

A Tale of Two Tensions:

Balancing Access to Credit and Credit Risk in Mortgage Underwriting

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January 7, 2015 (Submission to REE)

Abstract

Over the years 2000 through 2007, mortgage market underwriting conditions eased in response to public policy demands for increased homeownership. This easing of acceptable credit risk in order to accommodate increased access to credit, when coupled with the unanticipated house price declines during the Great Recession, resulted in substantial increases in delinquencies and foreclosures. The response to this mortgage market crisis led to myriad changes in the industry, including tightened underwriting standards and new market regulations. The result is a growing concern that credit standards are now too tight, restricting the recovery of the housing market.

Faced with this history, policy analysts, regulators, and industry participants have been forced to consider how best to balance the tension inherent in managing mortgage credit risk without unduly restricting access to credit. Our research is unique in providing explicit consideration of this tradeoff in the context of mortgage underwriting.

Using recent mortgage market data, we explore whether modern automated underwriting systems (AUS) can be used to extend credit to borrowers responsibly, with a particular focus on target populations that include minorities and those with low- and moderate incomes. We find that modern AUS do offer a potentially valuable tool for balancing the tensions of extending credit at acceptable risks, either by using scorecards that mix through-the-cycle and stress scorecard approaches or by adjusting the cutpoint—more relaxed cutpoints allow for higher levels of default while providing more access, tighter cutpoints accept fewer borrowers while allowing less credit risk.

Introduction

U.S. residential mortgage markets changed dramatically during the past several years. In the early 2000s, public policy focused on expanding credit access and homeownership and specifically targeted a reduction in the homeownership gap between minority and non-minority households and between higher- and lower-income families.¹ Relaxation of underwriting standards, accompanied by a surge in subprime lending and an attendant proliferation of new products, resulted in many borrowers who could not meet traditional underwriting standards being able to obtain home mortgages and achieve home ownership.

However the environment changed with the mortgage market crisis of 2007 and 2008 when the subprime sector collapsed nearly entirely and delinquency and foreclosure rates increased throughout the country. In response, underwriting standards tightened and legislation was passed imposing more stringent regulations on the mortgage industry, particularly the Dodd-Frank Act regulations, which introduced both Qualified Mortgage (“QM”) and Qualified Residential Mortgage (“QRM”) standards. While providing assurance that the performance of recent mortgage originations will reduce the likelihood of another housing crisis, this tightening of standards comes at a significant cost in terms of access to credit. Balancing the tension between access to credit and the management of credit risk remains an ongoing concern.

The rich history of mortgage performance data over this period offers an opportunity to better distinguish mortgage programs and combinations of borrower and loan characteristics that perform well in stressful economic environments from those that do not. The relaxed underwriting standards of the

¹ For example, former United States Department of Housing and Urban Development (HUD) Secretary Mel Martinez states in 2002 that “The Bush Administration is committed to increasing the number of Americans, particularly minorities, who own their own homes.”

2000s provide plentiful performance information on borrowers who stretched for credit, but then experienced the stressful post-origination environment of declining house prices and rising unemployment. While many of these loans performed poorly, a large number performed well. Our goal is to identify the characteristics that distinguish between these two groups.

We specifically examine whether the recent data can be used to create a modern automated underwriting scorecard that effectively and responsibly extends mortgage credit to the general population, and to underserved or targeted borrowers who reside in low-income communities, make low down payments, and have poorer credit histories. Our analysis focuses on mortgage underwriting, rather than mortgage pricing. This reflects the two-stage approach to mortgage lending broadly practiced in the United States—originators first underwrite applications to determine whether they qualify for origination, then price the loans that are originated successfully.

There are four steps necessary to complete this exercise. First, we empirically estimate a mortgage delinquency model. Second, we convert the estimated delinquency model to an underwriting scorecard for assessing risk, where higher scores signify higher risk. Third, we determine a scorecard value (a “cutpoint” or risk threshold) that demarcates the marginal risk tolerance—score values equal to or below the cutpoint are viewed as acceptable risk; score values above the cutpoint are not. Fourth, we process borrowers through this prototype of an automated underwriting system. We then determine the proportion of the population of mortgage applicants that is within acceptable risk tolerances, and the historic performance of these “acceptable” loans.

The main data we use for this analysis are loan-level observations from CoreLogic on mortgages originated in the conventional (prime and subprime) and government sectors from 1999 through 2009. For each of the three market sectors, we separately estimate the probability that borrowers will become 90-days or more delinquent on their loans within the first three years after origination. Included in the

model are standard controls for borrower and loan characteristics, as well as for key macroeconomic factors affecting mortgage performance post-origination (specifically, changes in house prices, interest rates, and unemployment rates).

Underwriting scorecards provide *ex ante* assessments of mortgage risk at origination, so creating scorecards requires appropriate treatment of the post-origination variables in our estimated models. Two broad approaches are possible. One approach attempts to forecast post-origination variables across borrower locations and over time. The other approach sets post-origination variables to constant values for all borrowers and all time periods. We use the latter approach. Specifically, we create two separate scorecards. The first scorecard sets post-origination values of house prices, interest rates, and unemployment rates to their constant long run average levels (a “through-the-cycle” scorecard). The through-the-cycle scorecard is inherently “optimistic” with respect to credit risk, and therefore reflects a focus on access to credit. The second scorecard sets post-origination values of house prices, interest rates, and unemployment rates to the varying *ex post* values defined by the Federal Reserve in an adverse scenario (a “stress” scorecard) as defined in the 2014 supervisory stress test for very large banking organizations.² The stress scorecard focuses on “tail” events which are unlikely to occur and is meant to prevent crisis outcomes such as those observed during the Great Recession. This scorecard, therefore, represents a focus on credit risk management.

The next challenge requires choosing appropriate scorecard cutpoints for delimiting loans within acceptable risk tolerances. This, in combination with the choice of scorecard, is where much of the tension between credit access and credit risk resides. Higher cutpoints provide greater access at the cost of increasing credit risk; lower cutpoints limit credit risk but restrict access.

² See <http://www.federalreserve.gov/bankinforeg/stress-tests/2014-appendix-a.htm>.

As the choice of a cutpoint is a complicated policy/business decision, we provide results for a variety of possible cutpoints, ranging from a low of a 5 percent delinquency rate, to a high of a 20 percent delinquency rate. In an effort to put forward a possible compromise between access and credit risk, we explore in more detail results for alternative cutpoints that are market segment-specific; 5 percent for prime loans, 15 percent for subprime loans, and 10 percent for government loans. We argue that these values represent reasonable risk tolerances by approximating the observed delinquency rates in these segments between 1999 and 2001.

The combination of scorecards and cutpoints creates working facsimiles of modern automated underwriting systems, and we apply these systems to both the full and target populations.³ For this exercise, our “target” population is defined as borrowers with loan-to-value (“LTV”) ratios of 90 percent or above, with FICO scores of 720 or below or missing, and who are located in census tracts with median incomes below 80 percent of area median income. This group is generally reflective of “underserved” borrowers for whom there is particular policy concern.

We find that automated underwriting, with a judicious combination of scorecard and cutpoint choice, offers a potentially valuable tool for balancing the tensions of extending credit at acceptable risks. One approach entails using scorecards that mix the through-the-cycle and stress scorecard approaches to post-origination values of key economic variables. Moving closer to a through-the-cycle scorecard provides more focus on access to credit. Moving closer to a stress scorecard provides more focus on the control of risk. The second approach is to adjust the cutpoint—more relaxed cutpoints allow for higher

³ We weight the data using weights based on the proportion of the target population in the Home Mortgage Disclosure data (“HMDA”) to ensure that the target population in our data is representative of the target population in HMDA. This allows us to draw inferences to the full population.

levels of default while providing more access, tighter cutpoints have accept fewer borrowers while allowing less credit risk.

Previous Literature

A considerable body of research has examined outcomes from the mortgage market crisis during the past decade. Of particular relevance for this research are studies that examine specific underwriting standards and products that may be intended for different segments of the population, or that address the balancing of access to credit and credit risk.

A recent paper by Quercia, Ding, and Reid (2012) specifically addresses the balancing of credit risk and mortgage access for borrowers – the two tensions on which we focus. Their paper narrowly focuses on the marginal impacts of setting QRM product standards more stringently than those for QM.⁴ They find that the benefits of reduced foreclosures resulting from the more stringent product restrictions on loan-to-value ratios (“LTV”), debt-to-income ratios (“DTI”) and credit scores do not necessarily outweigh the costs of reducing borrowers’ access to mortgages, as borrowers are excluded from the market.

Pennington-Cross and Ho (2010) examine the performance of hybrid and adjustable rate mortgages (ARMs). After controlling for borrower and location characteristics, they find that high default risk borrowers do self-select into adjustable rate loans and that the type of loan product can have dramatic impacts on the performance of mortgages. They find that interest rate increases over 2005–2006 led to large payment shocks and with house prices declining rapidly by 2008, only borrowers with excellent credit history and large amounts of equity and wealth could refinance.

⁴ For details of the QRM, see Federal Housing Finance Agency, Mortgage Market Note 11-02. For details of the QM, see http://files.consumerfinance.gov/f/201310_cfpb_qm-guide-for-lenders.pdf.

Amromin and Paulson (2009) find that while characteristics such as LTV, FICO score, and interest rate at origination are important predictors of defaults for both prime and subprime loans, defaults are principally explained by house price declines, and more pessimistic contemporaneous assumptions about house prices would not have significantly improved forecasts of defaults.

Courchane and Zorn (2012) look at changing supply-side underwriting standards over time, and their impact on access to credit for target populations of borrowers.⁵ They use data from 2004 through 2009, specifically focusing on the access to and pricing of mortgages originated for African-American and Hispanic borrowers, and for borrowers living in low-income and minority communities. They find that access to mortgage credit increased between 2004 and 2006 for targeted borrowers, and declined dramatically thereafter. The decline in access to credit was driven primarily by the improving credit mix of mortgage applicants and secondarily by tighter underwriting standards associated with the replacement of subprime by FHA as the dominant mode of subprime originations.

These studies all highlight the inherent tension between access to mortgage credit and credit risk. They also stress the difficulty in finding the “correct” balance between the two, and suggest the critical importance of treating separately the three mortgage market segments—prime, subprime, and government-insured (FHA)—because of the different borrowers they serve and their differing market interactions. The research also provides some optimism that a careful examination of recent lending patterns will reveal opportunities for responsibly extending credit while balancing attendant credit risks.

⁵ See also Courchane and Zorn (2011).

Data

Our analysis uses CoreLogic data for mortgages originated between 1999 and 2009. The CoreLogic data identify prime (including Alt-A), subprime, and government loans serviced by many of the large, national mortgage servicers. These loan-level data include information on borrower and loan product characteristics at the time of origination, as well as monthly updates on loan performance through 2012:Q3. Merged to these data are annual house price appreciation rates at a zip code level from the Freddie Mac Weighted Repeat Sales House Price Index, which allow us to update borrower home equity over time.⁶ We prefer this house price index to the FHFA's, as the latter are not available at the zip code level. The CoreLogic data do not provide Census tract information, so we use a crosswalk from ZIP codes to 2000 Census tracts.⁷ We also merge in county level unemployment rates from the Bureau of Labor Statistics, which are seasonally adjusted by Moody's Analytics.⁸ Finally, we include changes in the conventional mortgage market's average 30-year fixed mortgage ("FRM") rate reported in Freddie Mac's Primary Mortgage Market Survey.⁹

The CoreLogic data are not created through a random sampling process and so are not necessarily representative of the overall population, or our target population. This is not a problem for estimating our delinquency model, but it does create concern for drawing inference with our scorecards. To address this potential concern we apply appropriate post-sample weights based on HMDA data to enhance the representativeness of our sample. We develop weights by dividing both the HMDA and the CoreLogic data into categories, and then weight so that the distribution of CoreLogic loans across the

⁶ While these data are not publicly available, the metro/state indices can be found is available at: <http://www.freddiemac.com/finance/fmhpi/>.

⁷ Missouri Census Data Center, available at: <http://mcdc.missouri.edu/websas/geocorr12.html>.

⁸ The unemployment rate is from the BLS Local Area Unemployment Statistics (<http://www.bls.gov/lau/>).

⁹ These data are available publicly at: <http://www.freddiemac.com/pmms/pmms30.htm>.

categories is the same as that for HMDA loans. The categories used for the weighting are a function of loan purpose (purchase or refinance), state, year of origination, and loan amount. Because we rely on a post-sample approach and cannot create categories that precisely define our target population, our weighting does not ensure representativeness of the CoreLogic data for this group. Nevertheless, it likely offers a significant improvement over not weighting.

We also construct a hold out sample from our data to use for inference. This ensures that our estimated models are not over-fitted. The holdout sample was constructed by taking a random (unweighted) sample of 20 percent of all loans in our database. All summary statistics and estimation results (Exhibits 1-2 and Appendix) are reported based on the unweighted 80 percent estimation sample. Consistent with our focus on identifying responsible credit opportunities, we restrict our analysis to first lien, purchase money mortgage loans. Summary statistics for the continuous variables used in our delinquency estimation are found in Exhibit 1. Exhibit 2 contains summary statistics for the categorical variables.

