Consumer Literacy: What Price Perception?

Marsha Courchane
Principal, ERS Group
mcourchane@ersgroup.com

&

Peter Zorn
Vice President, Freddie Mac
peter_zorn@freddiemac.com

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Abstract

Several recent research papers and public policy initiatives have advocated the need for reducing gaps in home ownership between minorities and non-minorities, because of the importance to home ownership in asset building. Moreover, consumers, researchers, and policy analysts all have recognized the importance of credit to obtaining mortgages in the process of moving toward home ownership. We see, as a result, the growth of a cottage industry in the provision of credit scores and literacy programs under the presumption that accurate self-assessment of credit critically matters. There has not been, however, any research suggesting that inaccurate self-assessment is a widespread phenomenon or that inaccurate self-assessments lead to undesirable mortgage outcomes. Our research addresses this lacuna.

In this research, we explore three related questions in mortgage lending. First, we look at the accuracy of households in self-assessing their credit. Second, we identify characteristics of households that are more likely to self-assess with error. Third, we examine the question of whether inaccurate self-assessment (or self-assessment in general) has any impact on mortgage market outcomes, including the likelihood that those who self-assess inaccurately receive loans in the non-prime mortgage sector, or that they pay a higher price ("APR") for mortgage loans.

This research uses two different datasets. The first data are gathered through a unique survey conducted by Freddie Mac and include information about consumer financial knowledge, consumer behavior, and credit outcomes, as well as data gathered from the credit repositories on individuals' actual credit records. Combined with the data from the consumer financial literacy survey is data gathered from nearly 1.5 million loan level records from prime and non-prime lenders originated in 2004 and 2005, which includes Home Mortgage Disclosure Act ("HMDA") data elements combined with loan specific underwriting, pricing and borrower characteristics.

We find that survey respondents' perceptions of their credit do not completely comport with the norms within their subpopulations (e.g., African Americans combined with Hispanics, and Asians combined with White, Non-Hispanics). Specifically, we find that African Americans and Hispanics correctly assess about 40 percent of the time, while Asians and White, Non-Hispanics correctly assess nearly 50 percent of the time. We also find that there is a disproportionate number of African Americans and Hispanics who over-assess their credit while there is a disproportionate number of Asians and White, Non-Hispanics who under-assess their credit.

In examining the characteristics of respondents who poorly self-assess, we find that low income households and those with a poor economic safety net self-assess poorly relative to their peers. These outcomes are particularly true for Asian and White, Non-Hispanic respondents. Borrowers who believe they have control of their lives (relative to those who believe their life events are externally driven) are more likely to self-assess correctly, especially for Asian and White, Non-Hispanic respondents. Risk takers are less likely to assess accurately. We also find that financial literacy matters. Specifically, those with more formal education and those who say they have a high level of financial knowledge self-assess credit more accurately. Finally, respondents with adverse life events (divorce, medical problems, etc.) are much more likely to self-assess inaccurately.

The third question we address is whether different perceptions of self-assessed credit can lead borrowers to different mortgage outcomes. We explore the hypothesis that those who make mistakes in under-assessing or over-assessing their credit find themselves in the “wrong” market for their needs. We find little evidence that incorrect self-assessments result in substantially different mortgage outcomes. We do find, however, some evidence that borrowers with errors in self-assessments relative to others in their peer group are more likely to obtain non-prime mortgages and, when the errors are over-assessments of credit, the borrowers are more likely to have lower APRs. This might result from the confidence and persistence with which these borrowers conduct their financial transactions.

I. Introduction

Several recent research papers and public policy initiatives have advocated the need for reducing gaps in home ownership between minorities and non-minorities, because of its importance to asset building. Moreover, consumers, researchers, and policy analysts all have recognized the importance of credit to obtaining mortgages in the process of moving toward home ownership. We see, as a result, the growth of a cottage industry in the provision of credit scores and literacy programs under the presumption that accurate self-assessment of credit critically matters. There has not been, however, any research suggesting that inaccurate self-assessment is a widespread phenomenon or that inaccurate self-assessments lead to undesirable mortgage outcomes. Our research addresses this lacuna.

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We use the data from the financial literacy survey to compare actual credit to self-assessed credit and we examine characteristics of the survey respondents that self-assessed with error. Based on our initial analysis of credit distributions from the survey respondents, we develop different "actual credit" buckets for African Americans and Hispanics, combined, and for Asians and White, Non-Hispanics, combined. We examine, by race, the inaccuracy of self-assessment for those with different levels of education, income, safety nets, and control over their financial situations. Given the self-assessments, and self-assessment errors, we impute values to these variables in the loan level data and estimate the likelihood that borrowers would receive loans in the non-prime sector and estimate whether or not they would pay more, as measured by annual percentage rate ("APR") if they have increased error in self-assessment.

I. Previous Research

The past five years have witnessed significant interest in non-prime (or subprime) lending and the impact of credit scores and credit worthiness on mortgage market outcomes. The growth in subprime lending over the past five years has been dramatic, increasing from 13.17 percent of the market in 2000 to 21.31 percent of the market in 2005.[1] The literature addressing mortgage

[1] See Inside B & C Lending, Vol. 11, Issue 4, p. 4, 2006.

market outcomes related to subprime lending continues to grow and in the last few years it includes papers by Calem, Hershaff, and Wachter (2005), Boehm, Thistle, and Schlottman (2005), Courchane and Zorn (2006), Engel and McCoy (2005) and Pennington-Cross (2006) among others.

In developing our current research questions, we rely not only on the work of many others, but upon our own previous research, in which we addressed two related questions. First, in a survey of repeat mortgage borrowers, we examined whether or not borrowers "inappropriately" are channeled to the non-prime segment and whether, once they have taken out a non-prime mortgage, they are "stuck" in that segment. In that research we estimated the probability that borrowers would transition between prime and non-prime markets.[2] We found that about 40 percent of borrowers might transition from non-prime to prime or prime to non-prime as they take out a second mortgage. Moving among channels can affect the price paid for mortgages.

Using a second survey of borrowers, a part of the same data we use in this research, we examined the relationship between consumer financial knowledge, consumer behavior, and credit outcomes. The survey gathered detailed information on individuals' self-reported use of credit and we linked that information with the individual's publicly recorded credit record. The information gathered in the survey included experience, attitudes, behaviors, and perceptions of credit; sources of information about financial matters; measures of knowledge and familiarity with finances; as well as demographic factors and psychological characteristics of the respondent. We used the survey responses combined with credit bureau information obtained from Experian to help understand how financial knowledge affected a consumer's behavior and how that behavior, in turn, can lead to particular credit outcomes.[3]

In the current research, we move beyond use of the consumer literacy survey data and extend the research to include mortgage market outcomes based on actual lender loan level data. We impute derived values of self-assessed credit to mortgage market participants in the loan level data, and examine the impact of errors in self-assessment on mortgage market outcomes including the likelihood of non-prime and the average APR of the loan received.

II. Accuracy in Self-Assessment

Most advocates of financial counseling believe that as part of the process of improving financial literacy, consumers must develop accurate self-assessments of their credit situation. That is, improving credit profiles requires recognition by borrowers that there is a need to improve. Obtaining the appropriate loan requires understanding the market options faced. This requires both understanding what contributes to impaired credit and understanding, what, if anything, can be done to change the underlying circumstances that contribute to credit outcomes. As a first step in the current research, we measure the gaps between actual and self-assessed credit. We use FICO buckets to measure actual credit worthiness and self-assessments ranging from "very bad" to "very good." The self-assessments were in response to the survey question "How well would you rate you current credit?"

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[2] See Courchane, Surette, and Zorn (2004).
[3] See Courchane and Zorn (2005).

The data from our survey allow us to compare respondents' self-assessment of credit (using answers of "very bad", "bad", "average", "good", and "very good" to the question "How would you rate your current credit record?") to their actual FICO scores. Absent any widely agreed upon FICO score ranges representing good and bad credit, however, it necessarily is a subjective assessment as to how accurately respondents assess their credit records.

Certainly one approach would be to rely on credit grantors' standards in determining what are "very bad", "bad", "average", "good", and "very good" FICO scores. The problem, however, is that credit grantors' standards are not public information, and vary widely across industry. Prime mortgage lenders, for example, use relatively strict standards in assessing credit, while subprime/non-prime lenders traditionally are more flexible. Likewise, the credit card industry has different standards than does the mortgage industry, while other users of FICO scores such as insurance companies and potential employers likely use yet an entirely different standard.

Faced with this quandary, we choose to assess accuracy of credit assessments using respondent norms. That is, we let respondents tell us what "very bad", "bad", "average", "good", and "very good" FICO scores are by picking FICO score cutoffs for these categories that result in the greatest number of respondents correctly assessing their credit.

As the first step in this process we consider how FICO scores are separately distributed among the subset of respondents that classify themselves as having "very bad", "bad", "average", "good", and "very good" credit records. Recognizing the inherently relativistic nature of these classifications, we compare these distributions separately for the four racial/ethnic subgroups among our respondents—African Americans, Hispanics, Asians, and White, Non-Hispanics. We find a high degree of similarity of response among African Americans and Hispanics, and among Asians and White, Non-Hispanics. Throughout the rest of our analysis, therefore, we combine respondents into these two subgroups.

Chart 1 shows box plots of the FICO score distributions of respondents self-assessing their credit record as "very bad", "bad", "average", "good", and "very good", separately for African Americans and Hispanics combined, and for Asians and White, Non-Hispanics combined. The box plots are quite informative, and clearly highlight the fact that both subgroups of respondents have basic 'norms' about what represents "very bad", "bad", "average", "good", and "very good" credit records. Relative to their peers, for example, respondents have fairly distinct FICO score ranges associated with a "good" versus an "average" credit record, although the FICO score distinction get muddled a bit between respondents assessing their credit as "very bad" and "bad."

Also interesting is the fact that, relative to Asian and White, Non-Hispanic respondents, African American and Hispanic respondents tend to be more 'optimistic' in their assessments of credit. For example, the mean FICO score of African American and Hispanic respondents who self-assess as having "very good" credit records is well below that of similarly self-assessing African American and Hispanic respondents.

We use a variety of techniques to determine how best to create FICO score buckets for the two subgroups of respondents. Our goal is to pick 'cut points' that determine FICO score ranges for “very bad”, “bad”, “average”, “good”, and “very good” credit records, in a manner that most closely corresponds to how respondents themselves assess their credit. In this manner our method for determining the accuracy of respondents’ self-assessment of their credit records is ‘conservative’ in nature. That is, our technique imparts a bias towards finding accurate, rather than inaccurate self-assessments.

We primarily rely on variants of Kolmogorov-Smirnov (“KS”) test statistics for determining the FICO score cutpoints.[4] For example, in determining the FICO score cutpoint between “very bad’ and “bad”, we compare the separate FICO score cumulative distribution functions (“CDFs”) of the respondents who self-assess their credit as “very bad” and “bad.” We then compute the difference in the CDFs for each FICO score (a variant of the traditional KS test statistic), and determine the FICO score where the difference in the CDFs is greatest. This produces the FICO score cutpoint that best separates the two groups of respondents, in the sense that the sum of type 1 and type 2 errors is minimized. That is, this minimizes the total number of respondents who inaccurately self-assess by either self-assessing as “very bad” but actually only having “bad” credit, or self-assessing as “bad” but actually having “very bad” credit.

We “confirm” our KS statistic-determined cut points by independently running a CART analysis that uses FICO scores to best ‘predict’ self-assessed credit. We also experiment with various ordered probit estimations of self-assessed credit that include alternative versions of FICO score buckets. Both these techniques confirm our choice of cutpoints as determined by our KS statistic analysis.

The resulting cutpoints are presented in Table 1. As suggested by the box plots in Chart 1, the African American and Hispanic cutpoints vary quite considerably from the cutpoints for the Asian and White, Non-Hispanic respondents. In particular, it highlights the more ‘optimistic’ nature of African American and Hispanic respondents’ self-assessment. For example, the FICO score cutpoint for “very bad” credit for Asian and White, Non-Hispanic respondents is 580, while the same cutpoint for African American and Hispanic respondents is 545, and their “bad” cutpoint is only 585.

Using the cutpoints in Table 1, we are now able to compare ‘actual’ to self-assessed credit records, and therefore assess the accuracy of respondents. Tables 2 and 3 provide the five-by-five cross-tabulations separately for African American and Hispanic respondents and for Asian and White, Non-Hispanic respondents. Respondents arrayed on the main diagonal are viewed as accurately self-assessing their credit, while respondents on the off diagonals are self-assess with various degrees of inaccuracy.

[4] The Kolmogorov-Smirnov test (KS-test) tries to determine if two datasets differ significantly without making any assumptions about the distribution of data. It is non-parametric and distribution free.

Chart 1: Distribution of *Credit Score* by Self-Assessed Credit and Race

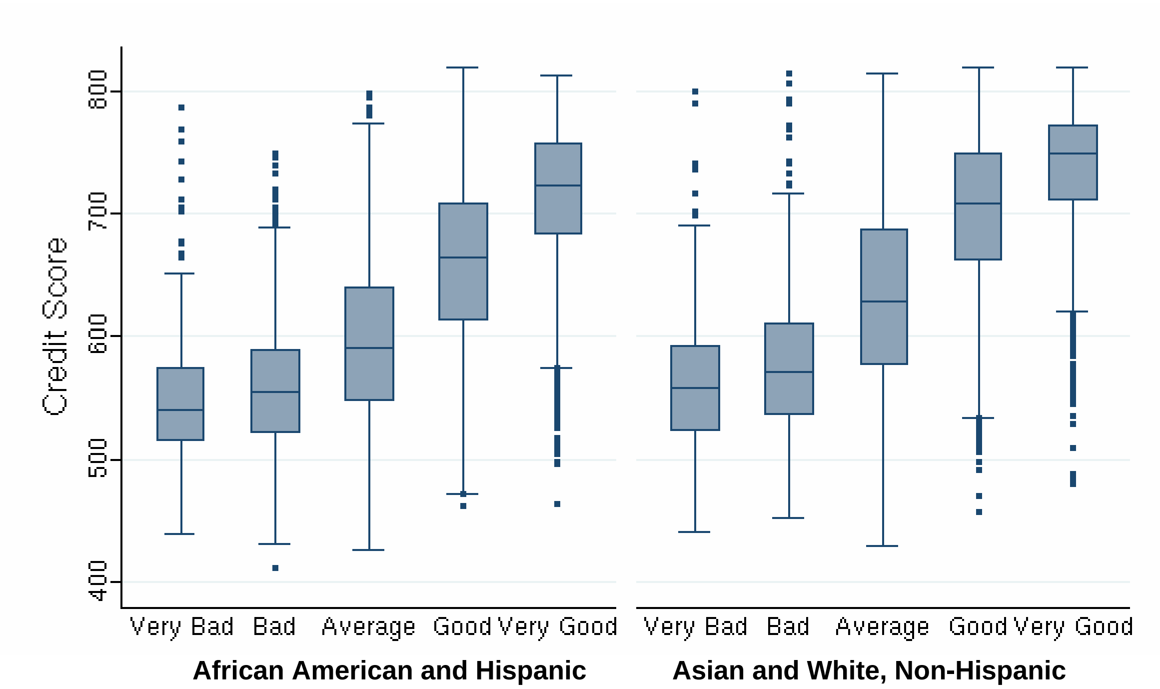


Table 1		
Definition of Actual Credit Categories		
	FICO Score Ranges	
Actual Credit Categories	African American and Hispanic	Asian and White, Non-Hispanic
Very Bad	450 - 545	450 – 580
Bad	546 – 585	581 – 605
Average	586 - 640	606 – 655
Good	641 – 695	656 – 725
Very Good	696 – 850	726 – 850

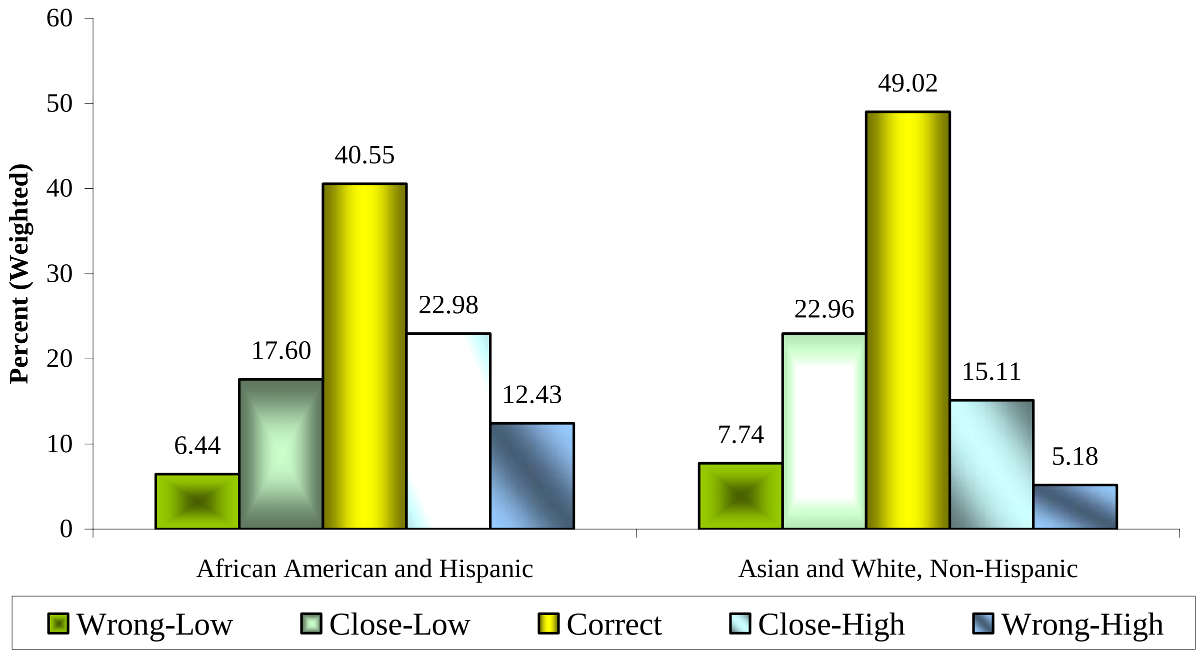
We measure error in self-assessment by categorizing those survey respondents who are very wrong or wrong in a “low” direction – that is, they believe they have very poor or poor credit when in fact they have good/very good credit. We categorize those that are correct as those respondents who are close to accurate in either direction. We similarly consider those that are very wrong or wrong in a “high” direction – that is they believe they have good to very good credit, when in fact they have very poor to average credit. Tables 2 and 3 show the result of the cutpoints for actual credit categories specified in Table 1, and breaks them down into degree of accuracy. Table 2 provides the results for African Americans combined with Hispanics. Table 3 displays the same information for Asians combined with White, Non-Hispanics. Chart 2 shows the resulting distributions of “wrong-low”, “close-low”, “correct”, “close-high” and “wrong-high”.

