Appraisals, Automated Valuation Models, and Mortgage Default

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Abstract

Previous research has suggested the possibility that professional appraisals or econometric estimates of collateral value may be indicative of credit risk. This paper examines the issue by estimating the probability of a mortgage default (defined both as 90 day delinquency and as a claim on mortgage insurance) as a function of the difference between sales price of a home and the estimated value of the home at the time of the purchase, produced by both an appraisal and by an Automated Valuation Model (AVM). Logistic regression is used to estimate the quarterly hazard of a serious delinquency, or claim, as a function of a host of standard control variables, and the percent difference between the sales price and the appraisal and/or AVM estimate. The data consist of a nationally representative random sample of about 5,000 FHA insured single family mortgages endorsed in Fiscal Years 2000, 2001, and 2002, observed through January 31, 2006, and a sample of about 1,000 FHA loans from the Atlanta MSA in the same time period. The records are augmented with the results from an AVM. The difference between the sale price and the appraisal or AVM estimate is found to significantly increase the probability of delinquency, and increase the probability of foreclosure, significantly so in the national sample. Also, transactions that are valued with higher precision have lower default propensities. Additionally, the differences are found to increase loss given default in the small subset of loans that had completed the property disposition process.

1. Introduction and Literature Review

The idea that equity plays an important role in the homeowner's decision to default is longstanding in the academic literature[1]. Empirical estimates of the relationship between equity and default go at least as far back as Herzog and Earley (1970), and a firm theoretical underpinning for the decision to default was provided by Kau and Kim (1994). Equity can come in two flavors – initial equity in the form of the down payment when a home is purchased, and contemporaneous equity, which adds in price appreciation (or depreciation) post purchase, amortization, and sometimes changes in the market value of the mortgage balance. Research finds that contemporaneous equity has a strong influence on credit risk, and some papers, such as Harrison, Noordewier, and Yavas (2004) find that initial equity has a modest additional impact, over and above it's effect on contemporaneous equity, perhaps because it reflects the household's ability to save, or because it is more precisely measured than accumulated equity, which is usually measured as a state or MSA wide average. An exception is the modeling of FHA mortgages, where initial LTV is sometimes found to have little additional impact,

[1]For a recent review of the literature on mortgage credit risk, see US GAO (2005).

possibly because the vast majority of FHA loans are at or near the maximum LTV allowed by FHA. For examples, see Technical Analysis Center (2005) or US GAO (2001)[2].

Appraisers provide the estimate of value used in determining initial equity. A handful of papers have examined the role of appraisers in the underwriting process. Horne and Rosenblatt (1996) examine the distribution of the differences between appraised values and purchase prices. They find that differences between appraised values and sale prices are almost always less than one percent, and appraisals for less than the purchase price are extremely rare. LaCour-Little and Malpezzi (2001) estimates a model similar to the one in this paper. Using a stratified sample of 224 loans originated at a credit union in Alaska, they calculate the differences between appraisal and a hedonic estimate of property value, and estimate the effect of this difference on delinquency probabilities, controlling for some standard underwriting variables. This paper extends the work of LaCour-Little and Malpezzi in several dimensions. First, it examines a much larger and geographically representative group of loans. Second, it uses much more recent loans (2000 to 2002, versus 1980's originations for LC-L and M) and uses a set of control variables that reflect current underwriting practice, such as FICO scores. Third, it examines the probability that a loan will actually produce a loss, in addition to examining the probability of a serious delinquency. Although delinquency is a valuable early indicator of credit risk, papers such as Ambrose and Capone (2000) and Danis and Pennington-Cross (2005) find that delinquencies often cure, rather than lead to losses for lenders or insurers. Finally, it incorporates more information into the credit risk model, examining the quality of the hedonic estimate as measured by its standard error, in addition to considering the level of the difference.

Shiller and Weiss (1999) lay out a framework for evaluating the profitability of AVM deployment. This paper takes a step towards filling the data requirements of their framework, estimating the correlation between appraisal/selling price and AVM valuation, and demonstrating the effectiveness of AVM systems in predicting default, foreclosure, and loss severity.

The rest of the paper is laid out as follows. Section 2 describes the model in general terms. Section 3 describes the data. Section 4 discusses the estimation strategy and the CTM software used to estimate the model. Section 5 provides the results for 90 day delinquency, claims, prepayments, and loss given default. Section 6 offers concluding remarks and some observations concerning the relative predictive power of appraisals and AVMs.

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[2]Both GAO and HUD have modeled FHA conditional termination rates as functions of LTV dummy variables, and find that default propensity rises sharply as LTV increases over ranges up to about 96% LTV. Beyond this point the relationship flattens out, perhaps because the bulk of FHA mortgages are at the maximum LTV allowed by program rules. Program rules allow slight variations in maximum LTV based on loan size and location in high or low closing cost states, and have varied over time. The fact that few loans are written for less than the maximum LTV means that, in high LTV ranges, the LTV variable is picking up location and vintage features along with “true” LTV effects.

2. Model

The focus of this paper is the effect of appraisal and AVM quality on the credit risk in mortgages. An appraisal is a measure of the "market value" of a property. In a highly liquid market with large numbers of identical commodities traded, this is a simple concept. In the housing market, with infrequently traded heterogeneous properties, market value is a more tenuous concept. To some extent, the fact that a buyer is willing to pay $X for a house sets $X as the market value, rendering an appraisal somewhat superfluous. From the perspective of the entity holding the credit risk on the mortgage (lender or, in this case, insurer), the most relevant concept might be the value that the second highest bidder is willing to spend on the property, a notion that mixes the concepts of "market value" and "liquidity." This is because the holder of the credit risk cares about the price at which the buyer could later sell the property, which determines the buyer's choice of prepayment or default in the face of trigger events, and determines the amount of recovery in case of default. This may be expressed as

$$\textit{Market Value} = \textit{Transaction Price} + \textit{Idiosyncrasies} \qquad (1)$$

where Market Value refers to the expected selling price if a property were immediately resold. Transaction Price is the price agreed upon by the buyer and seller. Idiosyncrasies represent any unique characteristics attached to the transaction, such as a buyer uniquely attracted to a particular property characteristic, or a seller motivated to sell exceptionally quickly, or, for that matter, fraud.

The appraisal process can provide an estimate of property value independent of the idiosyncratic circumstances that might cause a buyer to be the highest bidder. Single family appraisals are generally based upon the sale prices of comparable properties, with adjustments made for differences in characteristics between the property in question and the comparables, and with adjustments made for area-wide trends in price. An appraisal constitutes an estimate of the market value. Such an estimate may be biased or unbiased. Sources of bias to the high side are pressure from buyers, sellers, brokers, etc. who need an appraisal for at least the agreed upon price so that the transaction can take place. The holder of the credit risk on the transaction, for example, the insurer, would presumably wish to pressure appraisers for an accurate estimation, but in many cases the appraiser is hired by the lender, although the risk is borne primarily by the insurer.[3]

$$\textit{Appraisal Value} = \textit{Market Value} + \textit{Bias1} + \varepsilon_1 \qquad (2)$$

where Appraisal Value is the value assigned by an appraiser, Bias1 represents any possible tendency to assign a value other than the expectation of Market Value, and ε_1 is the inherent noise in any estimation process.