As shown in Exhibit 1, the average LTV at origination is 97 percent for government loans. This is considerably higher than for the prime market, where first lien loans have LTVs less than 80 percent, on average.¹⁰ We also observe the expected differences in FICO scores, with an average FICO score in the prime sector of 730, 635 for subprime, and 674 for government loans. The prime market loan amount (i.e., unpaid principal balance, or UPB, at origination) averages \$209,000, with the government loan amount the lowest at a mean of \$152,000. The mean value in the subprime population is below that for prime at \$180,000. DTI ratios do not differ much between prime and government loans, and the DTI for subprime is unavailable in the data. As DTI is a key focus in the efforts of legislators to tighten

¹⁰ The mean LTV for subprime mortgages is surprisingly low at 83 percent, although this likely reflects the absence of recording second lien loans, which would lead to a higher combined LTV.

underwriting standards, we use it when available for estimation. The equity measures post-origination reflect the LTV on the property as house prices change in the area.

Exhibit 1. Summary Stats for Continuous Variables (80% Estimation Sample) – Statistics Not Weighted				
	All	Prime	Subprime	Government
Loans (unweighted)	21,725,528	13,894,140	2,503,164	5,328,224
Chg in Mortgage Rate, 1 Yr Post-Orig.	-0.14%	-0.12%	0.04%	-0.30%
% Missing	0.00%	0.00%	0.00%	0.00%
St. Dev.	0.61%	0.60%	0.58%	0.64%
Chg. in Mortgage Rate, 2 Yrs Post-Orig.	-0.21%	-0.22%	-0.10%	-0.25%
% Missing	0.00%	0.00%	0.00%	0.00%
St. Dev.	0.56%	0.57%	0.54%	0.53%
Chg. in Mortgage Rate, 3 Yrs Post-Orig.	-0.24%	-0.23%	-0.27%	-0.29%
% Missing	0.00%	0.00%	0.00%	0.00%
St. Dev.	0.55%	0.55%	0.53%	0.55%
Debt-to-Income Ratio (DTI)	36.08%	35.86%	0.00%	36.84%
% Missing	62.03%	58.77%	99.98%	52.72%
St. Dev.	15.10%	15.21%	0.00%	14.69%
Equity Measure 1-year Post Orig.	95.72%	95.53%	93.86%	97.38%
% Missing	3.04%	2.06%	8.52%	3.02%
St. Dev.	10.35%	10.80%	9.33%	9.15%
Equity Measure 2-Yrs Post Orig.	94.79%	94.53%	94.53%	95.74%
% Missing	3.04%	2.06%	8.52%	3.02%
St. Dev.	20.20%	21.02%	22.12%	15.95%
Equity Measure 3-Yrs Post Orig.	96.04%	95.73%	100.67%	94.39%
% Missing	3.04%	2.06%	8.52%	3.02%
St. Dev.	28.50%	29.05%	34.64%	21.84%
FICO	701.9	727.9	635.1	665.1
% Missing	14.24%	15.77%	9.08%	12.70%
St. Dev.	69.8	55.1	63.6	68.8
Loan-to-Value Ratio (LTV), at Orig.	82.91%	78.34%	83.22%	96.94%
% Missing	1.62%	1.54%	2.43%	1.44%
St. Dev.	14.95%	14.64%	11.09%	7.07%
Loan Amount (Orig. UPB (\$))	\$190,565	\$207,370	\$180,374	\$144,534
% Missing	0.00%	0.00%	0.00%	0.00%
St. Dev.	\$328,141	\$362,915	\$267,006	\$227,522
Unemployment Rate 1-Year Post Orig.	5.58%	5.40%	5.03%	6.47%
% Missing	0.11%	0.10%	0.22%	0.08%
St. Dev.	2.27%	2.09%	1.53%	2.88%
Unemployment Rate 2-Yrs Post Orig.	6.02%	5.94%	5.40%	6.64%
% Missing	0.09%	0.09%	0.12%	0.09%
St. Dev.	2.56%	2.53%	1.93%	2.85%
Unemployment Rate 3-Yrs Post Orig.	6.57%	6.55%	6.45%	6.69%
% Missing	0.08%	0.08%	0.05%	0.09%
St. Dev.	2.78%	2.81%	2.72%	2.72%

All three markets faced significant house price declines, as captured by the change in home equity 1, 2 or 3 years after origination. For all three mortgage market segments, post-origination equity measures (post-origination estimated LTV) averaged over 90%. Post -origination unemployment rates are highest, on average, in the geographies with government loans, although the differentials among market segments fell after 3-years post origination.

Exhibit 2. Summary Statistics for Categorical (Class) Variables (80% Estimation Sample)				
Statistics Not Weighted				
	All	Prime	Subprime	Government
ARM	12.60%	48.50%	4.72%	14.91%
Balloon	0.39%	4.91%	0.05%	0.82%
FRM-15	7.68%	1.61%	1.16%	5.63%
FRM-30	68.25%	22.31%	90.14%	67.79%
FRM-Other	4.48%	1.71%	2.73%	3.81%
Hybrid	6.59%	20.97%	1.20%	7.04%
Other	41.05%	33.13%	43.57%	40.71%
Retail	33.70%	21.20%	22.12%	29.87%
Wholesale	25.25%	45.67%	34.31%	29.42%
Full Documentation	29.83%	49.38%	41.80%	34.52%
Missing	38.89%	18.44%	42.30%	37.35%
Not Full Documentation	31.27%	32.19%	15.90%	28.13%
Owner-Occupied	83.43%	85.88%	91.84%	85.48%
Not Owner-Occupied	16.57%	14.12%	8.16%	14.52%
Condo	13.82%	7.75%	6.97%	11.70%
Single Family	86.18%	92.25%	93.03%	88.30%

Exhibit 2 presents the summary statistics for the categorical (class) variables in our sample. Some expected results emerge. The subprime segment has the largest share of loans originated through the wholesale channel, at 45.7 percent, while the wholesale share for the prime segment was only 25.2 percent. Nearly half (48.5 percent) of subprime loans were adjustable rate mortgage (“ARM”) loans while only 22.3 percent of subprime loans were the standard 30-year FRM product. In contrast, 69.1

percent of prime loans were 30-year FRMs and an additional 7.8 percent were 15-year FRMs. Nearly all of the government loans (91.2 percent) were 30-year FRMs. The documentation figures are somewhat surprising, with nearly half (49.4 percent) of subprime loans indicating full documentation. The low share of full documentation loans in the prime sector (about 30 percent) likely reflects the inclusion of Alt-A loans, which are defined to be prime loans in the CoreLogic data.¹¹

In our analyses, we focus on access to credit and credit risk outcomes for all borrowers. However many homeownership and affordable lending programs focus more narrowly on assessing opportunities for responsibly extending mortgage credit to borrowers with low down payments and poor credit histories, or who are otherwise underserved by the prime market (“target population”). As a result of long standing public policy objectives focused on the value of homeownership, both government insured mortgage programs (such as FHA) and the GSEs have long held missions to meet the needs of underserved borrowers, including low income, minority and first time homebuyers.¹² Programs meeting this mission are tasked with balancing access to credit for borrowers with any attendant increases in credit risk.

Therefore, aside from our focus on the opportunities provided to the full population of borrowers, we also provide an analysis of scorecard outcomes for a specific target population. We define this target population as borrowers who receive first lien, purchase money mortgages on owner-occupied properties located in census tracts with median incomes below 80 percent of the area median income, with FICO scores less than or equal to 720, and with LTV ratios greater than or equal to 90 percent.

¹¹ Historically, Alt-A loans were originated through prime lenders, offering their more credit worthy customers a simpler origination process.

¹² Both the Community Reinvestment Act (CRA) and the Federal Housing Enterprises Financial Safety and Soundness Act of 1992 (the 1992 GSE Act) encouraged mortgage market participants to serve the credit needs of low- and moderate income borrowers and areas.

Limiting our analysis to borrowers who live in lower-income census tracts is especially constraining, as many borrowers with high LTVs and lower FICO scores live elsewhere. However, our data lack accurate income measures, and public policy considerations encourage us to include an income constraint in our definition of the target population.¹³ As a consequence, loans to target borrowers account for a small percentage of the total loans made during our period of study (roughly four percent). We can be assured, however, that our target population is composed of borrowers who are an explicit focus of public policy.

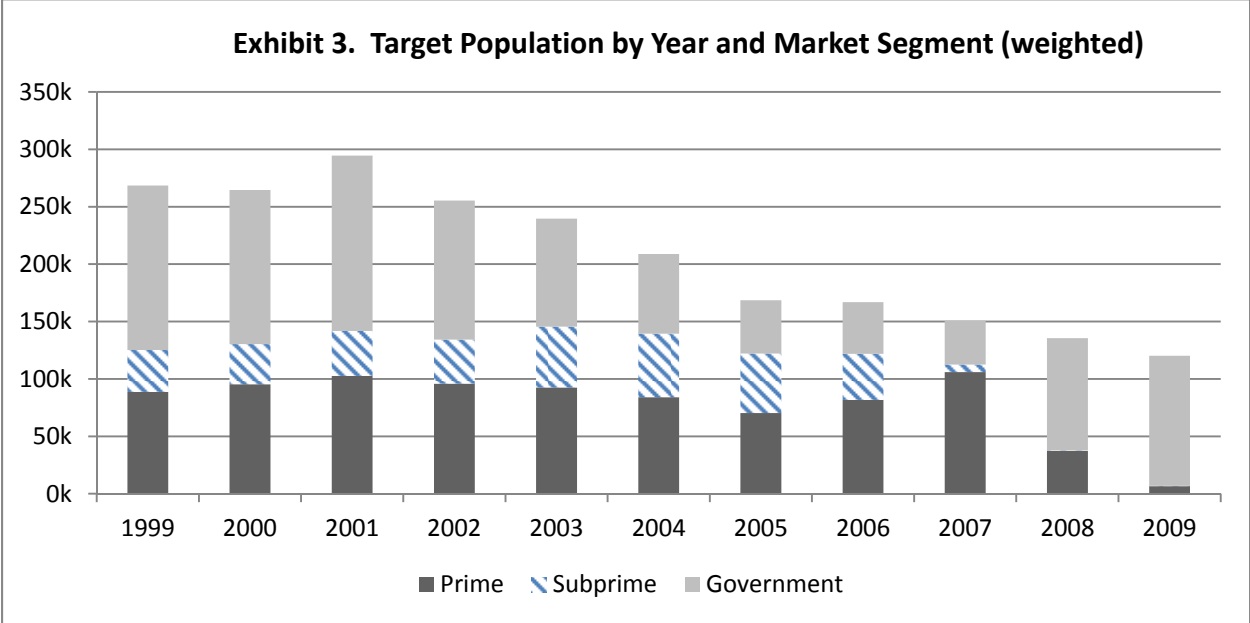


Exhibit 3 provides a graphical illustration of the HMDA-weighted distribution of target population loans in our sample across the three market segments. The dramatic shift over time in the share going to the government sector is obvious, as is the reduction in the number of loans originated to the target population by all three segments, combined, post-crisis.

¹³ For example, GSE affordable goals are stated with respect to low- and moderate income borrowers and neighborhoods.

Analysis

Our analysis begins with the estimation of mortgage performance models over the crisis period. We use loan-level origination data from 1999 through 2009 to estimate models of loans becoming 90-days or more delinquent in the first three years after origination. These models include standard borrower and loan characteristics at origination, as well as control variables measuring changes in house prices, unemployment rates, and interest rates post-origination. They also include several interaction terms for the borrower, loan, and control variables.

We then use our estimated delinquency models to specify two underwriting scorecards—a through-the-cycle scorecard and a stress scorecard.¹⁴ We next apply various cutpoints (risk thresholds) to our scorecards to define levels of acceptable risk. By definition, loans with risk scores (delinquency probabilities) at or below the cutpoint are assumed to be within appropriate (acceptable) risk tolerances.

The scorecard and cutpoint combinations provide working prototypes of an automated underwriting system. Our final step applies these prototypes to the full and target populations and assesses the results.

Estimating the Models

We estimate three separate delinquency models based on an 80 percent sample of first-lien, purchase money mortgage loans in our data. Separate models were estimated for prime loans (including Alt-A loans), subprime loans, and government loans, using an indicator provided in the CoreLogic data to

¹⁴ Additional scorecards constructed using “perfect foresight” and macroeconomic forecasts are available from the authors upon request.

assign each loan to its appropriate segment.¹⁵ We estimate separate models for each market sector because we believe there is clear market segmentation in mortgage lending. In the conventional market the lenders, industry practices, market dynamics, and regulatory oversight have differed between the prime and subprime segments.¹⁶ A similar distinction exists between the conventional and government segments—the latter focuses on first-time borrowers and lower-income households. Moreover, acceptable risk tolerances will necessarily vary across segments, as may concerns regarding access to credit.

Our process differs from the typical construction of underwriting systems in two important ways. First, while the CoreLogic data are reasonably rich in variables, they do not contain the detailed credit variables, such as tradeline balance to limits, number of open tradelines, and presence of mortgage late payments, that are a key component of most underwriting models. As a result our model assesses risk less accurately than production versions. Second, typical models are estimated on historical data, but the resulting scorecards are applied to future applications (i.e., out of sample). However, lacking knowledge and data on future states of the world, we use historical assessments and apply our scorecard to the 20 percent holdout sample. Thus, our scorecard may assess risk more accurately than production versions given that the data was contemporaneously generated. However we believe this is not a critical concern because we seek to illustrate how certain scorecard and cutpoint combinations might affect outcomes under future stressful market conditions.

¹⁵ Because this field is determined at CoreLogic, we are unable to define the specific parameters around the determination of subprime.

¹⁶ This structural segmentation also loosely translates into separation on the basis of risk—the prime segment generally caters to lower-risk borrowers, while the subprime segment generally caters to higher risk borrowers—however the distinction along this dimension is far from perfect. We are segmenting by market structure, not simply by market risk.

