		0.99186	0.001	*
constant	3.15000	0.013	*	1.03044	0.030	*	3.32000	0.019	*	0.86704	0.042	*	3.30000	0.019	*	2.97543	0.046	*

n=	6,950,612	3,756,823	3,193,789
LR c2	1,504,035	899,939	603,827
Prob> c2	0.000	0.000	0.000
Pseudo R2	0.230	0.246	0.211

This table presents the results of estimating equation multinomial logit model using panel estimation techniques. The dependent variable in this model is coded 1 if the loan ended in default during the observation period, 2 if the loan was prepaid and 3 if the loan was continued during one of the observation periods. The interest is in the potential for a change in the FICO score to be used as an early warning sign of potential change in status of a mortgage loan. This is accomplished with the inclusion of the variable ΔFICO residual as an interaction with the rank variables thereby accounting for the heterogeneity between the grade levels. These differences are established via the matrices previously presented. The value of this variable is the difference between the observed change in the FICO score from period to period and the predicted value from the Tobit model. Coefficients that are statistically at the 99 percent level are identified by * and those with 95 percent significance are identified by &.

[i] Fannie Mae has recently begun requesting FICO scores from individuals with multifamily mortgage loans in their portfolio as part of an annual credit soundness review.

[ii] The credit bureaus each have their own credit scores: Equifax produces the ScorePower, Experian's is the PLUS score, and TransUnion's credit score, and all three sell the VantageScore credit score produced in an arrangement with all three reporting firms. In addition, many large lenders, including the major credit card issuers, have developed their own proprietary scoring models. Fair Isaac provides credit scoring services around the globe and competes with domestic providers in many developed countries.

[iii] Underwriting data is often subdivided into hard (ability to document or third party origin) and soft (provided by borrower).

[iv] There is the potential for selection bias in the data as a material portion of the total data set does not include post origination credit scores.

[v] The categories used are actually the same as those provided by FAIR Isaac.

[vi] See Bangia et al. (2002), Cantor and Falkenstein (2001), Hamilton and Cantor (2004) and Lopez and Saidneberg (2000) for summaries of the recently developed approaches to corporate credit transition analysis.

[vii] The six month observation contradicts this statement because lenders are deferring credit checks for the first year.

[viii] Values for 2009 included solely for the purpose of illustrating the extent of inflation in FICO score requirements of mortgage applicants post the financial collapse.

[ix]FICO scores can increase as debts are retired even if no changes to income are available.

[x] Loans identified as cash out refinance loans are not included in the analysis.

[xi] Lacking specific information on the borrower or the location of the asset it is infeasible to determine precisely if there are additional mortgage obligations encumbering the residence or burdening the borrower.

[xii] One limitation in this approach is that volatility over the time period is not observed. The observations are irregular and capturing volatility in a consistent fashion to allow for comparison represents an opportunity for future work.

[xiii] A test of bias between those loans with post origination FICO scores and those without failed to reveal significant differences between the subsets.

[xiv] As Ambrose and Buttimer (2000) report, numerous studies that exam time to default indicate that borrower characteristics have a limited impact in predicting borrower default after the second year from origination (von Furstenberg and Green, 1974; and Williams, Beranek, and Kenkel, 1974). This is further support for the two year window from the point of new borrower information.

[xv] Archer and Smith (forthcoming) extend this contemporary LTV to account for nonlinearity in the decision process and variations in the borrower's expectation of future value changes in exercising the option. They construct a proxy for an in-the-money put option, *Put*, with a series of thresholds observing the impact that increasing LTV has on the probability of borrowers defaulting.

[xvi] As the dataset only includes first loans, the total LTV on the property could be substantially higher than observed in this single observed loan.

[xvii] It is also likely that this variable is serving as a fixed effect for the observation period as there is strong a correlation between the price adjusted LTVs and the date of observation. This relationship is particularly strong in the later months when the price index for Florida falls, dramatically increasing LTVs.

[xviii] According to Crouhy, Galai and Mark (2001), and Marrison (2002) the evaluation of risk constructs includes market, credit and operational risk.

[xix] Schuermann (2004) provides a useful review.