Table 2					
Summary of Credit Self-Assessment for African Americans and Hispanics					
Row Percent *Column Percent*	**Credit Self-Assessment**				
Actual Credit Score	Very Bad	Bad	Average	Good	Very Good
450 - 545	22.98 53.66	40.38 40.93	30.26 23.43	5.1 6.24	1.28 1.51
546 - 585	13.38 25.87	38.06 31.94	35.27 22.61	10.22 10.35	3.08 3
586 – 640	7.34 14.73	22.27 19.39	43.63 29.02	18.96 19.93	7.8 7.89
641 - 695	1.99 3.18	9.29 6.44	29.94 15.86	37.4 31.32	21.38 17.23
696 - 850	1.09 2.56	1.29 1.31	11.72 9.08	26.25 32.17	59.65 70.36

Table 3					
Summary of Credit Self-Assessment for Asian and White, Non-Hispanics					
Row Percent *Column Percent*	**Credit Self-Assessment**				
Actual Credit Score	Very Bad	Bad	Average	Good	Very Good
450 -580	20.09 70.91	42.09 55.39	28.72 26.94	6.99 6.27	2.1 1.02
581 - 605	9.32 11.09	39.41 17.49	36.33 11.49	11.32 3.42	3.61 0.6
606 – 655	5.79 12.7	20.74 16.97	39.32 22.93	20.84 11.61	13.32 4.04
656 - 725	0.44 2.06	4.71 8.32	21.55 27.16	33.08 39.84	40.22 26.4
726 - 850	0.46 3.23	0.71 1.84	6.22 11.49	22.01 38.87	70.6 67.94

As we noted earlier, self-assessments can be inaccurate in two directions. Borrowers can believe they have better credit than they have (wrong high) or worse (wrong low). Looking first at Table 2, we measure those that self-assess inaccurately by the percentages in the cells off the main diagonal. Those that self-assess high are in the upper right quadrant and those that self-assess low are in the lower left quadrant. For African Americans and Hispanics, of those who self-assess their credit as very good, 12.40 percent have actual credit that is average to very poor. For this same group, 20.47 of those who self-assess as very poor, have actual credit that is average to very good. For Asians and White, Non-Hispanics, we see that 5.66 self-assess with very good credit, when actual credit is average or below. In the group of those that believe they have very poor credit, 17.99 percent have average to very good actual credit. Another way of looking at this is to note that for those African Americans and Hispanics with good credit, 11.28 percent believe they have bad or very bad credit, and for those with very good credit, 14.10 percent rate their credit as no more than average. Both groups have errors in self-assessment, with African Americans more likely to over-assess and Asians and White, Non-Hispanics more likely to under-assess as demonstrated in Chart 2. About 35 percent of African Americans and Hispanics over-assess their credit while only 20 percent of Asians and White, Non-Hispanics over-assess. About 31 percent of Asians and White, Non-Hispanics under-assess their credit, while only 24 percent of African Americans and Hispanics error in that direction.

Chart 2: Distribution of *Self-Assessed Credit* by Race
Race Dependent Actual Credit Buckets



We turn from our overall examination of self-assessment to an examination of the factors associated with errors in self-assessment in our next section. In this section, we rely only on the data from the consumer financial literacy survey.

III. An Examination of Inaccurate Self-Assessment

Credit record information is relatively arcane, inaccessible, and difficult to interpret. Nor, perhaps until recently, has importance of having a good sense of your credit history and overall credit records been widely understood and appreciated. Moreover, the factors observable to credit grantors that statistically are linked to default performance often appear unintuitive or obscure to the uninitiated. It would not be surprising; therefore, if a significant number of survey respondents did a poor job of self-assessing their credit.

Because of the above, we expect that respondents will be more accurate in assessing their credit the greater their formal education and financial literacy and the more they ‘invest’ in learning about their credit. We measure knowledge across several dimensions: years of formal education, respondents’ self-assessment of their financial knowledge, and the percent of households holding mortgages in the census tract in which the respondents’ houses are located. The latter variable is included as a proxy for the accessibility to respondents of financially knowledgeable peers, assuming that accessibility increases with the percentage of mortgage-holding neighbors.

We also assess whether accuracy in respondents’ self-assessment of credit is related to their gaining knowledge from the ‘school of hard knocks.’ Respondents are classified as going the school of hard knocks if they have, for example, received eviction notices, had their utilities turned off for non-payment, been turned down for credit, been contacted by a collection agency or thought seriously about declaring bankruptcy. Arguably many of these respondents have learned first-hand the cost of inaccurately assessing their credit, and so have strong incentives to ‘invest’ in greater financial knowledge and are, therefore, more accurate in their credit self-assessments. Alternatively, of course, it also is possible that inaccurate self-assessment of credit ‘causes’ significant financial difficulties, so that respondents identified as going to the school of hard knocks are less likely to accurately self-assess.

We measure the incentive to ‘invest’ in information about own credit from a psychological perspective. Specifically, we postulate that risk-takers are less likely to invest in credit knowledge, as are respondents who believe that the primary drivers of their life events are largely beyond their control, because neither group sees significant value in the investment. We measure the latter relationship using a standard array of psychological questions to assess respondents’ ‘locus of control’—respondents with an external locus of control believe that major events affecting their lives largely are beyond their direct influence, while respondents with an internal locus of control believe they have a significant role in determining how their lives evolve.

We also explore whether accuracy of self-assessment is related to a standard array of socio-economic variables, including income, net worth, economic safety net, respondent age and presence of children.

We explore these broad hypotheses by looking at bivariate and multivariate relationships between accuracy in self-assessment and our ‘independent’ variables. Bivariate relationships are presented in graphical form in Charts 3 through 12, and in tabular form in Table 4A (for African American and Hispanic respondents) and Table 4B (for Asian and White, Non-Hispanic respondents). These Charts and Tables are provided in the Appendix. The graphs show stacked bar charts illustrating how the distributions of respondents’ self-assessment errors vary across the independent variables.

Multivariate relationships are explored using ordered probit estimations. There is a natural ranking of respondents’ extent of divergence from ‘correct’ self-assessment; however there is no clear ranking between equally diverging high and low self-assessments. As a consequence, we estimate separate ordered probits for over (high) and under (low) self-assessment of credit. In both, estimations are structured to explain divergence from correct self-assessment, so that positive coefficients indicate an increased likelihood of accurate self-assess credit. Our ordered probit results are presented in Table 5. The ordered probit estimations, obviously, are not based on a structural model of respondents' accuracy in assessing their credit records, which makes interpretation of the estimated coefficients somewhat problematic. As a consequence, we primarily utilize the ordered probit estimations as a robustness test of the relationships we observe in the bivariate framework.

Turning first to the knowledge variables, as hypothesized, (self-assessed) financial knowledge appears related to accuracy in self-assessing credit (see Chart 3). Generally we find that respondents who believe they have 'very little' financial knowledge are more likely to under-assess their credit (be classified as close-low or wrong-low), while any relationship with over-assessment of credit (close-high or wrong-high) appears relatively weak. Interestingly, the positive relationship between financial knowledge and accuracy of credit self-assessment reverses for Asian and White, Non-Hispanics in the multivariate analysis (see Table 5), where 'a fair amount' of financial knowledge appears positively related to over-, not accurate-, assessment of credit. This 'inverse' relationship may be the result of the normalistic criterion we use to assign credit accuracy—financially knowledgeable respondents who appear to over-assess their credit may, in fact, more closely mirror credit-grantors' views than do respondents' less financially knowledgeable peers, even those these views do not conform to overall respondent norms.

Formal education also appears related to accuracy of credit assessment (see Chart 4). Here we see that, especially for Asian and White, Non-Hispanic respondents, finishing college appears to substantially reduce the likelihood of over-assessing credit (being classified as close-high or wrong-high). We do not see any significant reduction in the tendency to under-assess from finishing college. These results are reaffirmed in the multivariate estimates presented in Table 5.

The presence of knowledgeable peers is measured as a continuous variable, so is not presented in either the stacked bar charts or Tables 4A or 4B. The multivariate results presented in Table 5, however, show that, at least for Asian and White, Non-Hispanic respondents, having nearby financially-knowledgeable peers significantly increases the probability of correct self-assessment.

As Chart 5 illustrates, the school of hard knocks ("bad stuff") is highly correlated with accuracy in assessing credit—respondents who have experienced significant financial problems are far more likely to assess inaccurately their credit than those that have experienced no problems. These results are confirmed in the multivariate analysis (see Table 5), and raise the question of whether inaccurate assessment of credit 'causes' financial problems, rather than the reverse. While such as relationship certainly is plausible, the temporal nature of our variable construction suggests financial problems cause inaccurate assessment—the financial problems variable is asked to reflect the past, while accuracy in assessing credit is measured contemporaneously.

We turn now to our two psychological variables. Chart 6 illustrates the relationship between propensity to take risks and accuracy of self-assessment. As hypothesized, respondents who are more likely to take risks are also more likely to assess inaccurately their credit (in this case they tend to over-assess their credit), although the relationship is not strong. As seen in Table 5, this result for Asians and White, Non-Hispanics confirmed in the multivariate relationships, but not for African Americans and Hispanics. The relationship between locus of control and accuracy of credit-assessment is less definitive, as illustrated in Chart 7. It does, however, suggest that Asian and White, Non-Hispanic respondents with an internal locus of control are more likely to accurately assess their credit, and in particular are less likely to under-assess. This result is confirmed in the multivariate results presented in Table 5.

Turning now to the socio-economic variables, Charts 8 and 9 illustrate the relationship between income and net worth, respectively, with accuracy of self-assessment. Clearly higher-income and higher-net worth respondents are more likely to accurately self-assess their credit, and this especially is true for Asians and White, non-Hispanics. This later relationship is confirmed in the multivariate analysis presented in Table 5. A similar relationship exists with the presence of an economic safety net—respondents who think it likely that they have an economic safety net are more likely to accurately self-assess, although the relationship with African American and Hispanic respondents is strongest in reducing under-assessment. Again, these findings are confirmed in the multivariate analysis presented in Table 5.

Finally we turn to the relationship between age and children and the accuracy of credit assessment (see Charts 11 and 12). There is some indication that older respondents and those without children are more accurate in their self-assessment. This might reflect less variability for those groups in terms of income or expenditures. These results are confirmed in the multivariate analysis presented in Table 5.

To conclude, therefore, we find, as hypothesized, that greater knowledge/education is associated with more accurate self-assessment of credit. We also find some evidence that respondents with more perceived incentives to invest in financial knowledge are more likely to accurately assess credit. Finally, unsurprisingly, we find that respondents with higher income and wealth, and those with a better economic safety net are more likely to accurately self-assess credit.

While the bivariate and multivariate analyses discussed in this section help improve our understanding of differences among respondents in terms of self-assessments of credit, an important goal of this research is to understand how inaccuracies in those self-assessments impact market outcomes. Unfortunately, there is not, at this time, a single survey that includes all of the questions about consumer financial literacy and provides loan level information about market outcomes, although the interest in this topic has broadened and other researchers are providing further insights to the relationships between credit, financial literacy and market outcomes.[5]

IV. Accuracy of Self Assessment and Market Outcomes

For this stage of our analysis, we use loan level "pricing" data made available following a change in reporting requirements for Home Mortgage Disclosure Act data. In September 2005, the Federal Reserve Board (FRB) publicly released data on about 80 percent of home loans originated in 2004 that were subject to new reporting requirements that included loan pricing

[5] See, for example, D. Haurin (2006) who focuses on financial literacy in the Columbus, OH market.

information for higher priced loans.[6] These data allow us to identify loans and loan level characteristics from the prime and non-prime segments of the mortgage market.[7] This ability to determine which differences in borrower and loan characteristics lead applicants to prime or non-prime loans allows those interested in improved access to financial markets to better focus financial literacy efforts. For our purposes, we categorize prime and non-prime by the lender, using the new data made available as of 2004 on spreads between mortgage rates and comparable Treasury rates. For those lenders with a high percentage of loans above the rate spread threshold, we categorize the lender as non-prime.[8]

We provide two types of estimation results for analyzing the impact of self-assessment of credit and errors in that process on market outcomes. First, we predict whether or not a borrower will have a non-prime mortgage loan using imputations of self-assessment, information from HMDA, from census and from particular lenders from prime and non-prime channels. We also measure the impact of the self-assessments, and errors in those self-assessments on the price paid for the mortgage as measured by APR. The lenders in our loan level sample originate loans across all fifty states and use both wholesale and retail channels for loan origination purposes.[9] We provide some summary statistics for our full sample and for our selected sample in Tables 6 – 7 in the Appendix. For the predictions of non-prime including measures of differences between self-assessed and actual credit, we restrict the sample only to borrowers with low incomes to be comparable to the data in the Freddie Mac survey.[10] Comparing the summary statistics on FICO, LTV, DTI, and loan amount, the values are approximately the same on the full sample and the restricted, lower income sample (see Table 6).

In order to focus on the impact on market outcomes of self-assessments of credit compared to actual credit (as measured by credit scores) and of inaccuracy in the self-assessment to those same market outcomes (likelihood of non-prime and APR) we need a methodology that allows us to impute information from the consumer financial literacy survey to the loan level data. The methodology we employ is the following. First, we impute a measure of self-assessment to each loan level observation in the lender data. To do this, we first identify the probability in the survey data of being very bad, bad, average, good, or very good for eight FICO by four income buckets (32 overall buckets). We take ten random draws of self-assessed credit from each of the 32 buckets for each observation in the lender data. The assigned credit category is determined by the probabilities associated with the five outcomes in each of the 32 buckets. This creates ten

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[6] The Federal Reserve Board released a comprehensive analysis of the data in September 2005, noting that it covered 8,853 lenders. See Avery, Canner, and Cook (2005).

[7] Prior to 2004 a researcher could use the list of subprime and manufactured housing lenders provided by the Department of Housing and Urban Development (HUD) but this identified lenders and not loans to be subprime.

[8] The loan level data used in this paper is being used with the permission of lenders. The data was pooled across many lenders and has been completely de-identified as to borrower or lender except for a designation that the lender was "prime" or "non-prime" according to our specific definition. The data remain proprietary.

[9] See Table 7 for geographic dispersion of the loan level data.

[10] The maximum income category we include is $75,000 adjusted upward for inflation from 1999 to 2004. This value is the income cut is: $90,327.36.

estimates of self assessed credit for each observation in the lender data.[11] FICO scores were grouped into categories for less than or equal to 530, 531 – 570, 571 – 605, 606 to 650, 651 to 680, 681 to 710, 711 to 740 and over 740. Unadjusted income categories were less than $35,000, $35,000 to less than $55,000, $55,000 to less than $75,000 and $75,000 to $100,000. Adjusted for income growth those categories are less than $42,153, $42,153 to less than $66,240, $66240 to less than $90,327 and $90,327 to less than $120,436.

We next structure the data so that we have one observation per estimated self-assessed credit (for a total of ten observations per original observation) – this increases the dataset tenfold. All characteristics for each of the ten draws are identical, except perhaps self-assessed credit. This dataset, ten times the size of the original dataset, is used for all regression and logit models.

To enhance our understanding of market outcomes, we provide two sets of results. We first provide Charts depicting lowess estimation results (Charts 13 to 18). We next provide results from multivariate estimates of the likelihood of non-prime. We provide these for both the levels of self-assessment ("very bad" to "very good") in Table 10 and for the self-assessment errors ("wrong low" to "wrong high") in Table 11. Finally we examine the "price" for the mortgage, as estimated by APR. Table 12 provides those results using levels of self-assessment and Table 13 provides those results on level of APR using errors in self-assessment.

First, we explore the visual depictions of the relationship between self-assessment and market outcomes, provided in graphs based on "lowess" estimation shown in Charts 13 to 18 in the Appendix. Lowess techniques are data intensive, and thus can not be performed on the full (10x) data set. In order to reduce the number of observations we collapse the data into groupings of size 50, such that the members of each grouping have the same FICO score and self-assessment[12] (and same race/ethnicity when examining the lowess by race/ethnicity). The data is sorted by APR, such that the first 50 observations in a FICO/self-assessment bucket will all have low APRs, the second grouping higher, and so forth. This is done to preserve the distribution of APR, and potentially that of "percent non-prime". We assign to each grouping the percent non-prime and the average APR for the grouping. With this collapsed data set we perform lowess estimations of APR and percent non-prime against actual FICO by self-assessed credit ("good" or "very good" compared with "bad" or "very bad"), using a ten percent bandwidth. This is a locally linear regression that uses the data from an area around ten percent of the actual data point.

Lowess Estimations

As a first stage in analyzing market outcomes, we examine bivariate data on the distribution of APR and self-assessment. The five-by-five Tables 8 and 9 reproduce the structure of Tables 2

[11] For example, let 100 persons be in each FICO/income bucket in the survey data. Let the probabilities of the five outcomes sum to 100 as in .10, .22, .41, .21, and .06. Then the first 10 persons would be very bad, the next 22 would be bad and so on. Draw a random number (49) for a person in the lender data. That observation would be assigned "average" self-assessment. This process repeats ten times. All ten draws are kept as observations.

[12] Combinations of FICO scores and self-assessment that have more than 25 observations are included. For example, if we have 94 persons with same fico, race, and self assessment we end up with 2 groupings, one with 50 and one with 44.

and 3, but contain market outcomes rather than respondent distributions. Specifically, Tables 8 and 9 allow us to observe how APR and percent non-prime vary with FICO score and (imputed) self-assessed credit. If inaccurate self-assessment leads to worse market outcomes, we would expect to see low APRs and low percent non-prime on the main diagonal, with monotonic increases associated with horizontal movement off the diagonal in either direction.