The dependent variable in our estimation is a loan becoming 90 days or more delinquent in the first three years after origination. Continuous explanatory variables include borrower FICO scores, mortgage market interest rates (Freddie Mac Primary Mortgage Market Survey rates), updated LTVs (derived using the Freddie Mac House Price Index), and local unemployment rates.¹⁷ The models also include categorical explanatory variables for loan amount (\$50,000-\$150,000, \$150,000-\$250,000, \$250,000-\$350,000, \$350,000-\$450,000, and greater than \$450,000); documentation type (full documentation, low documentation, missing documentation); origination channel (retail, wholesale, other); original LTV (less than 40 percent, 40 to 60 percent, 60 to 75 percent, 75 to 80 percent, 80 to 85 percent, 85 to 90 percent, 90 to 95 percent, 95 to 105 percent, 105 to 115 percent, and greater than 115 percent); product type (ARM, balloon, 15-year FRM (“FRM-15”), 30-year FRM (“FRM-30”), and other FRM and hybrids (“FRM-other”)); and condo and owner occupancy indicators. Finally, interactions were included between FICO score of borrower and whether FICO was missing, FICO score and loan amount, loan amount and LTV, and FICO score and LTV.¹⁸

The estimation results, based on the 80 percent sample, are presented in Appendix Tables A.1.a (prime), A.2.a (subprime), and A.3.a (government). Goodness-of-fit plots, applied to the holdout sample, are found in Tables A.1.b (prime), A.2.b. (subprime) and A.3.b. (government). Most of the variables in the

¹⁷ We include variables estimated to model post-origination home equity 1 year, 2 years, and 3 years post-origination. If equity one year post-origination is defined as ltv_1yr , then $ltv_1yr = ltv * upb_1yr / [upb / (1 + hpa_1yr_orig)]$ where ltv = LTV at origination, upb = upb at origination and hpa_1yr_orig = house price growth (in %) from origination to 1 year after origination and upb_1yr = upb 1 year after origination, assuming no delinquency/curtailment, and a fully amortizing loan. Then $upb_1yr = upb + FINANCE('CUMPRINC', initial_interest_rate/1200, original_term, upb, 1, 12)$; where $FINANCE$ is a SAS function used to compute the cumulative principal. See: <http://support.sas.com/documentation/cdl/en/lrdict/64316/HTML/default/viewer.htm#a003180371.htm>

¹⁸ We use an indicator variable for observations with missing DTI in the prime and government segments (this is the omitted category.) DTI is missing for all subprime loans. For missing FICO, we create a variable denoted as FICO2 and set scores when missing to 700 and to actual values otherwise. We interact FICO2 with a dummy for missing status.

prime delinquency model (Exhibit A.1.a) had the expected signs. Loans with LTV ratios less than 80 percent, full documentation loans, retail channel loans, loans under the conforming limits, and FRM loans are all less likely to become delinquent. As FICO score increases, the delinquency probability falls. Loans with higher LTV values have higher delinquency rates, with the loans in the over 100 LTV categories most likely to go delinquent. Owner occupants are less likely to become delinquent.

Most of the subprime results (Exhibit A.2.a) are similar to those in the prime model, with a few exceptions. As in the prime segment, owner-occupied and FRM loans are less likely to become 90 days delinquent. LTV also has a similar relationship with delinquency in both the prime and subprime models; however the parameter estimates on the high LTV prime loans exceed those for subprime, perhaps reflecting missing second lien loans in the subprime population. There are some differences in the two models, however. For example, full documentation subprime loans are more likely to become delinquent, as are loans from the retail channel. Higher FICO scores do not reduce the likelihood of subprime mortgage delinquency.

For the government segment, retail channel has the negative sign we observed in prime. Nearly all government loans are full documentation, so the result carries little meaning. Finally, higher LTV and lower FICO government loans scores have an increased probability of delinquency. Owner occupancy and the retail channel reduce the probability of delinquency, as do FRM loans.

We assess model fit by comparing model predictions to actual outcomes. The results of these comparisons are provided in the Appendix as Exhibits A.1.b, A.2.b, and A.3.b for the prime, subprime, and government estimations, respectively.¹⁹ In general we see that the models fit well. Specifically, the

¹⁹ Loans in each segment are first grouped by model prediction, and then divided into 200 equally-sized buckets of loans with similar model predictions. The mean model prediction and actual delinquency rates are calculated

scatter plots remain relatively close to the 45 degree reference line. To the extent that there is any systematic error in the model, it occurs for lower risk loans (toward the bottom left of the chart). This causes relatively little concern for our analysis because it is most important that the model well-fit in the area around likely cutpoints, which is located in the well-fitting higher risk (upper right-hand) section of the charts.

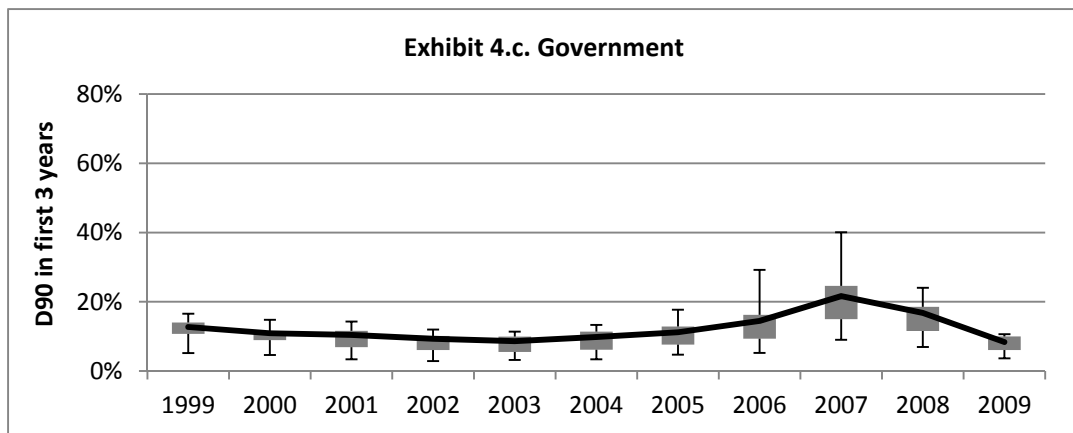
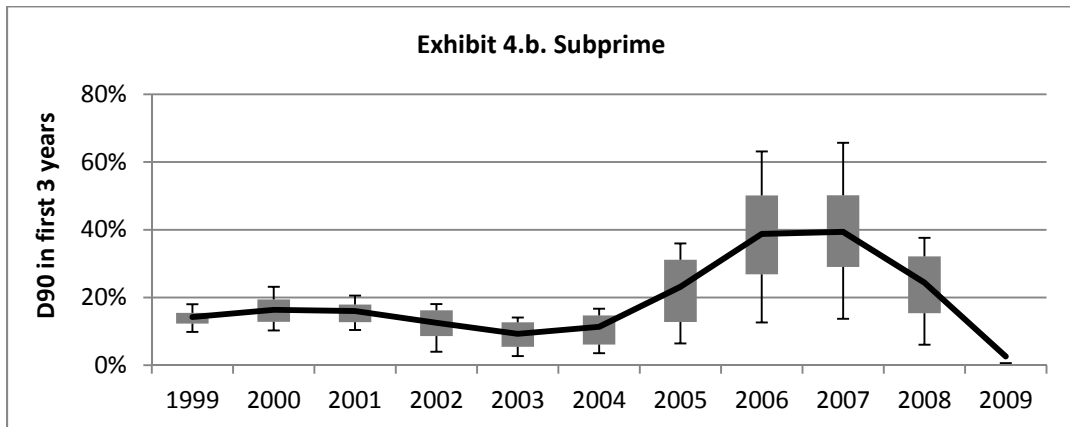
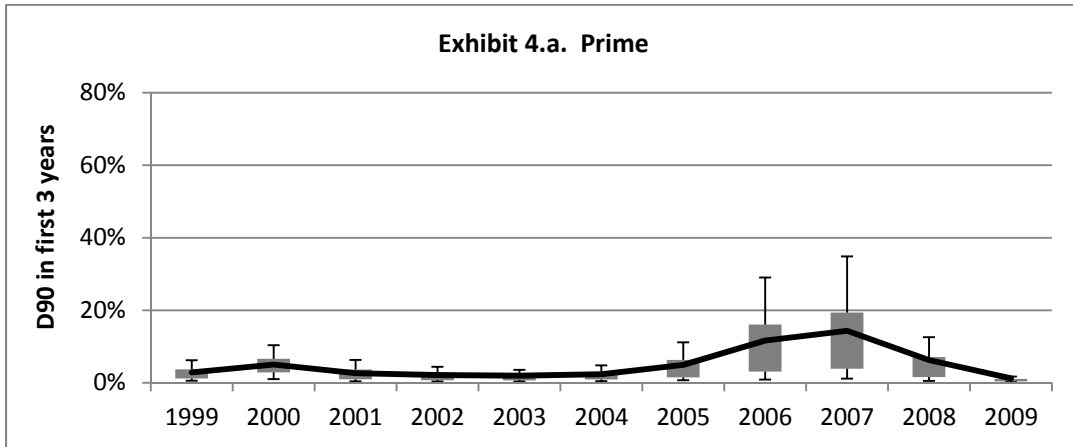
Finally, in Exhibits 4.a. (prime), 4.b. (subprime), and 4.c (government) we use predictions from our estimated model on the weighted holdout sample to provide a distributional sense of loans originated throughout the years in our sample. Specifically, using our predictions, we rank order loans within each market segment and origination year into approximately 200 buckets. For each bucket of loans, we compute the realized default rate. We then generate a box plot illustrating the distribution of average default rates over our 200 buckets by market segment and year.²⁰

The three charts below immediately highlight the dramatic increase in delinquency rates that occurred during the crisis years of 2005 through 2008. Clearly there is justification for a general concern over credit risk and the performance of loans under stressful conditions in particular. It is also interesting to compare the relative performance of loans across the market segments. In the years 1999 through 2004, prime loans were clearly the best performing, followed by government loans, and then subprime. However the government segment performed roughly as well as the prime segment during the crisis years. This is because Alt-A mortgages are primarily allocated to the prime segment (as they were

for each bucket, and then plotted in log-log scale. The model prediction is measured on the horizontal axis, and the actual delinquency rate is measured on the vertical axis. A 45-degree reference line is drawn in each chart, reflecting the combination of points where the models are perfectly predicting.

²⁰ The “box” in the box plot shows the interquartile range (“IQR”)—the scores between the 25th and the 75th percentiles. The “whiskers” go down to the 5th percentile, and up to the 95th percentile of scores. The 50th percentile (the median) falls within the box. The data are weighted via HMDA to more accurately reflect the underlying population.

primarily originated by prime lenders) and these loans performed very poorly. Regardless, both the prime and government segments look much better than subprime during the crisis years—as subprime delinquency rates reached an average of 40 percent for 2006 and 2007 originations.



Deriving the Scorecards

The second step of our analysis is to derive prime, subprime, and government scorecards from the estimated models. Scorecards are an *ex ante* assessment of the credit risk at origination associated with a particular borrower/loan combination. Our estimated delinquency models provide the basis for this assessment; although these models include both *ex ante* and *ex post* (post-origination) explanatory variables. The appropriate treatment of the post-origination explanatory variables is the key challenge for scorecard creation.

One approach, arguably the most typical, is to treat post-origination explanatory variables as controls in the scorecard.²¹ That is, to keep the value of these variables constant across borrowers and over time. This is the approach we use here, although we create two variants. The first version we call a “through-the-cycle” scorecard. For this scorecard we set post-origination variables to approximately their long run averages (house prices are set at a two percent annual increase, interest rates are assumed to remain unchanged after origination and unemployment rates are set at six percent). This provides a generally “friendly” view of credit risk, and so is reflective of a concern for access to credit issues. The through-the-cycle scorecard also has the policy advantage of being counter-cyclical.

We also create a second version that we call our “stress” scorecard. For this scorecard we incorporate the values of the *ex post* explanatory variables used by the Federal Reserve Board in its 2014 severely adverse stress test scenario. The Federal Reserve’s provides paths under the severely adverse scenario for several macroeconomic variables, including unemployment, house prices, and mortgage rates. This represents a hypothetical scenario containing both recession and financial market stress aimed to assess

²¹ An alternative approach is to forecast at origination the future values of the *ex post* explanatory variables. This is a challenging task in both theory and practice. A prototype version of such a scorecard is available from the authors on request.

the resiliency of U.S. financial institutions. In this regard our scorecard represents an outer-bound possibility of risk, and is clearly reflective of a concern for credit risk. For each loan scored under the stress scorecard, we use cumulative house price declines of 12.4 percent, 24.2 percent, and 24.7 for 1 year, 2 years and 3 years post origination respectively to update our equity variable in the stress scorecard. We expect the stress scorecard to be very tight with respect to access, which should limit its risk exposure during downturns. Separate scorecards are created for each of the models/markets: prime, subprime, and government. We believe it is enlightening to compare and contrast the results of the through-the-cycle and stress scorecards for each market. While we expect the through-the-cycle scorecard to lead to increased access to credit relative to the stress scorecard, it may achieve this at the cost of higher credit risk. We expect, for example, that it will perform significantly worse than the stress scorecard during down cycles.