[3] FHA does maintain a list of approved appraisers, and can remove an appraiser from the list for fraud or unethical behavior, but it is not clear how effective this might be in the case of modest upward bias of the sort considered here. See US GAO (2004) for a discussion of FHA's role in monitoring appraisers.

An AVM produces a second estimate of the market value of the property. An AVM estimate may be less subject to bias, as AVM services are sold to a wide variety of parties, such as lenders, insurers, GSEs, or MBS investors, with no clear incentive to produce "high" or "low" estimates. On the other hand, AVMs constitute a mass-appraisal approach, rely upon generally available characteristics, and do not involve visits to properties to ascertain condition or incorporate local knowledge (the announcement of a factory closing or plans for a new transit stop), so that their variances may be much higher than the variances of appraisals.

$$\textit{AVM Value} = \textit{Market Value} + \textit{Bias2} + \varepsilon \qquad (3)$$

where AVM value is the value assigned by an AVM, Bias2 is the tendency (if any) for an AVM to produce a value other than the expectation of market value, and ε is the inherent noise in the AVM estimation process.

The relevant questions for a holder of mortgage credit risk are, 1) "does an appraisal contain any information helpful to the assessment of default propensities, and 2) "does an AVM estimate contain any information beyond that contained in an appraisal?" The latter will be the case if the mean square error of the AVM is not too large, relative to the mean square error of the appraisal, and if the correlation between the two errors is not too high. One way to test this proposition is to estimate equations such as

$$\textit{Prob(Default)} = \textit{fn(Appraisal, AVM Estimate, other risk variables)} \qquad (4)$$

$$\textit{Loss Given Default} = \textit{fn(Appraisal, AVM Estimate, other risk variables)} \qquad (5)$$

and test the coefficients on the Appraisal and AVM Estimate values.

Underwriters, and FHA guidelines in particular, generally take the minimum of the sale price or the appraised value as the denominator when calculating the loan-to-value ratio, used as a key indicator of default probability. Thus, the extent to which an appraisal exceeds the transaction price has no effect on the underwriting decision, or perceived degree of risk attached to the loan by the underwriter. An appraisal less than the transaction price has serious consequences, however, generally requiring an increase in the cash that the buyer has to bring to the table, or a decrease in the price received by the seller, or the failure of the transaction to go through. Thus appraisals may produce benefits in ways not captured by transaction data, either by preventing transactions on overpriced properties, or by triggering renegotiated prices.

AVMs are generally not used in FHA underwriting[4]. However, AVM estimates may provide an additional source of information on the value of the collateral; therefore on the level of credit risk for a given mortgage. The extra predictive power could be useful for risk monitoring on the part of FHA or other insurers, risk accounting, and for investor evaluations of portfolios of mortgages.

[4]Although FHA does sometimes use AVMs in post endorsement reviews.

3. Data

3.1. Loan Data

The data for this paper consist of a nationally representative sample of just over 5,000 FHA single family purchase money loans, endorsed in fiscal years 2000, 2001, and 2002, that is, from October 1999 to September 2002. Their performance is observed through June 2005. These loans were drawn by Concentrance Corp, a HUD contractor, for a HUD-sponsored study of down payment assistance.[5] This file is one of only two large random samples of seasoned FHA loans with FICO scores[6], as HUD only began the routine collection of FICO scores as part of their Single Family Data Warehouse (SFDW) in 2004. In addition to FICO scores, the file contained many fields from the SFDW, such as the initial LTV ratio, mortgage payment, borrower income, type of mortgage, term, interest rate, and street address of the borrower. This file was merged with a July 2005 extract of the SFDW containing dates for prepayment of the loans that paid off early, date of first 90-day delinquency reported by the lender, and date of claim for loans that terminated with a loss to FHA, and the loss (or, for 12 foreclosures, profit) for loans that had completed the property disposition process.

In addition to the national file, Concentrance drew 1,000 loan samples from each of three MSAs, Atlanta, Indianapolis, and Salt Lake City, over the same time period. For reasons discussed later, this paper focuses on the national sample, and reports analysis for the Atlanta sample.

The Concentrance samples were limited to loans with LTV ratios greater than 95%, as defined in HUD's SFDW. Since HUD's definition of LTV excludes the upfront mortgage insurance premium, which is generally rolled into the mortgage, in effect almost all of these loans had LTV ratios, as conventionally defined, greater than 96.5%, as HUD's upfront premium was 1.5% for most of the sample period. Loans with LTVs greater than 96.5% constitute almost 90% of FHA's purchase money loans, and constitute over 90% of FHA's claims. Because FHA allows some closing costs to be financed, and allows the financing of the upfront premium, FHA loans can, in some circumstances, slightly exceed 100% LTVs. In this sample almost 85% of the records had LTVs in the narrow range of 98% to 100%, and about 99% were between 95% and 101%, as conventionally defined.

The median price in the national sample was $110,000. About 99% of the loans were for a term of 30 years, with the remainder generally for 15. About 6% of the loans were for condominiums, and about 8% of the loans were 1 year ARMs, with the balance being fixed rate mortgages (FHA did not offer hybrid ARMs at that time). Just over 80% of the loans were to first time home buyers, and about 40% were in underserved area census tracts. See Table I for sample summary statistics.

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[5]See Concentrance Consulting Group (2004).

[6]The other file was collected by HUD as part of their development of FHA's automated underwriting algorithm. The loan years covered precede the widespread deployment of AVM systems. See Cotterman (2004).

Table I.1

Summary Statistics

Variables	National Sample Mean	National Sample Sigma	Disclose State Sample Mean	Disclose State Sample Sigma	Atlanta Sample Mean	Atlanta Sample Sigma
Dependent						
Cumulative delinquent rate	12.47%		12.34%		16.40%	
Cumulative claim rate	4.90%		4.56%		9.64%	
Cumulative prepay rate	75.97%		77.95%		67.86%	
Loss severity rate	34%	21.30%	34%	22.70%	27%	12.10%
Time Invariant Independent						
frontend ratio	0.26	0.08	0.27	0.08	0.27	0.07
LTV ratio	0.99	0.01	0.99	0.01	0.99	0.01
FICO (/100)	6.55	0.61	6.55	0.61	6.43	0.58
NoFICO	8.2%		8.5%		7.3%	
reserves < 2 months	28.5%		28.3%		23.6%	
underserved area	40.5%		42.5%		40.3%	
condominium	6.1%		6.6%		4.1%	
first time buyer	81.8%		82.3%		82.0%	
ARM	7.6%		8.1%		10.1%	
Appraiseratio	0.02	0.06	0.02	0.07	0.02	0.03
Median	0.00	0.05	0.00	0.05	0.01	0.04
Avmratio	0.09	0.23	0.08	0.23	0.05	0.17
Median	0.04	0.41	0.03	0.56	0.02	0.29
Avmconfidence (/100)	0.75	0.15	0.75	0.14	0.80	0.00
Time Varying Independent						
GAOrisk	6.92	2.07	6.65	2.23	6.78	1.91
Growth	1.10	0.14	1.05	0.05	1.07	0.07
Number of Observations	3985		3403		1116	

Over 12% of the loans experienced at least one episode of serious delinquency by June 30, 2005[7]. About 5% of the loans resulted in a claim on FHA, generally through foreclosure, by January 31, 2006. For the few loans with a claim that had completed the property disposition process, the average loss was 34% of the original mortgage balance. Over 80% of the loans in the sample had terminated by the end of the observation window, either through prepayment or claim termination. Interest rates reached a local

[7]HUD provided an update file for claim and non-claim terminations through January 2006, but this file did not include delinquencies. Hence, claim regressions and statistics are though January 2006, while delinquency regressions are through June 2005. Additionally, HUD imposed a foreclosure moratorium for counties and parishes affected by hurricanes Katrina and Rita – loans in these areas still active in September 2005 are censored as of the end of September. This affected less than 1percent of the national sample.

minimum in 2003, and prepayment rates were fairly high for these cohorts.

