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Underwriting Standards, Loan Products and Performance: What Have We Learned?

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Abstract

Responses to the mortgage market crisis of the past decade led to myriad changes in the structure of the industry, expanded market regulations, and resulted in a shift in the composition of products being offered to borrowers. To name but a few changes, the subprime market virtually disappeared, the Dodd-Frank bill added both Qualified Mortgage ("QM") and Qualified Residential Mortgage ("QRM") requirements to the regulatory environment, the 30-year fixed rate mortgage ("FRM") almost monopolized product space, and lenders significantly tightened their underwriting standards. On the positive side, these changes reduce the likelihood of another foreclosure crisis, but they do so at the cost of significantly reducing access to credit for borrowers making small down payments or those with poor credit histories.

Mortgage histories from the past decade now contribute to unique data on the performance of a wide variety of products during stressful economic environments. The aim of this paper is to assess whether these data can be leveraged in a traditional automated underwriting system to responsibly extend credit to underserved borrowers.

We find that traditional automated underwriting systems do offer potential for addressing access to credit concerns for these borrowers. They are unlikely to be a panacea by themselves, but they appear to offer a valuable tool to those trying to extend credit to targeted borrowers at acceptable risks.

I. Introduction

The mortgage market crisis of the past decade led to many changes in the structure of the industry and in the products being offered to borrowers. The beginning of the decade witnessed a surge in non-prime lending with an attendant proliferation of new products, including many that allowed borrowers who could not meet traditional underwriting standards to obtain home mortgages and achieve home ownership. By the end of the decade, however, delinquency and foreclosure rates had increased throughout the country, the non-prime sector had collapsed nearly entirely, and these innovative products were largely gone from the offerings of mortgage lenders.

One immediate reaction to the crisis included a significant Congressional response aimed at tighter regulation of the mortgage industry. Among other actions this entailed passage of the Dodd-Frank bill, with its introduction of the Qualified Mortgage ("QM") and the Qualified Residential Mortgage ("QRM") requirements, and a variety of other restrictions on mortgage product offerings and extensions of consumer protections. Simultaneously, lenders themselves tightened underwriting standards across the board and virtually eliminated products offerings requiring little or no documentation of income and assets, products with negative amortization options, and products specifically designed to meet the needs of non-traditional or non-prime borrowers.

Moreover, as the subprime sector collapsed, the government sector surged.[1] By 2009, lower-income home-purchase borrowers were disproportionately more likely to take out Federal Housing Administration ("FHA") or the Veteran's Administration ("VA") loans.[2] As a result, by 2011, the market shares of the government insured products, combined with those that meet the credit standards of Freddie Mac and Fannie Mae (the government sponsored enterprises, or "GSEs"), grew to account for over 90 percent of the market.[3]

Both FHA and the GSEs have missions that support meeting the needs of underserved borrowers. The curtailment of non-prime mortgage offerings has nonetheless raised concerns that access to credit has been severely limited for borrowers with low downpayments or poor credit histories, or who are otherwise underserved by the prime market.[4] Moreover, underwriting and credit standards are currently as tight as they have been in decades. While likely providing assurance regarding the performance of current mortgage originations, this also restricts access to credit for targeted borrowers.

The history of mortgage performance over the last decade offers the opportunity to distinguish mortgage programs and combinations of borrower and loan characteristics that work (i.e., perform well in stressful economic environments) from those that don't. Underwriting standards varied considerably in the earlier part of this decade, changing from restrictive to relaxed. This provides rich data on the

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[1] See, for example, Courchane, Darolia, and Zorn (2013).

[2] See Avery, Brevoort, Bhutta, and Canner (2010) at A40.

[3] See *The 2012 Mortgage Market Statistical Annual, Volume I*, Mortgage Originations by Product, at 17.

[4] See, for example, Courchane and Zorn (2012).

performance of borrowers stretching for credit in a period of declining house prices and rising unemployment. Many of these loans performed poorly. However, throughout this critical period State Housing Finance Agencies and other homeownership programs offered loans to targeted populations that experienced reasonable performance. These programs, however, were typically small in scale and have not been widely reproduced.

In this paper we explore whether it is possible to achieve scale in providing underserved borrowers with access to mortgage credit at acceptable levels of risk. Specifically, we ask whether the data of the last decade offer the potential for creating a traditional automated underwriting scorecard that effectively and responsibly extends mortgage credit to borrowers who reside in low-income communities, make low downpayments, and have poorer credit histories.

There are four steps necessary to complete this exercise. First, empirically estimate a mortgage delinquency model. Second, convert the estimated delinquency model to an underwriting scorecard for assessing risk. Third, determine a scorecard value ("cutpoint") that demarcates the marginal risk tolerance—score values equal to or below the cutpoint are viewed as acceptable risk, while score values above the cutpoint are not. Fourth, run targeted borrowers through this prototype of an automated underwriting system and determine the proportion of the population that is within acceptable risk tolerances.

The main data we use for this analysis are loan-level observations from CoreLogic on mortgages originated in the prime, subprime, and government sectors from 1999 through 2009. Using an enhanced version of these data, 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 controls for borrower and loan characteristics, as well as controls 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 risk (i.e., asses risk at origination), so creating scorecards requires appropriate treatment of the post-origination variables in our estimated models. We create two separate scorecards to bracket the possible approaches—on one side making no forecast regarding the future values of post-origination variables, on the other side perfectly accurately forecasting their future values. The first scorecard sets post-origination values of house prices, interest rates, and unemployment rates to their constant long run levels (a "through-the-cycle" scorecard). The second scorecard sets post-origination values of house prices, interest rates, and unemployment rates to their varying *ex post,* realized values (a "perfect foresight" scorecard).

The next challenge is to determine appropriate scorecard cutpoints for delimiting loans within acceptable risk tolerances. The choice of cutpoint is a complicated policy/business decision, so we provide results for a variety of cutpoints, ranging from a low of a 5 percent delinquency rate, to a high of a 20 percent delinquency rate. We also provide results for a representative set of cutpoints, set at 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, and approximate the observed delinquency rates in 1999 through 2001 of the 90th percentile highest risk loans originated in the prime market, the 50th percentile highest risk loans in the subprime market, and the 60th percentile highest risk loans in the government market.

The combination of scorecards and cutpoints creates working facsimiles of traditional automated underwriting systems, and we apply these systems to the target population.[5] For this exercise, our target population is composed of 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.

Using our representative set of cutpoints we find that 34 percent of the prime targeted borrowers are viewed as acceptable risks by the through-the-cycle scorecard. The perfect foresight scorecard yields 42 percent. For the subprime market these values are 26 and 39 percent, respectively, and for the government market they are 39 and 44 percent, respectively. This suggests that automated underwriting systems offer some potential for responsibly extending credit to the target population. We also show that the through-the-cycle and perfect foresight scorecards offer competing policy tradeoffs. The through-the-cycle scorecard is more pro-cyclical. However it reduces credit losses and extends credit to a larger percentage of the target population, albeit by providing greater access during the up cycle.

II. Previous Literature

Many studies have looked at 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 outcomes for the target population.

Among many other studies produced over the last few years by the UNC Center for Community Capital is a recent paper by Quercia, Ding, and Reid (2012) that specifically addresses the balancing of risk and access for borrowers. The paper narrowly focuses on the marginal impacts of setting QRM product standards more stringently than those for QM.[6] They find that such a setting of QRM standards would exclude many loans with low or no income documentation, hybrid adjustable rate mortgages, interest only, and negative amortization mortgages.

Quercia, Ding, and Reid also found that the benefits of reduced foreclosures resulting from the more stringent QRM product restrictions do not necessarily outweigh the costs of reducing borrowers' access to QRM mortgages. In particular, they conclude that LTV requirements of 80 or 90 percent produce a

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[5] 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.

[6] For details of the QRM, see Federal Housing Finance Agency, Mortgage Market Note 11-02.

smaller benefit when the resulting reductions in defaults are weighed against the number of borrowers excluded from the market. The results for debt-to-income ("DTI") ratios and borrower credit scores similarly show that the most restrictive thresholds are less effective because they exclude a larger share of borrowers in relation to the percent of defaults they prevent. Of key importance is the finding that more stringent LTV, DTI, and credit score regulatory requirements could disproportionately deny low-income and minority borrowers access to mortgage credit.

Pennington-Cross and Ho (2010) specifically examine the performance of hybrid and adjustable rate mortgages. After controlling for borrower and location characteristics, they find that the type of loan product can have dramatic impacts on the performance of mortgages. Their specific focus is on hybrid adjustable rate loans. From 2001 through 2004 it was possible to refinance these products because house prices increased and interest rates decreased or stayed very low. However, interest rate increases over 2005–2006 led to large payment shocks. Loans initially could still be refinanced due to rapid house price appreciation, but by 2007 house prices began to stabilize, and by 2008 house prices were declining so rapidly that only borrowers with excellent credit history and large amounts of equity and wealth could refinance. With large and unaffordable payment shocks, the only remaining option for many subprime borrowers was to default on their loan.

Amromin and Paulson (2009) also analyze the default experience of prime and subprime loans, although only over the period of 2004 through 2007. They identify a decline in underwriting standards during this period for both prime and subprime loans. While they find that characteristics such as LTV, FICO score, and interest rate at origination are important predictors of defaults for both prime and subprime loans, they do not believe that those changes were enough to have led to the observed increase we see in prime and subprime mortgage defaults over the past years. The authors firmly lay the cause of these defaults on house price declines, but note that more pessimistic contemporaneous assumptions about house prices would not have significantly improved forecasts of defaults.

Courchane and Zorn (2012) look at changing underwriting standards over time, and their impact on access to credit for target populations of borrowers.[7] 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 by borrowers living in low-income and minority communities. The authors show 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 non-prime originations. Throughout the period of study, targeted borrowers also consistently paid higher prices for their mortgages; however, the extent of this differential varied considerably over time and across groups. These pricing trends were driven primarily by the market's increasingly aggressive pricing of credit risk, mitigated somewhat by FHA's increase in share and its more general reliance on average- rather than marginal-cost pricing.

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[7] See also Courchane and Zorn (2011).

These studies all suggest the critical importance of treating separately the three market segments—prime, subprime, and government—when assessing the changing access to credit over the past decade. They also provide some optimism that a careful examination of recent lending patterns will reveal opportunities for responsibility extending credit to targeted populations.

III. Data

Our analysis uses CoreLogic data on mortgages originated between 1999 and 2009.[8] 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 2012Q3. Merged to these data are annual house price appreciation rates at a zip code level from the Freddie Mac House Price Index and 2000 decennial Census information on census tracts.[9] We also merge in unemployment rates from the Bureau of Labor Statistics[10] as well as changes in the 30 conventional market average 30-year fixed rate mortgage ("FRM") rate reported in Freddie Mac's Primary Mortgage Market Survey.®[11]

The CoreLogic data are not necessarily representative of the overall population, or of our target population. This is not necessarily a problem for estimating our delinquency model, but it does create concern for drawing inference to our target population. To address this potential concern we apply appropriate post-sample weights based on HMDA 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 categories is the same as that for HMDA loans. The categories are a function of market segment (prime, subprime, and government), loan purpose (purchase or refinance), state, month 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. However it likely offers an improvement and is the best we can do under the circumstances.[12]

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[8] This data is made available to Freddie Mac by CoreLogic.