Choice of Cutpoints

The third step in our analysis is to choose scorecard cutpoints. The cutpoints set the marginal risk tolerance for the scorecards, and so determine the levels at which loans switch from “acceptable” to “unacceptable” risks. The cutpoints, therefore, set the extreme bounds of within-tolerance risk for the scorecards, and are critical in setting the balance between access to credit and credit risk concerns.

Both policy and business considerations influence the determination of cutpoints. For example, a 10 percent delinquency rate might be viewed as an acceptable prime cutpoint during boom years when the market is optimistic and public policy is focused on expanding access to credit. However, that same 10 percent delinquency rate might be viewed as too high for a prime cutpoint during a recession, when the market is trying to limit credit exposure and public policy has shifted its focus to managing systemic risks and taxpayer losses. Lenders with more tolerance for risk might choose to operate in the subprime market segment, and will accept higher risk thresholds than lenders who want to operate in the prime

segment. Government-insured risk tolerance levels may vary with the health of the mortgage insurance fund, as well as other policy considerations.

It is not our intention to propose “correct” cutpoints for our scorecards. Rather, our goal is to illustrate how the interactions between scorecards and possible cutpoints affect access to credit and the management of credit risk, and to illustrate the potential for possible compromises. Toward this end, we provide a set of potential cutpoints for each scorecard. Specifically, we provide results for cutpoints of 5 percent, 10 percent, 15 percent, and 20 percent delinquency rates for each of our scorecards. This allows us to provide a range of alternative impacts on both the full and target populations.

To simplify our presentation and focus our analysis, we also concentrate on a select cutpoint for each market that offers a possible compromise between managing access and credit risk. This is determined by choosing among our four cutpoints for each market the one that most closely approximates the actual delinquency rate of marginal loans originated in the years 1999 through 2001. These years provide origination cohorts that experienced a relatively benign economic environment for the first three years after origination (neither expansive nor depressed), and their realized performance is not unduly affected by factors outside the control of underwriting.

Underwriting in the prime market during the 1999 through 2001 period was relatively standardized (arguably, neither too loose nor too tight), so we set the select cutpoint at the realized performance of borrowers around the 90th risk percentile from the full model prediction. This performance is most closely approximated by a cutpoint of 5 percent delinquency rates for the prime market (see Exhibit 4.a.

above), and by construction this results in about 90 percent of the prime loans originated in 1999, 2000, and 2001 being viewed as acceptable risk.²²

The subprime performance distribution (see Exhibit 4.b. above) displays a markedly different time trend than that observed in the prime market. Realized performance in the years 1999 – 2001 was worse than the performance of the 2002 – 2004 cohorts. This suggests that subprime underwriting in the earlier period was not as standardized as it was in the prime market during those years. Moreover, the differential in risk between prime and subprime lending appears greater in the earlier years, suggesting that subprime lending was relatively less conservative than prime lending in 1999 – 2001. Finally, the overall tolerance for accepting risk in mortgage lending has clearly declined in the recent environment. These factors persuade us to use a more restrictive standard for determining marginal borrows in the subprime segment than we do in the prime segment. For the subprime market we choose a cutpoint of a 15 percent delinquency rate, which results in only about one-half of the subprime loans originated in 1999 – 2001 being viewed as acceptable risk in terms of their realized outcomes.

The performance distribution of government-insured loans is shown in Exhibit 4.c. above. As with the subprime market, the box plots for government mortgage lending suggest that underwriting was not as standardized or (relatively) conservative as in the prime market from 1999 – 2002. Particularly striking is the more limited relative increase in the risk distributions of the 2006, 2007 and 2008 originations compared to the increase experienced by these cohorts in the subprime market. We therefore again impose a more restrictive standard for determining the marginal borrowers in the government market, but mitigate this somewhat because of the government sector's explicit goal of providing credit to first time and traditionally underserved home buyers. This yields a select cutpoint for the government sector

²² The 90th risk percentile is the scorecard prediction level that separates the 10 percent of borrowers with the highest predicted risks from the remained 90 percent of borrowers with lower predicted risks.

of a 10 percent delinquency rate, which results in about 60 percent of the 1999 through 2001 cohort being viewed as acceptable risk in terms of their realized outcomes.

Applying Scorecards to the Full and Target Populations

Our last step applies our automated underwriting scorecards to the full and target populations. As noted earlier, the target population represents only about four percent of overall originations during our period of study. Although a restrictive definition, we believe our resulting target population is highly reflective of the population focused on by most affordable housing initiatives. We use our through-the-cycle and stress scorecards to separately score borrowers, and then determine the percent of the population assessed as acceptable risks by each scorecard using the alternative cutpoints (expressing risk thresholds of 5, 10, 15, and 20 percent delinquency rates). Exhibit 5.a presents the results for the full population while Exhibit A.4.a., in the Appendix, presents the results for the target population. Exhibit 5.b. presents the share of defaults for the full population for each scorecard, in each risk threshold range. Exhibit A.4.b in the Appendix provides similar values for the target population.

As indicated in Exhibit 5.a., using a cutpoint of 5 percent we find that 85.1 percent of all prime borrowers are viewed as acceptable risks by the through-the-cycle scorecard over 1999-2009, while the stress scorecard yields only 60.8 acceptable risks among prime borrowers. If the risk threshold is relaxed to a level of 10 percent, 97.6 percent of the prime market borrowers are acceptable risk. Over time, at a 5 percent prime cutpoint, the percent of acceptable risks falls as the origination population reflects the historic relaxation of underwriting standards—the market includes more high risk borrowers, so a lower percent are accepted with the 5 percent cutpoint.

For the subprime market segment, the through-the-cycle scorecard assesses 39.7 percent as acceptable risk with a default risk threshold set at 15 percent, while only 4.7 percent are acceptable using the stress scorecard. If the risk threshold is held to 5 percent, only 2.5 percent are accepts.

Finally, in the government segment, using a 10 percent threshold, 61.1 percent of borrowers are acceptable risks with the through-the-cycle scorecard. At a 5 percent threshold, only 4.7 percent would have been able to receive mortgages.

As expected, the through-the-cycle scorecard accepts more borrowers than does the stress scorecard during a stressful environment, with the differential impacts of the two scorecards varying by market segment. The prime market, even with a lower risk threshold (5 percent cutpoint), accepts a significantly higher percentage of borrowers using either scorecard. The stress scorecard, because of its very pessimistic view of post-origination outcomes, completely eliminates access to credit in the subprime segment, and nearly eliminates the possibility of acceptable credit risks in the government segment.

Appendix Exhibit A.4.a., as shown in the Appendix, provides results for acceptable risks among target borrowers. Using our select set of cutpoints we find that 55.1 percent of the prime targeted borrowers are viewed as acceptable risks by the through-the-cycle scorecard. The stress scorecard yields 12.8 percent. For the subprime market these values are 24.9 and 0.2 percent, respectively, and for the government market they are 54.3 and 5.2 percent, respectively.

All of the borrowers in the full population received loans under the standards present at the time of origination. Applying a modern version of a through-the-cycle or stress scorecard, many of those borrowers would have failed to qualify for a loan. This suggests that automated underwriting systems also offer some potential for responsibly extending credit to the target population. However the

through-the-cycle and stress scorecards offer competing policy tradeoffs. The through-the-cycle scorecard extends credit to a larger percentage of the target population by providing greater access during expansionary cycles. The stress scorecard severely restricts access during periods of financial stress, as designed.

Exhibit 5.b. provides the share of defaults by risk threshold. In the prime market, at a 5 percent cutpoint, 85.1 percent of the borrowers are accepted but this group is responsible for only 55.9 percent of the defaults. In contrast, at a 15 percent subprime cutpoint, the through-the-cycle scorecard accepted 39.7 percent of borrowers representing 26.3 of defaults. Finally, in the government segment, while 61.1 percent were acceptable at a 10 percent cutpoint, that group's share of defaults was 44.6 percent.

Only the prime market is of interest when assessing the default share by cutpoint using the stress scorecard for the full population (Exhibit 5.b.). The stress scorecard accepted 60.8 percent using the 5 percent cutpoint and this resulted in loans which comprised 25.5 percent of the total defaults in the population. For the target population (Exhibit A.4.b.), the share of defaults for target borrowers in the prime segment is 35.1 percent with a 5 percent cutpoint; while it is 17.5 percent for subprime with a 15 percent cutpoint and 45.7 percent for government with a 10 percent cutpoint. In every case, the percent of acceptable risks outweighs the default share.

In summary, acceptable levels of risk can be achieved in two ways. Either the scorecard can reflect a more stressful environment post-origination, which means that the post-origination values of the macroeconomic variables are more pessimistic relative to the through-the-cycle scorecard, or the cutpoints can be adjusted. For example, in examining the results for the prime scorecard, 85.1 percent of the full population posed acceptable risks using the through-the-cycle scorecard using a 5 percent cutpoint. That dropped to 60.8 percent using the stress scorecard. Approximately the same percentage

of prime mortgages (88.0 percent) could be accepted using the stress scorecard, but that requires relaxing the cutpoint to 10 percent. It is similarly likely that using the through-the-cycle scorecard and tightening the cutpoints would lower the percent of acceptable risks in a manner similar to the application of the stress scorecard.

It is clear that using both levers to manage credit risk (a stress scorecard and tight cutpoints) virtually eliminates credit access in the subprime and the government market segments. For example, a 15 percent cutpoint and a stress scorecard in the subprime segment results in only 4.7 percent of the full population being approved for loans. Using the stress scorecard in the government segment, with a cutpoint 10 percent, would mean that only 10.3 percent of borrowers are acceptable credit risks. For the target population borrowers, using the stress scorecard and tighter cutpoints means that no borrowers are viewed as posing acceptable risks.

Exhibit 5.a. Percent of Acceptable Risk Borrowers by Risk Threshold Range, Full Population												
Scorecard: Through-the-Cycle												
Prime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	ALL
Less than 5%	89.1	85.6	91.0	89.8	87.5	85.5	83.6	78.5	71.2	83.1	92.1	85.1
5% to 10%	9.3	12.0	7.7	9.1	10.9	12.5	13.9	17.4	22.2	13.9	7.2	12.5
10% to 15%	1.0	1.5	0.8	0.7	1.1	1.3	1.7	2.5	3.6	1.9	0.5	1.5
15% to 20%	0.4	0.6	0.3	0.2	0.3	0.4	0.4	0.8	1.4	0.6	0.1	0.5
Greater than 20%	0.2	0.3	0.2	0.2	0.2	0.3	0.3	0.7	1.6	0.5	0.1	0.4
Subprime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.9	0.8	0.7	1.6	4.1	3.9	3.0	2.5	2.6	5.7	2.2	2.5
5% to 10%	8.4	8.0	7.6	13.7	19.7	14.8	13.9	12.0	9.9	8.3	8.4	12.9
10% to 15%	21.0	19.8	19.1	23.5	25.7	28.5	27.3	23.6	19.8	33.4	74.3	24.3
15% to 20%	30.9	35.7	35.8	35.2	28.9	33.6	31.6	29.4	29.1	39.4	8.1	32.2
Greater than 20%	38.7	35.8	36.7	26.0	21.6	19.3	24.2	32.4	38.6	13.2	7.1	28.1
Government	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	3.4	2.5	3.6	4.7	5.3	6.5	5.3	4.7	4.3	4.5	5.1	4.7
5% to 10%	45.6	31.8	52.7	51.7	56.8	55.8	49.4	44.2	48.1	57.8	62.1	56.4
10% to 15%	44.9	59.3	36.8	38.3	33.6	32.2	39.2	41.6	42.4	34.9	30.1	34.8
15% to 20%	1.5	3.1	3.3	2.0	1.2	1.2	2.3	4.8	1.3	0.5	0.3	1.2
Greater than 20%	4.6	3.4	3.7	3.3	3.2	4.3	3.8	4.7	4.0	2.3	2.5	2.9
Scorecard: Stress												
Prime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	65.5	55.6	66.8	66.6	63.5	60.1	56.8	51.9	46.9	57.3	75.1	60.8
5% to 10%	26.0	32.7	26.6	25.7	26.8	28.4	30.1	30.2	28.8	29.3	18.6	27.2
10% to 15%	6.1	8.3	4.7	5.8	7.1	8.3	9.0	11.6	14.7	8.8	4.8	8.2
15% to 20%	1.3	1.9	1.1	1.1	1.6	2.0	2.4	3.3	4.6	2.4	1.0	2.1
Greater than 20%	1.1	1.6	0.8	0.8	1.1	1.3	1.7	2.9	5.0	2.2	0.5	1.7
Subprime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.0	0.0	0.0	0.0	0.2	0.6	0.3	0.2	0.2	0.0	0.0	0.2
5% to 10%	0.5	0.3	0.3	0.8	2.6	2.3	2.1	1.7	1.8	4.7	4.8	1.5
10% to 15%	2.5	1.9	1.8	2.4	4.7	3.6	3.2	3.0	3.0	3.1	1.7	3.0
15% to 20%	4.5	4.6	4.2	6.9	8.5	5.9	6.0	5.5	5.2	4.9	4.1	5.9
Greater than 20%	92.5	93.3	93.6	89.9	83.9	87.7	88.4	89.6	89.9	87.3	89.5	89.3
Government	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.7	0.5	0.1	0.2	0.6	0.9	0.7	0.9	0.7	0.6	0.4	0.5
5% to 10%	5.0	3.8	6.9	9.0	10.4	11.9	9.8	8.8	8.1	10.3	11.5	9.8
10% to 15%	22.5	15.2	26.0	29.9	30.8	31.3	28.1	25.9	29.2	35.0	38.5	32.4
15% to 20%	50.1	35.9	42.5	40.3	39.1	36.3	34.7	32.7	36.9	37.2	34.8	37.6
Greater than 20%	21.6	44.5	24.6	20.6	19.1	19.6	26.7	31.8	25.0	17.0	14.8	19.8