3.2. External Data

These files were merged with several external sources to incorporate time-varying covariates for the hazard analysis. State level unemployment rates were obtained from BLS, the state level constant quality house price index was obtained from OFHEO, 30 year fixed-rate mortgage rates were taken from Freddie Mac's Primary Mortgage Market Survey, and one-year Treasury rates were taken from the Fed.

Finally, the addresses in the file were submitted to First American Real Estate Solutions in July 2005, for the purpose of appending the results of their AVM models to each transaction. First American is a large vendor of real estate data, and maintains several AVMs that are in wide commercial use among mortgage lenders. First American was given the address, an "as-of" date, defined as 30 days prior to the settlement date of the mortgage, and indicators for whether the property was 1-unit or 2- to 4-unit, and whether the property was a condominium. First American used a "cascading AVM" approach. A loan was first submitted to their PASS model, a hedonic model[8]. If there was insufficient data to produce a high confidence estimate, it was then submitted to HPA, which First American describes as a primarily hedonic model, with some repeat sale index hybrid elements. About 95% of the successfully valued loans had results from either PASS or HPA. In about 5% of the cases, if these failed to produce high confidence estimates, the loan was submitted to PB6 or VP4, which First American describes as neural net models.

For each successfully valued loan, First American returned the predicted mean value from the model, as-of the month prior to settlement, a high value, defined as the 90th percentile estimate from the AVM, and a Confidence Score, defined as the probability that the true value is within 10% of the AVM produced value. Confidence Scores ranged from 40 to 98, with a median of 78. Records with Confidence Scores below 40 were deemed failures by First American and values were not returned.

First American returned values for 3,985 loans in the national sample of 5,101, a success rate of 78%. A record might not be valued for several reasons. There could be a problem merging the address fields in the HUD database to the First American database. There could be too few transactions of a property type in an area to allow for a high confidence estimate. Additionally, 8 states are "non-disclosure" states[9] – that is, local officials do not release property transaction data to firms such as First American. While First American gets some data from lenders on transactions in these states, they have less than complete coverage, leading to low hit rates in most of these states. Unfortunately, both Utah and Indiana are non-disclosure states, leading to questionable model fits for two of the three MSAs that were also sampled. Georgia is a disclosure state, and the

[8]First American regards the details of their AVM algorithms as proprietary. For a general discussion of hedonic, repeat sale index, and hybrid models, see Case (1991). For a discussion of neural net models, see Kershaw and Rossinni (1999).

[9]They are Alaska, Indiana, Kansas, Mississippi, Missouri, New Mexico, Texas, and Utah. Texas is a middle case – although First American does not get data from local officials, they have arrangements with the MLS in some Texas MSAs and get nearly complete data for those parts of the state.

Atlanta sample had a hit rate of 95%, with a median Confidence Score of 85. Hence, analysis is done for the Atlanta MSA, but not for Indianapolis or Salt Lake City, where hit rates were under 70%. For the national sample, results are presented for both the "full" national sample – that is, the full sample of loans for which First American produced an AVM value, and for a subset (3,403 loans) that includes only loans made in disclosure states. For this subset of the national sample, hit rates are about 85%, and the median Confidence Score is 80.

The mean of the ratio of the AVM value to the sale price is 1.09, substantially exceeding 1 (Table I). However, as both sale price and AVM value are random variables, being noisy signals of a "true value," this number represents the mean of a ratio of two random variables. Assuming the variables are both Normal, the result has a Cauchy distribution, with an undefined expectation. In general, the mean of a ratio is not the ratio of the means. For that reason, the median AVM ratio may be preferred as an indicator for the ability of the AVM values to match the transaction prices. The median AVM ratio is 1.04 for the national sample, 1.03 for the disclosure states, and 1.02 for the Atlanta sample.

As the off-the-shelf commercial AVM models used here are proprietary, it is impossible to ascertain why the AVM values tend to exceed the transaction prices, but there are at least two (non-exclusive) possibilities. The years 2000 to 2002 were noteworthy for double digit annual appreciation in housing prices. If the timing of the valuation process is off by even a month the result could be an upward bias of a percentage point. Another possibility is a form of selection bias. As these are all FHA mortgages, and the FHA program has a maximum loan amount, there will be some tendency for cheaper properties to have higher probabilities of being financed with an FHA mortgage, conditional on the observed characteristics of the property. The fact that the disclosure states have a smaller bias than the non-disclosure states lends some credence to this explanation, as the greater the ability to model the price with covariates, the smaller is the problem from unobservables correlated with FHA status. The fact that the Atlanta sample has the smallest bias is also consistent with these stories, as Atlanta had lower than average appreciation, and has a lower than average median house price, meaning that the FHA ceiling is a binding constraint in fewer cases. So long as the unobservables are uncorrelated with default, the selection problem would not produce an upward bias in the significance of the AVM ratio. To the extent that such unobservables may be positively correlated with default the problem would lead to an underestimate of the impact of AVM value. For example, properties adjacent to a nuisance, not accounted for in the AVM model, may be assigned an AVM value above the FHA ceiling but may sell for less than the FHA ceiling. If such properties had higher default propensities, then the high AVM ratio observations would be associated with default in a sample of only FHA properties, weakening the ability to measure the true effect of high AVM ratios in lessening the probability of default.

4. Estimation Strategy

The loan records from the Concentrance study were merged with recent data on claims and delinquencies. The merged loan records were then used to produce loan quarter records, which were merged with time-varying data, such as house price appreciation, unemployment, and interest rates. To measure the influence of appraisals on default propensity, a variable was created equal to the percent difference between the appraised value and the purchase price of the house. To measure the influence of AVM value on default propensity, a variable was created equal to the percent difference between the AVM estimate and the purchase price of the house. Additionally, the confidence score attached to the AVM estimate was entered as a regressor in some specifications.

$$AppraiseRatio = (appraisal\text{-}price)/price \tag{6}$$

$$AVMRatio = (AVM\text{-}price)/price \tag{7}$$

Two strategies were employed in choosing other covariates for the logistic regression. In one, time-invariant variables of the type used in FHA's TOTAL scorecard automated underwriting system were chosen[10]. These are FICO score[11], LTV at origination, an indicator for whether the borrower will have at least 2 months of reserves after closing, and the Front End ratio. These variables were augmented by other loan, borrower, and property variables that might influence credit risk, such as indicators for first-time home buyers and properties in underserved areas. A time-varying covariate is also included to measure post-origination price appreciation. This is defined as the state level percentage change in the OFHEO price index, measured quarterly. For the first two quarters of the loan's life, this value is set to 1; starting with the third quarter, the value is calculated as the ratio of the price index 2 quarters prior to the current quarter and the price index at origination (the claim process is fairly lengthy for FHA loans). Additionally, 3 time splines constitute the baseline hazard; the nodes for the splines are at 2 years, and 3.5 years.