[9] The house price index is the Freddie Mac House Price Index, Weighted Repeat Sales Index (WRSI) at the zip code level. While this data is not publicly available, the metro/state index can be found at: http://www.freddiemac.com/finance/fmhpi/. The CoreLogic data does not provide Census tract information, so we use a crosswalk from ZIP code tabulation areas to Census 2000 tracts. This crosswalk can be found at the Missouri Census Data Center: http://mcdc.missouri.edu/websas/geocorr12.html

[10] The unemployment rate is from the BLS Local Area Unemployment Statistics (http://www.bls.gov/lau/). We use county level unemployment rates. These rates are seasonally adjusted by Moody's Analytics.

[11] This data is available publicly at: http://www.freddiemac.com/pmms/pmms30.htm

[12] We do not use the weights for our delinquency estimations, but do use them to draw any inferences about the population

Consistent with our focus on identifying responsible credit opportunities for targeted populations, we restrict our analysis to first lien, purchase money 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 for government loans is 97 percent. This is considerably higher than for the prime market, where first lien loans tend to have LTVs under 90 percent.[13] We also observe the expected differences in FICO scores, with an average FICO score in the prime sector of 728, a subprime average of just 630, and an average for government loans of 666. The prime market loan amount (i.e., unpaid principal balance at origination) averages $207,000, with the government loan amount the lowest at a mean of $143,000. While many claims about subprime loans focused on their fueling of the jumbo market, the mean value in this population is below that for prime at $173,000. DTI ratios do not differ much between prime and government loans, and the DTI for subprime is unavailable in the data.

[13] While mean LTV for subprime is 83 percent, this may reflect the absence of second lien loans, which led to resulting higher combined LTV ("CLTV") ratios for subprime borrowers.

Exhibit 1: Summary Statistics for Continuous Variables used in the Estimations					
Variable		**All Loans**	**Prime**	**Subprime**	**Government**
LTV	Mean	83	78	83	97
	St. Dev.	15	15	11	7
	% Missing	1.80%	10.10%	2.80%	1.90%
FICO	Mean	703	728	630	666
	St. Dev.	69	55	62	68
	% Missing	15.50%	16.80%	8.10%	15.20%
Loan amount	Mean	190	207	173	143
	St. Dev.	336	360	324	243
	% Missing*	-	-	-	-
DTI	Mean	36	36		37
	St. Dev.	15	15		15
	% Missing	67.30%	62.60%	100.00%	65.50%
House Price Growth	Mean	4.10%	4.20%	6.90%	2.20%
(1 Year Post Origination)	St. Dev.	10.30%	10.60%	10.10%	8.90%
	% Missing*	-	-	-	-
House Price Growth	Mean	6.60%	6.80%	9.50%	4.70%
(2 Years Post Origination)	St. Dev.	19.80%	20.30%	20.70%	16.90%
	% Missing*	-	-	-	-
House Price Growth	Mean	7.40%	7.40%	7.50%	7.60%
(3 Years Post Origination)	St. Dev.	27.50%	28.30%	29.10%	23.80%
	% Missing*	-	-	-	-
Change in Mortgage Rate	Mean	-0.1	-0.1	0	-0.3
(1 Year Post Origination)	St. Dev.	0.6	0.6	0.6	0.6
	% Missing*	-	-	-	-
Change in Mortgage Rate	Mean	-0.2	-0.2	-0.1	-0.3
(2 Years Post Origination)	St. Dev.	0.6	0.6	0.5	0.5
	% Missing*	-	-	-	-
Change in Mortgage Rate	Mean	-0.2	-0.2	-0.3	-0.3
(3 Years Post Origination)	St. Dev.	0.6	0.6	0.5	0.6
	% Missing*	-	-	-	-
Unemployment Rate	Mean	5.6	5.4	5	6.5
(1 Year Post Origination)	St. Dev.	2.3	2.1	1.5	2.9
	% Missing*	-	-	-	-
Unemployment Rate	Mean	6	5.9	5.4	6.7
(2 Years Post Origination)	St. Dev.	2.6	2.5	1.9	2.9
	% Missing*	-	-	-	-
Unemployment Rate	Mean	6.6	6.6	6.4	6.7
(3 Years Post Origination)	St. Dev.	2.8	2.8	2.7	2.7
	% Missing*	-	-	-	-

*We drop missing observations for continuous variables in the estimations except for FICO, where missing vales are included through the use of a dummy variable. We include a missing observation category for discrete variables with missing observations.

The areas where the subprime loans were originated had the highest house price growth at 6.9 percent one year after origination and 9.5 percent two years after origination. By the third year after origination there was little appreciable difference in house price growth across market segments. The standard deviation of house price growth rates increased considerably over time, rising from about 10 percent the first year after origination to around 28 percent three years after origination. For all three time periods after origination, unemployment rates are highest, on average, in the geographies with government loans.

Exhibit 2: Summary Stats for Variables used in Estimation (Class Variables)					
Variable	**Class**	**All**	**Prime**	**Subprime**	**Government**
Property Type	Not Condo	88.30%	86.20%	92.20%	93.00%
	Condo	11.70%	13.80%	7.80%	7.00%
Occupancy	Owner-Occupied	85.50%	83.40%	85.90%	91.90%
	Not Owner-Occupied	14.50%	16.60%	14.10%	8.10%
Channel	Other	40.70%	41.00%	33.20%	43.60%
	Retail	29.90%	33.70%	21.20%	22.10%
	Wholesale	29.40%	25.30%	45.70%	34.30%
Product Type	ARM	14.90%	12.60%	48.50%	4.70%
	Balloon	0.80%	0.40%	4.90%	0.00%
	FRM-15	5.60%	7.70%	1.60%	1.20%
	FRM-30	67.80%	68.20%	22.30%	90.10%
	FRM-Other	3.80%	4.50%	1.70%	2.70%
	Hybrid	7.10%	6.60%	21.00%	1.20%
Documentation	Full Documentation	34.50%	29.90%	49.40%	41.80%
	Missing	37.30%	38.80%	18.40%	42.30%
	Not Full Doc	28.10%	31.30%	32.20%	15.90%

Exhibit 2 presents the summary statistics for the class variables in the CoreLogic population. Some expected results emerge. The subprime segment has the largest share of loans originated through the wholesale channel, at 45.7 percent. The wholesale share for the prime segment was only 25.3 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, 68.2 percent of prime loans were 30-year FRMs with another 5.6 percent 15-year FRMs. Nearly all of the government loans were 30-year FRMs. The documentation figures are somewhat surprising, with nearly half of subprime loans as full documentation. The low share of full documentation loans in the prime sector likely reflects the inclusion of Alt-A loans, which are defined to be prime loans in the CoreLogic data.

Many homeownership and affordable lending programs take a broad view of their constituent population. However our interest is narrowly focused on assessing opportunities for responsibly extending mortgage credit to borrowers with low downpayments and poor credit histories, or who are otherwise underserved by the prime market ("targeted population"). We define this specific population as borrowers taking out 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.

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 policy considerations encourage us to include an income constraint in our definition of the targeted population. As a consequence, loans to targeted 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.

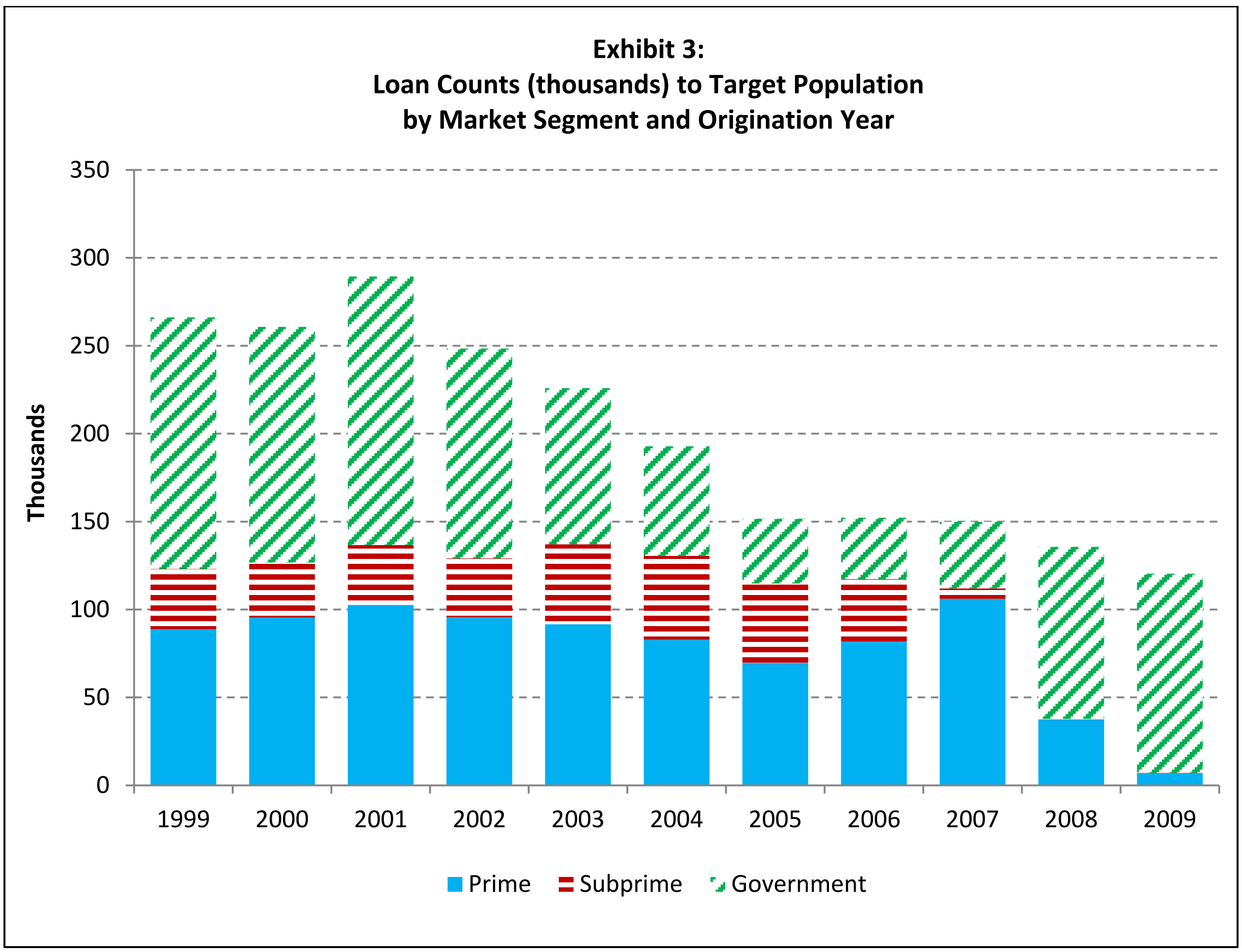

Exhibit 3 provides a graphical illustration of the distribution of target population loans across the three market segments. The dramatic shift over time in the share going to the government sector is obvious, as is the reduction in the reduction in the number of loans originated to the target population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

IV. Analysis

The first step in our analysis is to estimate a model of loan performance over the crisis period. We use augmented CoreLogic loan-level data on originations from 1999 through 2009 to estimate a model of loans becoming 90-days or more delinquent in the first three years after origination. This model includes borrower and loan characteristics at origination, as well as control variables measuring changes in house prices, unemployment rates, and interest rates post-origination. It also includes several interaction terms for the borrower, loan, and control variables.

We then use our estimated delinquency model to specify two representative underwriting scorecards—a through-the-cycle scorecard and a perfect foresight scorecard. We next apply a variety of cutpoints to our scorecards. Loans with risk scores (delinquency probabilities) at or below the cutpoint are by definition assumed to be within appropriate risk tolerances.