Exhibit 5.b. Share of Total Defaults by Risk Threshold Range, Full Population

Scorecard: Through-the-Cycle

Prime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	71.9	71.7	74.4	66.4	61.9	60.6	61.9	58.2	41.3	50.5	55.1	55.9
5% to 10%	19.7	19.7	18.1	24.0	28.3	29.3	28.7	30.6	37.8	31.3	36.9	30.7
10% to 15%	4.4	4.4	4.0	4.4	4.2	5.0	5.6	5.9	9.0	8.4	3.1	6.5
15% to 20%	2.2	2.3	1.6	2.2	2.5	2.2	1.9	2.3	5.1	4.6	2.2	3.1
Greater than 20%	1.9	1.9	1.8	3.1	3.2	3.0	1.9	2.9	6.7	5.1	2.7	3.9
Subprime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.6	0.3	0.6	0.5	1.2	1.0	0.6	0.5	0.4	0.6	0.0	0.6
5% to 10%	7.4	5.7	10.0	7.1	11.7	8.0	5.5	4.4	4.5	5.5	4.2	6.5
10% to 15%	21.1	18.4	18.3	22.4	25.0	20.6	18.8	17.0	13.4	26.6	57.3	19.2
15% to 20%	31.9	34.1	31.5	38.2	34.9	36.7	35.0	33.2	32.0	45.3	15.5	34.3
Greater than 20%	39.1	41.6	39.6	31.7	27.3	33.7	40.1	44.9	49.7	22.0	23.1	39.5
Government	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.7	0.5	1.0	1.7	1.7	2.0	1.7	1.6	2.1	1.7	2.1	1.6
5% to 10%	36.9	28.2	34.2	39.9	44.7	42.2	37.9	35.2	38.2	47.4	52.9	43.0
10% to 15%	49.2	54.8	45.7	41.9	38.5	39.0	44.7	45.7	46.1	38.9	36.7	42.2
15% to 20%	1.7	2.7	6.3	3.4	2.3	2.0	2.8	3.3	1.3	0.6	0.3	1.9
Greater than 20%	11.5	13.8	12.8	13.2	12.9	14.8	12.9	14.2	12.4	11.5	8.0	11.3

Scorecard: Stress

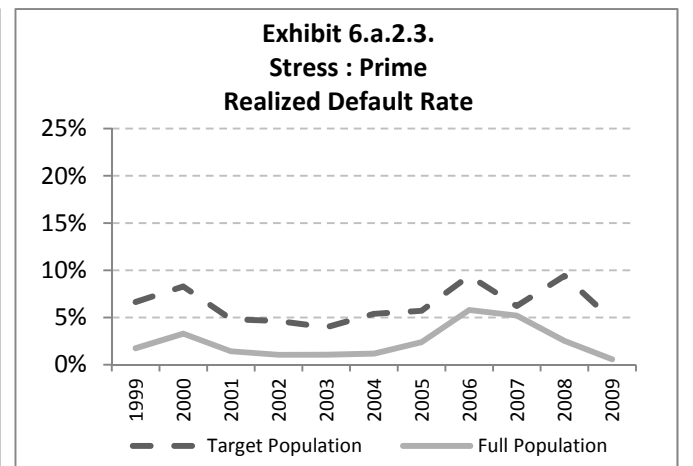
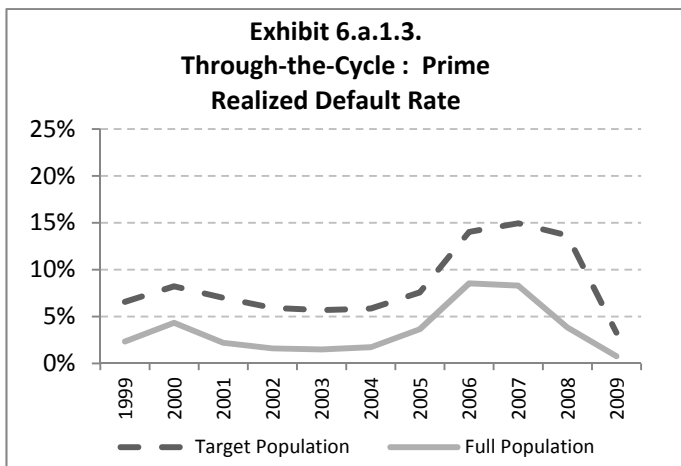
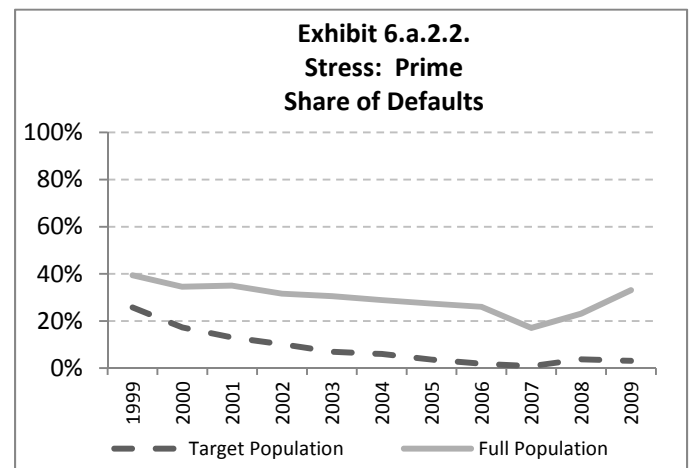
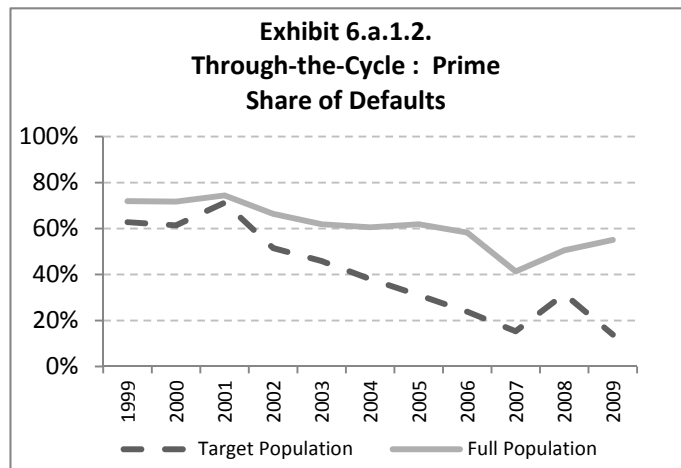
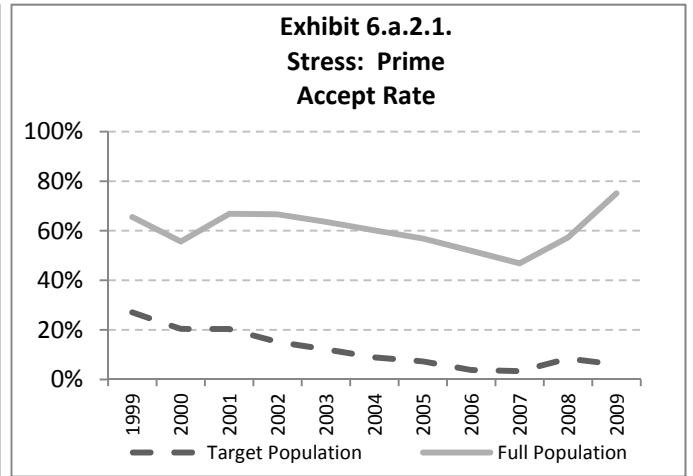
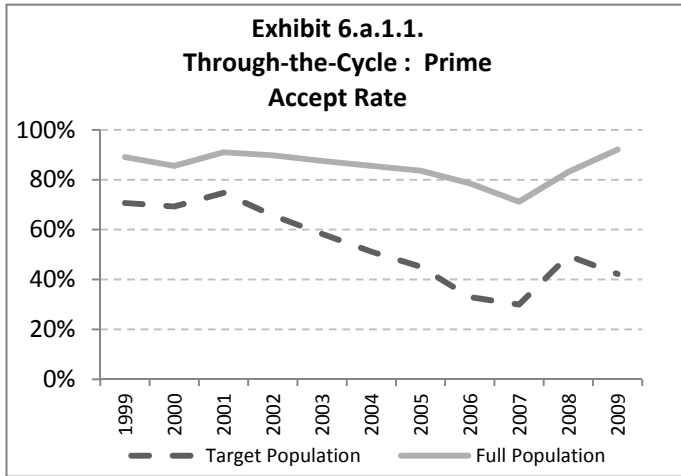
Prime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	39.4	34.5	35.0	31.6	30.5	28.9	27.4	26.0	17.0	23.1	33.1	25.5
5% to 10%	36.5	40.2	44.6	39.7	36.5	36.8	40.3	37.7	29.7	33.2	26.7	35.7
10% to 15%	12.4	14.2	10.6	16.3	19.9	20.5	19.1	20.7	26.0	20.5	25.8	20.8
15% to 20%	5.6	4.7	4.6	4.4	4.8	5.4	6.2	7.0	10.0	8.2	7.1	7.3
Greater than 20%	6.0	6.4	5.3	8.0	8.3	8.3	6.9	8.6	17.2	15.0	7.4	10.7
Subprime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5% to 10%	0.4	0.1	0.3	0.1	0.9	0.6	0.4	0.3	0.2	0.0	0.0	0.4
10% to 15%	1.8	1.1	1.6	1.1	1.5	1.2	1.0	0.7	1.0	1.6	0.0	1.1
15% to 20%	4.3	3.3	6.2	3.1	4.9	3.6	2.2	2.1	2.3	2.6	4.2	3.1
Greater than 20%	93.6	95.4	91.7	95.6	92.7	94.5	96.3	96.9	96.5	95.8	95.8	95.4
Government	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.0	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.2	0.1	0.0	0.1
5% to 10%	1.8	1.3	2.0	3.7	4.5	4.5	4.7	3.7	3.9	5.0	5.9	4.2
10% to 15%	19.3	13.8	16.9	20.9	22.7	22.7	21.6	20.6	22.8	27.6	30.9	23.9
15% to 20%	49.3	43.7	39.7	38.4	37.6	36.5	31.6	32.0	36.1	38.4	38.4	38.7
Greater than 20%	29.6	41.2	41.3	36.9	35.1	36.2	42.1	43.5	37.0	28.8	24.8	33.2