The second strategy was designed to control for more covariates, despite the relatively small sample size (less than 4,000 in the national sample and 1,116 in the Atlanta sample[12], after dropping loans that could not be valued by the AVM). In 2001, GAO estimated competing risk hazard models using millions of FHA loans originated between 1975 and 1999[13]. Explanatory variables for credit risk included LTV at origination, an estimate of contemporaneous LTV, geographic controls for Census division and judicial foreclosure states, contemporaneous unemployment rates, and, for ARM loans, changes in payments over time. A similar spline structure was used for the baseline hazard. Separate models were run for 30-year fixed, investor, 15-year fixed, and ARM loans. The coefficients from this prior study were combined with the Concentrance data to form a mortgage score, and this score (GAOrisk), was used as an independent variable along

[10]FHA releases general information about TOTAL, such as the characteristics that influence the score, but regards precise details, such as the definition of the reserves or FICO score variables, or functional form, as proprietary.

[11]About 8% of the borrowers did not have a FICO score. For these cases, the median FICO score for the sample was inserted, and a dummy variable (NOFICO) was set to 1. The results, therefore, show the extent to which borrowers without a FICO score are riskier than borrowers with a median score.

[12]The Atlanta sample consists of just over 1,000 records from the MSA sample and about 150 records from the National sample that represented loans in the Atlanta MSA.

[13]The model is documented in US GAO (2001).

with important variables not in the GAO model, such as FICO score and reserves.

In order to estimate the effect of the source of the down payment on claim and delinquency propensities, the instantaneous conditional claim (or delinquency) rate was modeled using James Heckman's CTM program (Yi, Walker and Honoré, 1985). Prepaid loans were treated as censored on the date of prepayment. The hazard rate framework was chosen to allow for the inclusion of time varying covariates, such as post origination price appreciation.

CTM (Continuous Time Models) is a Fortran based package with a long history in labor econometrics. It estimates competing risk termination models with a flexible (Box-Cox) parametric baseline hazard, and allows for the choice of any of several parametric forms of unobserved heterogeneity, or Heckman-Singer non-parametric heterogeneity (Yi, Walker, and Honoré 1985). Unobserved heterogeneity is usually referred to in mortgage modeling as "burnout" - the tendency for some loans to terminate faster than observationally similar loans, so that conditional termination rates fall over time, despite unchanging conditions. Essentially, borrowers who are "slow terminators" for some reason not observed by the econometrician remain in the pool after all the "fast terminators" have left.

CTM was first applied to mortgage analysis in GAO's third report on the actuarial soundness of the FHA single family program (GAO 1996), and has also been used to model FHA multifamily mortgage terminations (Ondrich and Huang 2002). Regressions incorporating unobserved heterogeneity have also been estimated with other routines. For example, Stanton (1995) estimates a single termination risk model of prepayment with a gamma heterogeneity distribution, and Deng, Quigley, and VanOrder (2000) estimate a competing risk model with Heckman-Singer non-parametric heterogeneity using McCall's software program[14].

CTM estimates an equation of the form

$$h_{ij}(t_{ij}\ \{x(u)\}_0^{\infty}, \theta) = \exp\{\gamma_{ij0} + \Sigma(t_{ij} + \tau_{ijk})\beta_{ijk} + \tau_{ij}(t^{\tau} - 1)/\tau \quad + c_{ij}\theta$$

where i indexes the origination state (active loan), j indexes the destination state, default or prepayment, t is time (measured in days divided by 100), tau and beta are independent variables and their coefficients, lambda is the Box-Cox parameter for the baseline hazard, and the c's and thetas are the points of support for the non-parametric heterogeneity distribution and their coefficients (factor loadings).

The final regressions were of the form

$$L(Default_{t,\,t+1}/Survivor_t) = Risk\ Covariates_t,\ AVM\ Ratio,\ AVM\ Confidence,\ Appraise\ Ratio,\ Time,\ Heterogeneity) \qquad (8)$$

[14] A non parametric baseline with competing risks and unobserved heterogeneity, as in McCall's program, has to be estimated with some care, as unreliable results may be obtained from singularities. See Ridder and Woutersen (2003).

5. Estimation Results

Tables II.1, II.2, II.3, and II.4 present logistic regression results for the national sample, with 90 day delinquency[15] as the dependent variable. The next set of tables, III.1, III.2, III.3, and III.4 show results with claim as the dependent variable. For each set of tables, there are two specifications, one using the set of regressors used by FHA in its TOTAL scorecard, and one using the GAOrisk variable, both augmented with extra variables. Each specification is repeated twice, once for all observations with an AVM result, and once for observations in disclosure states only. The first columns of results in each table show regressions with just the Appraisal ratio, the second with just the AVM ratio, while the third column shows results when both variables are entered, and the last shows the results when both variables are entered, along with the confidence level associated with the AVM.

At the bottom of each table is the distribution of the heterogeneity parameters. At least two points of support are estimated. The location of the first point of support is fixed at zero, and that of the second is fixed at one. Any additional points of support are constrained to lie in this interval. Along with the location of (additional) points of support, the cumulative probability to that point is estimated. There is no formal way to determine the number of heterogeneity parameters to include in an estimation; usual practice is to start with two points of support, and continue adding until the convergence routine fails. With the national termination samples, 3 points of support were the most that could be estimated.[16] When the number of observations were limited, as in the Atlanta sample, it was sometimes the case that only two points of support could be estimated. While CTM jointly estimates the default parameters, the prepayment parameters, and the heterogeneity distribution, in the interest of space the prepayment parameters are presented only for the national sample, and later in the paper.

[15]The dependent variable indicates 90-day delinquency, or other "bad outcomes" such as the initiation of foreclosure proceedings or a loss mitigation foreclosure alternative. Although lenders are required to report delinquencies to FHA after 90 days, sometimes a delinquency is never reported but the loan appears as a claim or claim alternative. In over 90% of the "delinquencies" in this file, the event is 90-day delinquency.

[16]The same number of support points are in the GAO 1996 model and Denq, Quigley, VanOrder (2000).

Table II.1 **Delinquency**

National All State Sample / GAORISK Specification

Parameter	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**
intercept	6.122	0.610	10.039	6.665	0.663	10.059	6.663	0.667	9.989
gamma	0.166	0.102	1.633	0.153	0.096	1.593	0.153	0.096	1.593
lambda	-1.418	0.440	3.221	-1.463	0.448	3.265	-1.462	0.448	3.264
GAOrisk	-0.022	0.029	0.758	-0.018	0.030	0.595	-0.018	0.030	0.598
FICO	-1.242	0.081	15.371	-1.249	0.081	15.484	-1.249	0.081	15.456
frontend	1.763	0.607	2.905	1.803	0.607	2.969	1.805	0.610	2.958
noFICO	0.617	0.140	4.394	0.625	0.141	4.439	0.625	0.141	4.437
reserve	-0.014	0.097	0.148	-0.004	0.097	0.041	-0.004	0.097	0.040
underserved	0.057	0.089	0.644	0.049	0.089	0.550	0.048	0.089	0.546
firsttime	0.029	0.133	0.218	0.036	0.133	0.268	0.036	0.134	0.268
condo	-0.130	0.204	0.637	-0.098	0.204	0.482	-0.098	0.204	0.481
factor_loading	-0.162	0.356	0.456	-0.235	0.360	0.652	-0.234	0.361	0.650
Appraise_ratio	-0.562	0.833	0.674	0.000	0.000	0.000	0.041	0.884	0.046
AVM_ratio	0.000	0.000	0.000	-0.487	0.209	2.334	-0.491	0.217	2.266
AVMconfidence	0.000	0.000	0.000	-0.655	0.283	2.314	-0.654	0.284	2.302
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.15	0		0.14	0		0.14	0	
	0.48	0.62		0.46	0.61		0.46	0.6	
	1	1		1	1		1	1	