Table 8
Summary of APR and Percent Non-Prime for African American and Hispanics

Mean APR *Percent Non-Prime*	**Credit Self-Assessment**				
Actual Credit Score	Very Bad	Bad	Average	Good	Very Good
450 - 545	9.69 91.33	9.57 92	9.55 91.81	9.4 91.47	9.49 90.63
546 - 585	8.82 90.18	8.72 89.7	8.65 89.2	8.55 89.33	8.57 88.67
586 – 640	8.11 73.48	8.03 72.93	7.94 71.39	7.87 70.11	7.81 69.18
641 - 695	7.23 49.72	7.19 48.71	7.06 45.88	6.92 41.94	6.82 39.85
696 - 850	6.14 17.5	6.23 17.86	6.26 19.27	6.15 17.27	6.01 14.38

Table 9
Summary of APR and Percent Non-Prime for Asian and White, Non-Hispanics

Mean APR *Percent Non-Prime*	**Credit Self-Assessment**				
Actual Credit Score	Very Bad	Bad	Average	Good	Very Good
450 - 580	9.05 89.43	8.89 89.11	8.8 88.51	8.68 87.94	8.6 87.4
581 - 605	8.09 76.79	8.03 76.65	7.99 76.36	7.94 75.98	7.86 74.94
606 – 655	7.47 56.57	7.34 54.64	7.28 53.9	7.2 51.98	7.12 50.48
656 - 725	6.3 22.33	6.43 26.47	6.26 22.41	6.13 19.43	6 16.49
726 - 850	5.72 6.36	5.7 4.8	5.73 5.92	5.67 5.01	5.57 4.21

Perusal of Tables 8 and 9 shows that this pattern is not observed. What we see instead is a fairly monotonic decrease in both APR and percent non-prime as we move from “very bad” to “very good” self-assessed credit, holding FICO score constant. Contemplation suggests that this relationship may not be surprising. All things equal, borrowers with a worse opinion of their credit may “accept,” for example, a higher APR as appropriate, while borrowers with a better opinion of their credit, even if an over-assessment, may shop/bargain harder to get a better rate than their otherwise identical peers. Alternatively, of course, self-assessments may accurately reveal relevant credit information known to both borrowers and credit-grantors, but not included in FICO score (e.g., net wealth, length/terms of employment), and so be highly positively correlated with APR. We can at least partially control for these latter such ‘omitted’ variables in our multivariate analysis.

Regardless, both self-assessed and actual credit score clearly affect market outcomes. This relationship is explored from a more continuous perspective in the lowess regressions illustrated in Charts 15 through 18. Charts 15 and 16 refer to the African American and Hispanic subpopulation, while Charts 17 and 18 refer to the Asian and White, non-Hispanic subpopulation. Chart 15, for example, illustrates the relationship between APR and FICO score, separately for combined borrowers who self-assess as “good” and “very good” and for borrowers who self-assess as “bad” and “very bad”. As expected, APR declines for both groups with an increase in FICO score. And, as observed in Table 8, holding constant FICO score, borrowers with a more pessimistic self-assessment of credit generally pay higher APRs. Interestingly, however, this relationship reverses for FICO scores less than 500 or so, consistent with our initial view that inaccurate self-assessment (borrowers with low FICO scores that self-assess as having “good” or “very good” credit) face less favorable market outcomes. Moreover, this same ‘inversion’ holds true for the other three Charts at roughly the same FICO score level.

In summary, the basic bivariate-like analyses of Tables 8 and 9 and Charts 15 through 18 suggest that self-assessments of credit clearly affect market outcomes, but not necessarily in the way initially anticipated. Although there is some small evidence in the lowess regressions for worse market outcomes to be broadly associated with inaccurate self-assessments, the more general trend is that better market outcomes are associated with more optimistic self-assessments.

Estimations of Non-Prime and APR

As done in the estimations for predictions of over- and under-assessments, we provide multivariate analyses to provide support for the lowess estimations. While we provide the logit estimations for the likelihood of non-prime for both levels of self-assessment (see Table 10) and errors in self-assessment (see Table 11), we focus in our discussion on the estimations of the odds of non-prime using errors in self-assessment (Table 11). Similarly, for our discussion purposes, we focus on the level of APR as a function of errors in self-assessment (Table 13) while providing the APR estimation as a function of the level of self-assessment in Table 12. We provide these estimations by the two groups of borrowers we have considered throughout this research: African Americans combined with Hispanics and Asians combined with White, Non-Hispanics. We provide an excerpt from Table 11 below.

Table 11				
Logit Model of Loan from Non-Prime Lender - Low Income Sample - Accuracy of Self Assessed Credit				
Number of Observations[1]	84,495		443,328	
Pseudo R-Square	0.70		0.73	
Population	African American and Hispanic		Asian and White, Non-Hispanic	
Variable	Odds Ratio	P (Z)	Odds Ratio	P (Z)
Wrong Low	1.02	0.17	0.99	0.63
Close Low	1.03	0.01	0.99	0.15
Close High	1.03	0.01	1.00	0.81
Wrong High	0.99	0.62	1.03	0.00
Hispanic/Asian	0.56	0.00	0.78	0.00
Female	0.94	0.00	1.10	0.00

The logit model includes several independent explanatory variables in addition to those pertaining to self-assessment. An important category of those included variables are the actual credit scores for the borrowers in this sample, included as splines of FICO categories. The self-assessment errors, then, impart only a marginal impact on the likelihood of non-prime, after controlling for the actual credit score buckets. We find that for African Americans and Hispanics, errors in self-assessment (close low or close high) significantly impact the odds of receiving a non-prime loan. The coefficients for wrong low and wrong high are not statistically significant for this group. For Asians and White, Non-Hispanics, we find that being very wrong high is associated with an increase in the likelihood of non-prime. For those borrowers who cannot accurately assess, and who believe they have much better credit than they do, they are more likely to receive, ultimately, a non-prime loan. This might be because they are unprepared when they first apply for a loan, imagining they can receive a better rate than their actual credit would justify, and after being disappointed, end up at a non-prime lender.

With respect to the other explanatory variables, we find that most have the expected signs. Higher LTV values are associated with higher odds of non-prime. Having prepayment penalties has a large, positive impact on likelihood non-prime. Being in tracts with a higher percentage of those who have only completed high school or that have a higher percentage of those without mortgages increases the odds of non-prime, consistent with our hypothesis that being more financially literate or more educated might increase odds of better mortgage outcomes. We see a higher likelihood of non-prime for adjustable rate mortgages, full documentation mortgages and loans with shorter terms. All else equal, within the group of African Americans and Hispanics, the control variable for Hispanics indicates they are less likely than African Americans to receive non-prime loans. As most of these signs on the explanatory variables are consistent with our expectations, we believe the self-assessment results are reasonable within the context of the estimation.

Given we find that errors in self-assessment can affect the likelihood of non-prime, we also expect that this will impact the price of the loan received. For the estimation results for the level of APR, we turn to Table 13. A portion of the table is included here and the full table can be found in the Appendix.

Table 13				
Regression Model of APR - Low Income Sample - Accuracy of Self Assessed Credit				
Number of Observations[1]	84,499		443,328	
Adjusted R-Square	0.72		0.74	
Population	African American and Hispanic		Asian and White, Non-Hispanic	
Variable	Coef (in BPS)	P (t)	Coef (in BPS)	P (t)
Wrong Low	1.59	0.00	1.77	0.00
Close Low	0.94	0.00	1.11	0.00
Close High	0.17	0.61	0.43	0.00
Wrong High	-2.34	0.00	-3.46	0.00
Non-Prime	200.66	0.00	197.53	0.00
Hispanic/Asian	-0.72	0.01	-5.10	0.00
Female	3.15	0.00	5.27	0.00

In the estimations of APR, the coefficient for each explanatory variable can be interpreted in terms of basis points. Positive coefficients are associated with higher basis points. In terms of the above results, we find that once one controls for whether the borrower is getting a loan from a non-prime lender compared to a prime lender, for which one pays, on average, another 200 basis points approximately, the marginal impact of self-assessment is low. For those who seriously under-assess credit (in either group), APR might go up by 1.5 or so basis points. This is statistically significant but economically negligible. A larger impact is felt by those who wrongly assess high – those borrowers end up with lower priced mortgages by 2 – 3 basis points, on average. Perhaps believing one has better credit than is true, in fact, leads those borrowers to argue more strongly for better priced mortgages. Those who under-assess likely do not pay much as their actual credit score will be used by the lender for the final price assessment.

We include several other explanatory variables in these APR estimations, as we do not want the self-assessment errors to be biased due to other omitted effects. For the other explanatory variables, as we found in the estimations of non-prime, the signs are nearly always as expected. In terms of education, one pays more, relative to tracts with higher percentages of post-graduates, if tract percent education is lower. One pays more in tracts that have lower percentages of housing occupancy and lower percentages of those with mortgages. One pays more for shorter term loans and for fixed rate mortgages. Price, in terms of APR, will be lower if one agrees to take a prepayment penalty. Higher LTVs have a significant and positive impact on APR. Borrowers who go through brokers pay about 20 basis points more (for African Americans and Hispanics) and 10 basis points more for Asians and White, Non-Hispanics. Loan amounts less than $100,000 cost the borrower more. Generally, lenders rationalize this outcome by noting high fixed costs of origination.

For both sets of market outcome estimations, we find nearly all explanatory variables to have signs that were anticipated and impacts as expected. This provides support for our conclusions about the impacts of errors in self-assessment of credit on mortgage market outcomes.

Conclusions

The importance of good credit in applying for home mortgages cannot be under estimated. Nearly every lender relies, at least in part, on credit bureau scores (for example, FICO scores) in making determinations about underwriting decisions (approval/denial) and about pricing decisions (note rate, APR). Recognizing the importance of credit to mortgage market outcomes, and recognizing the inherent complexity of the mortgage application and decision process in the United States, it is natural to draw conclusions that improving financial literacy is important to improving access to credit for home mortgages. As a significant body of research has noted the importance to asset building of home equity, there appears strong support for the need to understand credit in order to improve one's financial well-being. That said, no previous research has examined the divergence between credit scores and one's perception of those scores, nor has previous research addressed the impact of inaccurate self-assessment of credit on mortgage market outcomes.

We find, in this research, that errors in self-assessment vary with economic, psychographic, and demographic characteristics of potential mortgage market participants. In examining the characteristics of respondents who poorly self-assess, we find that low income households and those with a poor economic safety net self-assess poorly relative to their peers. These outcomes are particularly true for Asian and White, Non-Hispanic respondents. Those who believe they have control of their lives (relative to those who believe their life events are externally driven) are more likely to self-assess correctly, especially for Asian and White, Non-Hispanic respondents. Risk takers are less likely to assess accurately. We also find that financial literacy matters. Specifically, those with more formal education and those who say they have a high level of financial knowledge self-assess credit more accurately. Finally, respondents with adverse life events (divorce, medical problems, etc.) are much more likely to self-assess inaccurately.

Once we impute values for self-assessment to loan level mortgage market data, we find some interesting effects. The basic bivariate analyses we perform suggest that self-assessments of credit clearly affect market outcomes, but not necessarily in the way initially anticipated. Although there is some small evidence in the lowess regressions for worse market outcomes to be broadly associated with inaccurate self-assessments, the more general trend is that better market outcomes are associated with more optimistic self-assessments.

Our conclusion from this research is that while financial literacy does matter, a sense of confidence about one's credit can also be helpful, even when inaccurately derived. This may simply reflect that potential borrowers may be inclined to drive a better bargain, if they believe their credit is good, even when, in fact, they are wrong. The bargaining might balance the otherwise negative impact of actual poor credit.

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Appendix

I. Documentation for Census Variables Used

All data are from the U.S. Census file SF3. The source variables are summarized in the table below.

Summary of Census Variable Source

Data Set Variable	SF3 Source Variables
tract_pop	P006001
tract_perc_asian	P006001 and P007006
tract_perc_aa	P006001 and P007004
tract_perc_hisp	P006001 and P007010
tract_perc_wnh	P006001 and P007003
tract_perc_age_18_64	P006001 and P019024
tract_perc_age_18	P006001 and P019002
tract_perc_less_high	P006001, P037003-P037010 and P037020-P037027
tract_perc_high	P006001, P0370011 and P037028
tract_perc_some_coll	P006001, P037012, P037013, P037029 and P037030
tract_perc_assoc	P006001, P037014 and P037031
tract_perc_bach	P006001, P037015 and P037032
tract_perc_post_grad	P006001, P037033-P037035 and P037016-P037018
total_units	H006001
tract_perc_occ	H006001 and H006002
tract_perc_own_occ	H006001 and H011002
tract_median_yr_built	H035001
tract_median_income	HCT012001

II. Overview of Survey and Data Development

The survey contains information about 12,140 respondents compiled from three sources: survey data collected from individuals who responded to a 12-page consumer credit survey (CCS) questionnaire; demographic data kept on file by Market Facts, Inc. and The NPD Group to support their panels used for surveys; and individual credit data from Experian, a consumer credit repository agency.

The CCS was completed by panel members aged 20 to 40 with household incomes under $75,000. These cutoffs were chosen to represent a segment of the population for which home ownership and credit issues are important. The CCS data development process of 1999 included two firms which maintain national databases of mail survey panels, Market Facts, Inc., the lead firm on this project Inc. and the NPD Group. The sample frame consisted of lists of pre-recruited survey respondents provided by the two survey panel companies. As the members of these panels had agreed to complete surveys, the panels represent known populations with relatively high response rates. Both of these panels included more than 500,000 households covering the U.S. Panel information previously collected by Market Facts and NPD provided some background for sample selection, but contained no credit information. Experian, Inc., a consumer credit repository, provided the credit data key to our study. The sample was selected on the basis of payment history in order to obtain an adequate sample with "impaired" credit. Freddie Mac assisted with survey design and initial analysis of some of the key data elements.

Market Facts and NPD prepared files containing the names and address of all available African American, Hispanic and Asian panel members meeting the age and income criteria, plus a geographically balanced sample of Whites.[13] In their databases, married couple mail panel households designated one head of household as the primary contact, most often the female head. As marital status was known, survey mailings were targeted to the male or female head of married panel members to ensure more gender balance in the responses.[14] The file sent to Experian included 68,854 single household members. For the purpose of this survey, respondents are classified into only one racial/ethnic group. While Hispanics can be of any race, we categorized those with minority racial status as that race, rather than Hispanic.

Next, Experian appended credit files to the name and address file provided. The process was designed to ensure confidentiality of consumer credit information in that neither the survey panel companies nor Freddie Mac could match an individual's credit record to that individual's name, address or other unique identifying information. Experian matched and provided credit information for 85,597 individual householders and spouses (excluding the out-of-range Asians)

[13] For the Asian sample, there were insufficient persons to achieve the sampling objectives. However, national estimates from the survey exclude Asians who are outside the age or income specifications.

[14] The CCS uses individuals, not households, as the unit of observation. Many, if not most, credit decisions involve more than one family or household member and the survey includes several questions about the role of the spouse/partner in the questionnaire. While records can be merged, each individual consumer has his or her own payment and credit record. Attitudes, perceptions and opinions, moreover, are inherently personal and require that survey participants answer as an individual, not a household.

or 91,223 (including out-of-range Asians). These matched files were used for selection of the survey samples.

If first name and race/ethnicity of spouses of panel members were not available, the following decision rules were adopted for the credit reporting agency to use for the purpose of achieving the greatest accuracy in the appending of credit records. An adult of the opposite gender living at the same address as a married panel member was assumed to be the spouse (or partner) and was deemed eligible for the sample. An individual classified as the spouse of the panel member was assumed to share the race/ethnicity category of the respective spouse/partner when this information was absent for the spouse.

After credit records for all panel members and married spouses (when found) were appended to the files, the files were forwarded to Freddie Mac where each panelist was grouped into a credit quality group. The sampling plan partitioned by race/ethnicity (White, African American, Hispanic, and Asians) and payment history (impaired, indeterminate, good, and non-matches).[15] Each panelist in the sample was categorized in one of three credit quality groups ("buckets") using actual payment behavior extracted from credit files.

[15] The goal was to obtain approximately 1,000 surveys in each of the 12 cells of this four-by-four matrix.