The scorecard and cutpoint combinations provide working prototypes of an automated underwriting system. Our final step is to apply these prototypes to the target population and assess the results.

A. Estimating the Models

We estimate three separate delinquency models based on the CoreLogic population of first-lien, purchase money loans. Separate models were estimated for prime loans (including Alt-A loans), subprime loans, and government loans, using an indicator provided in the CoreLogic data.[14] The prime market estimation results are presented in Appendix Tables A.1.a, subprime in A.2.a, and government in A.3.a.

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 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). In our case, however, we apply our scorecard to the same historical data we use for model estimation (i.e., in sample). This, as a consequence, will tend to make our scorecard assess risk more accurately than production versions. These two factors counteract each other, and as a result we believe they do not significantly bias our results.

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

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, interest rates (Freddie Mac Primary Mortgage Market Survey rates), house prices (based on the Freddie Mac House Price Index), and unemployment rates. 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); channel (retail, wholesale, other); LTV (less than 40 percent, 40 to 60 percent, 6 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 and loan amount, loan amount and LTV, FICO score and LTV, and post-origination house price changes and LTV.

Most of the variables in the prime delinquency model (Exhibit A.1.a) had the expected signs. Full documentation loans, retail channel loans, loans under the conforming limits, and FRM-30 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. As in the prime segment, subprime borrowers with higher FICO scores are associated with lower delinquency rates, as are owner-occupied and FRM-30 loans. LTV also has a similar relationship with delinquency in both the prime and subprime models, however the parameter estimates on the high LTV subprime loans are among the highest for both market segments. 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.

For the government segment, retail channel has the negative sign we observed in prime. Full documentation loans are still marginally more likely to fall into delinquency, but given that nearly all government loans are full documentation, this result carries little weight. Finally, higher LTV and lower FICO government loans scores have an increased probability of delinquency.

In summary, the signs and magnitudes of our estimation parameters generally fit our expectations. We next 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.[15] In general we see that the models fit well. Specifically, the scatter plots remain relatively close to the 45 degree reference line. To the extent that there is any

[15] 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 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.

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 the target population, which is located in the well-fitting higher risk (upper right-hand) section of the charts.

B. 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* (i.e., at origination) assessment of the credit risk associated with a particular borrower/loan combination. Our estimated delinquency models provide the basis for this assessment, however these models include both *ex ante* and *ex post* (i.e., 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 simply treat post-origination explanatory variables as controls in the scorecard. That is, to keep the value of these variables constant across borrowers and over time. We call this version a "through-the-cycle" scorecard. In our application we set post-origination variables to approximately their long run means (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).

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, and developing a representative prototype of this exercise is beyond the scope of our current analysis. Instead we pursue a simpler alternative that captures the concept of a scorecard incorporating forecasting.

The goal of forecasting is to accurately predict the future values of the *ex post* explanatory variables. Our estimation data include the actual future values of these variables. Our approach, therefore, is to incorporate the actual future values of the *ex post* explanatory variables directly into our scorecard. We call this version our "perfect foresight" scorecard because it reflects the outcome of a scorecard with perfect forecasting. In this regard our scorecard represents an outer-bound possibility; scorecards that incorporate realistic forecasting will likely be less accurate.

Separate scorecards will be 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 perfect forecasting scorecards for each market. The through-the-cycle scorecard has the policy advantage of being relatively tight during the boom years and relatively loose during recessions (i.e., it is counter-cyclical). As a result we expect it to be more "friendly" to the target population during recessionary periods such as those experienced recently. However the through-the-cycle scorecard achieves this increased access to credit at the cost of potentially greater accuracy. For example, it systematically under-assesses risk during down cycles.

In contrast, the perfect forecasting scorecard very accurately assesses the risk of loans. Realistic forecasting alternatives will not be as accurate, but nonetheless can potentially do a better job than the through-the-cycle scorecard. The result is that scorecards incorporating forecasting can arguably better control risk, but at the cost of a significant reduction in access to credit during recessionary periods. We expect the perfect foresight scorecard to be particularly "unfriendly" to the target population in recent years.

C. 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. All loans that the scorecards assess as less risky than the cutpoints are viewed as acceptable risks, all loans assessed as more risky than the cutpoint are viewed as unacceptable (i.e., too high) risks. The cutpoints, therefore, set the extreme bounds of within-tolerance risk for the scorecards.

Both policy and business considerations impact the judgmental 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, the same 10 percent delinquency rate might be viewed as too high a prime cutpoint during a post-crisis recession, such as recently, when the market is trying to limit credit exposure and public policy has shifted to managing systemic risks and taxpayer losses.

It is not our intention to propose "correct" cutpoints for our scorecards. Rather, our goal is to illustrate how scorecards with reasonable cutpoints affect access to credit for the target population. Toward this end, we provide a set of potentially reasonable 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 provides a range of alternative impacts on the target population.

To simplify our presentation and focus our analysis, we also concentrate on a "representative" set of cutpoints that are determined by choosing among our four cutpoints for each market the one that most closely approximates the observed 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 so 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 representative cutpoint at the realized performance of borrowers around the 90th risk percentile of the perfect foresight scorecard. This performance is most closely approximated by a cutpoint of 5 percent delinquency rates, and by construction this results in about 90 percent of the prime loans originated in 1999, 2000, and 2001 being viewed as acceptable risk.[16]

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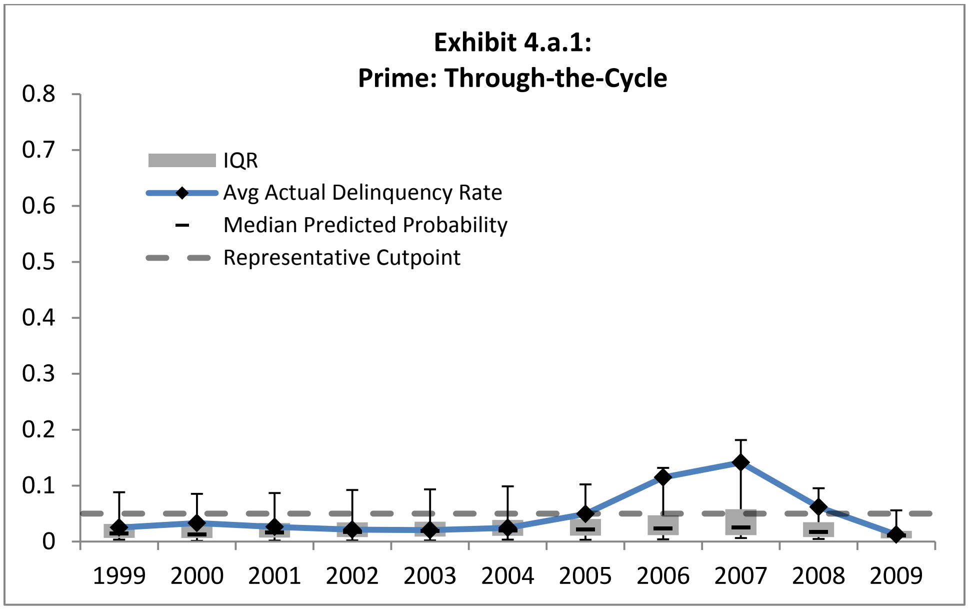
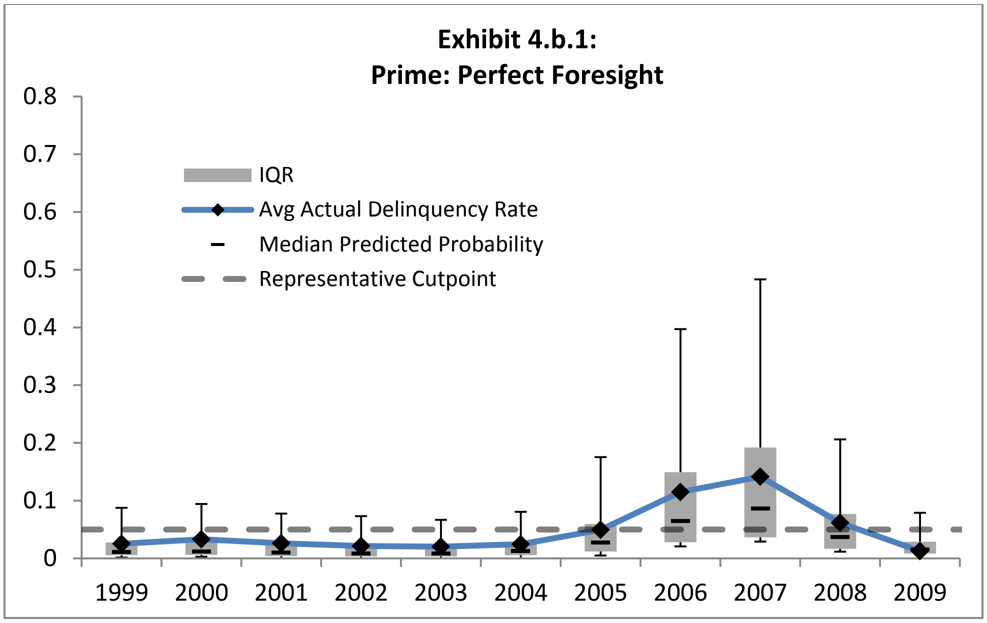
[16] The 90th risk percentile is the scorecard prediction level that separates the 10 percent of borrowers with the highest predicted risks from the remained 90 percent of borrowers with lower predicted risks.

The implication of this cutpoint for our two scorecards is illustrated in Exhibit 4. Exhibit 4 shows box plots of the of the scorecard score distributions, separately by scorecard, market, and year.[17] The box plots for the through-the-cycle scorecard are provided in Exhibits 4.a.1 – 4.a.3, the perfect foresight scorecard boxplots are in Exhibits 4.b.1 – 4.b.3. The prime market is shown in Exhibits 4.a.1 and 4.b.1, the subprime market in Exhibits 4.a.2 and 4.b.2, and the government market in Exhibits 4.a.3 and 4.b.3. We plot our representative cutpoints in each market as horizontal lines.



[17] 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) is shown within the box as a short line. The average actual delinquency rate of loans originated in each year is shown with a diamond. The data are weighted via HMDA to more accurately reflect the underlying population.



The through-the-cycle scorecard makes specific, constant assumptions about the values of post-origination variables. As a consequence, variation over time in the score distributions of the through-the-cycle scorecard is solely reflective of variation in observable-at-origination risk characteristics of the individual year cohorts. In contrast, variation over time in the score distributions of the perfect foresight scorecard also reflects variation in the economic environment experienced post-origination. Moreover, because the perfect foresight scorecards are simply our model predictions from the first step, the models fit the data relatively well. That is, the box plots of the perfect foresight scorecard are closely reflective of the distributions of actual delinquency rates, as can be seen by the fact that the average actual delinquency rate (represented by a diamond) is generally toward the center of the interquartile range.

The resulting score distributions of the two scorecards are quite distinct. The box plots of the perfect foresight scorecard show relatively consistent risk distributions in years 1999 through 2004, a significant increasing of risk in the 2005 through 2007 period, and then declining risk with an ultimate return to the earlier levels by 2009. The impacts of the changing risk distributions are a function of a worsening credit mix of originations (due in part to loosening underwriting standards), and declining house prices after origination.