Table II.2 **Delinquency**

National All State Sample / TOTAL Scorecard Specification

Parameter	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**
intercept	10.765	4.145	2.597	10.490	4.146	2.530	10.506	4.210	2.496
gamma	0.878	0.216	4.064	0.839	0.210	4.001	0.839	0.210	3.999
lambda	-0.357	0.227	1.570	-0.387	0.230	1.683	-0.387	0.230	1.680
FICO	-1.252	0.081	15.468	-1.254	0.081	15.513	-1.254	0.081	15.505
frontend	2.347	0.618	3.794	2.332	0.616	3.783	2.334	0.619	3.772
noFICO	0.598	0.141	4.251	0.603	0.141	4.287	0.603	0.141	4.284
reserve	-0.003	0.098	0.028	0.004	0.098	0.041	0.004	0.098	0.043
underserved	0.089	0.089	1.002	0.079	0.089	0.890	0.079	0.089	0.885
ARM	-0.353	0.190	1.857	-0.362	0.191	1.897	-0.362	0.191	1.895
firsttime	0.046	0.133	0.344	0.052	0.133	0.395	0.052	0.133	0.394
condo	-0.020	0.219	0.093	0.010	0.220	0.045	0.010	0.220	0.044
growth	-4.424	0.732	6.046	-4.403	0.733	6.005	-4.403	0.734	5.997
LTV	0.142	4.069	0.035	0.878	4.068	0.216	0.859	4.141	0.207
factor_loading	0.034	0.384	0.089	-0.093	0.385	0.243	-0.091	0.385	0.237
Appraise_ratio	-0.649	0.850	0.764	0.000	0.000	0.000	0.050	0.896	0.056
AVM_ratio	0.000	0.000	0.000	-0.542	0.213	2.543	-0.547	0.220	2.490
AVMconfidence	0.000	0.000	0.000	-0.497	0.280	1.775	-0.496	0.281	1.764
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.15	0		0.15	0		0.14	0	
	0.44	0.61		0.42	0.6		0.42	0.6	
	1	1		1	1		1	1	

Table II.3 **Delinquency**
National Disclosure State Sample / GAORISK Specification

Parameter	Estimate	Std. Error	T	Estimate	Std. Error	T	Estimate	Std. Error	T
intercept	6.180	0.682	9.067	6.774	0.751	9.017	6.752	0.756	8.933
gamma	0.142	0.100	1.429	0.127	0.092	1.375	0.131	0.094	1.395
lambda	-1.514	0.486	3.115	-1.581	0.499	3.169	-1.564	0.494	3.170
GAOrisk	-0.034	0.037	0.925	-0.033	0.038	0.885	-0.035	0.038	0.928
FICO	-1.262	0.089	14.109	-1.267	0.089	14.194	-1.266	0.089	14.176
frontend	1.993	0.664	3.000	2.021	0.666	3.035	2.046	0.670	3.054
noFICO	0.615	0.152	4.042	0.621	0.153	4.070	0.617	0.153	4.041
reserve	-0.016	0.107	0.148	-0.004	0.107	0.042	-0.002	0.107	0.021
underserved	0.056	0.096	0.581	0.061	0.096	0.637	0.059	0.096	0.614
firsttime	0.061	0.149	0.411	0.066	0.149	0.445	0.066	0.150	0.440
condo	-0.221	0.225	0.983	-0.188	0.226	0.832	-0.186	0.226	0.822
factor_loading	-0.082	0.370	0.222	-0.200	0.371	0.538	-0.181	0.373	0.485
Appraise_ratio	-0.271	0.838	0.323	0.000	0.000	0.000	0.460	0.911	0.506
AVM_ratio	0.000	0.000	0.000	-0.501	0.237	2.113	-0.554	0.248	2.229
AVMconfidence	0.000	0.000	0.000	-0.674	0.314	2.147	-0.663	0.315	2.106
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.14	0		0.13	0		0.13	0	
	0.48	0.62		0.45	0.61		0.45	0.61	
	1	1		1	1		1	1	

Table II.4 **Delinquency**
National Disclosure State Sample / TOTAL Scorecard Specification

Parameter	Estimate	Std. Error	T	Estimate	Std. Error	T	Estimate	Std. Error	T
intercept	8.092	4.855	1.667	7.695	4.863	1.583	7.798	4.926	1.583
gamma	0.921	0.240	3.832	0.846	0.231	3.661	0.847	0.231	3.663
lambda	-0.325	0.239	1.36	-0.380	0.248	1.53	-0.380	0.248	1.53
FICO	-1.277	0.089	14.29	-1.274	0.089	14.31	-1.273	0.089	14.3
frontend	2.642	0.674	3.919	2.600	0.673	3.863	2.612	0.676	3.862
noFICO	0.590	0.153	3.867	0.591	0.152	3.879	0.588	0.153	3.856
reserve	0.002	0.108	0.015	0.010	0.108	0.090	0.011	0.108	0.103
underserved	0.064	0.096	0.670	0.068	0.096	0.704	0.066	0.096	0.689
ARM	-0.397	0.200	1.99	-0.394	0.201	1.97	-0.393	0.201	1.96
firsttime	0.079	0.151	0.526	0.086	0.150	0.574	0.086	0.150	0.571
condo	-0.063	0.244	0.26	-0.030	0.246	0.12	-0.031	0.246	0.13
growth	-4.703	0.796	5.91	-4.567	0.795	5.74	-4.561	0.796	5.73
LTV	3.259	4.767	0.684	3.906	4.761	0.821	3.778	4.839	0.781
factor_loading	0.041	0.412	0.100	-0.111	0.410	0.27	-0.103	0.410	0.25
Appraise_ratio	-0.476	0.849	0.56	0.000	0.000	0.000	0.253	0.915	0.276
AVM_ratio	0.000	0.000	0.000	-0.498	0.242	2.06	-0.529	0.253	2.1
AVMconfidence	0.000	0.000	0.000	-0.438	0.307	1.43	-0.433	0.308	1.41
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.14	0		0.13	0		0.13	0	
	0.43	0.62		0.41	0.60		0.41	0.6	
	1	1		1	1		1	1	