Chart 1: Distribution of *Credit Score* by Self-Assessed Credit and Race

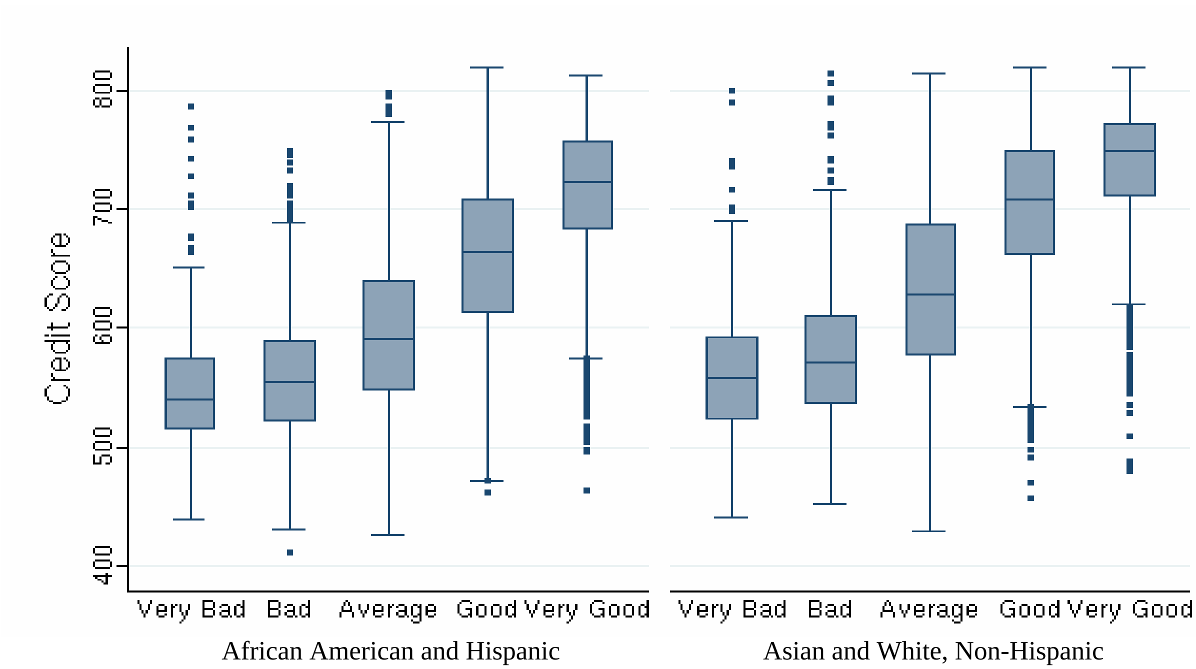


Table 1		
Definition of Actual Credit Categories		
	FICO Score Ranges	
Actual Credit Categories	African American and Hispanic	Asian and White, Non-Hispanic
Very Bad	450 - 545	450 – 580
Bad	546 – 585	581 – 605
Average	586 - 640	606 – 655
Good	641 – 695	656 – 725
Very Good	696 – 850	726 – 850

Table 2					
Summary of Credit Self-Assessment for African Americans and Hispanics					
Row Percent *Column Percent*	**Credit Self-Assessment**				
Actual Credit Score	Very Bad	Bad	Average	Good	Very Good
450 - 545	22.98 53.66	40.38 40.93	30.26 23.43	5.1 6.24	1.28 1.51
546 - 585	13.38 25.87	38.06 31.94	35.27 22.61	10.22 10.35	3.08 3
586 – 640	7.34 14.73	22.27 19.39	43.63 29.02	18.96 19.93	7.8 7.89
641 - 695	1.99 3.18	9.29 6.44	29.94 15.86	37.4 31.32	21.38 17.23
696 - 850	1.09 2.56	1.29 1.31	11.72 9.08	26.25 32.17	59.65 70.36

Table 3					
Summary of Credit Self-Assessment for Asian and White, Non-Hispanics					
Row Percent *Column Percent*	**Credit Self-Assessment**				
Actual Credit Score	Very Bad	Bad	Average	Good	Very Good
450 -580	20.09 70.91	42.09 55.39	28.72 26.94	6.99 6.27	2.1 1.02
581 - 605	9.32 11.09	39.41 17.49	36.33 11.49	11.32 3.42	3.61 0.6
606 – 655	5.79 12.7	20.74 16.97	39.32 22.93	20.84 11.61	13.32 4.04
656 - 725	0.44 2.06	4.71 8.32	21.55 27.16	33.08 39.84	40.22 26.4
726 - 850	0.46 3.23	0.71 1.84	6.22 11.49	22.01 38.87	70.6 67.94

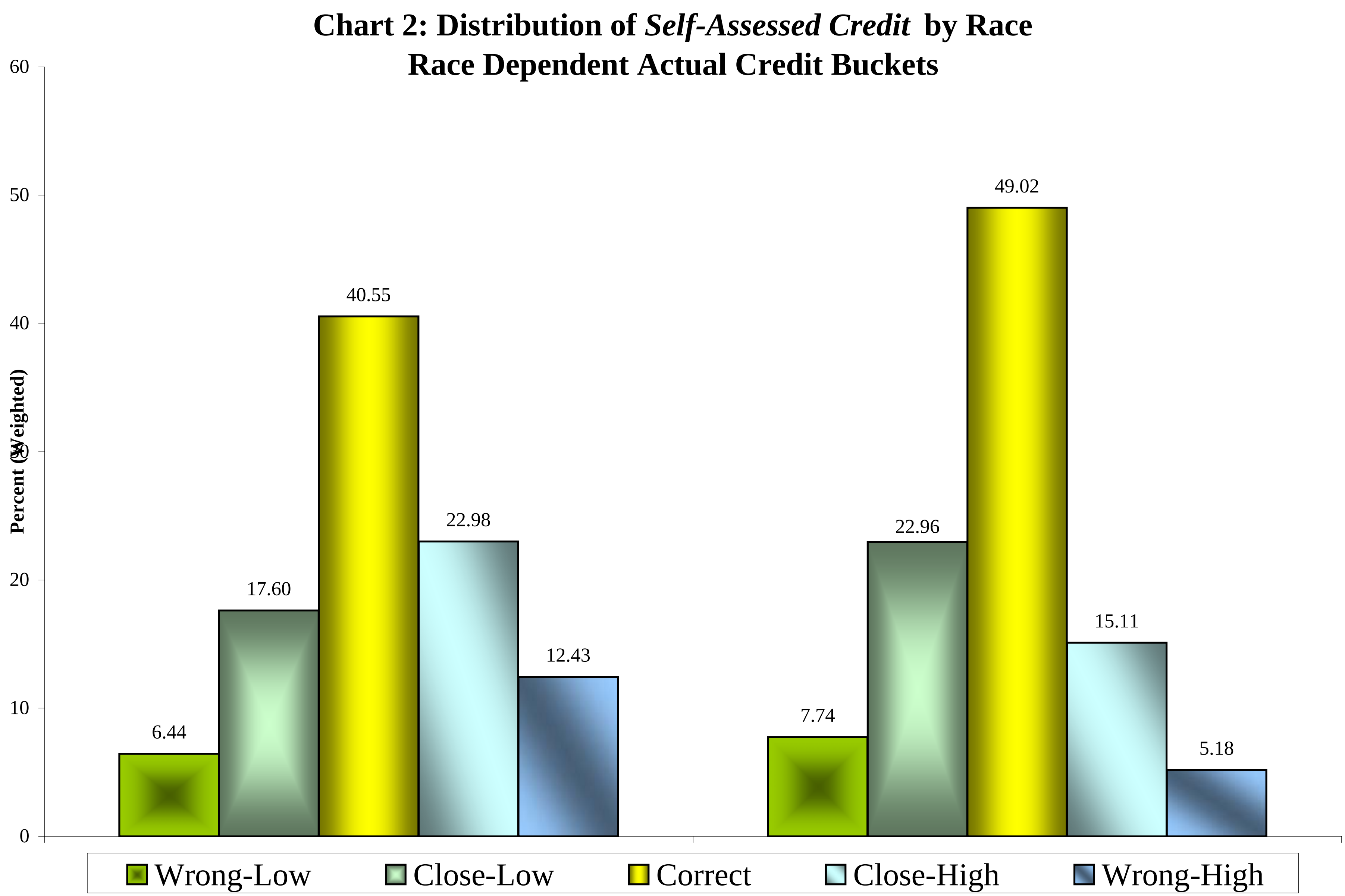


Chart 2: Distribution of *Self-Assessed Credit* by Race
Race Dependent Actual Credit Buckets
Percent (Weighted)
0
10
20
30
40
50
60
6.44
17.60
40.55
22.98
12.43
7.74
22.96
49.02
15.11
5.18
Wrong-Low
Close-Low
Correct
Close-High
Wrong-High

Chart 3: *Self-Assessed Knowledge* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets

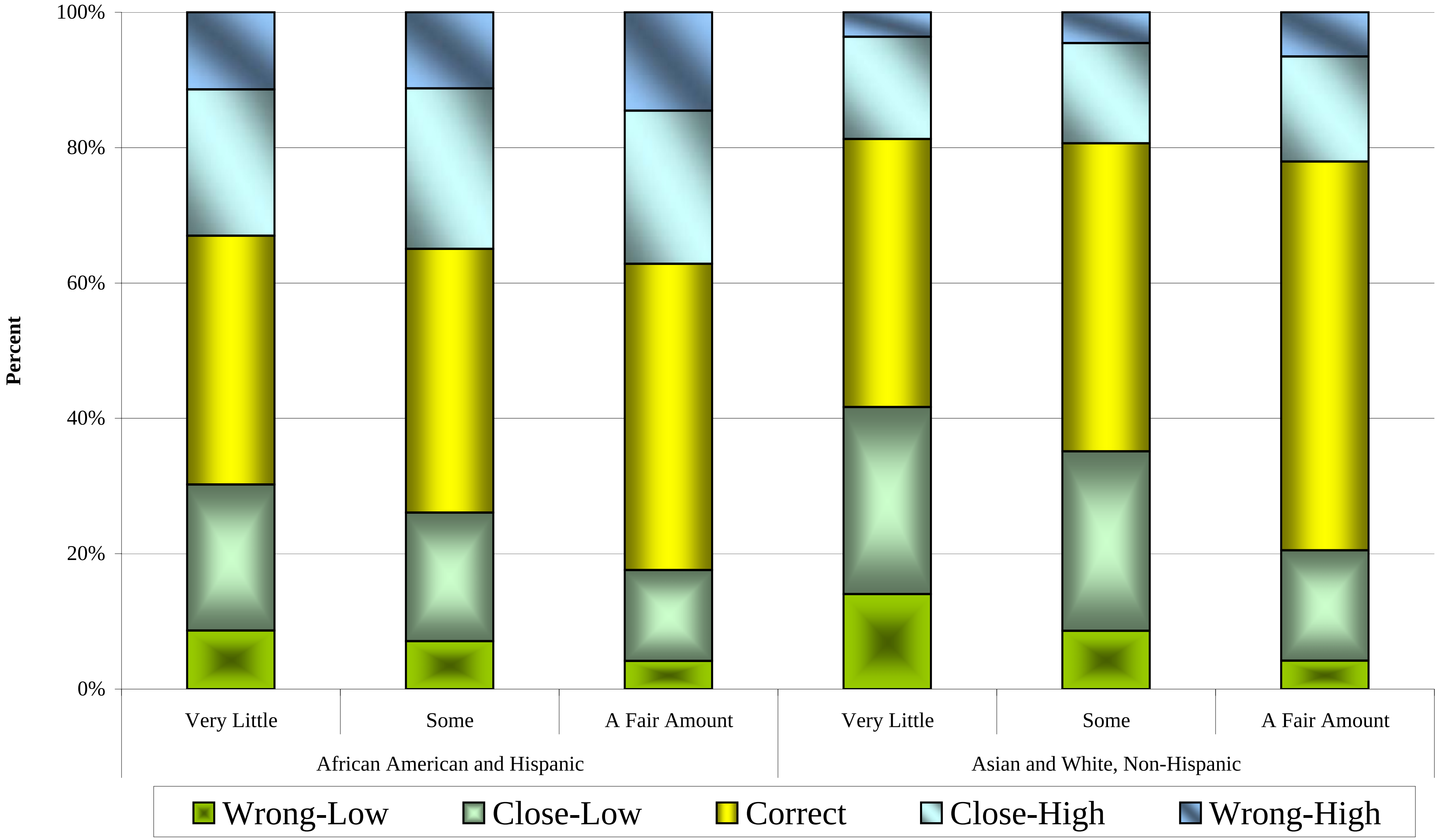


Chart 4: *Education* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets

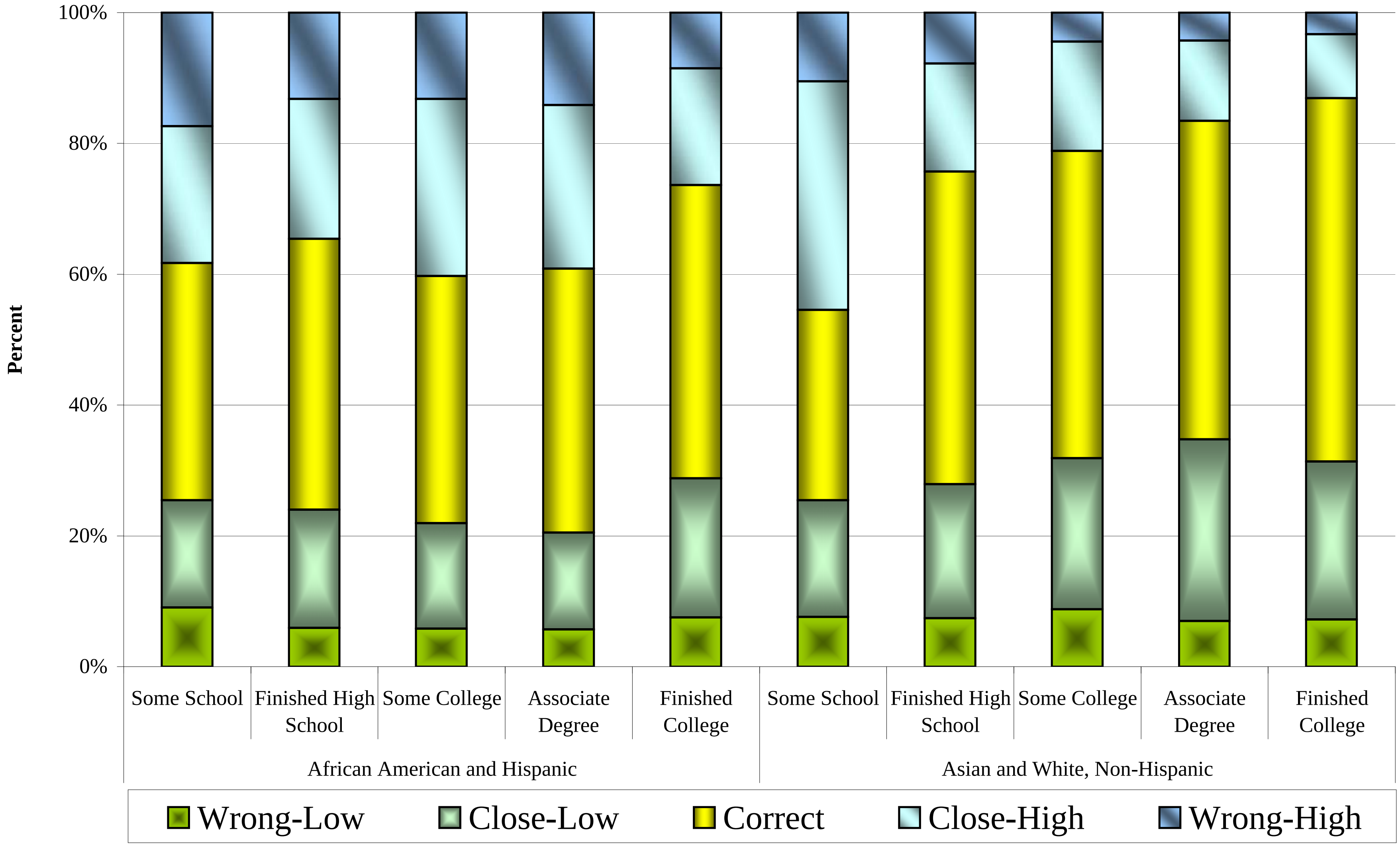
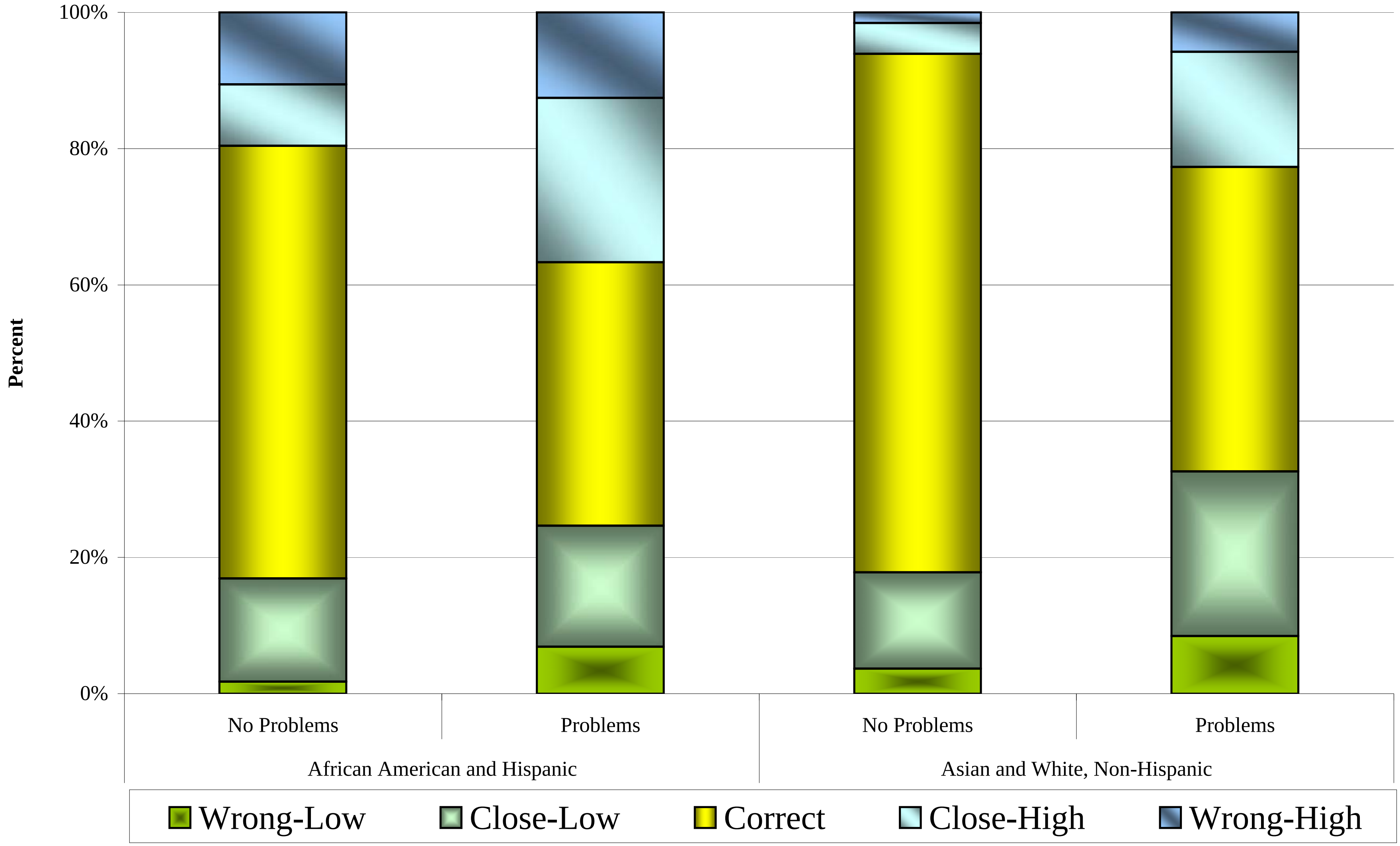