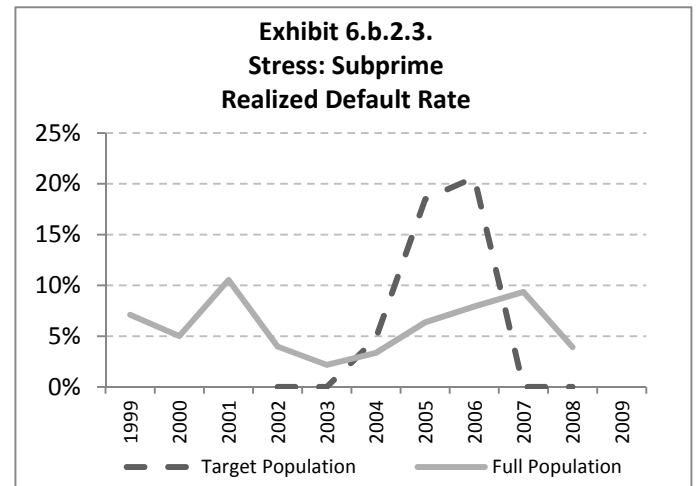
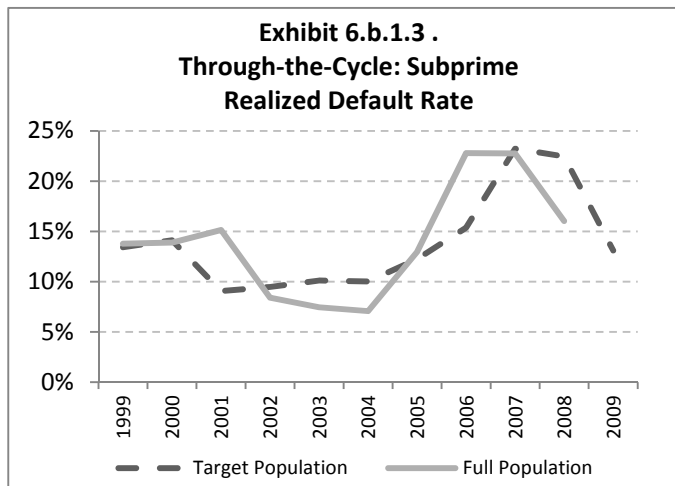
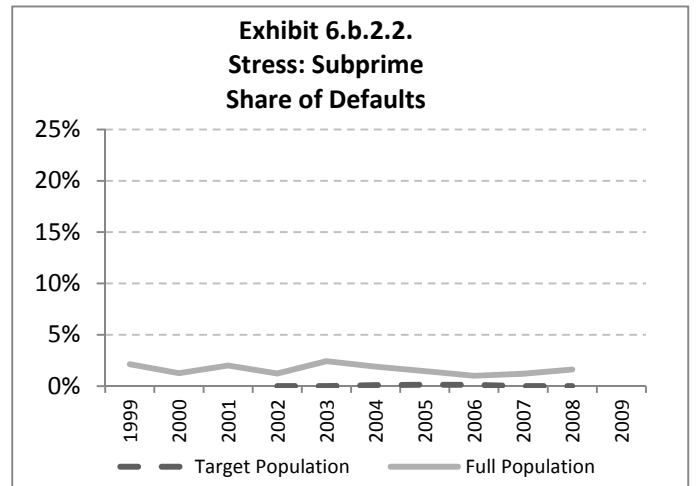
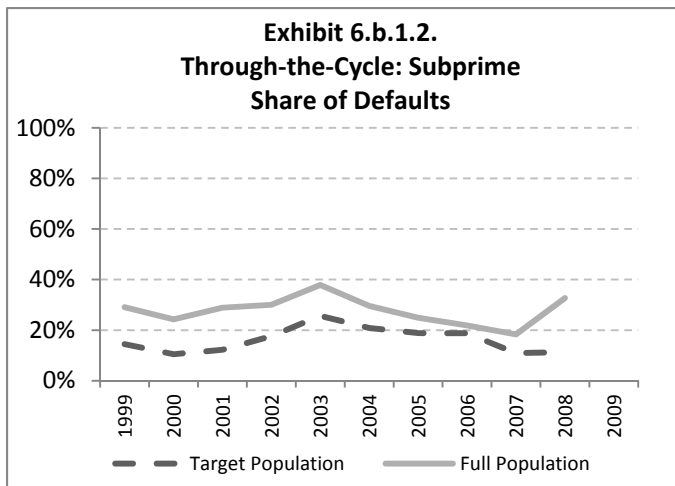
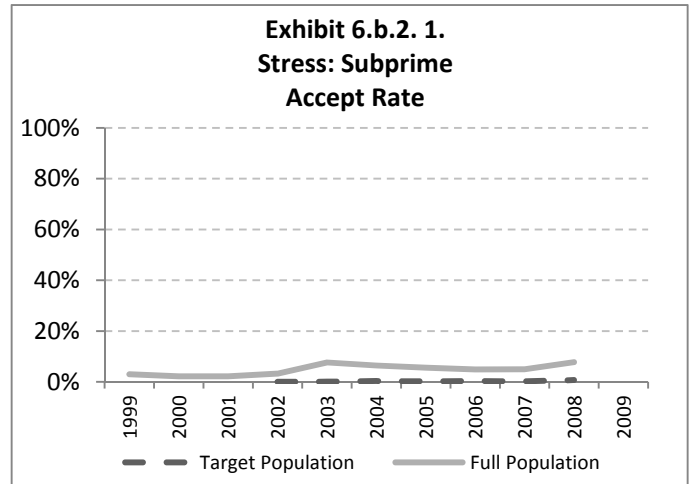
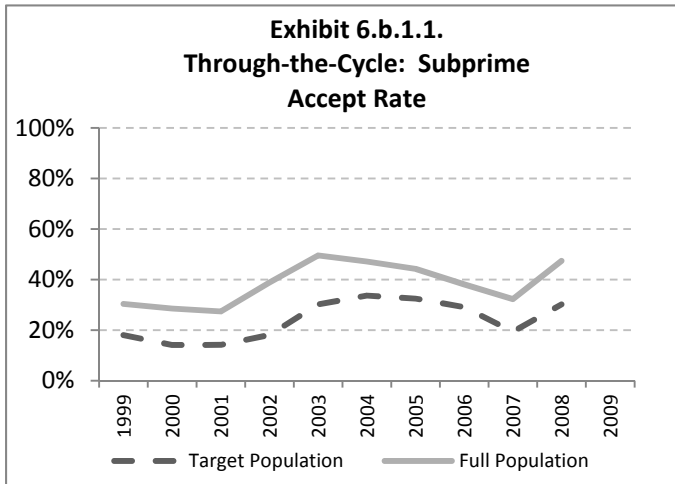
In Exhibits 6.a.1., 6.a.2., 6.b.1., 6.b.2., 6.c.1., and 6.c.2., we provide accept rates (1), the share of defaults (2) and realized default rates (3) for the prime (a), subprime (b) and government (c) segments respectively, for the through-the-cycle (1) and stress (2) scorecards. These exhibits provide information for the full and target populations. All of these exhibits are based on the select cutpoints using the holdout sample for the given markets.

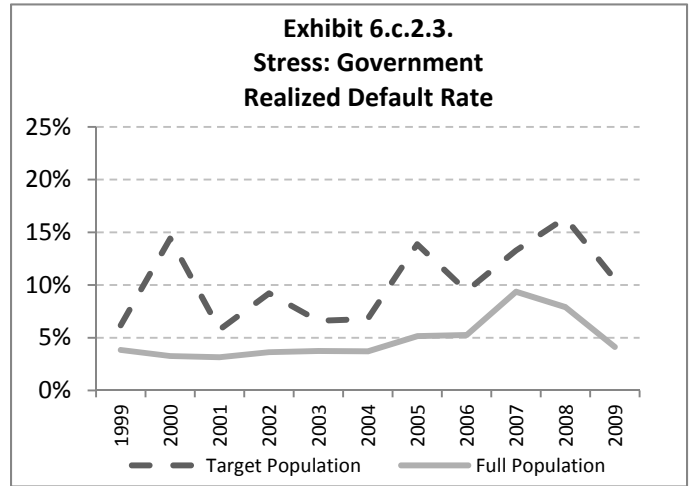
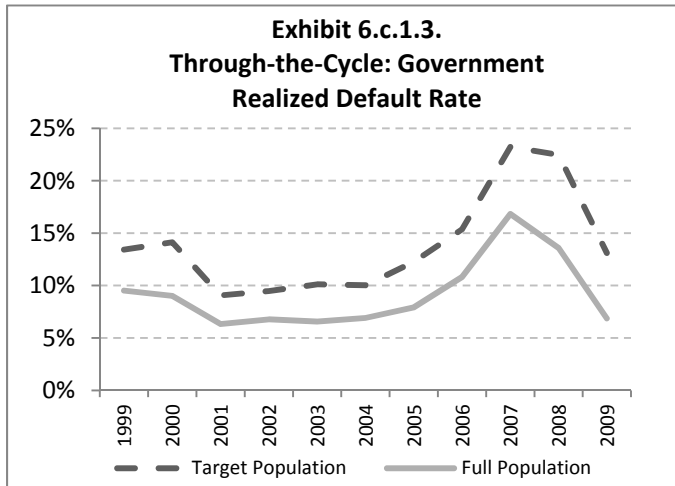
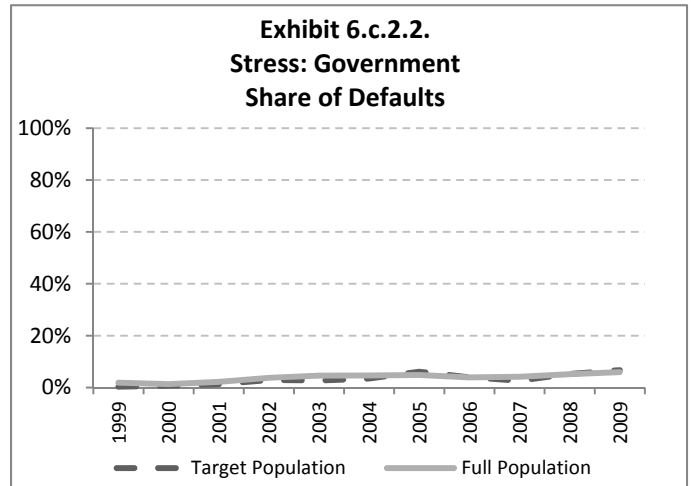
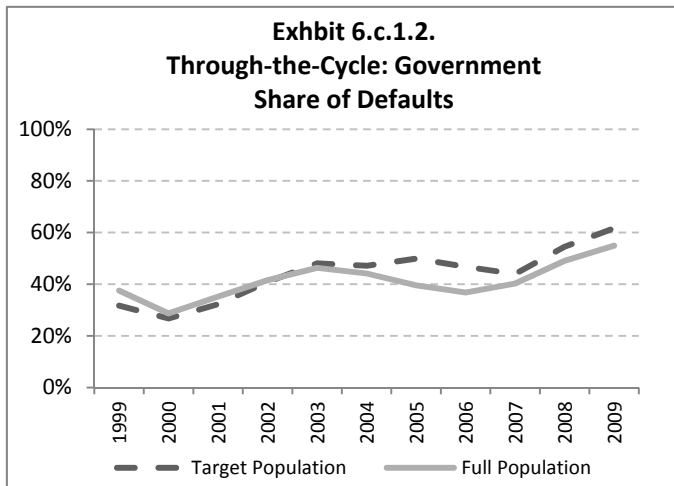
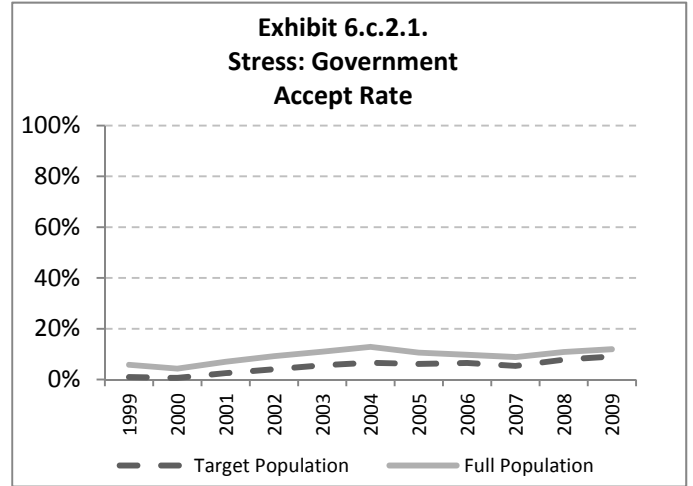
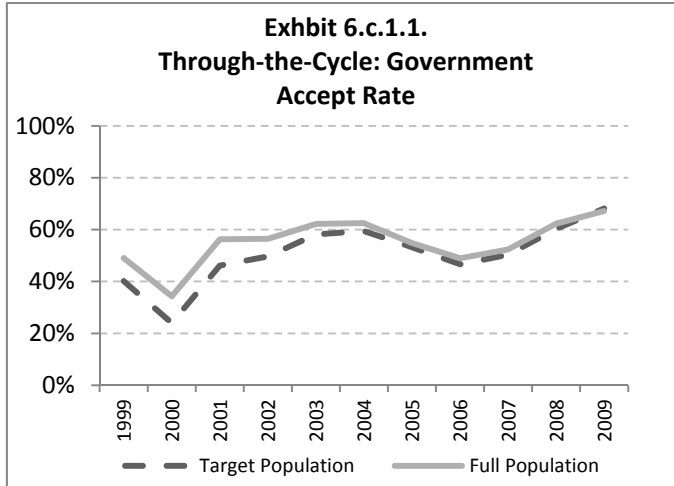
The accept rate trend lines provide information similar to that found in Exhibit 5.a. and A.4.a., but the results across segments and across scorecards for the full and target populations can be more readily compared in the figures. It is clear that the stress scorecard has reduced access to credit with lower accept rates (e.g. Exhibit 6.a.1.1. compared to Exhibit 6.a.2.1.), but also results in a lower share of defaults (e.g. Exhibit 6.a.1.2. compared to Exhibit 6.a.2.2.).

The figures also provide the average realized default rates for those loans that were judged to be acceptable credit risk for each scorecard. In viewing the realized default rate for the through-the-cycle scorecard, it is interesting to note that even though the scorecard and risk threshold are the same for the full and target populations (Exhibit 6.a.1.3.), the target population performs worse in every year because it includes the riskier borrowers that are meeting the uniformly applied cutpoints. Further, even though the scorecard's through-the-cycle values and the cutpoint are identical over time, the realized performance of the acceptable loans meeting the cutpoint is much worse in the years when the actual macroeconomic post-origination variables were at higher "stress" levels. This same effect can be observed for the stress scorecard (Exhibit 6.a.2.3.), although it is attenuated because that scorecard already uses higher "stress" levels of the macroeconomic variables.

Exhibits 6.b.2.1. (subprime) and 6.c.2.1. (government) clearly demonstrate that using a stress scorecard, with cutpoints that are reasonable for the through-the-cycle scorecard, would nearly completely eliminate any subprime or government lending.







We provide Exhibit 7 as a final part of our analysis, which gives summary statistics on key variables by scorecard and by market segment. This provides some detail on the types of loans, loan characteristics and performance for the loans that are in the acceptable risk class. The loans categorized as requiring more “caution” are those that would not be approved as their level of risk is higher than the risk threshold. If judgmental overrides are applied to waive the cutpoint, this requires the use of “caution.”

The acceptable risk loans are characterized by having higher mean FICO scores and lower LTV values than the caution loans. For both the prime and subprime segments, acceptable risk loans are more likely to carry fixed rates, although the difference is not very great in subprime. In the government segment, as nearly 90 percent of the market is FRM, there is less distinction. Results for the stress scorecard are marginally different. For the full population, mean FICO scores of the acceptable risk loans are higher and LTV values lower for the prime market segment, and even a higher percent of the loans are FRM. Mean FICOs are also higher in the government market.