Table II.5 **Delinquency**
Atlanta MSA / GAORISK Specification

Parameter	Estimate	Std. Error	T	Estimate	Std. Error	T	Estimate	Std. Error	T
intercept	5.453	1.096	4.975	5.467	1.166	4.690	5.462	1.175	4.649
gamma	0.127	0.143	0.884	0.135	0.152	0.893	0.130	0.147	0.881
lambda	-1.709	0.802	2.130	-1.669	0.797	2.093	-1.696	0.804	2.110
GAOrisk	-0.055	0.052	1.065	-0.057	0.052	1.109	-0.057	0.052	1.102
FICO	-1.210	0.151	8.008	-1.213	0.149	8.144	-1.210	0.152	7.981
frontend	3.825	1.133	3.375	3.772	1.133	3.328	3.787	1.134	3.340
noFICO	0.712	0.229	3.106	0.715	0.230	3.104	0.713	0.231	3.084
reserve	-0.218	0.182	1.197	-0.217	0.182	1.196	-0.216	0.182	1.190
underserved	0.200	0.146	1.367	0.191	0.148	1.292	0.192	0.148	1.299
firsttime	-0.061	0.213	0.287	-0.064	0.213	0.302	-0.063	0.213	0.295
condo	0.548	0.348	1.576	0.537	0.346	1.552	0.544	0.347	1.569
factor_loading	0.488	0.446	1.095	0.517	0.450	1.151	0.493	0.453	1.089
Appraise_ratio	-0.944	2.265	0.417	0.000	0.000	0.000	-0.658	2.305	0.286
AVM_ratio	0.000	0.000	0.000	-0.344	0.554	0.621	-0.317	0.560	0.566
AVMconfidence	0.000	0.000	0.000	0.043	0.567	0.076	0.038	0.573	0.067
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.37	0		0.37	0		0.37	0	
	1	1		1	1		1	1	

Table III.1 **Claim Rate**

National All State Sample / GAORISK Specification

Parameter	**Estimate**	**Std.Error**	**T**	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**
intercept	1.657	1.096	1.512	3.115	1.184	2.630	3.170	1.198	2.646
gamma	0.376	0.273	1.378	0.367	0.267	1.374	0.393	0.275	1.430
lambda	-2.167	0.808	2.681	-2.176	0.816	2.668	-2.112	0.791	2.669
GAOrisk	0.208	0.043	4.790	0.216	0.047	4.638	0.220	0.045	4.848
FICO	-0.904	0.141	6.417	-0.947	0.142	6.685	-0.949	0.141	6.713
frontend	2.128	0.984	2.164	2.579	0.983	2.624	2.423	0.997	2.429
noFICO	0.929	0.210	4.423	0.918	0.215	4.271	0.943	0.214	4.397
reserve	-0.153	0.168	0.914	-0.113	0.169	0.668	-0.127	0.170	0.746
underserved	-0.124	0.148	0.837	-0.152	0.150	1.018	-0.144	0.149	0.967
firsttime	-0.162	0.207	0.784	-0.159	0.209	0.761	-0.153	0.207	0.739
condo	-0.246	0.393	0.626	-0.091	0.399	0.228	-0.115	0.397	0.290
factor_loading	-1.067	0.860	1.241	-1.193	0.883	1.351	-1.017	0.852	1.194
Appraise_ratio	-4.767	2.721	1.752	0.000	0.000	0.000	-4.460	2.743	1.626
AVM_ratio	0.000	0.000	0.000	-1.087	0.422	2.574	-0.797	0.430	1.852
AVMconfidence	0.000	0.000	0.000	-1.873	0.479	3.912	-1.947	0.482	4.037
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.17	0		0.19	0		0.19	0	
	0.47	0.58		0.48	0.59		0.49	0.59	
	1	1		1	1		1	1	

Table III.2 **Claim Rate**
National All State Sample / TOTAL Scorecard Specification

Parameter	Estimate	Std. Error	T	Estimate	Std. Error	T	Estimate	Std. Error	T
intercept	11.410	8.840	1.291	14.125	8.982	1.572	11.374	8.783	1.295
gamma	1.623	0.373	4.349	1.558	0.361	4.310	1.589	0.368	4.319
lambda	-0.853	0.344	2.481	-0.881	0.351	2.510	-0.864	0.350	2.472
FICO	-0.942	0.137	6.886	-0.966	0.137	7.060	-0.965	0.137	7.071
frontend	3.187	1.027	3.104	3.375	1.014	3.320	3.346	1.021	3.277
noFICO	0.888	0.207	4.290	0.875	0.211	4.140	0.885	0.211	4.198
reserve	-0.107	0.168	0.638	-0.081	0.168	0.480	-0.088	0.169	0.520
underserved	-0.038	0.149	0.252	-0.059	0.149	0.400	-0.051	0.149	0.343
ARM	-0.928	0.397	2.339	-0.919	0.390	2.350	-0.933	0.395	2.360
firsttime	-0.156	0.210	0.744	-0.138	0.209	0.660	-0.137	0.208	0.657
condo	-0.201	0.430	0.467	-0.116	0.435	0.266	-0.084	0.436	0.192
growth	-4.603	0.866	5.314	-4.513	0.874	5.160	-4.497	0.872	5.154
LTV	-2.940	8.814	0.334	-4.525	8.935	0.506	-1.758	8.764	0.201
factor_loading	-0.310	0.821	0.377	-0.530	0.831	0.637	-0.385	0.817	0.472
Appraise_ratio	-4.340	2.858	1.518	0.000	0.000	0.000	-3.867	2.895	1.336
AVM_ratio	0.000	0.000	0.000	-0.978	0.433	2.260	-0.777	0.438	1.773
AVMconfidence	0.000	0.000	0.000	-1.479	0.470	3.150	-1.511	0.473	3.195
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.15	0		0.15	0		0.15	0	
	0.43	0.59		0.42	0.58		0.42	0.58	
	1	1		1	1		1	1	

Table III.3 **Claim Rate**

National Disclosure State Sample / GAORISK Specification

Parameter	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**
intercept	2.054	1.296	1.585	4.054	1.460	2.778	4.155	1.510	2.751
gamma	0.103	0.207	0.496	0.101	0.203	0.498	0.101	0.204	0.495
lambda	-4.128	2.548	1.620	-4.143	2.567	1.614	-4.135	2.585	1.599
GAOrisk	0.223	0.058	3.831	0.204	0.065	3.150	0.221	0.065	3.391
FICO	-1.028	0.165	6.217	-1.063	0.167	6.349	-1.077	0.170	6.346
frontend	2.694	1.095	2.461	3.305	1.103	2.997	3.102	1.126	2.756
noFICO	1.085	0.233	4.667	1.053	0.236	4.467	1.094	0.238	4.603
reserve	-0.059	0.185	0.319	0.009	0.189	0.047	-0.010	0.189	0.052
underserved	-0.134	0.165	0.811	-0.122	0.168	0.726	-0.126	0.167	0.754
firsttime	-0.105	0.237	0.441	-0.130	0.240	0.539	-0.104	0.238	0.437
condo	-0.459	0.472	0.972	-0.266	0.478	0.556	-0.279	0.476	0.585
factor_loading	-1.116	0.875	1.275	-1.327	0.921	1.440	-1.272	0.914	1.392
Appraise_ratio	-5.467	3.048	1.794	0.000	0.000	0.000	-5.139	3.102	1.657
AVM_ratio	0.000	0.000	0.000	-1.287	0.481	2.675	-0.906	0.490	1.848
AVMconfidence	0.000	0.000	0.000	-2.404	0.544	4.423	-2.526	0.560	4.512
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.17	0		0.16	0		0.17	0	
	0.46	0.57		0.46	0.57		0.46	0.57	
	1	1		1	1		1	1	