Chart 5: *Bad Stuff* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets



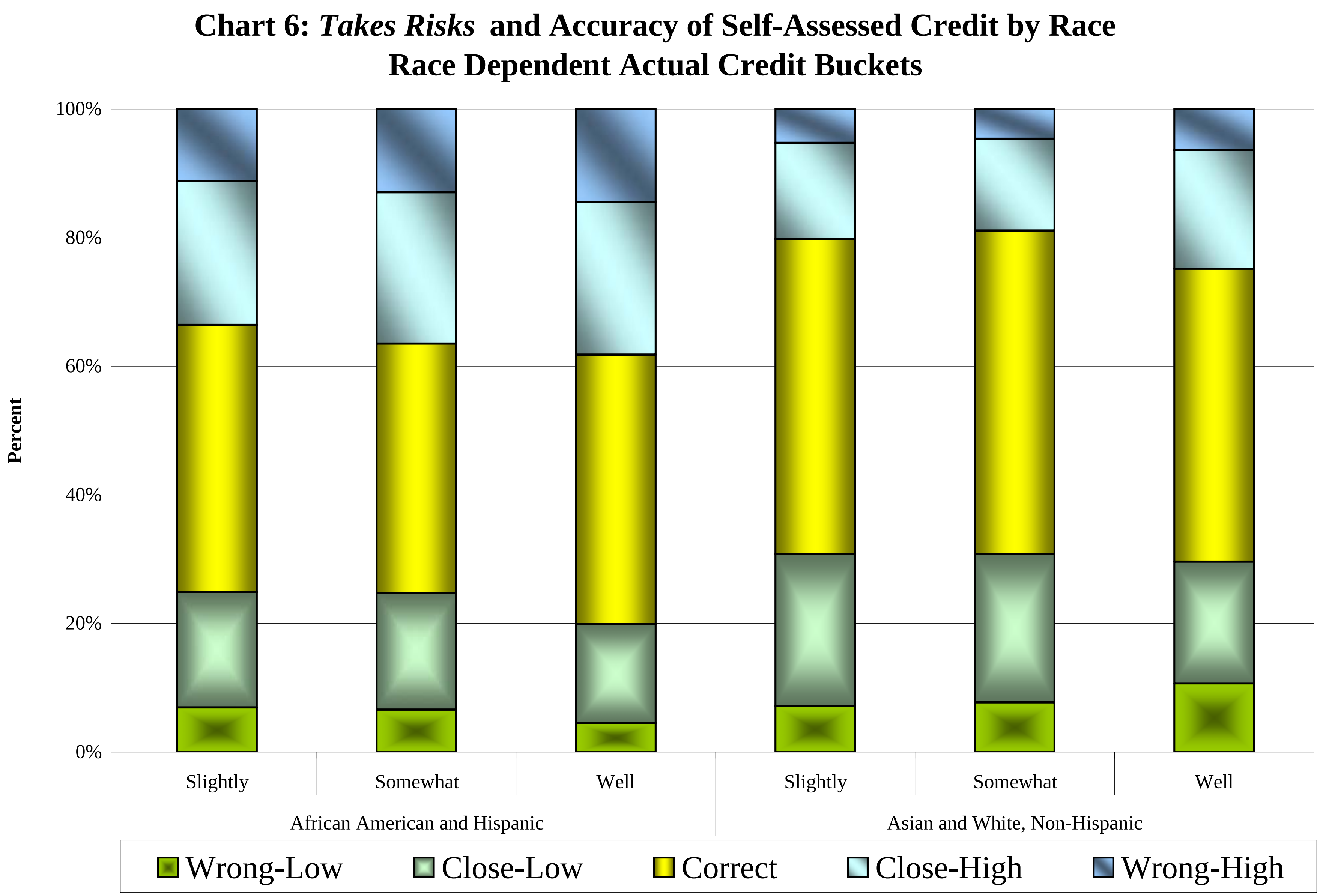


Chart 6: *Takes Risks* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets
100%
80%
60%
40%
20%
0%
Percent
Slightly
Somewhat
Well
Slightly
Somewhat
Well
African American and Hispanic
Asian and White, Non-Hispanic
Wrong-Low
Close-Low
Correct
Close-High
Wrong-High

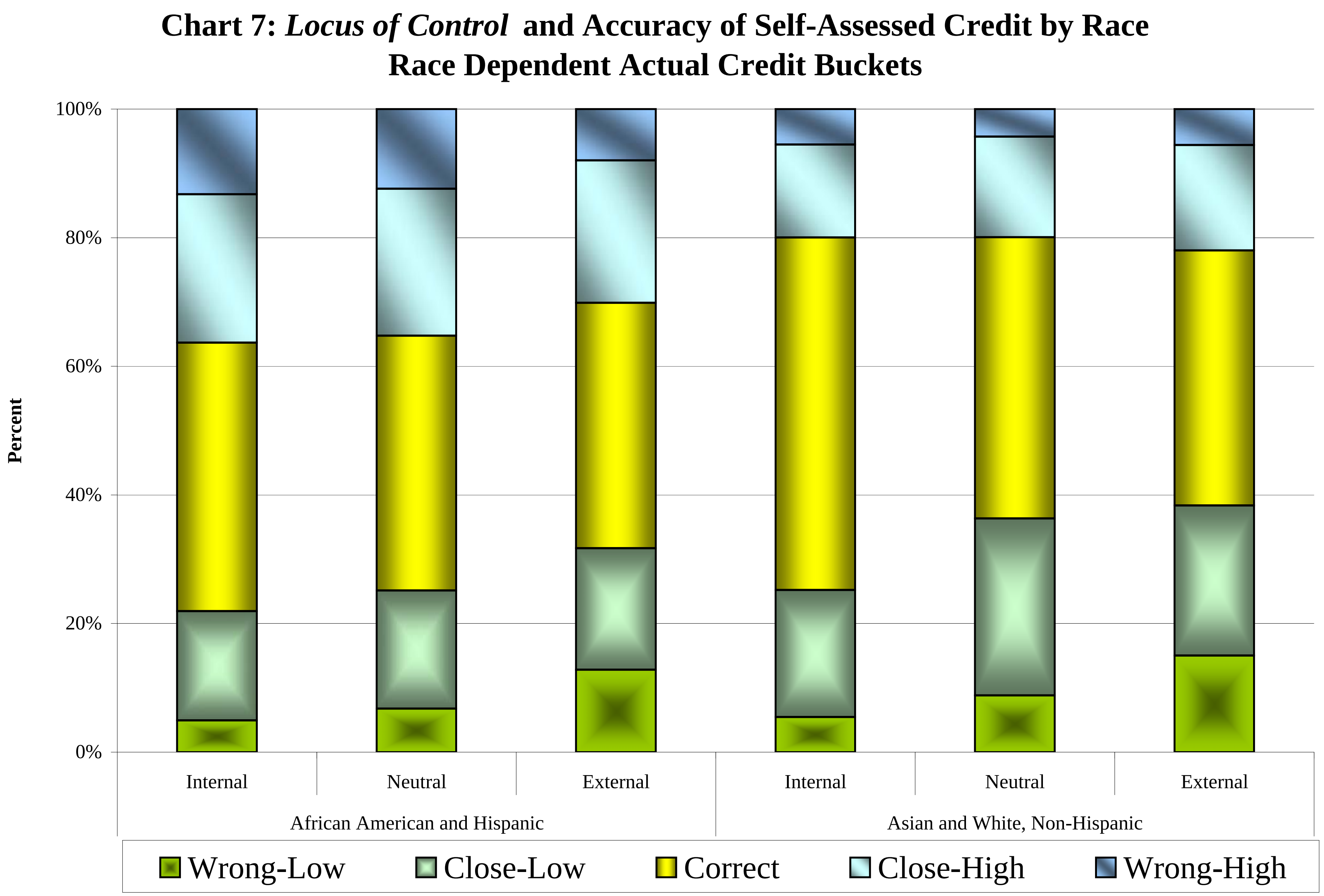


Chart 7: *Locus of Control* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets
100%
80%
60%
40%
20%
0%
Percent
Internal
Neutral
External
Internal
Neutral
External
African American and Hispanic
Asian and White, Non-Hispanic
Wrong-Low
Close-Low
Correct
Close-High
Wrong-High

Chart 8: *Income* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets

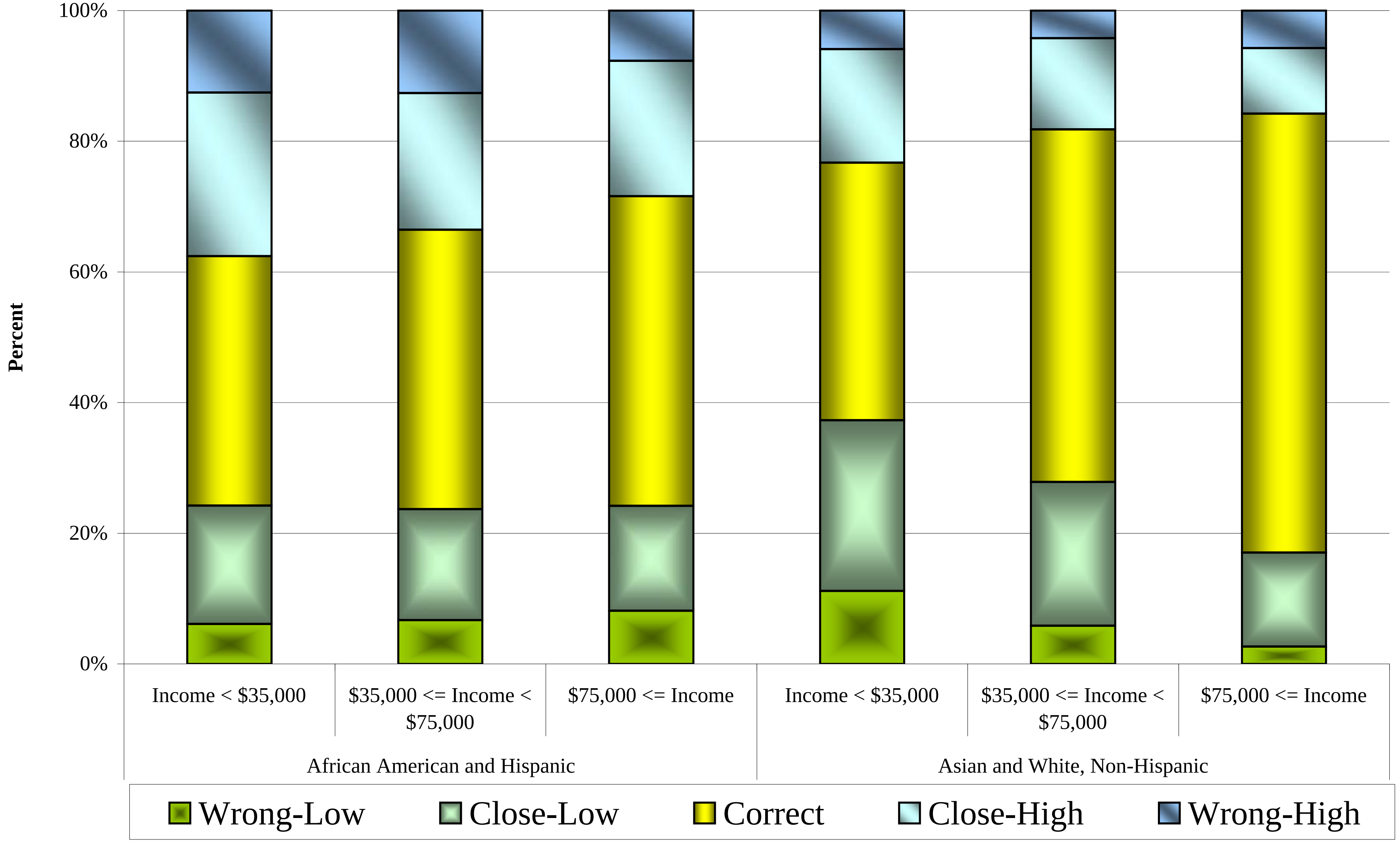
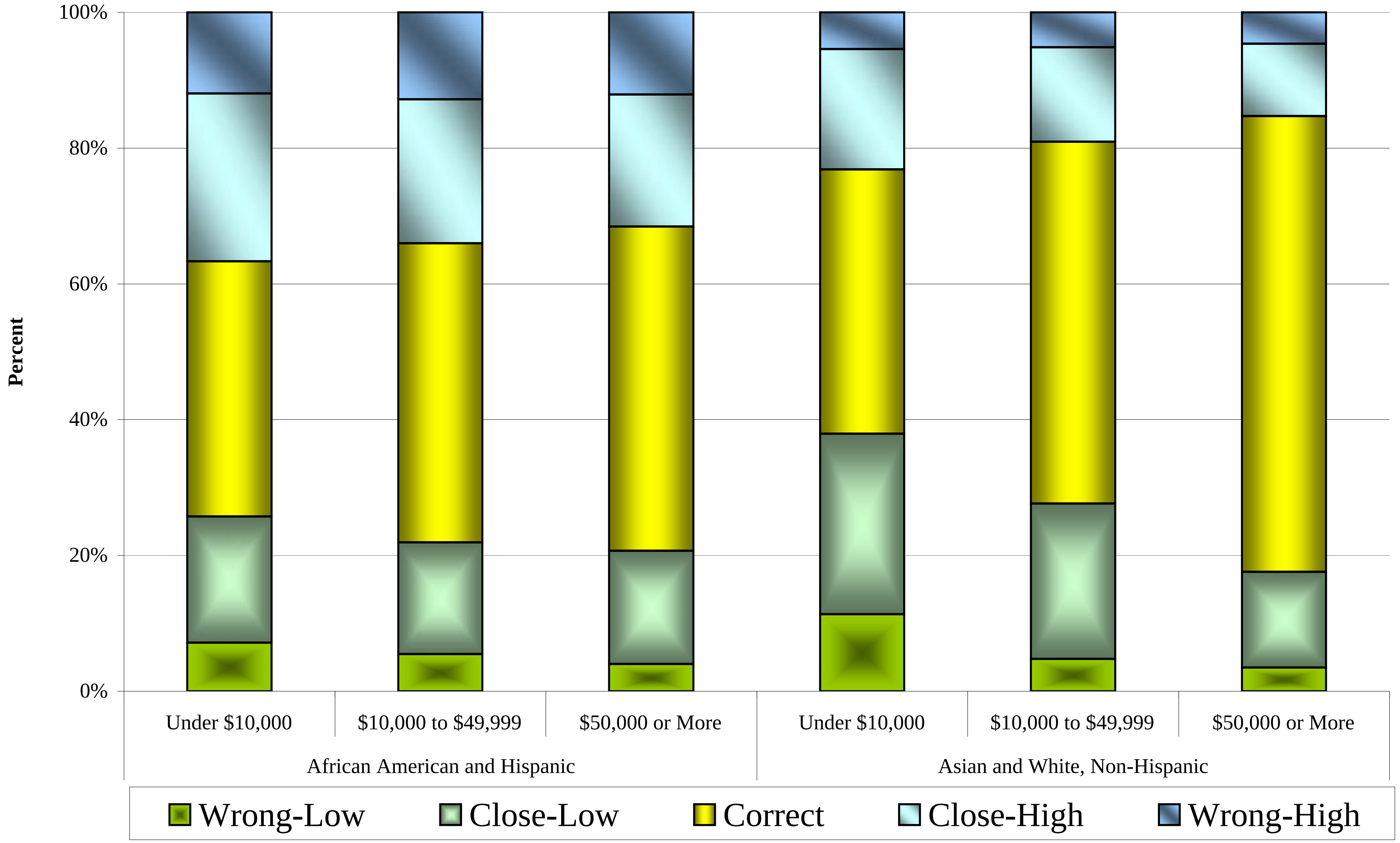


Chart 9: *New Worth* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets



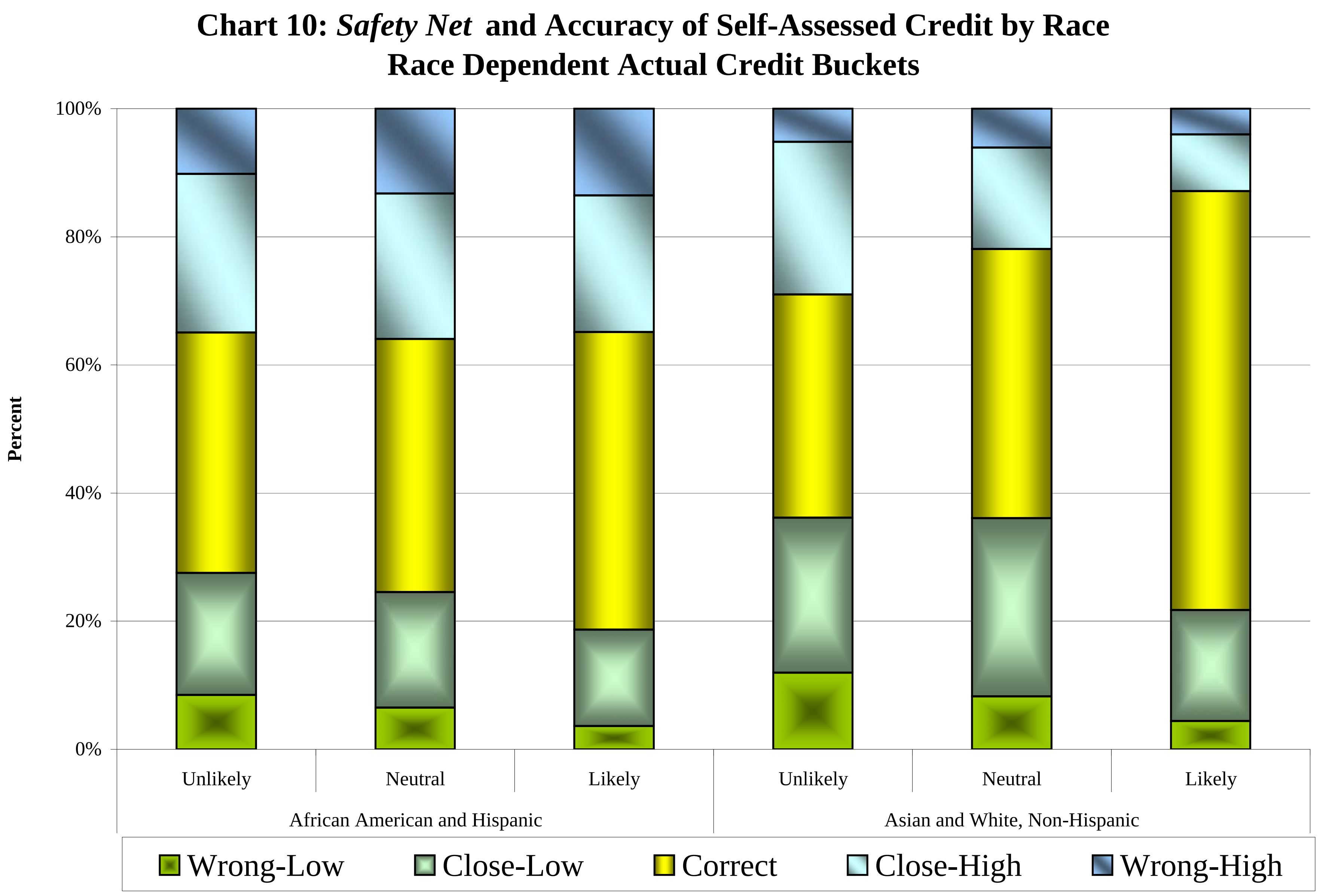


Chart 10: *Safety Net* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets
Percent
100%
80%
60%
40%
20%
0%
Unlikely
Neutral
Likely
Unlikely
Neutral
Likely
African American and Hispanic
Asian and White, Non-Hispanic
Wrong-Low
Close-Low
Correct
Close-High
Wrong-High