Exhibit 7. Summary Statistics by Scorecard and Market Segment							
Scorecard: Through-the-Cycle							
		Prime		Subprime		Government	
Variable	Risk Class	Target Population	Total Population	Target Population	Total Population	Target Population	Total Population
D90 in 3 Yrs	Accept	8%	3%	13%	11%	11%	7%
D90 in 3 Yrs	Caution	18%	14%	24%	22%	16%	13%
Mean FICO	Accept	650	735	611	629	623	662
Mean FICO	Caution	645	701	598	620	68	98
LTV	Accept	93%	75%	92%	78%	98%	96%
LTV	Caution	97%	92%	92%	85%	99%	99%
Condo	Accept	14%	14%	9%	9%	10%	10%
Condo	Caution	9%	10%	5%	7%	1%	1%
FRM	Accept	95%	85%	28%	30%	91%	93%
FRM	Caution	86%	74%	27%	21%	95%	96%

Scorecard: Stress							
		Prime		Subprime		Government	
Variable	Risk Class	Target Population	Total Population	Target Population	Total Population	Target Population	Total Population
D90 in 3 Yrs	Accept	6%	2%	9%	8%	10%	5%
D90 in 3 Yrs	Caution	13%	9%	22%	19%	14%	10%
Mean FICO	Accept	649	740	610	631	635	689
Mean FICO	Caution	648	714	601	623	632	673
LTV	Accept	91%	71%	93%	77%	97%	93%
LTV	Caution	95%	88%	92%	83%	98%	98%
Condo	Accept	13%	14%	7%	9%	17%	17%
Condo	Caution	11%	12%	6%	8%	5%	5%
FRM	Accept	98%	88%	2%	17%	71%	83%
FRM	Caution	90%	75%	32%	29%	95%	96%

*Note: Statistics calculated using HMDA derived weights. FICO score only calculated using observations with non-missing FICO.

Conclusions and Implications

Using residential mortgage default models for each of the three segments of the U.S. market (prime, subprime, and government), we construct two scorecards (through-the-cycle and stress), and then apply each scorecard to the full population of borrowers and to a specific group of targeted borrowers to determine expected performance. Such scorecards can be used to balance the competing tensions between access to credit and credit risk.

Responsible lending requires the choice of an appropriate scorecard and/or the appropriate setting of risk tolerances, and in automated underwriting systems this is operationalized by setting post-origination macroeconomic values (choice of scorecard) or by choosing the scorecard cutpoints that determine the maximum level of acceptable risk. This process requires judgment that balances policy, regulatory, and business considerations, all of which may and do change over time. This simple observation highlights the temporal nature of responsible lending—risks that are viewed as acceptable in one period may be viewed as excessive in another.

As expected, for a given cutpoint, a through-the-cycle scorecard accepts more borrowers than the stress scorecard during a stressful time period, with the differentials varying by market segment. The prime market, with a lower risk threshold (5 percent cutpoint), accepts a significantly higher percentage of borrowers using either scorecard, while the subprime market yields the lowest percentage of borrowers using the through-the-cycle scorecard (but slightly higher acceptable rate than the government market when using the stress scorecard).

We find the scorecards offer potential for responsibly extending credit to the target population. However, our results again indicate that the through-the-cycle and stress scorecards offer competing policy tradeoffs. The through-the-cycle scorecard extends credit to a larger percentage of the target population by providing greater access during expansionary cycles. The stress scorecard severely restricts access during periods of financial stress, as designed.

Our analysis is suggestive rather than definitive. It is sensitive to the scorecard used and to the choice of cutpoint (risk tolerance). It is encouraging, however, because it suggests that automated underwriting systems offer potential for responsibly extending credit to all borrowers, including those in a target population. The size of this impact depends critically on the risk tolerances incorporated into the automated underwriting systems. Regardless of the chosen level of risk, our analysis identifies a portion of the population to whom lenders can responsibly extend credit, even during stressful environments. This requires either adopting a scorecard that reflects a stress scenario or tightening cutpoints. Doing both, however, results in almost no loans being offered to the target population by either the subprime market or government market, and a significant reduction in the percent of the target population getting loans in the prime market.

To conclude, we find that automating underwriting scorecards can provide a valuable tool for managing risks for mortgage originations. However, modern automated underwriting systems are unlikely by

themselves to be a panacea for providing access to credit to targeted populations.²³ With tight standards, target borrowers face significant challenges in obtaining mortgage credit. Successful homeownership outreach programs may well require additional enhancements to the underwriting process such as pre-purchase counseling and high-touch origination and servicing. These programs also often consider non-traditional sources of data, such as rental payment history, when assessing borrower risk. Enhancing modern automated underwriting along these dimensions is not a simple matter, but doing so offers the potential of further expanding credit access, while managing the attendant risks and increasing accuracy, albeit at potentially higher cost.²⁴

Our analysis also highlights how the treatment of the post-origination environment has significant policy implications. From a macro-economic perspective, the through-the-cycle scorecard has the desirable characteristic of extending access to credit—it is more counter-cyclical during recessions. The stress scorecard, in contrast, is more pro-cyclical in design. It also reduces total credit losses because it views the post-origination environment as more risky. This presents a challenging policy conundrum, requiring a balancing of the two tensions.

Acknowledgements

We thank seminar participants at *Government Intervention in Residential Mortgage Markets*, held December 3 and 4, 2013, Charlotte NC and at the *IBEFA/WEA* conference in Denver, June 30, 2014. In particular, we thank Paul Willen for his helpful suggestions. All views and opinions are those of the

²³ It is worth pointing out that most actual automated underwriting systems include many more detailed credit variables than are available in the CoreLogic data or included in our scorecard. The addition of these variables would certainly improve the accuracy of our delinquency model, but we expect would have relatively little impact on extending credit to the target population.

²⁴ See for example Avila, Nguyen, and Zorn (2013) on the value of counseling and Moulton and Quercia (2013) on the use of high-touch servicing.

authors and do not reflect the views or opinions of Charles River Associates or its Board of Directors, of Freddie Mac or its Board of Directors, or of the Federal Housing Finance Agency or any of Freddie Mac's regulators. An earlier version of this paper appears in *Homeownership Built to Last: Lessons from the Housing Crisis on Sustaining Homeownership for Low-Income and Minority Families*, 2014.

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Exhibit A.1.a. Prime Market Estimation Results (Estimated on the 80% Sample)				
Variable	Value	Estimate	Std Error	Prob Chi Sq
Intercept		-5.2079	0.0164	<.0001
LTV Ratio	40 to 60	-1.5594	0.0126	<.0001
	60 to 75	-0.5847	0.00767	<.0001
	75 to 80	-0.3424	0.00678	<.0001
	80 to 85	0.1571	0.0134	<.0001
	85 to 90	0.1765	0.00864	<.0001
	90 to 95	0.4264	0.00913	<.0001
	95 to 105	0.5239	0.00803	<.0001
	105 to 115	1.7391	0.0183	<.0001
DTI ratio	> 115	1.8144	0.0218	<.0001
	< 20	-0.364	0.00678	<.0001
	20 to 30	-0.2646	0.00479	<.0001
	30 to 40	0.0802	0.00329	<.0001
	40 to 45	0.2991	0.00382	<.0001
	45 to 50	0.285	0.00453	<.0001
FICO	> 50	0.33	0.00427	<.0001
		-0.00009	6.15E-06	<.0001
Loan amount	50-150k	0.1187	0.00711	<.0001
	150-250k	-0.1391	0.00848	<.0001
	250-350k	-0.1926	0.0122	<.0001
	350-450k	-0.1026	0.014	<.0001
	> 450k	-0.1327	0.0163	<.0001
Documentation type	Full	-0.3297	0.00222	<.0001
	Missing	0.0917	0.00247	<.0001
Origination channel	Other	0.176	0.00189	<.0001
	Retail	-0.1676	0.00204	<.0001
Owner-occupied	yes	-0.00108	0.00191	0.57
Product	ARM	-0.0317	0.00483	<.0001
	Balloon	0.4432	0.0153	<.0001
	FRM-15	-1.0696	0.00981	<.0001
	FRM-30	-0.416	0.00402	<.0001
	FRM-Other	0.73	0.00523	<.0001
Condo	no	0.0595	0.00189	<.0001
Mortgage rate	1-year after	-0.0986	0.00301	<.0001
	2-years after	-0.1032	0.00339	<.0001
	3-years after	-0.0761	0.0031	<.0001
Unemployment rate	1-year after	-0.1493	0.00127	<.0001
	2-years after	0.055	0.00145	<.0001
	3-years after	0.0761	0.00101	<.0001
House price appreciation	1-year after	1.2707	0.0257	<.0001
	2-years after	-0.1657	0.0195	<.0001
	3-years after	1.6098	0.01	<.0001

Note: Also included in the estimation are interactions between: (1) FICO score and loan amount, (2) loan amount and LTV ratio, and (3) FICO score and LTV ratio.

Exhibit A.1.b.
Conventional Prime Estimation Goodness of Fit

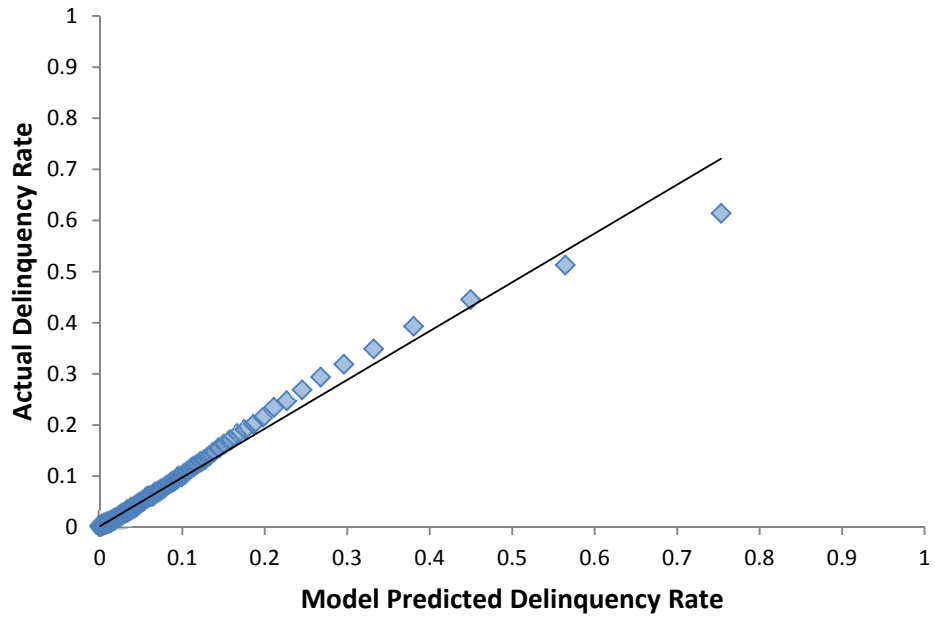


Exhibit A.2.a. Subprime Market Estimation Results (Estimated on the 80% Sample)				
Variable	Value	Estimate	Std Error	Prob Chi Sq
Intercept		-6.6489	0.0379	<.0001
LTV	40 to 60	-1.0644	0.0384	<.0001
	60 to 75	-0.4261	0.0206	<.0001
	75 to 80	0.0908	0.017	<.0001
	80 to 85	0.2529	0.021	<.0001
	85 to 90	0.1539	0.0187	<.0001
	90 to 95	0.2071	0.0203	<.0001
	95 to 105	0.1302	0.0193	<.0001
	105 to 115	1.1918	0.0413	<.0001
	> 115	0.9405	0.0568	<.0001
FICO		0.00056	1.7E-05	<.0001
Loan amount	50-150k	0.273	0.0156	<.0001
	150-250k	-0.02	0.0187	0.2845
	250-350k	-0.1659	0.0313	<.0001
	350-450k	-0.1991	0.0448	<.0001
	> 450k	-0.3163	0.0419	<.0001
Documentation type	Full	0.2814	0.00306	<.0001
	Missing	-0.4448	0.00431	<.0001
Origination channel	Other	0.1597	0.00297	<.0001
	Retail	0.0811	0.00363	<.0001
Owner-occupied	yes	-0.0281	0.00287	<.0001
Product	ARM	-0.1136	0.00489	<.0001
	Balloon	0.294	0.00735	<.0001
	FRM-15	-0.4165	0.0168	<.0001
	FRM-30	-0.3156	0.00546	<.0001
	FRM-Other	0.3038	0.0111	<.0001
Condo	no	0.0776	0.00364	<.0001
Mortgage rate	1-year after	0.0854	0.00387	<.0001
	2-years after	-0.0917	0.00475	<.0001
	3-years after	-0.2461	0.00496	<.0001
Unemployment rate	1-year after	-0.0189	0.00236	<.0001
	2-years after	-0.0617	0.00257	<.0001
	3-years after	0.0852	0.00163	<.0001
Equity	1-year after	5.0494	0.056	<.0001
	2-years after	-1.3697	0.0358	<.0001
	3-years after	1.2129	0.0149	<.0001

Note: Also included in the estimation are interactions between: (1) FICO score and loan amount, (2) loan amount and LTV ratio, and (3) FICO score and LTV ratio.