The through-the-cycle scorecard box plots show relatively consistent risk distributions in the origination cohorts throughout the entire period, albeit with a small change in the years 2005 through 2009. This suggests that a worsening post-origination macroeconomic environment was more likely to have been the cause of the poor credit performance of the 2005 through 2007 origination cohorts than a loosening in underwriting standards.

The horizontal line in Exhibit 4.a.1 plots the prime market representative cutpoint at 5 percent delinquency rates. A comparison of this line with the through-the-cycle scorecard distributions shows that the percentage of loans viewed as acceptable risk by this scorecard remains relatively constant throughout the period, albeit with a slight decline during the crisis years. That is, in most years the horizontal line runs between the 75th and 95th percentile risks (i.e., between the top of the "box" and the highest "whisker"). In contrast, the perfect foresight scorecard (Exhibit 4.b.1) shows a significant reduction in the percent of originations viewed as acceptable risk in the 2005 through 2008 originations. In this regard the perfect foresight scorecard is clearly more pro-cyclical during the recessionary period of 2007 and 2008.

Exhibit 4.a.2:
Subprime: Through-the-Cycle

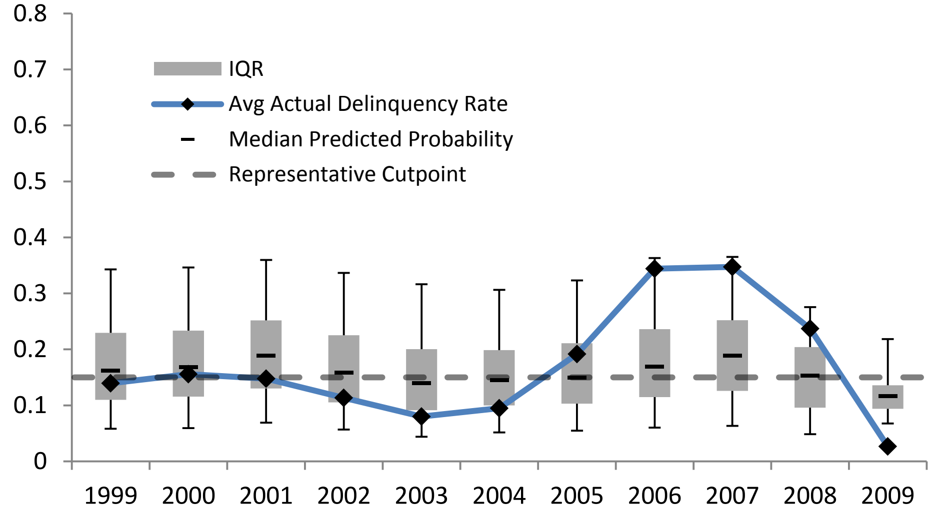
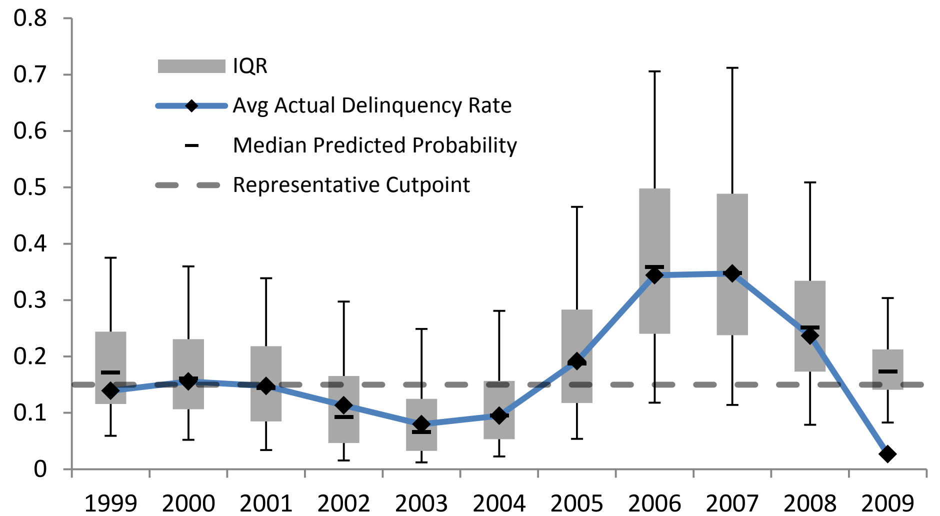
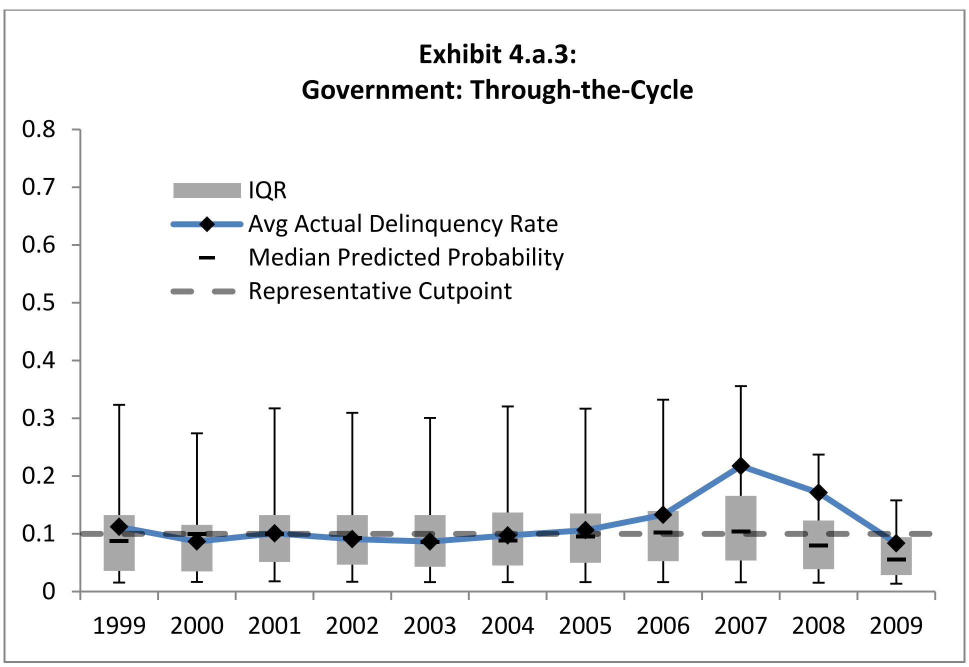


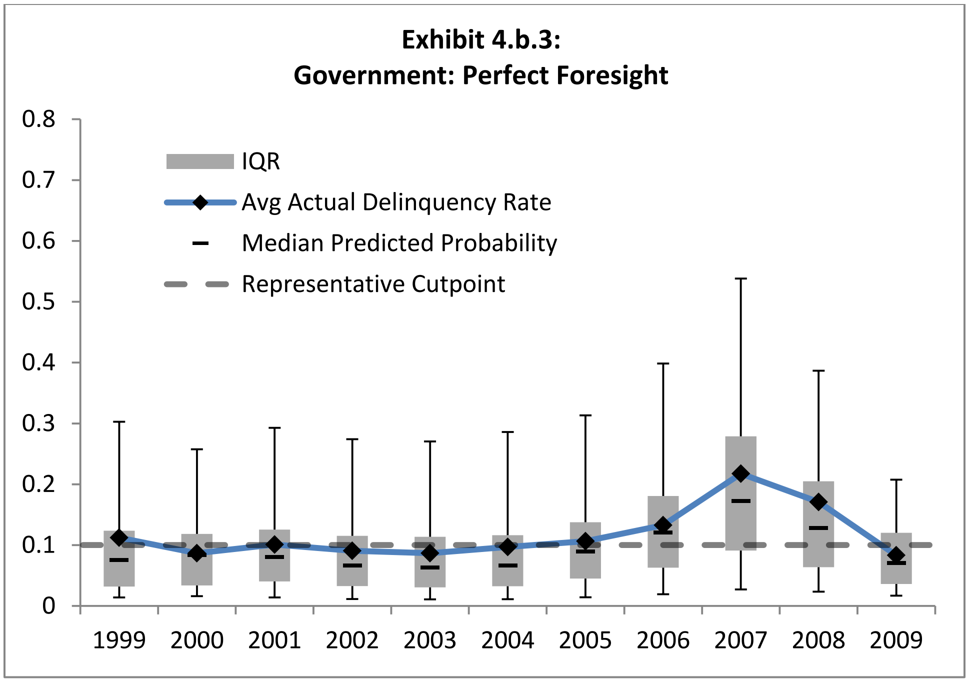
Exhibit 4.b.2:
Subprime: Perfect Foresight



Subprime score distributions are shown Exhibits 4.a.2 and 4.b.2, and have a markedly different time trend than the prime market. Both the box plots for the perfect foresight scorecard (Exhibit 4.b.2) and the average actual delinquency rates show that realized performance of origination cohorts in the years 1999 through 2001 was significantly worse than performance of the 2002 through 2004 cohorts. This suggests that subprime underwriting in the 1999 through 2001 period was not as standardized in orientation as in the prime market. Moreover, the differential in risk between prime and subprime lending appears somewhat greater in 1999 through 2001 than in 2002 through 2004, suggesting that subprime lending was relatively less conservative than prime lending in the earlier period. Finally, the overall tolerance for accepting risk in mortgage lending has clearly declined in the recent environment. Reflecting these factors, we use a more restrictive standard for determining marginal borrowers in the subprime market than we do in the prime market. For the subprime market we choose a representative cutpoint of 15 percent delinquency rates, which results in only about one-half of the subprime loans in the 1999 to 2001 cohort being viewed as acceptable risk.

Comparing the representative cutpoint lines and the subprime box plots in Exhibit 4 also shows that the through-the-cycle scorecard (Exhibit 4.a.2) is the more counter-cyclical. Throughout the period, the through-the-cycle scorecard consistently assesses about one-half of the subprime loans as being acceptable risk (i.e., about 50 percent of subprime loans score below the cutpoint). The perfect foresight scorecard (Exhibit 4.b.2), however, shows significant variation in its assessment over the period—there is an increase in the percentage of acceptable-risk-loans from 1999 through 2003, at which point the percentage of acceptable loans declines rapidly to near zero levels, with only a slight rebound in 2009.





Government market scorecard distributions are shown in Exhibits 4.a.3 and 4.b.3. As with the subprime market, the box plots for the perfect scorecard (Exhibit 4.b.3) suggest that underwriting was not as standardized or (relatively) conservative as in the prime market during 1999 through 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 and prime markets. 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 underserved borrowers. This yields a representative cutpoint for the government sector of a 10 percent delinquency rate, which results in about 60 percent of the 1999 through 2001 cohort being viewed as acceptable risk.

D. Applying Scorecards to the Target Population

Our last step applies our automated underwriting scorecards to the target population. The target population includes only borrowers residing in census tracts with median incomes below 80 percent of the area median, low down payments (90 percent <= LTV), and lower credit scores (FICO <= 720 or missing). As noted earlier, this represents only about four percent of overall originations during our period of study. In this regard it is a restrictive definition of the overall set of borrowers for whom there has been public policy concern (e.g. first-time homeowners, low-income borrowers, minority borrowers, and borrowers underserved by the conventional mortgage market). We choose this more restrictive definition partially because we lack the data to accurately identify broader populations of policy focus, and partially to reflect post-crisis regulatory and market tightening (such as the QM and QRM criteria being promulgated by the Consumer Finance Protection Bureau) that has made it especially difficult for borrowers with poorer credit records and/or low downpayments to obtain a mortgage. Moreover, although restrictive, we believe our target population is highly reflective of the population focused on by most affordable- and underserved-policy initiatives.