Chart 11: *Age* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets

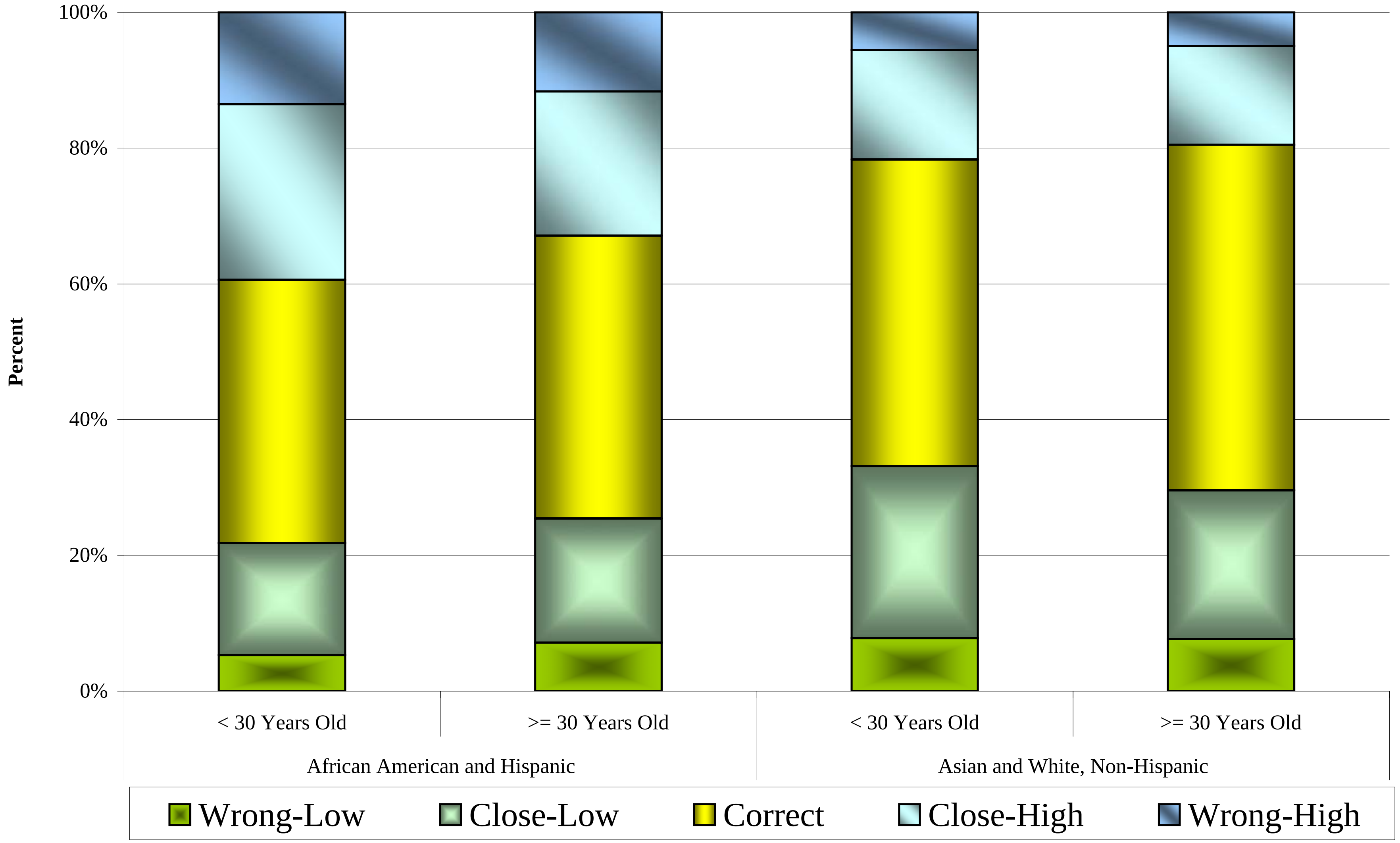


Chart 12: *Kids* and Accuracy of Self-Assessed Credit by Race
Race Dependent Actual Credit Buckets

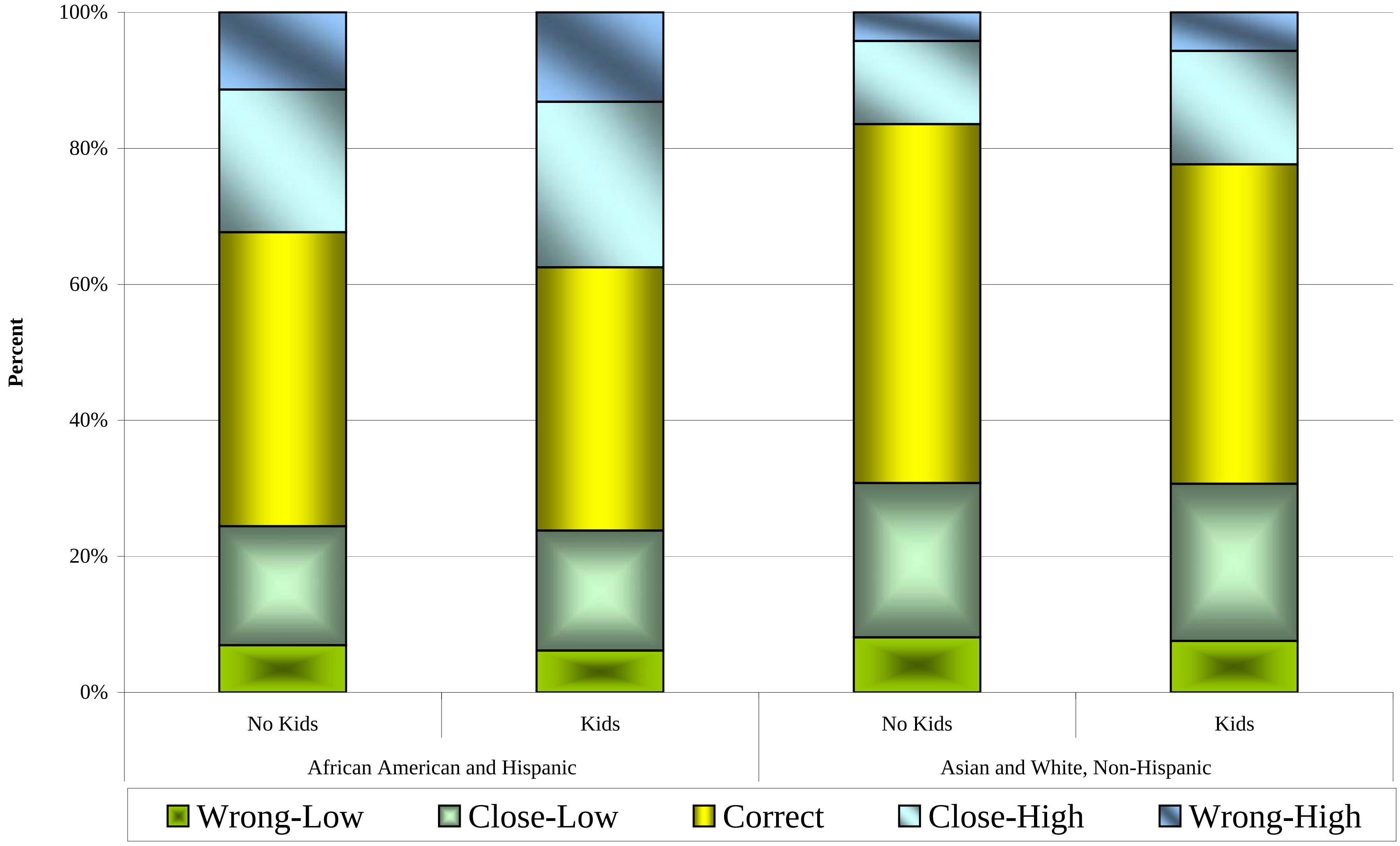


Table 4A					
Summary of Key Variables by Self-Assessed Credit Accuracy - African American and Hispanic					
	Row Percents				
Variable/*Value*	**Wrong - Low**	**Close - Low**	**Correct**	**Close - High**	**Wrong - High**
Self-Assessed Knowledge					
Very Little	8.65	21.55	36.77	21.64	11.39
Some	7.07	18.99	38.98	23.72	11.24
A Fair Amount	4.14	13.43	45.26	22.61	14.56
Education					
Some School	9.02	16.43	36.26	20.92	17.37
Finished High School	5.93	18.08	41.38	21.40	13.22
Some College	5.79	16.12	37.81	27.06	13.21
Associates Degree	5.67	14.82	40.35	25.00	14.15
Finished College	7.51	21.28	44.84	17.86	8.52
Bad Stuff					
No Problems	1.76	15.15	63.49	9.04	10.57
Problems	6.88	17.77	38.66	24.13	12.56
Take Risks					
Slightly	6.96	17.92	41.54	22.34	11.25
Somewhat	6.61	18.13	38.77	23.53	12.96
Well	4.52	15.35	41.93	23.72	14.48
Locus of Control					
Internal	4.92	16.98	41.75	23.11	13.24
Neutral	6.76	18.38	39.60	22.87	12.38
External	12.83	18.88	38.16	22.14	7.99
Income					
Under $35,000	6.11	18.10	38.17	25.04	12.57
$35,000 - $74,999	6.68	17.01	42.77	20.91	12.63
$75,000 or more	8.11	16.06	47.43	20.69	7.71
Net Worth					
Under $10,000	7.14	18.59	37.57	24.73	11.97
$10,000 - $49,999	5.47	16.46	44.06	21.18	12.83
$50,000 or more	4.00	16.70	47.73	19.47	12.10
Safety Net					
Unlikely	8.47	19.06	37.51	24.75	10.20
Netutral	6.50	18.05	39.51	22.69	13.25
Likely	3.61	15.05	46.46	21.34	13.54
Age					
Less than 30 years old	5.33	16.48	38.80	25.84	13.56
>= to 30 years old	7.16	18.26	41.68	21.23	11.68
Kids					
No Kids	6.90	17.50	43.24	20.99	11.36
Kids	6.12	17.67	38.70	24.34	13.17
Race					
Hispanic	8.05	18.54	44.78	19.29	9.34
African-American	4.85	16.68	36.41	26.60	15.46

Table 4B					
Summary of Key Variables by Self-Assessed Credit Accuracy - Asian and White, Non-Hispanic					
	Row Percents				
Variable/*Value*	**Wrong - Low**	**Close - Low**	**Correct**	**Close - High**	**Wrong - High**
Self-Assessed Knowledge					
Very Little	14.03	27.63	39.60	15.11	3.64
Some	8.60	26.51	45.54	14.77	4.58
A Fair Amount	4.19	16.29	57.44	15.55	6.53
Education					
Some School	7.59	17.85	29.11	34.92	10.52
Finished High School	7.38	20.51	47.80	16.54	7.78
Some College	8.76	23.09	46.98	16.73	4.44
Associates Degree	6.98	27.76	48.69	12.29	4.28
Finished College	7.22	24.15	55.53	9.79	3.31
Bad Stuff					
No Problems	3.68	14.11	76.09	4.56	1.55
Problems	8.46	24.16	44.68	16.89	5.81
Take Risks					
Slightly	7.18	23.64	48.96	14.96	5.26
Somewhat	7.72	23.07	50.30	14.27	4.64
Well	10.67	18.93	45.57	18.46	6.37
Locus of Control					
Internal	5.44	19.76	54.82	14.43	5.54
Neutral	8.81	27.52	43.72	15.64	4.30
External	15.00	23.36	39.65	16.39	5.61
Income					
Under $35,000	11.16	26.15	39.40	17.38	5.92
$35,000 - $74,999	5.84	21.99	53.96	13.96	4.25
$75,000 or more	2.63	14.40	67.17	10.06	5.73
Net Worth					
Under $10,000	11.35	26.59	38.92	17.73	5.42
$10,000 - $49,999	4.75	22.87	53.30	13.91	5.17
$50,000 or more	3.49	14.09	67.12	10.66	4.64
Safety Net					
Unlikely	11.93	24.23	34.81	23.82	5.21
Netutral	8.24	27.84	42.01	15.82	6.08
Likely	4.42	17.31	65.38	8.87	4.02
Age					
Less than 30 years old	7.82	25.31	45.19	16.10	5.58
>= to 30 years old	7.68	21.89	50.93	14.51	4.99
Kids					
No Kids	8.09	22.68	52.78	12.20	4.24
Kids	7.54	23.11	46.99	16.67	5.68
Race					
Asian	10.06	26.37	48.54	11.05	3.99
White, Non-Hispanic	7.62	22.79	49.05	15.30	5.24

Table 5

Ordered Probit Estimations of Self-Assessment Error

	African American and Hispanic				Asian and White, Non-Hispanic			
	Under-Assess		Over-Assess		Under-Assess		Over-Assess	
Parameter & Values	**Estimate**	**Prob (ChiSq)**	**Estimate**	**Prob (ChiSq)**	**Estimate**	**Prob (ChiSq)**	**Estimate**	**Prob (ChiSq)**
Intercept	0.57	0.0477	0.2638	0.2983	0.5707	0.0002	0.2231	0.1909
Intercept 2	1.0051	<.0001	0.9524	<.0001	1.1057	<.0001	0.9895	<.0001
Self-Assessed Knowledge								
Very Little	-0.4264	<.0001	0.0444	0.6566	-0.4214	<.0001	0.417	<.0001
Some	-0.2483	0.0039	0.023	0.7487	-0.3048	<.0001	0.2201	<.0001
A Fair Amount	0	.	0	.	0	.	0	.
Education								
Some School	0.0082	0.9647	-0.5814	0.0005	0.1334	0.2474	-0.7136	<.0001
Finished High School	0.2104	0.0514	-0.2371	0.0195	0.207	<.0001	-0.2926	<.0001
Some College	0.1735	0.0648	-0.2965	0.0005	0.0321	0.49	-0.1718	0.0023
Associates Degree	0.169	0.1861	-0.3366	0.0023	-0.0578	0.367	-0.1355	0.0917
Finished College	0	.	0	.	0	.	0	.
Percent with Mortgage	0.1463	0.4715	0.11	0.5428	0.3877	0.0021	0.7007	<.0001
Bad Stuff								
No Problems	0.4947	0.0004	0.4969	0.0001	0.5368	<.0001	0.8251	<.0001
Problems	0	.	0	.	0	.	0	.
Take Risks								
Slightly	-0.1934	0.0751	0.0883	0.3294	0.1013	0.0899	0.1969	0.0022
Somewhat	-0.2405	0.0357	-0.0203	0.8302	0.0682	0.2766	0.2557	0.0002
Well	0	.	0	.	0	.	0	.
Locus of Control								
Internal	0.1881	0.0918	-0.2103	0.0496	0.1898	0.0012	0.0011	0.9868
Neutral	0.1707	0.1281	-0.1156	0.2903	0.0493	0.3929	-0.0358	0.6041
External	0	.	0	.	0	.	0	.
Income								
Under $35,000	0.1205	0.5183	-0.0776	0.6519	-0.3193	0.0002	-0.1666	0.0722
$35,000 - $74,999	0.0272	0.8794	-0.0805	0.6265	-0.1815	0.0257	-0.0799	0.3547
$75,000 or more	0	.	0	.	0	.	0	.
Net Worth								
Under $10,000	-0.1943	0.1185	-0.0623	0.57	-0.3497	<.0001	-0.1144	0.0678
$10,000 - $49,999	-0.0952	0.4553	-0.0125	0.9106	-0.1583	0.0048	-0.0547	0.362
$50,000 or more	0	.	0	.	0	.	0	.
Safety Net								
Unlikely	-0.2959	0.0043	0.0263	0.7631	-0.3783	<.0001	-0.46	<.0001
Netutral	-0.2108	0.0254	-0.0183	0.8168	-0.3271	<.0001	-0.3634	<.0001
Likely	0	.	0	.	0	.	0	.
Age								
Less than 30 years old	0.1019	0.1786	-0.1355	0.0369	0.0372	0.3424	-0.1051	0.0189
>= to 30 years old	0	.	0	.	0	.	0	.
Kids								
No Kids	0.0102	0.8902	0.1302	0.0495	0.0235	0.5463	0.2014	<.0001
Kids	0	.	0	.	0	.	0	.
Race								
Hispanic	-0.1006	0.1678	0.3452	<.0001	.	.	.	.
Asian	.	.	.	.	-0.2335	0.0045	-0.1307	0.2251
Number of Observations	2390		2786		3261		2884	
Log Likelihood	-1035.47		-1384.55		-4012.59		-3017.82	

