Consumer Credit Literacy: What Price Perception?

Marsha Courchane
Vice President, CRA International
mcourchane@crai.com

Adam Gailey
Consulting Associate, CRA International
agailey@crai.com

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

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Abstract

Our research focuses on two questions: (1) how accurately consumers self-assess their credit, and (2) whether inaccurate self-assessment of credit is associated with undesirable financial market outcomes. Our analysis is empirical and relies on two different datasets—a consumer survey conducted in 2000 by Freddie Mac and 1.2 million mortgage loans originated in 2004.

We find that consumers' perceptions of their credit quality do not completely comport with their objective credit records as measured by their FICO scores. This is especially true for African-American and Hispanic consumers, but these race and ethnicity differences in accuracy are explained almost entirely by differences in distributions of credit scores.

We hypothesize that financial knowledge and factors that encourage investment in understanding and assessing credit records will be associated with increased accuracy of self-assessment. We find some support for this hypothesis. We also find some support for our hypothesis that inaccurate self-assessments will lead to increased probabilities of being denied credit, experiencing a "bad" financial event, or having a higher annual percentage rate on a mortgage.

An intriguing finding, however, is that the consumers we expect to most accurately self-assess their credit records appear disproportionately to over-optimistically self-assess, and that consumers who appear to over-assess tend to have more desirable financial outcomes. A potential reconciliation of these results is that FICO scores do not fully capture consumers' credit, and that there are other observable factors that both consumers and lenders also recognize as being important in assessing credit. We find some support for this hypothesis as well.

I. Introduction

Consumers, researchers, and policy analysts all recognize the increasingly important role played by credit history in today's financial and nonfinancial markets. We have seen, as a result, the growth of a burgeoning industry in credit literacy programs and the provision of credit scores, under the presumption that accurate self-assessment of credit critically matters. This focus is especially prevalent in the mortgage market, where several public policy efforts currently are under way to reduce the minority homeownership gap. There has been, however, little empirical research suggesting that inaccurate self-assessment is a widespread phenomenon, or that inaccurately assessing credit leads to undesirable mortgage or financial outcomes. Our research addresses this lacuna.

Our research relies on two different datasets, both of which are unique. The first data come from a consumer survey conducted in 2000 by Freddie Mac, and include information about consumers' financial knowledge, behavior, and credit outcomes, as well as data gathered from credit repositories on individuals' actual credit records. The second data contain nearly 1.2 million loans originated in 2004 and include Home Mortgage Disclosure Act (HMDA) data elements, specific underwriting and pricing variables, loan characteristics, and annual percentage rate (APR).

We find that consumers' perceptions of their credit quality do not completely comport with their objective credit records as measured by FICO scores, and that this is especially true for African-American and Hispanic respondents in our survey. We find, in particular, that there are a disproportionate number of African-American and Hispanic consumers who over-assess their credit, at least relative to FICO score guidelines conventionally used in mortgage underwriting. These differences in self-assessment accuracy across race and ethnicity, however, are explained almost entirely by differences in the distributions of FICO scores. Lower FICO score consumers are especially prone to inaccurately self-assess their credit, and once this is accounted for, we find little difference in self-assessment accuracy across African-Americans, Hispanics, Asians, and white non-Hispanics.

We hypothesize that financial knowledge and factors that encourage investment in understanding and assessing credit records will be associated with increased accuracy of self-assessment. We find some support for this hypothesis. We also find, however, that these factors are associated with more "optimistic" rather than accurate self-assessment of credit.

Our survey data uniquely provide direct measures of consumers' self-assessment of their credit records, and also include measures of undesirable financial outcomes such as being denied credit or experiencing a bad financial event like eviction or furniture repossession. We next look for empirical evidence to support our hypothesis that inaccurate self-assessments lead to less desirable financial outcomes. We find that consumers who under-assess their credit tend to more frequently experience undesirable financial outcomes. However, our results are not entirely consistent with the view that inaccurate self-assessment leads to "bad" outcomes. In particular, we find, all things equal, the higher consumers self-assess their credit, the better the outcome. So, for example, consumers have better outcomes when they assess their credit as better than their FICO scores reflect, implying that inaccurately over-assessing credit actually improves outcomes.