We use our two scorecards to separately score target borrowers, and then determine the percent of the population assessed as acceptable risks by the alternative cutpoints (5, 10, 15, and 20 percent delinquency rates). The results of this exercise for the through-the-cycle scorecard and the perfect foresight scorecard are provided in Exhibit 5.

Exhibit 5: Percent of Acceptable Risk Borrowers within the Target Population

Scorecard	Market	Cutoff	1999	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
Through-the- Cycle	Prime	5%	47%	48%	36%	33%	27%	26%	18%	15%	32%	31%	34%
		10%	83%	86%	80%	78%	75%	73%	63%	53%	77%	74%	75%
		15%	91%	93%	92%	91%	89%	86%	79%	72%	88%	90%	87%
		20%	95%	96%	96%	96%	94%	92%	87%	82%	93%	95%	93%
	Subprime	5%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
		10%	4%	3%	4%	8%	8%	10%	9%	5%	9%	22%	7%
		15%	16%	17%	23%	33%	35%	32%	26%	17%	38%	78%	26%
		20%	36%	40%	50%	60%	62%	54%	44%	37%	61%	90%	49%
	Government	5%	3%	4%	4%	6%	6%	5%	4%	4%	6%	9%	5%
		10%	34%	33%	37%	42%	43%	38%	35%	36%	49%	60%	39%
		15%	69%	75%	75%	75%	73%	74%	75%	67%	80%	89%	77%
		20%	79%	84%	85%	85%	83%	84%	84%	79%	91%	96%	86%
Perfect Foresight	Prime	5%	55%	65%	64%	67%	55%	26%	2%	1%	4%	15%	41%
		10%	84%	89%	89%	90%	86%	65%	20%	8%	33%	58%	66%
		15%	92%	95%	95%	95%	93%	81%	42%	23%	60%	81%	77%
		20%	95%	97%	97%	97%	96%	89%	58%	39%	74%	91%	84%
	Subprime	5%	0%	3%	11%	20%	12%	1%	0%	0%	0%	0%	7%
		10%	5%	19%	38%	51%	41%	10%	0%	0%	0%	0%	23%
		15%	17%	40%	58%	71%	63%	27%	3%	3%	3%	29%	39%
		20%	36%	58%	75%	84%	78%	44%	9%	7%	21%	63%	54%
	Government	5%	8%	13%	23%	25%	23%	9%	2%	0%	1%	3%	11%
		10%	46%	51%	61%	61%	60%	44%	22%	7%	14%	38%	44%
		15%	73%	80%	83%	82%	80%	74%	54%	24%	37%	72%	72%
		20%	83%	87%	90%	89%	88%	84%	74%	46%	60%	89%	83%

Exhibit 5 clearly shows that the choice of cutpoint has a dramatic impact on the percent of the target population obtaining access to credit. For example, over the entire period 34 percent of the target population are viewed as acceptable risk by the through-the-cycle scorecard using a cutpoint of 5 percent, while at a cutpoint of 10 percent this figure jumps to 75 percent. The differential risk distributions of loans across the three markets are also clearly illustrated. Using the through-the-cycle scorecard, 75 percent of the target population in the prime market is viewed as acceptable risk at a cutpoint of 10 percent, but this declines to only 7 percent in the subprime market and to 39 percent in the government market. These three markets clearly, and deliberately, serve significantly different risk borrowers.   This should appropriately be reflected in appropriately setting cutpoints across the markets.

It is also interesting to compare results across the two scorecards. Overall, there is surprising similarity in the overall percentage of acceptable-risk loans for the through-the-cycle and perfect foresight scorecards with the same cutpoints. For example, with a cutpoint of 5 percent, the through-the-cycle scorecard finds 34 percent of the prime market target population as acceptable risk, while the perfect foresight scorecard finds 41 percent. Similarly, at a cutpoint of 10 percent in the government market, the through-the-cycle scorecard finds 39 percent of the loans to target population as acceptable risk, while the perfect foresight scorecard finds 44 percent. The difference is somewhat larger in the subprime market, where a cutpoint of 15 percent results in 26 percent of loans being acceptable risk, while the perfect foresight scorecard finds 39 percent.

Moreover, there is a distinct pattern in these results. All things equal, the perfect foresight scorecard yields a higher overall percentage of acceptable loans in the target population than the through-the-cycle scorecard. Looking at the yearly columns in the Exhibit 5 shows why. The perfect foresight scorecard views a substantially higher percentage of loans as acceptable risk in the years 1999 through 2004 than does the through-the-cycle scorecard. The pattern reverses in the 2006 through 2009 period, but the net impact is that over the entire period more in total loans are viewed as acceptable risk by the perfect foresight scorecard.

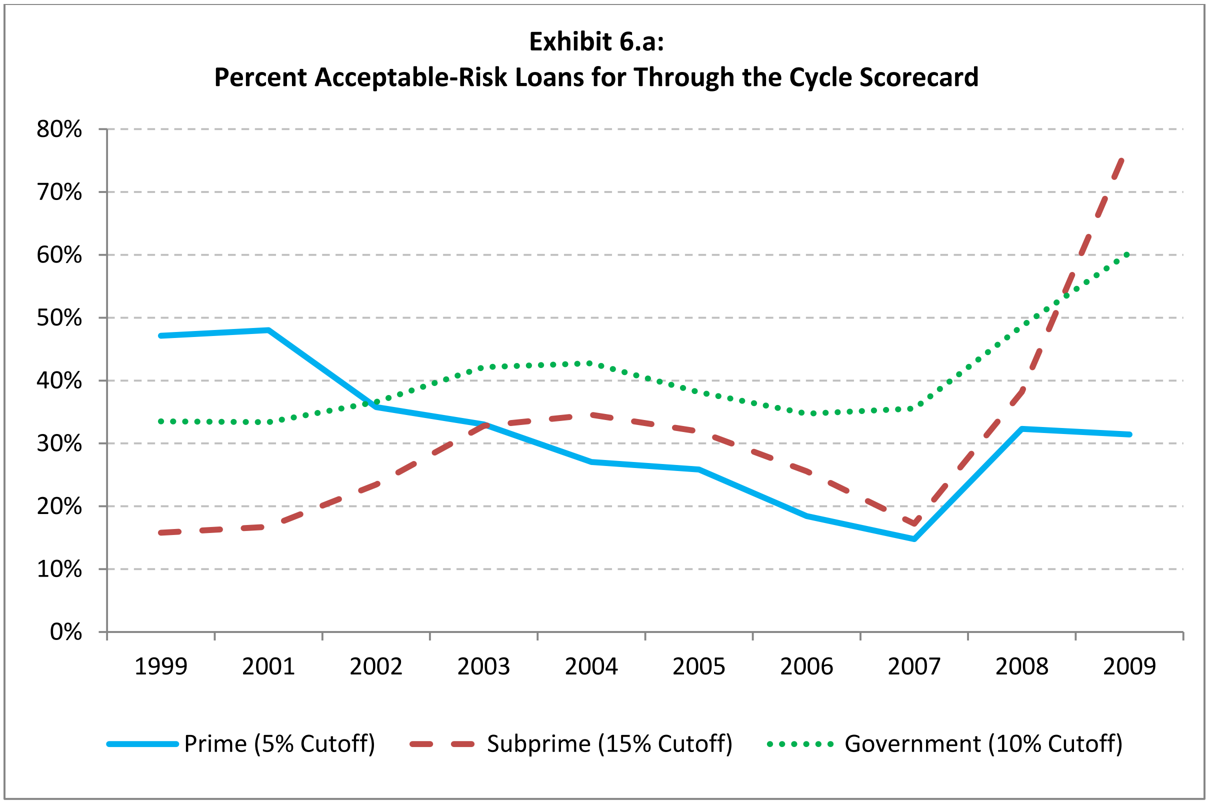


Exhibit 6.a:
Percent Acceptable-Risk Loans for Through the Cycle Scorecard
80%
70%
60%
50%
40%
30%
20%
10%
0%
1999
2001
2002
2003
2004
2005
2006
2007
2008
2009
Prime (5% Cutoff)
Subprime (15% Cutoff)
Government (10% Cutoff)

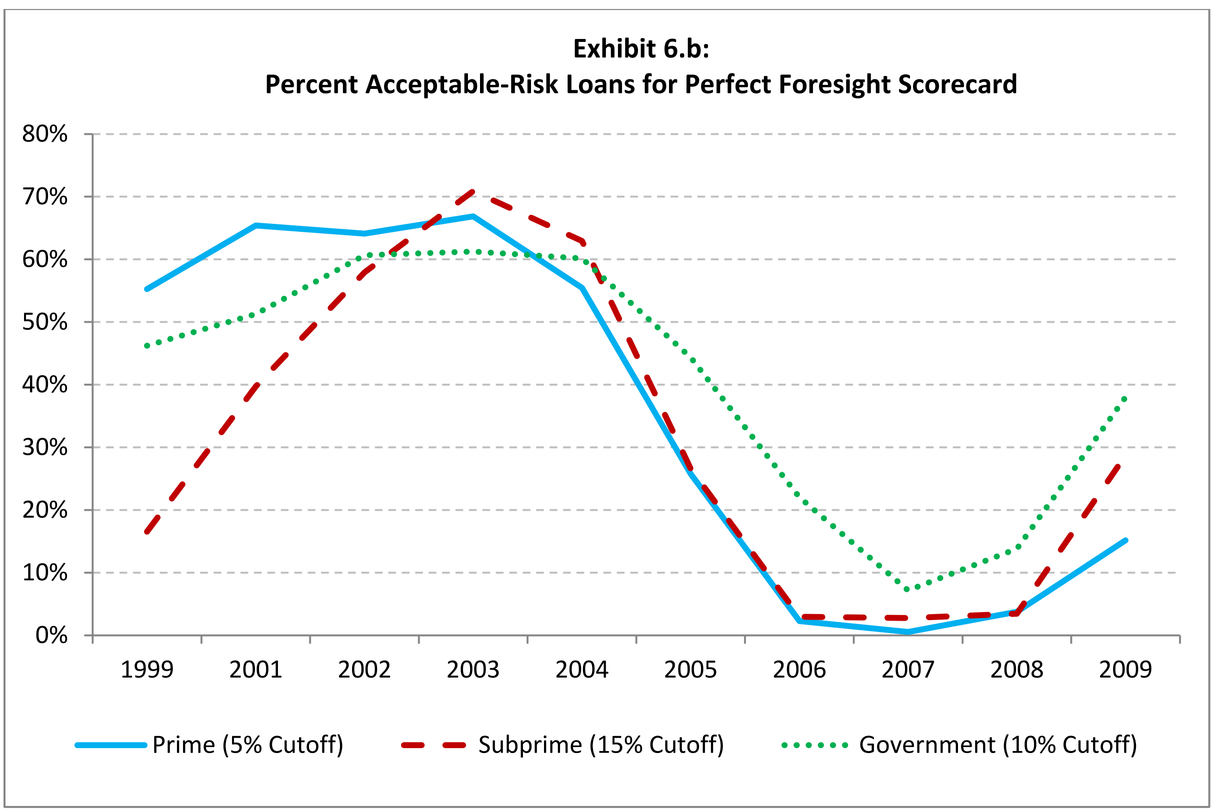


Exhibit 6.b:
Percent Acceptable-Risk Loans for Perfect Foresight Scorecard
80%
70%
60%
50%
40%
30%
20%
10%
0%
1999
2001
2002
2003
2004
2005
2006
2007
2008
2009
Prime (5% Cutoff)
Subprime (15% Cutoff)
Government (10% Cutoff)

These trends are more clearly illustrated graphically in Exhibits 6a and 6b, which plot the time trend of the percent of acceptable-risk loans to the targeted population for the through-the-cycle and perfect foresight scorecards, respectively. In comparing the two Exhibits, it is clear that in the years leading up to the boom (2000 through 2005) the perfect foresight scorecard offers credit to a far greater percentage of the target population than the through-the-cycle scorecard.