Table III.4 **Claim Rate**

National Disclosure State Sample / TOTAL Scorecard Specifications

Parameter	Estimate	Std. Error	T	Estimate	Std. Error	T	Estimate	Std. Error	T
intercept	9.481	10.399	0.912	14.725	10.104	1.457	10.257	10.215	1.004
gamma	1.367	0.437	3.130	0.979	0.390	2.513	1.208	0.414	2.919
lambda	-1.284	0.554	2.319	-1.662	0.680	2.444	-1.421	0.600	2.366
FICO	-1.045	0.160	6.548	-1.081	0.168	6.434	-1.068	0.160	6.680
frontend	3.917	1.159	3.380	4.040	1.149	3.516	4.121	1.147	3.592
noFICO	1.051	0.229	4.583	1.059	0.243	4.362	1.041	0.232	4.485
reserve	0.014	0.188	0.076	0.055	0.192	0.286	0.037	0.190	0.194
underserved	-0.057	0.166	0.344	-0.028	0.169	0.165	-0.039	0.166	0.238
ARM	-0.896	0.428	2.095	-0.810	0.424	1.912	-0.802	0.430	1.865
firsttime	-0.132	0.248	0.531	-0.094	0.246	0.385	-0.101	0.241	0.420
condo	-0.403	0.512	0.786	-0.313	0.522	0.600	-0.242	0.517	0.468
growth	-4.712	0.919	5.127	-4.048	0.907	4.463	-4.374	0.925	4.728
LTV	-0.389	10.348	0.038	-4.389	9.961	0.441	0.191	10.187	0.019
factor_loading	-0.416	0.890	0.467	-1.412	1.058	1.330	-0.688	0.893	0.770
Appraise_ratio	-4.722	3.250	1.453	0.000	0.000	0.000	-4.401	3.282	1.341
AVM_ratio	0.000	0.000	0.000	-0.995	0.481	2.068	-0.709	0.492	1.441
AVMconfidence	0.000	0.000	0.000	-2.636	0.544	4.849	-2.164	0.536	4.042
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.15	0		0.17	0		0.14	0	
	0.42	0.58		0.46	0.56		0.41	0.57	
	1	1		1	1		1	1	

Table III.5 **Claim Rate**
Atlanta MSA / GAORISK Specification

Parameter	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**
intercept	-4.485	2.439	1.839	-1.787	1.871	0.955	-1.571	1.827	0.860
gamma	0.965	0.418	2.309	0.995	0.648	1.536	1.049	0.661	1.587
lambda	-1.412	0.818	1.725	-1.481	1.029	1.439	-1.435	0.995	1.442
GAOrisk	0.447	0.094	4.772	0.340	0.074	4.603	0.337	0.073	4.608
FICO	-0.564	0.212	2.659	-0.581	0.212	2.742	-0.594	0.214	2.781
frontend	1.839	1.575	1.168	1.509	1.524	0.990	1.414	1.531	0.924
noFICO	0.707	0.312	2.266	0.560	0.312	1.798	0.569	0.314	1.808
reserve	-0.169	0.252	0.672	-0.143	0.246	0.581	-0.135	0.248	0.542
underserved	0.062	0.212	0.294	0.050	0.211	0.238	0.033	0.213	0.153
firsttime	0.106	0.300	0.351	0.079	0.300	0.265	0.075	0.302	0.248
condo	0.166	0.533	0.311	0.270	0.490	0.552	0.235	0.506	0.464
factor_loading	2.398	1.522	1.575	1.106	0.768	1.440	1.183	0.772	1.533
Appraise_ratio	0.737	3.271	0.225	0.000	0.000	0.000	2.292	2.734	0.839
AVM_ratio	0.000	0.000	0.000	-0.850	0.849	1.001	-1.000	0.872	1.147
AVMconfidence	0.000	0.000	0.000	-0.149	0.837	0.183	-0.146	0.857	0.171
Heterogeneity Distribution									
	Cum_Prob	**Location**		**Cum_Prob**	**Location**		**Cum_Prob**	**Location**	
	0.14	0		0.37	0		0.38	0	
	1	1		1	1		1	1	

Signs were as expected for both the appraisal and AVM variables. When the dependent variable was 90-day delinquency, the appraisal ratio had the expected sign but a fairly low significance level. The AVM ratio had the correct sign, and was always significant at 5 percent in one-tailed tests in the national samples. When the dependent variable was the claim hazard, AVM, considered separately, was always significant in one-tailed tests at 5 percent, and Appraisal was often significant. When entered together, the AVM variable was predictive of claim rates at one-tailed significance levels of 0.02 to 0.08, depending on the specification and sample. The Appraisal variables are sometimes significant. There is a modest degree of multicollinearity between the appraisal and AVM ratios; the r-squared between them is about 0.4. The AVM ratio had higher significance, but a slightly smaller standardized Beta. The coefficients on the Appraisal ratio were about 6 times the magnitude of the AVM ratio coefficients, but the AVM ratio's standard deviation was 4 times that of the Appraisal ratio, 6 percentage points for Appraisal vs. 23 percentage points for the AVM ratio[17].

The confidence score associated with the AVM was also highly significant, indicating that harder to value properties have higher claim rates. This result may be consistent with the work of Rachlis (1992) who hypothesized that neighborhoods with few transactions would result in appraisal problems that could lead to higher risk and less lending activity. The result is not consistent with Rachlis' hypothesis if lenders rationed credit in such neighborhoods on unobservables, but is consistent with lenders rationing on observables that are in the claim regression equation, and may also be consistent with lenders rationing in such neighborhoods with conventional loans, but not with FHA loans where the government, not the lender (or PMI), bears the bulk of the credit risk.

Results were mostly favorable for other covariates. The FICO score has a very strong effect with the expected sign, as does the Front end ratio, and the measure of post-origination price appreciation. The GAOrisk variable is also positive and highly significant for claim, but not delinquency, prediction. Significance levels and goodness of fit statistics are generally better for the specification using the GAOrisk variable, indicating the usefulness of capturing risk characteristics using a mortgage score in small samples where including a large number of covariates might not be feasible. LTV is not significant, presumably because there is so little variation in LTV in this sample of very high LTV loans. Reserves are also not significant; again few FHA borrowers have significant reserves after closing. The indicators for first-time homebuyers, condominium loans, and loans in underserved areas were not significant, but there was no theoretical expectation for a particular sign for these variables.

The heterogeneity results are similar to those found in GAO (1996) or Deng, Quigley, and VanOrder (2000). For the national sample, the model estimates that there are three categories of borrowers, with about 10% to 20% in the very slow prepayment category, about 30% to 40% in the medium speed prepayment category, and the remainder in the rapid prepayment category. Because the factor loadings are opposite in sign for the claim

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[17]The standard deviation may overstate the degree to which appraisals differ from price, as it is driven largely by a few positive outliers. About half of appraisals are exactly the sale price, and the interquartile range is 1.9%. For AVMs, the interquartile range for the difference between AVM and transaction price is 17.5%, or 9 times as large. The AVM and Appraisal ratios were truncated at +/- 50% of price.

and prepayment regressions, borrowers who are fast prepayers are predicted to be slow claim terminators, a result consistent with adverse selection at time of prepayment. The Box-Cox baseline hazard parameter, lambda, is negative and generally about -1, implying that a baseline of the form 1/time gives the best fit to the data, a remarkably sensible form for the baseline, as it allows a rapidly rising hazard in the early part of a loan's life followed by an essentially flat hazard. Except for GAO (1996) which finds a similar form, to the best of my knowledge no one has used such an inverse transform for a baseline mortgage termination hazard.