Table 6						
Summary of Selected Variables						
	Entire Sample			Low Income Sample		
Variable	Min	Mean	Max	Min	Mean	Max
FICO Score	450	702.88	800	450	696.52	800
LTV	0.00	74.01	65849.39	0.00	75.55	65849.39
DTI	-0.17	38.67	529298.00	0.00	40.17	529298.00
Pre-Payment Penalty	0.00	0.09	1.00	0.00	0.11	1.00
Income	1000	98176	106000000	1000	63336.71	120000
Loan Amount	500	200330	8260000	500	154462.10	1500000

Table 7

Summary of Counts by State in Low Income Sample

State	Total	African American and Hispanic		Asian and White, Non-Hispanic	
		Count	Percent	Count	Percent
Alabama	10,341	1,926	19	8,415	81
Alaska	2,107	83	4	2,024	96
Arizona	15,130	2,822	19	12,308	81
Arkansas	5,290	491	9	4,799	91
California	60,012	13,917	23	46,095	77
Colorado	14,429	1,432	10	12,997	90
Connecticut	2,629	339	13	2,290	87
Delaware	2,560	394	15	2,166	85
District of Columbia	1,118	584	52	534	48
Florida	35,709	8,508	24	27,201	76
Georgia	15,697	3,857	25	11,840	75
Hawaii	504	21	4	483	96
Idaho	4,944	185	4	4,759	96
Illinois	21,678	4,494	21	17,184	79
Indiana	10,516	957	9	9,559	91
Iowa	10,238	320	3	9,918	97
Kansas	4,217	351	8	3,866	92
Kentucky	5,153	377	7	4,776	93
Louisiana	7,488	1,942	26	5,546	74
Maine	1,730	30	2	1,700	98
Maryland	14,455	4,207	29	10,248	71
Massachusetts	6,799	729	11	6,070	89
Michigan	13,973	1,770	13	12,203	87
Minnesota	27,673	851	3	26,822	97
Mississippi	5,545	1,246	22	4,299	78
Missouri	11,802	1,451	12	10,351	88
Montana	2,983	22	1	2,961	99
Nebraska	5,316	299	6	5,017	94
Nevada	9,195	1,722	19	7,473	81
New Hampshire	2,339	61	3	2,278	97
New Jersey	11,013	1,959	18	9,054	82
New Mexico	3,649	1,234	34	2,415	66
New York	12,634	2,189	17	10,445	83
North Carolina	16,778	2,865	17	13,913	83
North Dakota	2,072	14	1	2,058	99
Ohio	18,076	1,912	11	16,164	89
Oklahoma	3,727	412	11	3,315	89
Oregon	9,369	391	4	8,978	96
Pennsylvania	18,059	1,483	8	16,576	92
Rhode Island	1,106	155	14	951	86
South Carolina	7,784	1,626	21	6,158	79
South Dakota	3,397	38	1	3,359	99
Tennessee	12,176	1,606	13	10,570	87
Texas	25,664	8,455	33	17,209	67
Utah	5,007	191	4	4,816	96
Vermont	501	8	2	493	98
Virginia	14,451	2,889	20	11,562	80
Washington	14,920	839	6	14,081	94
West Virginia	1,831	69	4	1,762	96
Wisconsin	12,643	763	6	11,880	94
Wyoming	2,188	56	3	2,132	97
Puerto Rico	41	35	85	6	15
Missing	8	1	13	7	88
Total	528,664	84,578	16	444,086	84

Table 8					
Summary of APR and Percent Non-Prime for African American and Hispanics					
Mean APR *Percent Non-Prime*	**Credit Self-Assessment**				
Actual Credit Score	Very Bad	Bad	Average	Good	Very Good
450 - 545	9.69 91.33	9.57 92	9.55 91.81	9.4 91.47	9.49 90.63
546 - 585	8.82 90.18	8.72 89.7	8.65 89.2	8.55 89.33	8.57 88.67
586 – 640	8.11 73.48	8.03 72.93	7.94 71.39	7.87 70.11	7.81 69.18
641 - 695	7.23 49.72	7.19 48.71	7.06 45.88	6.92 41.94	6.82 39.85
696 - 850	6.14 17.5	6.23 17.86	6.26 19.27	6.15 17.27	6.01 14.38

Table 9					
Summary of APR and Percent Non-Prime for Asian and White, Non-Hispanics					
Mean APR *Percent Non-Prime*	**Credit Self-Assessment**				
Actual Credit Score	Very Bad	Bad	Average	Good	Very Good
450 - 580	9.05 89.43	8.89 89.11	8.8 88.51	8.68 87.94	8.6 87.4
581 - 605	8.09 76.79	8.03 76.65	7.99 76.36	7.94 75.98	7.86 74.94
606 – 655	7.47 56.57	7.34 54.64	7.28 53.9	7.2 51.98	7.12 50.48
656 - 725	6.3 22.33	6.43 26.47	6.26 22.41	6.13 19.43	6 16.49
726 - 850	5.72 6.36	5.7 4.8	5.73 5.92	5.67 5.01	5.57 4.21

Chart 13
Lowess of *APR* and FICO by Self-Assessed Credit for *All Races*

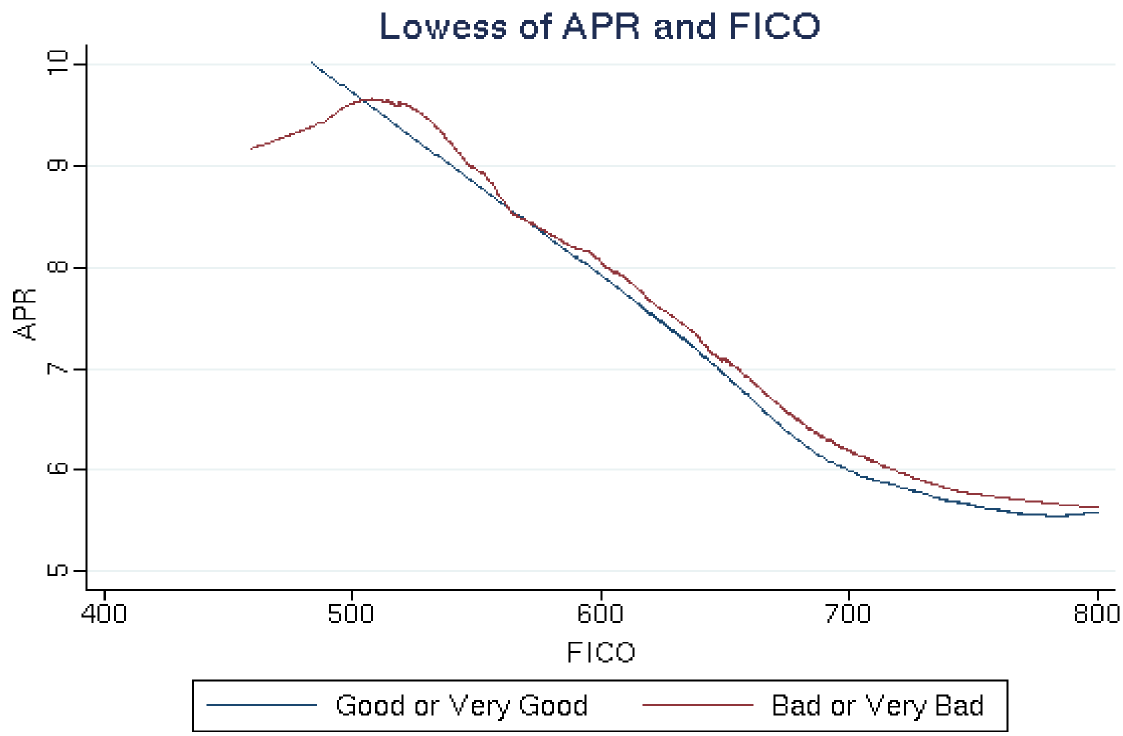


Chart 14
Lowess of *Percent Non-Prime* and FICO by Self-Assessed Credit for *All Races*

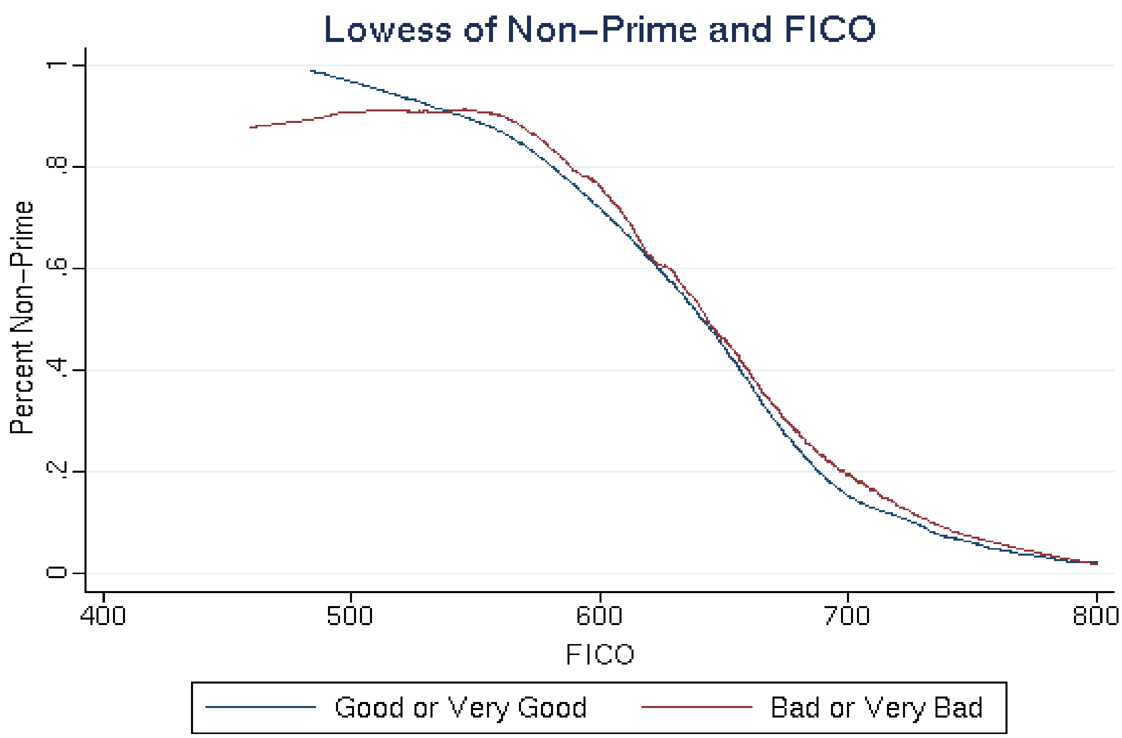


Chart 15
Lowess of *APR* and FICO by Self-Assessed Credit for *African American and Hispanic*

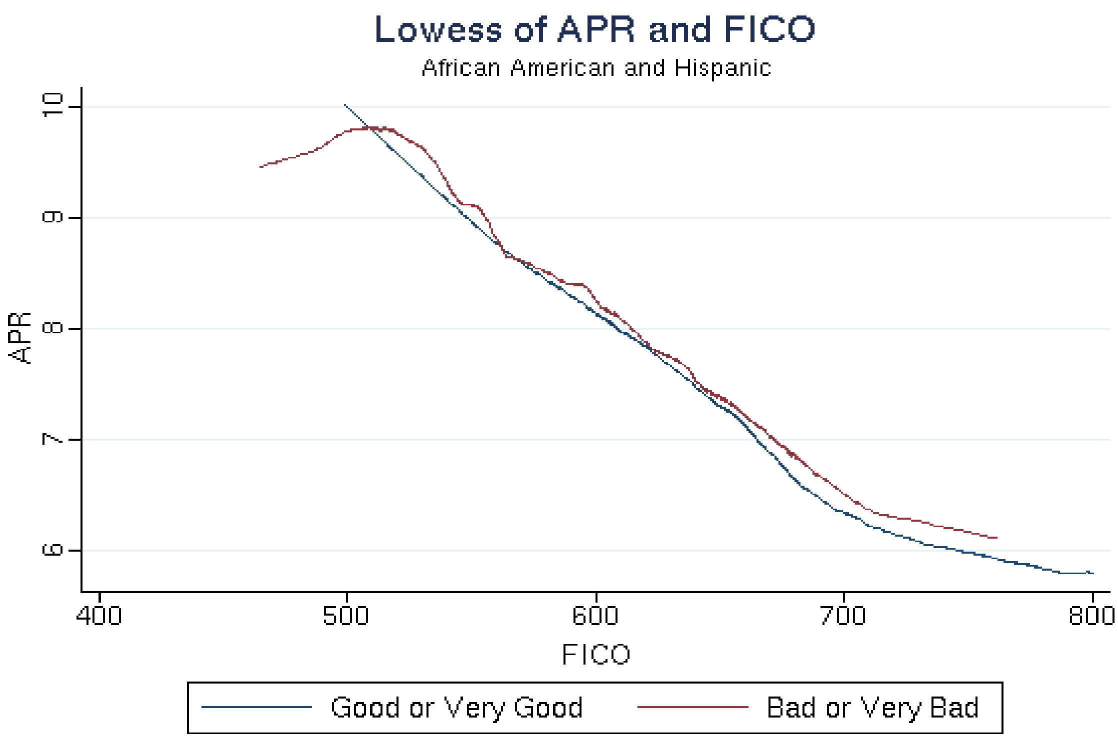


Chart 16

Lowess of *Percent Non-Prime* and FICO by Self-Assessed Credit for *African American and Hispanic*

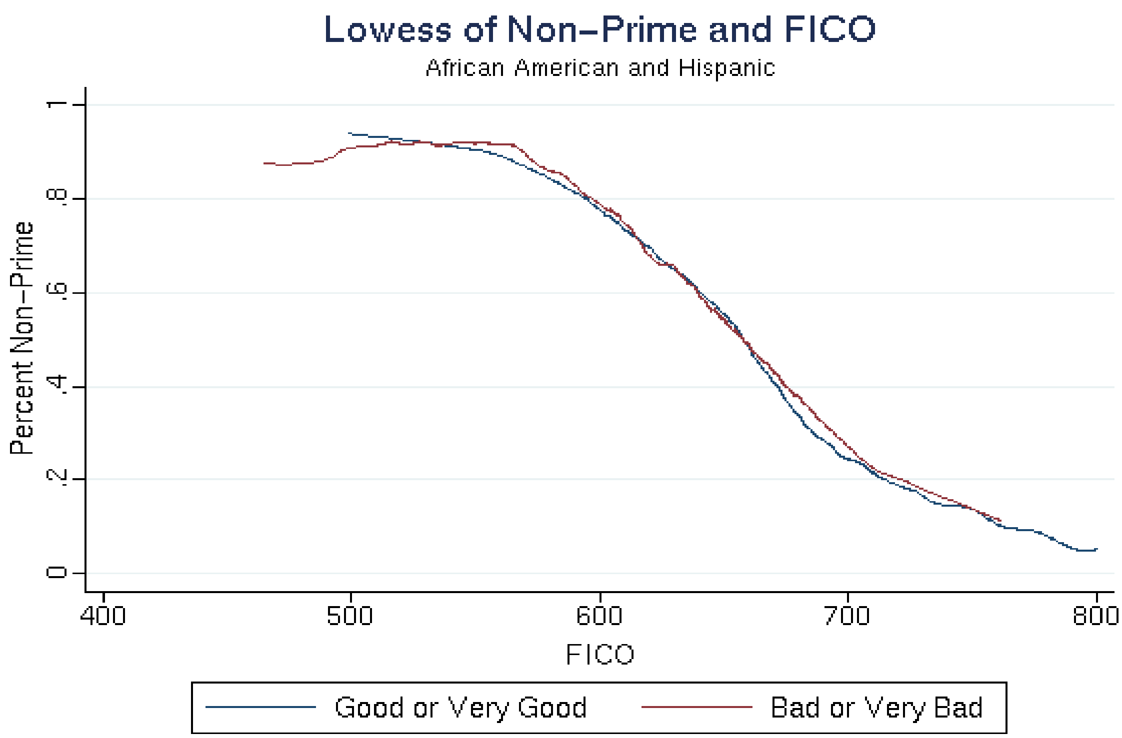


Chart 17
Lowess of *APR* and FICO by Self-Assessed Credit for *Asian and White, Non-Hispanic*

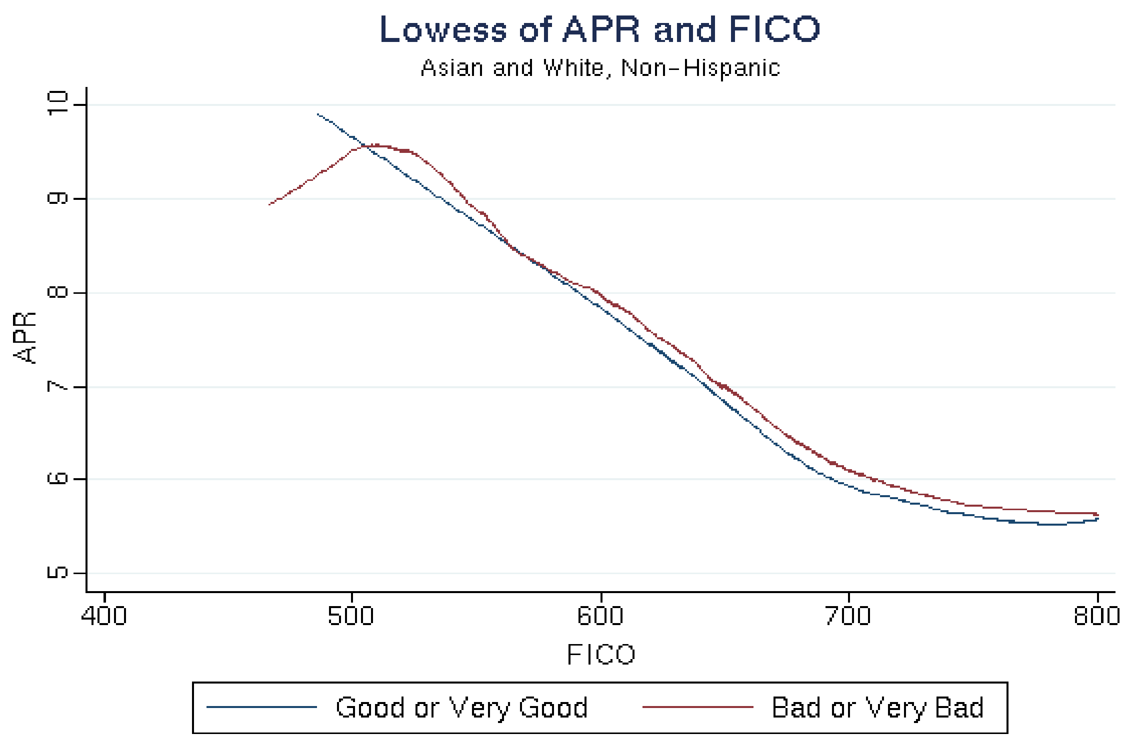


Chart 18

Lowess of *Percent Non-Prime* and FICO by Self-Assessed Credit for *Asian and White, Non-Hispanic*