This increased access to credit is a two-edged sword. On one hand, the increased lending activity arguably contributed to the over-stimulated housing market that was such a contributor to the recent recession—a public policy negative. On the other hand, however, the perfect foresight scorecard grants significantly more credit to the target population overall, albeit especially in the early years of the decade—a public policy plus. Determining the preferred tradeoff between these two outcomes is a public policy challenge.

Exhibits 6a and 6b also suggest that, at least using our representative cutpoints, it is possible to use automated underwriting systems such as our prototype scorecards to responsibly extend credit to targeted borrowers. Targeted borrowers have had difficulty obtaining credit in the recent market, arguably because of lower FICO scores and/or low downpayments. Evidence that many of these loans may be acceptable risks offers a positive sign to people concerned with the access to credit of this population.

As a final part of our analysis, we provide Exhibits that provide the distributions of key risk characteristics of targeted borrowers with acceptable risk. Exhibit 7.1 provides the FICO Distribution for targeted acceptable-risk borrowers, and Exhibits 7.2 and 7.3 provide the LTV and DTI distributions, respectively.[18] Of most interest is examining the range of acceptable-risk values across these key characteristics in every market segment.

[18] The box and whiskers in box plots are constructed the same as in Exhibits 4, but in this instance the diamond represents the average (mean) of the distribution.

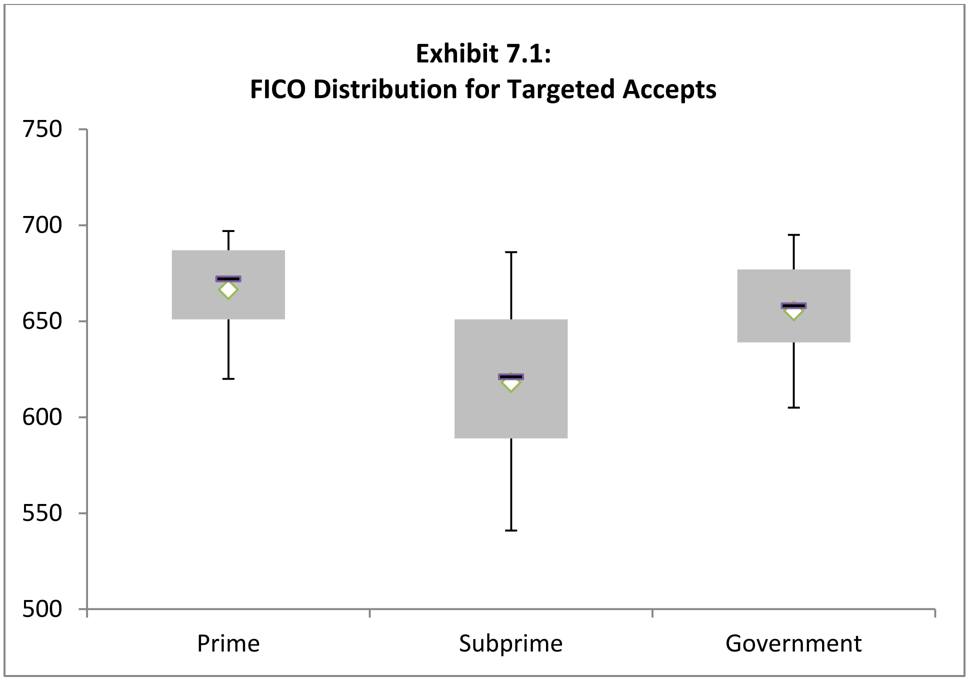


Exhibit 7.1:
FICO Distribution for Targeted Accepts
750
700
650
600
550
500
Prime
Subprime
Government

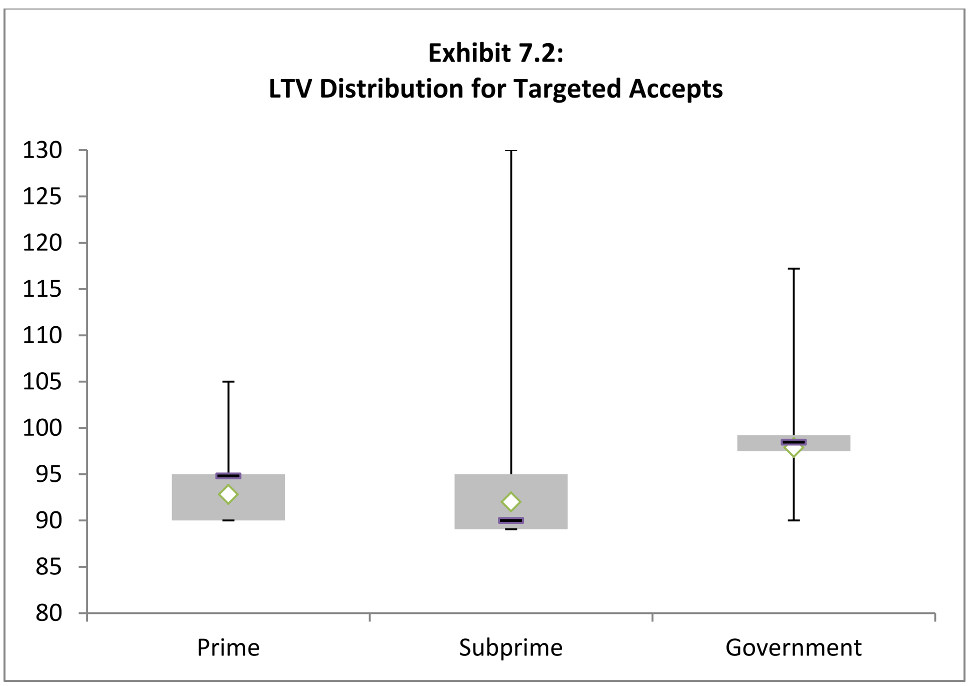
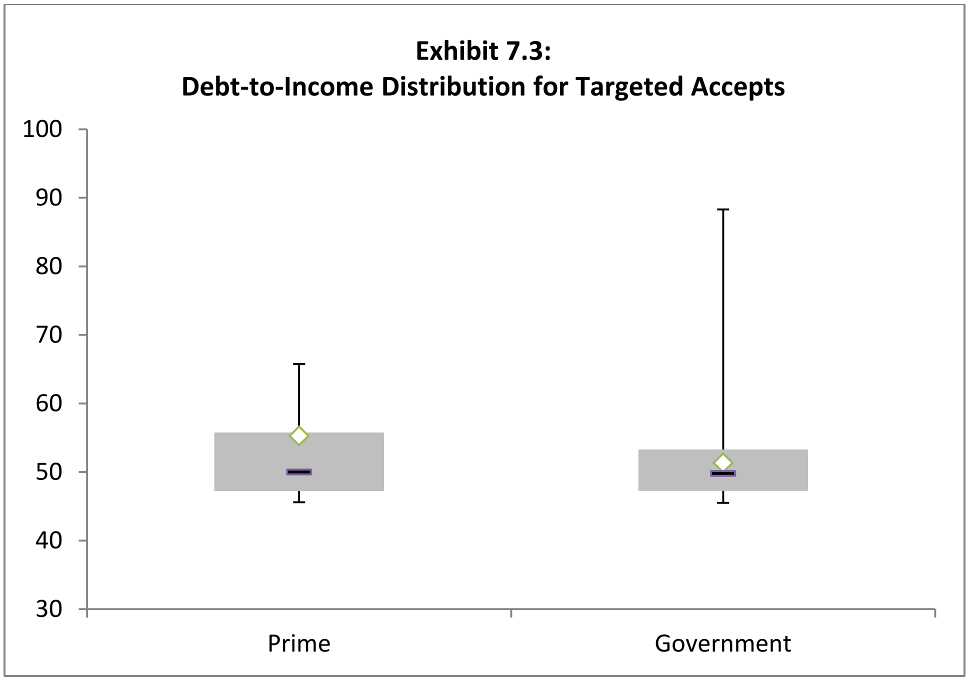


Exhibit 7.2:
LTV Distribution for Targeted Accepts
130
125
120
115
110
105
100
95
90
85
80
Prime
Subprime
Government



At a representative cutpoint, Exhibit 7.1 shows that acceptable-risk prime target borrowers have a FICO scores distribution that has an interquartile range of 687 to 651, with an average of 666. For subprime the IQR falls between 651 and 589, with an average of 618. In the government segment, the IQR is from 677 to 639, with an average of 655. While these score ranges and averages vary by segment, all of them are considerably lower than the observed credit score averages of originations in the recent conventional or government markets. Rather, they represent scores that the current market considers very poor, and would likely make it difficult to obtain credit.

A similar story occurs for LTV (Exhibit 7.2). Acceptable-risk prime target borrowers have an LTV distribution with an interquartile range of 95 to 90 percent. Acceptable-risk subprime target borrowers also have an interquartile range of approximately 90 to 95 percent, while government borrowers' interquartile range varies from 98 to 99 percent. These are values well outside the cutoffs often discussed under QRM.

Finally, while we lack DTI data for the subprime market, acceptable-risk prime targeted borrowers have a DTI distribution with an interquartile range from around 47 to 56 percent. For the government market the interquartile range goes from 47 to 53. In both instances these are values that are well above the proposed 43 percent threshold for QM. In fact, over 95 percent of the acceptable risk prime and government target borrowers have DTIs above the QM threshold.

V. Conclusions and Implications

Our delinquency estimations well fit our data, indicating the basic reasonability of the statistical models underlying automated underwriting systems. We use these estimations to construct two scorecards (through-the-cycle and perfect forecast), and then apply each scorecard to the historic population of targeted borrowers. Because these borrowers have lower FICO scores and make smaller downpayments, they likely would face challenges obtaining mortgages in the current environment. It is instructive, therefore, to determine whether our scorecards suggest that it is possible to responsibly extend credit to a significant portion of this population.

The key to responsible lending is the appropriate setting of risk tolerances, and in automated underwriting systems this is operationalized by choosing the scorecard cutpoints that determine the maximum level of acceptable risk. This is not a science. Rather, it is a judgment that balances policy, regulatory, and business considerations that all can change over time. The results of our analysis are very sensitive to the cutpoints we use. This simple observation highlights the temporal nature of responsible lending—risks that are viewed as acceptable in one period may be viewed as too high in another.

We focus our analysis on a representative set of cutpoints that we believe take a long run view of risk. Using these cutpoints we find that it is possible to responsibly extend credit to a significant percentage of the targeted borrowers. Specifically, using the through-the-cycle scorecard we assess 34 percent of the prime targeted borrowers as acceptable risk, 26 percent of the subprime targeted borrowers, and 39 percent of the government targeted borrowers. Using the perfect foresight scorecard we find it is possible to responsibly lend to 42 percent, 39 percent, and 44 percent of the prime, subprime, and government targeted borrowers, respectively.