One potential disadvantage to working with conditional hazard rates is the potential for the competing risk of prepayment to influence the default regression results. It would be possible, for example, for appraisal or AVM estimates to have an impact on conditional claim rates, but not on unconditional claim rates, if low appraisals or AVM estimates resulted in higher prepayment rates. The conditional claim rates would be high, not because claims were high, but because survival was low. To test for this possibility, the conditional prepayment rate was also modeled as a function of standard prepayment variables, such as the ratio of book-to-market value of the mortgage (splined at 1), standard underwriting variables, and appraisal and AVM estimate variables. The logistic regression results for prepayment are in Table IV.1. The AVM ratio has a statistically significant impact on prepayment rates, but the coefficients on both AVM and Appraisal ratios are small in magnitude, indicating that the conditional claim rate results reflect higher claims, and not merely lower survival. To establish this, a simulation was run in which the average conditional claim rates and conditional prepayment rates for the full national sample were integrated over 5 years to produce a 5-year claim rate. The coefficients from the claim regressions were used to adjust the conditional claim rates upward, assuming that the AVM estimate was 10% below the sale price. For example, using the full sample GAOrisk coefficient of 0.7, the 5-year claim rate increased by 6.5%. When the AVM Ratio coefficient from the prepayment regression was also used to adjust the conditional prepayment rate upward, the 5-year claim rate rose by 4.5%. Therefore, the increase in prepayment rate acted as a partial offset to the elevated conditional claim rates.

Table IV.1 All	Prepay								
Parameter	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**	**Estimate**	**Std. Error**	**T**
intercept	-17.05	1.12	15.22	-17.49	1.11	15.75	-17.45	1.11	15.79
gamma	0.36	0.08	4.52	0.37	0.08	4.48	0.38	0.08	4.47
lambda	-0.88	0.14	6.22	-0.88	0.14	6.20	-0.87	0.14	6.09
GAOrisk	-0.05	0.02	2.08	-0.05	0.02	2.13	-0.05	0.02	2.08
FICO	0.39	0.05	7.81	0.41	0.05	8.21	0.41	0.05	8.24
frontend	1.45	0.40	3.61	1.30	0.40	3.23	1.30	0.40	3.23
noFICO	-0.31	0.10	3.05	-0.34	0.10	3.34	-0.34	0.10	3.31
reserve	0.09	0.06	1.38	0.08	0.06	1.21	0.08	0.06	1.22
underserved	-0.23	0.06	3.76	-0.21	0.06	3.51	-0.21	0.06	3.50
ARM	0.95	0.14	6.57	0.89	0.14	6.24	0.89	0.14	6.22
firsttime	-0.30	0.08	3.88	-0.29	0.08	3.42	-0.29	0.08	3.81
Condo	0.01	0.12	0.11	0.08	0.12	0.63	0.08	0.12	0.63
releqphi	4.32	0.29	14.91	4.24	0.29	14.61	4.26	0.29	14.62
releqplo	7.31	0.83	8.78	7.17	0.83	8.59	7.14	0.84	8.54
Factor_loading	3.78	0.48	7.81	3.60	0.43	8.44	3.56	0.39	9.19
Appraise_ratio	0.14	0.59	0.22	0.00	0.00	0.00	0.50	0.63	0.79
AVM_ratio	0.00	0.00	0.00	-0.25	0.17	1.45	-0.29	0.18	1.60
AVMconfidence	0.00	0.00	0.00	1.07	0.20	5.42	1.06	0.20	5.37

Table V.1	All		Disclose		Atlanta	
	rsq=.185 n=163		Rsq=.215 N=129		Rsq=.166 N=83	
Variable	Estimate	T	Estimate	T	Estimate	T
intercept	1.474	0.640	1.930	0.700	1.380	0.570
LTV	-0.656	0.270	-1.206	0.410	-1.011	0.400
FICO	-0.023	0.730	-0.021	530	-0.025	0.900
noFICO	0.094	1.920	0.100	1.710	-0.016	0.370
appreciation	-0.324	1.540	-0.331	1.380	0.152	0.560
noterate	0.032	1.460	0.043	1.680	-0.008	0.470
Log origination$	-0.002	4.990	-0.003	4.910	-0.001	2.170
Appraise_ratio	-0.183	0.300	-0.063	0.080	0.539	0.800
AVM_ratio	-0.193	2.610	-0.228	2.490	-0.346	2.920
AVMconfidence	0.300	0.030	0.079	0.620	0.138	1.190

Turning to loss given default, OLS regressions indicate that loss rates, defined as the dollars lost on a defaulted loan divided by the original mortgage balance, are a function of the AVM estimate of the property value (Table V.1). In the national samples, the higher is the AVM estimate, the lower is FHA's percentage lost. Original mortgage amount and post-origination price appreciation are also significant determinants of losses, with smaller losses in faster appreciating states, and smaller (percent) losses on larger loans, consistent with a substantial fixed cost component of total losses (foreclosure costs, for example). Appraisal differences have the right sign, but are small in magnitude and never close to significance.

In the Atlanta sample, neither the AVM nor the Appraisal ratios are a significant predictor of 90-day delinquency, although the AVM ratio always gets the right sign (see Table II.5).[18] Neither ratio is a significant predictor of claim rates, although the AVM ratio gets the right sign with an asymptotic T statistic near 1 (Table III.5). In Atlanta, the AVM ratio is also a significant predictor of loss rates, while the appraisal difference is not (Table V.1). Presumably the small number of claims in the Atlanta sample (107 out of a sample of 1116) limits the ability of any model to predict claim rates or losses effectively.

6. Conclusions

AVM estimates are predictive of both claim and delinquency propensities. Appraisal ratios also have predictive power for claims. Examined separately, each is useful as a predictor of the claim propensity of a mortgage. Entered together, the correlation between the two estimates is weak enough that each serves as a useful indicator of credit

[18]In the interest of space, only the full model for the GAOrisk specification is included for the Atlanta results. Other results were similar, with AVM values predictive of risk and appraisal ratios insignificant, and with the GAOrisk specification slightly outperforming the TOTAL scorecard specification.

risk, although the significance levels are higher on the AVM estimate when both are in the regression.

The confidence measure attached to the AVM estimate also serves as a predictor of credit risk. Properties that are easier to value have lower credit risk, even after conditioning on a host of standard underwriting variables. Additionally, AVM estimates are a significant predictor of loss given default, an important but often ignored dimension of credit risk.

Much of the value of an appraisal presumably comes prior to origination, in preventing transactions at prices far above market value, or contributing to the renegotiation of price prior to closing. The results here should not be taken to imply that appraisals have less value than AVMs, only that appraisal values have less post-origination predictive power than do AVMs.

These results confirm the value of econometric estimates of property value first found by LaCour-Little and Malpezzi, using a more recent, larger, and nationally representative sample, and focusing on claims and losses, not just delinquency. Additionally, this work demonstrates the utility of commercial, off-the-shelf, AVM estimates for predicting credit risk. Finally, the results demonstrate the usefulness of appraisal estimates in the prediction of claim propensities, over and above the information contained in AVMs.

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