Exhibit A.2.b.
Conventional SubPrime Estimation Goodness of Fit

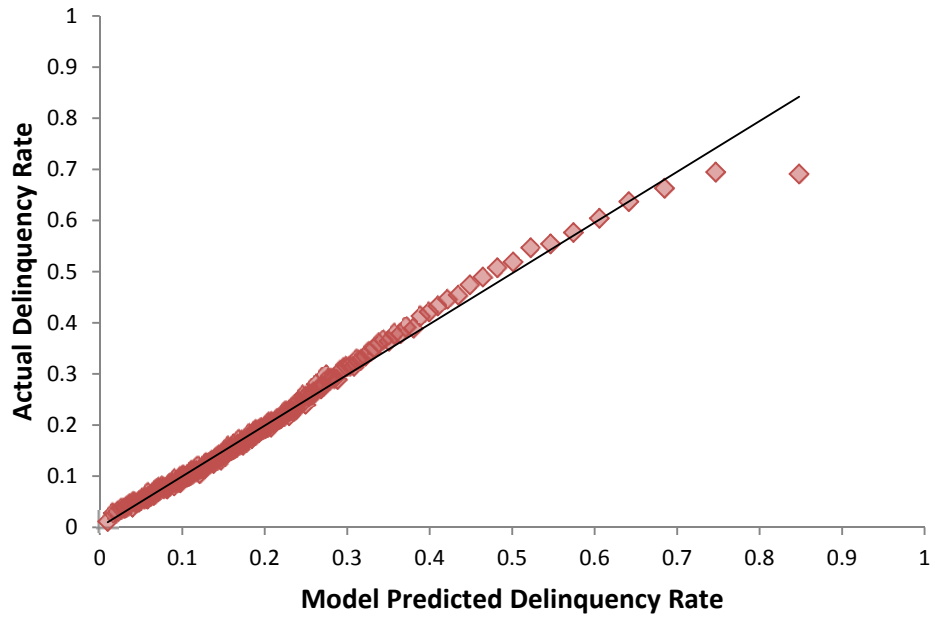


Exhibit A.3.a. Government Market Estimation Results (Estimated on the 80% Sample)				
Variable	Value	Estimate	Std Error	Prob Chi Sq
Intercept		-9.5488	0.066	<.0001
LTV ratio	< 40	n/a	n/a	n/a
	40 to 60	3.9636	0.1215	<.0001
	60 to 75	4.8392	0.0691	<.0001
	75 to 80	5.1345	0.064	<.0001
	80 to 85	5.2071	0.0693	<.0001
	85 to 90	5.2011	0.0644	<.0001
	90 to 95	5.3195	0.0625	<.0001
	95 to 105	5.5381	0.0608	<.0001
	105 to 115	6.9456	0.0775	<.0001
	> 115	7.3719	0.0553	<.0001
DTI ratio	< 20	-0.5595	0.00982	<.0001
	20 to 30	-0.0545	0.00668	<.0001
	30 to 40	0.0912	0.0048	<.0001
	40 to 45	0.2243	0.00564	<.0001
	45 to 50	0.2035	0.00622	<.0001
	> 50	0.131	0.00653	<.0001
FICO		-0.0002	0.00002	<.0001
Loan amount	50-150k	5.7136	0.0612	<.0001
	150-250k	5.3771	0.0667	<.0001
	250-350k	5.2903	0.0791	<.0001
	350-450k	4.9765	0.109	<.0001
	> 450k	-26.984	0.272	<.0001
Documentation type	Full	0.0563	0.00263	<.0001
	Missing	-0.1174	0.00303	<.0001
Origination channel	Other	0.0558	0.0025	<.0001
	Retail	-0.1423	0.00287	<.0001
Owner-occupied	yes	-0.0967	0.00327	<.0001
Product	ARM	-0.1674	0.0138	<.0001
	Balloon	0.1649	0.0549	0.0026
	FRM-15	-0.5724	0.02	<.0001
	FRM-30	-0.263	0.0123	<.0001
	FRM-Other	1.3566	0.0133	<.0001
Condo	no	0.1757	0.00378	<.0001
Mortgage rate	1-year after	-0.0033	0.00305	0.2872
	2-years after	-0.0391	0.00361	<.0001
	3-years after	0.1369	0.0035	<.0001
Unemployment rate	1-year after	-0.1026	0.00135	<.0001
	2-years after	0.0934	0.00204	<.0001
	3-years after	0.0304	0.00149	<.0001
Equity	1-year after	1.4957	0.0418	<.0001
	2-years after	-1.1064	0.0422	<.0001
	3-years after	1.5974	0.0244	<.0001

Note: Also included in the estimation are interactions between: (1) FICO score and loan amount, (2) loan amount and LTV ratio, and (3) FICO score and LTV ratio.

Exhibit A.3.b.
Government Estimation Goodness of Fit

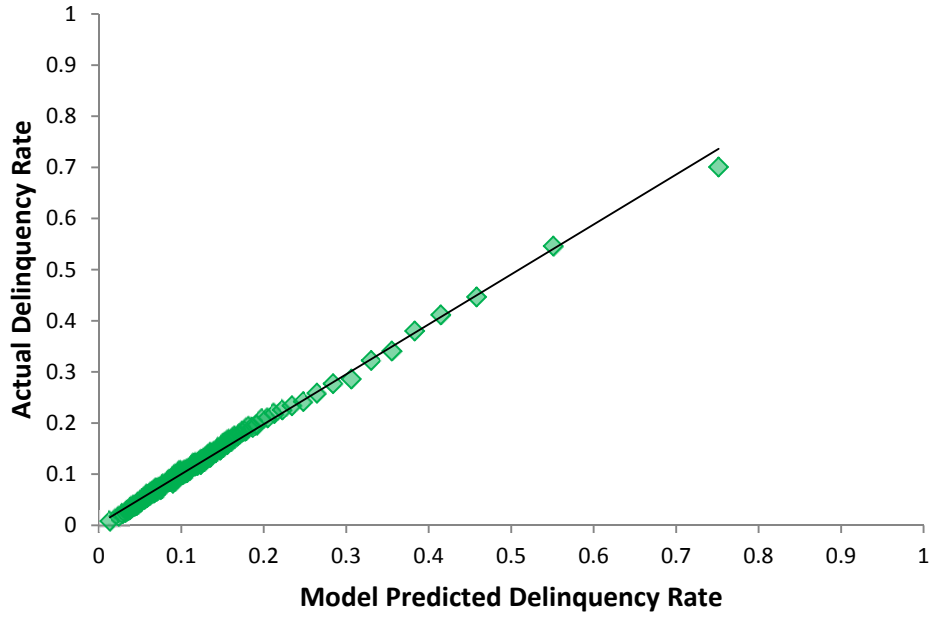


Exhibit A.4.a. Percent of Acceptable Risk Borrowers, by Risk Threshold Range, Target Population

Scorecard: Through-the-Cycle												
Prime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	ALL
Less than 5%	70.7	69.2	74.7	65.7	58.2	51.1	45.1	33.0	29.9	49.5	42.2	55.1
5% to 10%	24.3	24.9	21.0	30.3	36.9	42.3	43.9	50.3	49.1	39.1	51.9	36.0
10% to 15%	2.8	2.8	2.8	2.2	2.7	3.9	6.6	9.0	10.4	6.1	2.7	4.7
15% to 20%	1.7	1.9	1.0	1.0	1.2	1.2	2.1	3.2	4.1	2.2	0.6	1.9
Greater than 20%	0.6	1.2	0.4	0.8	1.0	1.5	2.3	4.6	6.5	3.1	2.7	2.2
Subprime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	ALL
Less than 5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	1.6	0.0
5% to 10%	2.0	2.9	1.5	1.8	5.5	5.1	7.2	7.2	3.9	5.7	8.3	4.4
10% to 15%	16.0	11.2	12.7	16.3	24.8	28.6	25.3	21.9	15.5	23.8	43.2	20.5
15% to 20%	27.7	26.4	25.3	36.1	32.6	35.2	30.1	23.1	26.8	33.8	28.6	29.7
Greater than 20%	54.3	59.5	60.4	45.8	37.0	31.1	37.5	47.8	53.8	36.1	18.3	45.4
Government	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	ALL
Less than 5%	0.3	0.2	0.9	1.4	1.5	1.6	1.6	1.7	1.5	1.8	2.8	1.6
5% to 10%	39.8	23.8	45.3	48.1	56.6	57.6	51.4	44.9	48.9	58.4	65.3	52.7
10% to 15%	52.9	68.4	45.0	43.5	37.3	35.1	39.7	38.4	44.0	36.7	29.4	40.2
15% to 20%	1.8	3.8	4.9	3.3	1.4	1.2	2.9	9.2	1.3	0.6	0.3	2.2
Greater than 20%	5.2	3.8	4.0	3.6	3.3	4.4	4.4	5.8	4.4	2.5	2.2	3.4
Scorecard: Stress												
Prime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	ALL
Less than 5%	27.0	20.4	20.3	15.2	12.1	8.8	7.3	3.8	3.3	8.4	6.0	12.8
5% to 10%	49.9	54.5	61.5	59.6	54.8	51.0	46.9	38.7	37.2	51.2	48.1	50.6
10% to 15%	16.1	17.2	12.2	19.0	25.4	29.4	28.6	33.9	31.5	23.3	31.0	23.7
15% to 20%	3.7	3.7	3.1	3.4	4.2	6.3	9.2	10.3	10.8	8.5	10.6	6.2
Greater than 20%	3.2	4.3	2.9	2.8	3.6	4.5	8.0	13.4	17.1	8.6	4.2	6.7
Subprime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	ALL
Less than 5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5% to 10%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	1.6	0.0
10% to 15%	0.0	0.5	0.0	0.0	0.1	0.3	0.2	0.3	0.2	0.0	0.0	0.2
15% to 20%	1.2	1.9	0.9	1.0	2.1	2.1	3.4	3.8	2.5	3.2	4.7	2.1
Greater than 20%	98.8	97.6	99.1	99.0	97.8	97.5	96.4	95.9	97.3	96.1	93.8	97.7
Government	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	ALL
Less than 5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
5% to 10%	1.0	0.6	2.6	4.0	5.5	6.6	6.1	6.5	5.4	7.8	9.0	5.2
10% to 15%	18.4	10.6	21.8	25.9	28.8	29.9	27.8	25.8	30.6	33.9	35.3	27.3
15% to 20%	53.1	35.4	44.1	44.5	44.4	41.8	36.4	31.5	38.2	40.6	40.8	42.1
Greater than 20%	27.5	53.3	31.5	25.6	21.2	21.6	29.7	36.1	25.8	17.7	14.8	25.4

Exhibit A.4.b. Share of Total Defaults by Risk Threshold Range, Target Population												
Scorecard: Through-the-Cycle												
Prime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	62.8	61.4	71.2	51.5	45.9	38.0	31.0	23.8	15.3	31.5	13.9	35.1
5% to 10%	26.7	25.2	20.8	34.4	39.7	46.2	44.8	45.3	47.1	41.0	66.7	40.3
10% to 15%	5.1	7.8	3.6	7.1	5.4	5.3	9.8	13.8	15.0	11.5	9.4	10.4
15% to 20%	3.8	3.1	1.3	2.9	3.8	4.5	6.4	6.5	7.8	5.7	0.0	5.4
Greater than 20%	1.6	2.6	3.0	4.0	5.2	5.9	7.9	10.6	14.7	10.3	10.0	8.8
Subprime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	n/a	0.0
5% to 10%	2.4	0.8	2.4	0.9	2.6	2.7	2.5	3.6	1.1	0.0	n/a	2.4
10% to 15%	12.1	9.7	9.8	16.7	23.0	18.1	16.3	15.1	9.8	11.3	n/a	15.1
15% to 20%	31.6	28.7	23.5	34.9	35.3	30.0	26.4	21.3	28.4	48.0	n/a	27.5
Greater than 20%	53.9	60.9	64.3	47.4	39.0	49.1	54.7	59.9	60.7	40.7	n/a	55.0
Government	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.2	0.1	0.6	1.0	0.7	0.9	1.7	0.8	0.5	1.1	2.1	1.0
5% to 10%	31.6	26.6	31.7	39.9	47.4	46.3	48.2	46.0	43.5	53.4	59.5	44.7
10% to 15%	58.7	57.8	49.4	41.4	38.6	40.1	39.0	36.5	45.7	37.1	31.2	42.5
15% to 20%	1.7	2.4	7.1	4.7	2.1	2.1	2.8	3.3	0.7	0.1	0.3	2.3
Greater than 20%	7.9	13.0	11.3	13.1	11.1	10.7	8.3	13.4	9.6	8.3	6.8	9.6
Scorecard: Stress												
Prime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	25.8	17.3	13.0	10.2	6.9	6.0	3.7	1.9	0.8	3.8	3.1	6.4
5% to 10%	43.4	48.6	62.1	47.3	45.0	38.7	34.6	27.6	21.4	35.0	18.6	34.9
10% to 15%	17.4	17.9	13.7	24.6	31.3	34.7	31.1	32.0	32.9	27.1	38.9	28.3
15% to 20%	6.6	7.6	4.7	6.1	3.6	6.4	9.2	11.7	12.4	11.1	22.1	9.4
Greater than 20%	6.9	8.6	6.5	11.8	13.2	14.2	21.4	26.9	32.5	23.1	17.3	21.0
Subprime	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	n/a	0.0
5% to 10%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	n/a	0.0
10% to 15%	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	n/a	0.1
15% to 20%	0.8	0.8	1.3	0.3	0.8	1.1	0.7	1.7	0.6	0.0	n/a	1.0
Greater than 20%	99.2	99.2	98.7	99.7	99.2	98.8	99.1	98.2	99.4	100.0	n/a	98.9
Government	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Less than 5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5% to 10%	0.3	0.7	1.3	2.9	2.7	3.4	6.1	4.0	2.6	5.3	6.7	3.4
10% to 15%	12.9	12.1	15.4	19.7	24.1	22.9	26.2	27.4	26.5	31.1	34.1	23.7
15% to 20%	59.0	47.8	41.6	39.9	41.1	42.6	32.6	33.0	40.7	41.8	39.2	42.9
Greater than 20%	27.8	39.4	41.6	37.5	32.1	31.1	35.1	35.7	30.2	21.8	20.0	30.0