Our analysis is not definitive; it is sensitive to the choice of cutpoint (risk tolerance). It is, however, encouraging because it suggests that automated underwriting systems offer potential for responsibly extending credit to the target population. The size of this impact depends critically on the risk tolerances incorporated into the automated underwriting systems. But regardless of the chosen level of risk, our analysis identifies a portion of the target population to whom lenders can responsibly extend credit.

However, traditional automated underwriting systems are unlikely to be a panacea for providing access to credit to the targeted population.[19] Successful homeownership outreach programs typically rely on 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. None of these program aspects are recorded in the CoreLogic data, nor are they typically captured by automated underwriting models. Enhancing traditional automated underwriting along these dimensions is not a simple matter, but doing so offers the potential of further expanding access and increasing accuracy.[20]

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[19] 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.

[20] 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.

Even without this enhancement, however, automated underwriting is likely to remain only one of the effective tools used to responsibly extend credit to targeted populations.

Our analysis also highlights that choosing how a scorecard treats the post-origination environment has significant policy implications. From a macro-economic perspective, the through-the-cycle scorecard has the desirable characteristic of being counter-cyclical—it tends to restrict credit during over-heated markets and expand credit during recessions. The perfect foresight scorecard, in contrast, extends more overall credit (the expansion during the boom years is larger than the contraction during the recession). It also reduces total losses because it "recognizes" when the post-origination environment will be more risky. This presents a challenging policy conundrum.

It is important to note that the benefits of a perfect foresight scorecard presume precisely that, a perfect foresight. The overly optimistic view of most economic forecasters leading up to the last crisis suggests that this is an unrealistic expectation. It is beyond the scope of this paper to create a scorecard that more reasonably mimics real life forecasting. It seems reasonable to assume, however, that real-life forecasts will often be incorrect, and that the promised loss reduction from incorporating forecasting into automated underwriting systems may be elusive.

Our analysis also has implications for QM and QRM regulations. QM focuses on ability to repay concerns while QRM addresses downpayment considerations (i.e., skin in the game). Very few if any of the target population borrowers would qualify for mortgages under strict QM and QRM constraints. For example, our analysis suggests that virtually all of the prime and government market target borrowers of acceptable risk have DTIs in excess of the 43 percent threshold proposed in QM regulations. Similarly, by construction our target borrowers make less than 10 percent downpayments, well below the minimum 20 percent frequently proposed for QRM. This illustrates both the disadvantage of regulation through single-metric thresholds, and the advantage of taking into account compensating factors through statistical models. Model-based rather than simple threshold-based regulations offer the possibility of expanded access to credit at acceptable risk.

Finally, we note that mortgage products, especially the 30-year FRM, and market segmentation likely play an important role in responsibly extending credit to the targeted population. There is no doubt that the 30-year FRM has attractive characteristics from a risk perspective. And in our data, nearly 50 percent of the target prime borrowers taking out 30-year FRMs met our acceptable risk tolerances. However this does not necessarily imply that all targeted prime borrowers could have, or should have, taken out a 30-year FRM. Many non-FRM products offer significant reductions in monthly mortgage payments, at least initially, and have more relaxed underwriting standards.

Similarly, the prime market has historically provided a mortgage origination process that arguably would reduce the risk of lending relative to the subprime channel. It is tempting, therefore, to believe that moving borrowers from the subprime to the prime market could be a useful tool in responsibly extending credit. As with the 30-year FRM, however, it is unclear whether this would ultimately benefit borrowers. The subprime market, for example, clearly has higher risk tolerances than the prime market, so all things equal it offers more access to credit. Fully exploring the value of the 30-year FRM or prime lending for extending credit to targeted borrowers is an interesting but complex issue beyond the scope of our analysis.

VI. References

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Exhibit A.1.a: Prime Market Estimation Results				
Variable	**Value**	**Estimate**	**Std Error**	**Prob Chi Sq**
Intercept		6.0511	0.0185	<.0001
LTV ratio	< 40	-2.0216	0.0383	<.0001
	40 to 60	-1.2569	0.0134	<.0001
	60 to 75	-0.4266	0.00841	<.0001
	75 to 80	-0.3532	0.00758	<.0001
	80 to 85	0.2441	0.0141	<.0001
	85 to 90	0.1925	0.00934	<.0001
	90 to 95	0.3963	0.00977	<.0001
	95 to 105	0.5549	0.00893	<.0001
	105 to 115	1.8594	0.0191	<.0001
	> 115	1.9365	0.0233	<.0001
DTI ratio	< 20	-0.2833	0.0062	<.0001
	20 to 30	-0.2094	0.00438	<.0001
	30 to 40	0.0668	0.003	<.0001
	40 to 45	0.2626	0.00348	<.0001
	45 to 50	0.2196	0.00413	<.0001
	> 50	0.2832	0.00389	<.0001
FICO score		-0.0123	0.000023	<.0001
Missing FICO	0	0.000145	0.000006301	<.0001
Loan amount	50-150k	-0.0346	0.00708	<.0001
	150-250k	-0.1429	0.00817	<.0001
	250-350k	-0.0867	0.0113	<.0001
	350-450k	0.043	0.0143	0.0026
	> 450k	0.0297	0.0164	0.0698
Documentation type	Full	-0.3883	0.00201	<.0001
	Missing	0.1165	0.00221	<.0001
Origination channel	Other	0.1946	0.0017	<.0001
	Retail	-0.1757	0.00185	<.0001
Owner-occupied	yes	-0.0675	0.00173	<.0001
Product	ARM	-0.0608	0.00644	<.0001
	Balloon	0.3316	0.0145	<.0001
	FRM-15	-1.021	0.01	<.0001
	FRM-30	-0.2932	0.00614	<.0001
	FRM-Other	0.6934	0.00677	<.0001
Condo	no	0.0191	0.00172	<.0001
Mortgage rate	1-year after	-0.0928	0.0028	<.0001
	2-years after	-0.0324	0.0031	<.0001
	3-years after	-0.0309	0.00283	<.0001
Unemployment rate	1-year after	-0.1203	0.00114	<.0001
	2-years after	0.0532	0.00131	<.0001
	3-years after	0.0661	0.000928	<.0001
House price appreciation	1-year after	-1.0398	0.0348	<.0001
	2-years after	-1.1007	0.0338	<.0001
	3-years after	-0.9109	0.0228	<.0001

Note: Also included in the estimation are interactions between: (1) FICO score and loan amount, (2) loan amount and LTV ratio, (3) FICO score and LTV ratio, (4) house price appreciation after 3 years and LTV ratio, and (5) FRM and LTV ratio.

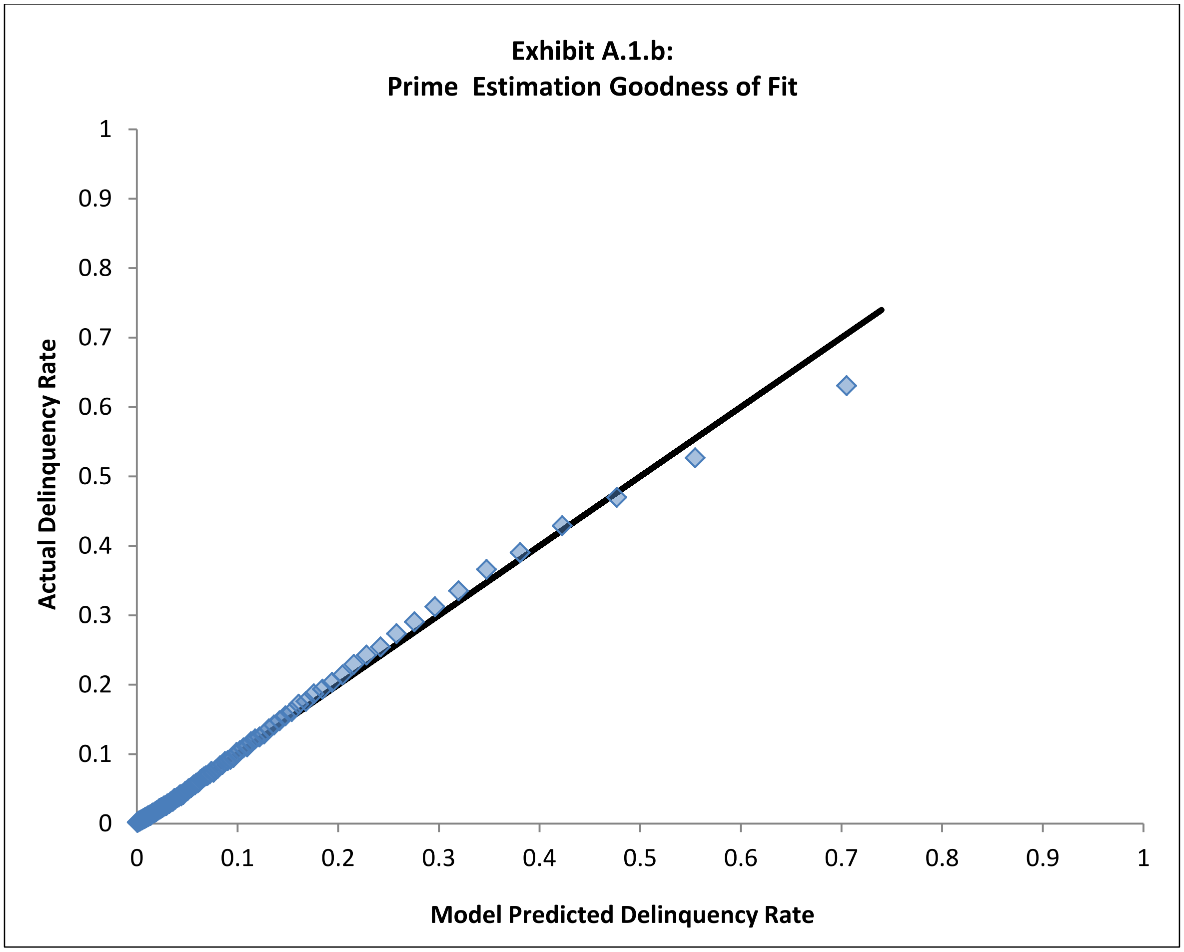
Exhibit A.1.b:
Prime Estimation Goodness of Fit
Actual Delinquency Rate
Model Predicted Delinquency Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Exhibit A.2.a: Subprime Market Estimation Results				
Variable	**Value**	**Estimate**	**Std Error**	**Prob Chi Sq**
Intercept		2.5799	0.0265	<.0001
LTV ratio	< 40	-1.2988	0.1078	<.0001
	40 to 60	-0.8914	0.0347	<.0001
	60 to 75	-0.3043	0.0185	<.0001
	75 to 80	0.152	0.0151	<.0001
	80 to 85	0.339	0.019	<.0001
	85 to 90	0.2675	0.0168	<.0001
	90 to 95	0.3507	0.0182	<.0001
	95 to 105	0.3202	0.0173	<.0001
	105 to 115	1.1622	0.0396	<.0001
	> 115	0.9493	0.0568	<.0001
FICO score		-0.00681	0.000032	<.0001
Missing FICO	0	0.000375	0.000016	<.0001
Loan amount	50-150k	0.2089	0.0133	<.0001
	150-250k	-0.0131	0.016	0.4133
	250-350k	-0.1402	0.0273	<.0001
	350-450k	-0.1274	0.038	0.0008
	> 450k	-0.2051	0.0357	<.0001
Documentation type	Full	0.2048	0.00273	<.0001
	Missing	-0.4793	0.00387	<.0001
Origination channel	Other	0.2316	0.00265	<.0001
	Retail	0.0579	0.00322	<.0001
Owner-occupied	yes	-0.1238	0.0026	<.0001
Product	ARM	-0.1223	0.00595	<.0001
	Balloon	0.2676	0.00769	<.0001
	FRM-15	-0.5023	0.0154	<.0001
	FRM-30	-0.2281	0.00687	<.0001
	FRM-Other	0.3455	0.0106	<.0001
Condo	no	0.0474	0.00325	<.0001
Mortgage rate	1-year after	0.0445	0.0036	<.0001
	2-years after	-0.0712	0.00429	<.0001
	3-years after	-0.1784	0.00439	<.0001
Unemployment rate	1-year after	-0.00534	0.00208	0.0103
	2-years after	-0.0566	0.00223	<.0001
	3-years after	0.0774	0.00146	<.0001
House prices	1-year after	-2.5146	0.0603	<.0001
	2-years after	-0.3572	0.0518	<.0001
	3-years after	-0.7534	0.0298	<.0001

Note: Also included in the estimation are interactions between: (1) FICO score and loan amount, (2) loan amount and LTV ratio, (3) FICO score and LTV ratio, (4) house price appreciation after 3 years and LTV ratio, and (5) FRM and LTV ratio.