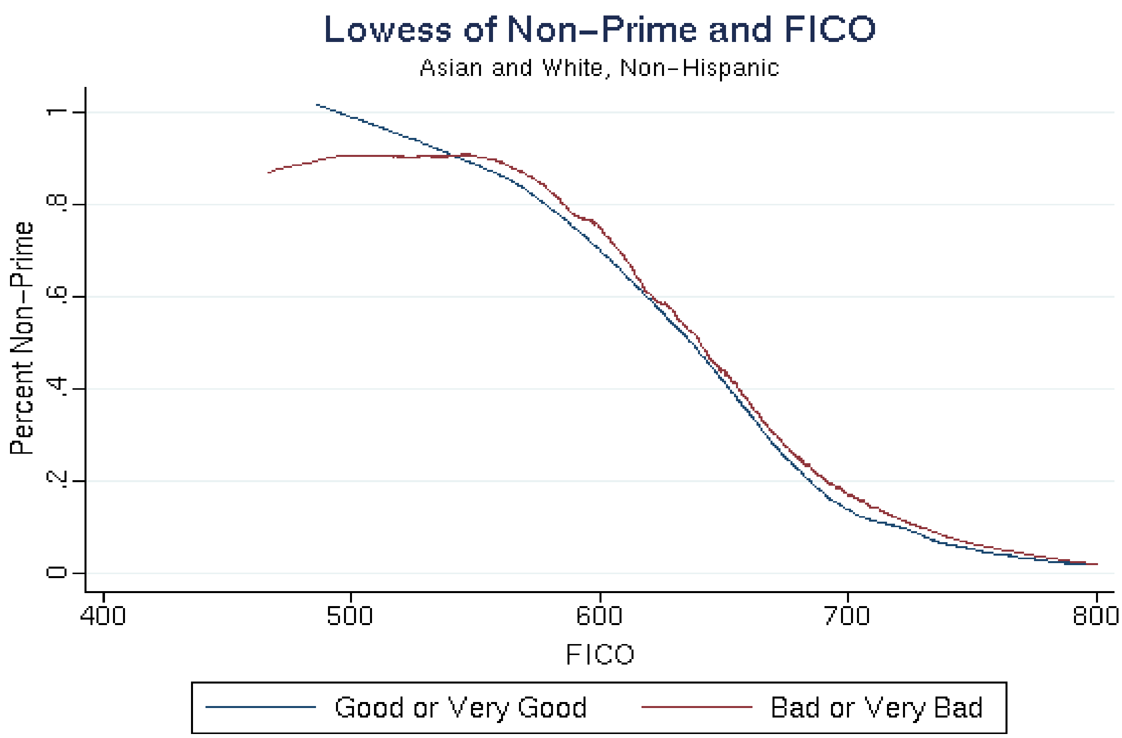


Table 10				
Logit Model of Loan from Non-Prime Lender - Low Income Sample -- Self Assessed Credit				
Number of Observations[1]	84,495		443,328	
Pseudo R-Square	0.70		0.73	
Population	African American and Hispanic		Asian and White, Non-Hispanic	
Variable	Odds Ratio	P (Z)	Odds Ratio	P (Z)
Good	1.01	0.34	0.98	0.00
Average	1.01	0.38	0.98	0.01
Bad	1.03	0.08	0.98	0.03
Very Bad	1.00	0.95	0.96	0.02
Hispanic/Asian	0.56	0.00	0.78	0.00
Female	0.94	0.00	1.10	0.00
Tract % Less than High School	1.27	0.07	0.27	0.00
Tract % High School	12.06	0.00	3.44	0.00
Tract % Less than College	1.04	0.76	0.05	0.00
Tract % Associates Degree	2.23	0.00	2.61	0.00
Tract % Bachelors	3.62	0.00	0.21	0.00
Tract % Occupied	1.30	0.00	2.26	0.00
Tract % Owner Occupied	0.99	0.82	0.93	0.00
Tract % Asian	0.55	0.00	0.90	0.02
Tract % African American	1.46	0.00	2.53	0.00
Tract % Hispanic	1.62	0.00	2.57	0.00
Tract % Without a Mortgage	2.38	0.00	1.41	0.00
Fixed Rate Mortgage	0.16	0.00	0.12	0.00
Unknown Fix/Arm	0.01	0.00	0.01	0.00
Loan Term >=15 & < 30 Years	1.29	0.00	1.62	0.00
Loan Term < 15 Years	3.99	0.00	6.91	0.00
Missing Term			0.35	0.00
Prepayment Penalty	1316.09	0.00	281.47	0.00
Unknown Prepayment Penalty	87.57	0.00	94.47	0.00
Not Owner Occupied	0.89	0.00	1.29	0.00
FICO Spline < 580	0.99	0.00	0.98	0.00
FICO Spline 580 - 680	0.98	0.00	0.98	0.00
FICO Spline > 680	0.99	0.00	0.98	0.00
LTV > 70 & <= 80	1.80	0.00	1.50	0.00
LTV > 80 & <=85	3.69	0.00	5.04	0.00
LTV > 85 & <= 90	2.47	0.00	3.81	0.00
LTV > 90 & <= 95	2.73	0.00	4.93	0.00
LTV > 95 & <= 100	2.31	0.00	6.04	0.00
LTV > 100	13.79	0.00	23.90	0.00
Unknown LTV	225.35	0.00	132.12	0.00
DTI >=50 & < 75	0.92	0.00	1.02	0.05
DTI > 75	0.15	0.00	0.20	0.00
DTI Missing	0.76	0.00	0.87	0.00
Brokered Loan	0.94	0.00	1.21	0.00
Refinance	3.12	0.00	4.22	0.00
Home Improvement	7.34	0.00	5.38	0.00
Loan Amount < 100,000	0.78	0.00	0.95	0.00
Loan Amount >= 100,000 & <= 333,700	0.77	0.00	0.98	0.05
Unknown Income / Loan Amount	0.61	0.00	1.00	0.87
Income / Loan Amount < 0.25	0.91	0.00	1.03	0.00
Income / Loan Amount >= 0.5 & < 0.75	1.22	0.00	0.98	0.01
Income / Loan Amount >= 0.75 & < 1	1.23	0.00	0.93	0.00
Income / Loan Amount >= 1 & < 5	0.82	0.00	0.68	0.00
Not Full Documentation	0.93	0.00	0.73	0.00
Unknown Documentation	2.19	0.00	1.04	0.00

[1]Number of observations/10 (10 random draws per individual observation)

Table 11				
Logit Model of Loan from Non-Prime Lender - Low Income Sample - Accuracy of Self Assessed Credit				
Number of Observations[1]	84,495		443,328	
Pseudo R-Square	0.70		0.73	
Population	African American and Hispanic		Asian and White, Non-Hispanic	
Variable	Odds Ratio	P (Z)	Odds Ratio	P (Z)
Wrong Low	1.02	0.17	0.99	0.63
Close Low	1.03	0.01	0.99	0.15
Close High	1.03	0.01	1.00	0.81
Wrong High	0.99	0.62	1.03	0.00
Hispanic/Asian	0.56	0.00	0.78	0.00
Female	0.94	0.00	1.10	0.00
Tract % Less than High School	1.27	0.07	0.27	0.00
Tract % High School	12.04	0.00	3.43	0.00
Tract % Less than College	1.04	0.76	0.05	0.00
Tract % Associates Degree	2.22	0.00	2.61	0.00
Tract % Bachelors	3.62	0.00	0.21	0.00
Tract % Occupied	1.29	0.00	2.26	0.00
Tract % Owner Occupied	0.99	0.83	0.93	0.00
Tract % Asian	0.55	0.00	0.90	0.02
Tract % African American	1.46	0.00	2.53	0.00
Tract % Hispanic	1.62	0.00	2.57	0.00
Tract % Without a Mortgage	2.38	0.00	1.41	0.00
Fixed Rate Mortgage	0.16	0.00	0.12	0.00
Unknown Fix/Arm	0.01	0.00	0.01	0.00
Loan Term >=15 & < 30 Years	1.29	0.00	1.62	0.00
Loan Term < 15 Years	3.99	0.00	6.90	0.00
Missing Term			0.35	0.00
Prepayment Penalty	1316.16	0.00	281.42	0.00
Unknown Prepayment Penalty	87.58	0.00	94.46	0.00
Not Owner Occupied	0.89	0.00	1.29	0.00
FICO Spline < 580	0.99	0.00	0.98	0.00
FICO Spline 580 - 680	0.98	0.00	0.98	0.00
FICO Spline > 680	0.99	0.00	0.98	0.00
LTV > 70 & <= 80	1.80	0.00	1.50	0.00
LTV > 80 & <=85	3.69	0.00	5.04	0.00
LTV > 85 & <= 90	2.47	0.00	3.81	0.00
LTV > 90 & <= 95	2.73	0.00	4.93	0.00
LTV > 95 & <= 100	2.31	0.00	6.04	0.00
LTV > 100	13.79	0.00	23.91	0.00
Unknown LTV	225.30	0.00	132.10	0.00
DTI >=50 & < 75	0.92	0.00	1.01	0.05
DTI > 75	0.15	0.00	0.20	0.00
DTI Missing	0.76	0.00	0.87	0.00
Brokered Loan	0.94	0.00	1.21	0.00
Refinance	3.12	0.00	4.22	0.00
Home Improvement	7.34	0.00	5.38	0.00
Loan Amount < 100,000	0.78	0.00	0.95	0.00
Loan Amount >= 100,000 & <= 333,700	0.77	0.00	0.98	0.05
Unknown Income / Loan Amount	0.61	0.00	1.00	0.87
Income / Loan Amount < 0.25	0.91	0.00	1.03	0.00
Income / Loan Amount >= 0.5 & < 0.75	1.22	0.00	0.98	0.01
Income / Loan Amount >= 0.75 & < 1	1.23	0.00	0.93	0.00
Income / Loan Amount >= 1 & < 5	0.82	0.00	0.68	0.00
Not Full Documentation	0.93	0.00	0.73	0.00
Unknown Documentation	2.19	0.00	1.04	0.00

[1]Number of observations/10 (10 random draws per individual observation)

Table 12				
Regression Model of APR - Low Income Sample - Self Assessed Credit				
Number of Observations[1]	84,499		443,328	
Adjusted R-Square	0.72		0.74	
Population	African American and Hispanic		Asian and White, Non-Hispanic	
Variable	Coef (in BPS)	P (t)	Coef (in BPS)	P (t)
Good	0.51	0.05	0.77	0.00
Average	1.88	0.00	1.45	0.00
Bad	3.66	0.00	3.72	0.00
Very Bad	7.36	0.00	7.71	0.00
Non-Prime	200.66	0.00	197.52	0.00
Hispanic/Asian	-0.73	0.01	-5.10	0.00
Female	3.12	0.00	5.25	0.00
Tract % Less than High School	32.27	0.00	30.49	0.00
Tract % High School	27.71	0.00	19.71	0.00
Tract % Less than College	13.32	0.00	-7.38	0.00
Tract % Associates Degree	12.02	0.04	9.79	0.00
Tract % Bachelors	-7.12	0.15	-40.07	0.00
Tract % Occupied	-34.66	0.00	6.16	0.00
Tract % Owner Occupied	7.24	0.00	3.00	0.00
Tract % Asian	-35.33	0.00	-22.56	0.00
Tract % African American	19.20	0.00	17.00	0.00
Tract % Hispanic	2.66	0.00	-15.02	0.00
Tract % Without a Mortgage	46.09	0.00	18.93	0.00
Fixed Rate Mortgage	38.97	0.00	66.27	0.00
Unknown Fix/Arm	23.04	0.00	24.94	0.00
Loan Term >=15 & < 30 Years	-13.71	0.00	-28.47	0.00
Loan Term < 15 Years	29.46	0.00	-13.45	0.00
Missing Term	163.28	0.00	92.95	0.00
Prepayment Penalty	-28.78	0.00	-17.38	0.00
Unknown Prepayment Penalty	-59.81	0.00	-52.89	0.00
Not Owner Occupied	46.41	0.00	35.31	0.00
FICO Spline < 580	-1.70	0.00	-1.84	0.00
FICO Spline 580 - 680	-0.98	0.00	-1.02	0.00
FICO Spline > 680	-0.10	0.00	-0.08	0.00
LTV > 70 & <= 80	4.29	0.00	3.87	0.00
LTV > 80 & <=85	23.41	0.00	27.26	0.00
LTV > 85 & <= 90	49.58	0.00	51.35	0.00
LTV > 90 & <= 95	63.87	0.00	59.91	0.00
LTV > 95 & <= 100	103.39	0.00	96.01	0.00
LTV > 100	133.05	0.00	98.20	0.00
Unknown LTV	17.75	0.00	22.74	0.00
DTI >=50 & < 75	3.90	0.00	2.90	0.00
DTI > 75	-7.10	0.00	-8.50	0.00
DTI Missing	3.43	0.00	-8.72	0.00
Brokered Loan	21.17	0.00	10.77	0.00
Refinance	-12.40	0.00	-9.24	0.00
Home Improvement	10.40	0.00	11.74	0.00
Loan Amount < 100,000	61.71	0.00	43.08	0.00
Loan Amount >= 100,000 & <= 333,700	23.08	0.00	10.79	0.00
Unknown Income / Loan Amount	-8.77	0.00	1.63	0.00
Income / Loan Amount < 0.25	-19.38	0.00	-10.58	0.00
Income / Loan Amount >= 0.5 & < 0.75	14.13	0.00	7.21	0.00
Income / Loan Amount >= 0.75 & < 1	19.70	0.00	8.95	0.00
Income / Loan Amount >= 1 & < 5	31.27	0.00	12.29	0.00
Not Full Documentation	3.16	0.00	-0.95	0.00
Unknown Documentation	65.32	0.00	79.70	0.00
Constant	1573.44	0.00	1641.63	0.00

[1]Number of observations/10 (10 random draws per individual observation)

Table 13				
Regression Model of APR - Low Income Sample - Accuracy of Self Assessed Credit				
Number of Observations[1]	84,499		443,328	
Adjusted R-Square	0.72		0.74	
Population	African American and Hispanic		Asian and White, Non-Hispanic	
Variable	Coef (in BPS)	P (t)	Coef (in BPS)	P (t)
Wrong Low	1.59	0.00	1.77	0.00
Close Low	0.94	0.00	1.11	0.00
Close High	0.17	0.61	0.43	0.00
Wrong High	-2.34	0.00	-3.46	0.00
Non-Prime	200.66	0.00	197.53	0.00
Hispanic/Asian	-0.72	0.01	-5.10	0.00
Female	3.15	0.00	5.27	0.00
Tract % Less than High School	32.41	0.00	30.54	0.00
Tract % High School	27.83	0.00	19.75	0.00
Tract % Less than College	13.40	0.00	-7.38	0.00
Tract % Associates Degree	12.08	0.03	9.83	0.00
Tract % Bachelors	-7.08	0.15	-40.06	0.00
Tract % Occupied	-34.81	0.00	6.15	0.00
Tract % Owner Occupied	7.25	0.00	2.99	0.00
Tract % Asian	-35.42	0.00	-22.59	0.00
Tract % African American	19.21	0.00	17.01	0.00
Tract % Hispanic	2.63	0.00	-15.03	0.00
Tract % Without a Mortgage	46.13	0.00	18.97	0.00
Fixed Rate Mortgage	38.98	0.00	66.28	0.00
Unknown Fix/Arm	23.04	0.00	24.94	0.00
Loan Term >=15 & < 30 Years	-13.71	0.00	-28.47	0.00
Loan Term < 15 Years	29.48	0.00	-13.44	0.00
Missing Term	163.16	0.00	93.00	0.00
Prepayment Penalty	-28.79	0.00	-17.38	0.00
Unknown Prepayment Penalty	-59.80	0.00	-52.87	0.00
Not Owner Occupied	46.39	0.00	35.31	0.00
FICO Spline < 580	-1.72	0.00	-1.86	0.00
FICO Spline 580 - 680	-1.01	0.00	-1.05	0.00
FICO Spline > 680	-0.11	0.00	-0.08	0.00
LTV > 70 & <= 80	4.27	0.00	3.85	0.00
LTV > 80 & <=85	23.39	0.00	27.27	0.00
LTV > 85 & <= 90	49.55	0.00	51.34	0.00
LTV > 90 & <= 95	63.84	0.00	59.87	0.00
LTV > 95 & <= 100	103.41	0.00	96.01	0.00
LTV > 100	132.99	0.00	98.20	0.00
Unknown LTV	17.75	0.00	22.76	0.00
DTI >=50 & < 75	3.90	0.00	2.90	0.00
DTI > 75	-7.11	0.00	-8.52	0.00
DTI Missing	3.42	0.00	-8.72	0.00
Brokered Loan	21.16	0.00	10.76	0.00
Refinance	-12.41	0.00	-9.25	0.00
Home Improvement	10.42	0.00	11.75	0.00
Loan Amount < 100,000	61.99	0.00	43.20	0.00
Loan Amount >= 100,000 & <= 333,700	23.20	0.00	10.83	0.00
Unknown Income / Loan Amount	-8.73	0.00	1.64	0.00
Income / Loan Amount < 0.25	-19.31	0.00	-10.54	0.00
Income / Loan Amount >= 0.5 & < 0.75	14.05	0.00	7.17	0.00
Income / Loan Amount >= 0.75 & < 1	19.56	0.00	8.88	0.00
Income / Loan Amount >= 1 & < 5	31.06	0.00	12.19	0.00
Not Full Documentation	3.14	0.00	-0.96	0.00
Unknown Documentation	65.30	0.00	79.68	0.00
Constant	1589.73	0.00	1657.27	0.00

[1]Number of observations/10 (10 random draws per individual observation)