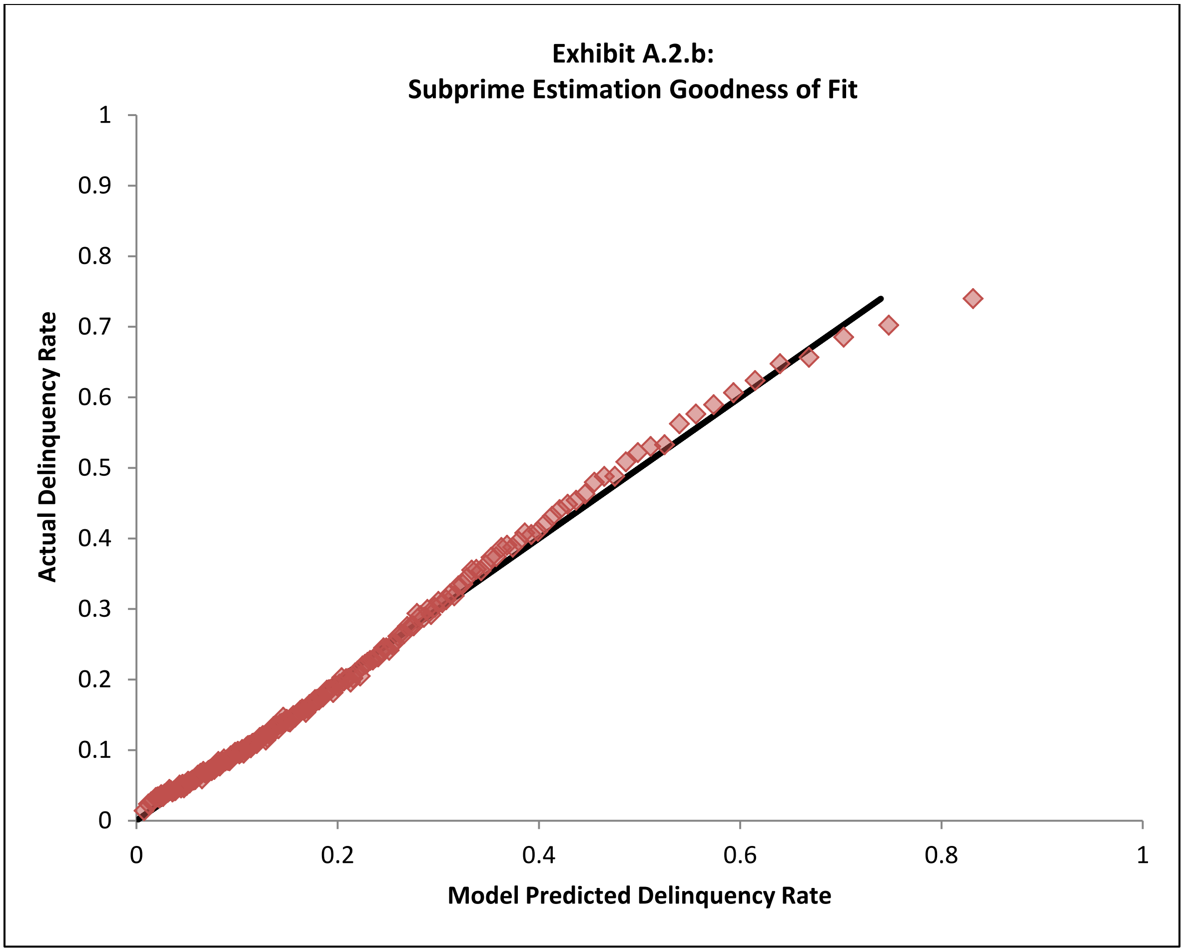
Exhibit A.2.b:
Subprime Estimation Goodness of Fit
Actual Delinquency Rate
Model Predicted Delinquency Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1

Exhibit A.3.a: Government Market Estimation Results				
Variable	**Value**	**Estimate**	**Std Error**	**Prob Chi Sq**
Intercept		6.0472	0.1869	<.0001
LTV ratio	< 40	-2.0861	1.834	0.2553
	40 to 60	-1.2143	0.2119	<.0001
	60 to 75	-0.252	0.1885	0.1813
	75 to 80	0.1252	0.1865	0.5021
	80 to 85	-0.0228	0.1884	0.9036
	85 to 90	-0.0116	0.1868	0.9506
	90 to 95	0.0871	0.1864	0.6403
	95 to 105	0.2927	0.1856	0.1148
	105 to 115	1.7592	0.1943	<.0001
	> 115	2.3596	0.2018	<.0001
DTI ratio	< 20	-0.5326	0.00905	<.0001
	20 to 30	-0.0622	0.00621	<.0001
	30 to 40	0.0422	0.00445	<.0001
	40 to 45	0.1667	0.00522	<.0001
	45 to 50	0.2094	0.00574	<.0001
	> 50	0.1949	0.00599	<.0001
Missing FICO	0	-0.00048	0.000019	<.0001
FICO score		-0.0127	0.000027	<.0001
Loan amount	50-150k	0.2099	0.1855	0.258
	150-250k	0.0202	0.1871	0.9139
	250-350k	0.1636	0.1925	0.3955
	350-450k	-0.0661	0.2177	0.7616
	> 450k	-0.4885	0.9169	0.5942
Documentation type	Full	0.0511	0.00241	<.0001
	Missing	-0.1051	0.00275	<.0001
Origination channel	Other	0.0923	0.00229	<.0001
	Retail	-0.1545	0.00264	<.0001
Owner-occupied	yes	-0.0981	0.00301	<.0001
Product	ARM	-0.3573	0.023	<.0001
	Balloon	-0.0615	0.0563	0.2748
	FRM-15	-0.5927	0.0264	<.0001
	FRM-30	-0.1334	0.0221	<.0001
	FRM-Other	1.1765	0.0226	<.0001
Condo	no	0.0853	0.00346	<.0001
Mortgage rate	1-year after	-0.0135	0.00279	<.0001
	2-years after	-0.047	0.00329	<.0001
	3-years after	0.0458	0.00329	<.0001
Unemployment rate	1-year after	-0.0392	0.00125	<.0001
	2-years after	0.0551	0.00187	<.0001
	3-years after	0.0247	0.00134	<.0001
House prices	1-year after	-2.3437	0.0486	<.0001
	2-years after	0.5796	0.0471	<.0001
	3-years after	-0.838	0.0403	<.0001

Note: Also included in the estimation are interactions between: (1) FICO score and loan amount, (2) loan amount and LTV ratio, (3) FICO score and LTV ratio, (4) house price appreciation after 3 years and LTV ratio, and (5) FRM and LTV ratio.

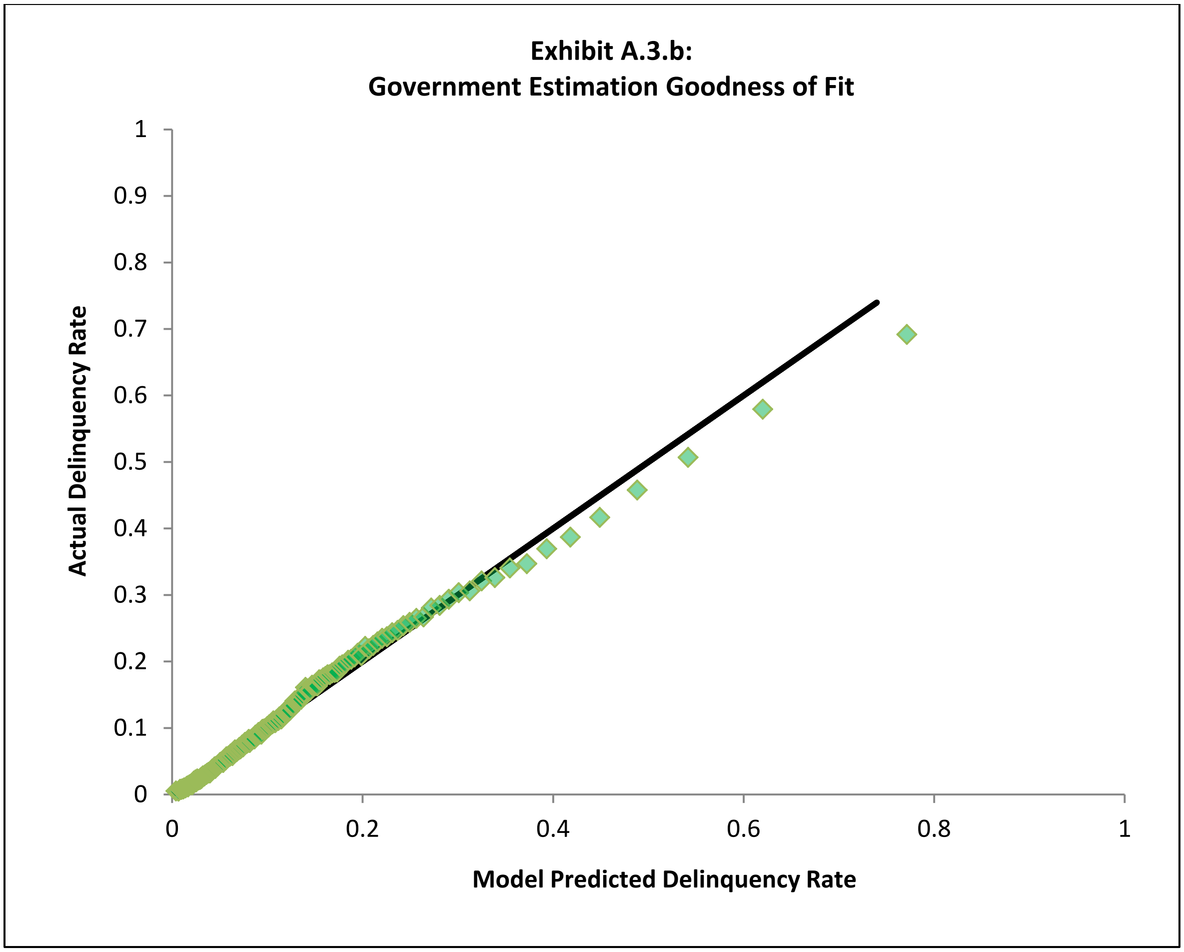
Exhibit A.3.b:
Government Estimation Goodness of Fit
Actual Delinquency Rate
Model Predicted Delinquency Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1