We have a concern about the direction of causality in the analysis of our survey data, however. In particular, consumers' self-assessments are measured at best contemporaneously, but often after the occurrence of our financial outcome measures. Arguably, therefore, these financial outcomes may have "caused" self-assessment accuracy rather than vice versa. To address this concern we turn to our lender data. Here we use relationships observed in the survey data to impute borrowers' self-assessments of credit, and then look for an effect of self-assessment accuracy on APR. Again, we find that consumers who under-assess their credit experience worse outcomes (higher APRs), but we also find, consistent with our survey results, that more optimistic self-assessments reduce APRs.

A potential alternative explanation for these empirical results is that consumers are correct—consumers that appear to under-assess their credit relative to their FICO scores actually generally have poor credit records (i.e., are high credit risks) and those that appear to over-assess their credit relative to their FICO scores actually generally have good credit records (i.e., are low credit risks). We create a simple alternative credit score using our survey and lender data, and find empirical support for the view that consumers may (appropriately) assess their credit using more than just FICO scores.

We interpret our results as supporting the value of financial literacy. First and foremost, financial literacy plays a far broader role than simply providing participants an accurate assessment of their credit record. Second, while good financial literacy programs educate consumers about FICO scores, they also, appropriately, help consumers understand the broader array of factors that go into assessing credit risk. Third, while our data are unusually rich as compared to most available sources, they are nonetheless less than ideal for empirically identifying the potential affect of inaccurate credit self-assessment on financial outcomes. Definitive answers to our research questions likely await a specifically designed and as yet nonexistent source of data.

II. Previous Research

The past years have witnessed significant interest in credit scores, creditworthiness and mortgage market outcomes. Much of this has been stimulated by the recent expansion of the Home Mortgage Disclosure Act (HMDA) data to include variables identifying higher-prices mortgages (see, for example, Avery, Canner, and Cook 2005 for a discussion of the 2004 HMDA data).

Part of this focus has been on the accuracy of credit repository data and credit scores (see, for example, Consumer Federation of America 2002; Avery, Calem, and Canner 2004). Another strand of the literature has focused on financial counseling and financial literacy (see, for example, Hornburg (2004) for a recent overview). Several studies have also focused on the effectiveness of financial counseling and literacy in affecting market outcomes (see, for example, Hirad and Zorn 2001 and Hartarska and Gonzalez-Vega 2005 for studies of the effectiveness of counseling in mitigating mortgage delinquency and default, and Haurin and Morrow-Jones 2007 for the impact of financial knowledge on homeownership).

However, there has been little research exploring the accuracy of consumers' self-assessment of their credit and the potential impacts of inaccurate self-assessment on financial outcomes. We are aware of only two such papers, both of which use the Freddie Mac survey data in their analyses. Ards and Myers (2001) broadly explore what they call the “myth” of bad credit in the African-American community. As part of their analysis, Ards and Myers focus on African-American consumers who appear to under-assess their credit (i.e., believe they have worse credit records than their FICO scores indicate), and they express concern that these African-American consumers likely are unwitting targets of predatory lenders. Courchane and Zorn (2005) also briefly note that African-American and Hispanic consumers appear disproportionately to inaccurately assess their credit. They do not, however, further explore this finding, nor do they attempt to assess whether inaccurate self-assessment of credit leads to undesirable market outcomes.

Our current research builds and expands on these two previous studies in several ways. First, we more fully explore the issue of how to subdivide FICO scores in a way that best correlates with consumers’ self-assessment of their credit as “very bad,” “bad,” “average,” “good,” or “very good.” Second, we explore and identify key factors explaining the large differences across race/ethnicity in the accuracy of consumers’ self-assessments. Third, we identify more broadly the factors that are associated with inaccurate self-assessment of credit. And fourth, we empirically test whether inaccurate self-assessment of credit disproportionately is associated with undesirable financial outcomes.

III. Accuracy in Self-Assessment

It seems intuitively plausible that inaccurately assessing credit leads to undesirable outcomes. For example, consumers who over-assess their credit (i.e., believe their credit record is better than it actually is) may disproportionately experience denials of credit while borrowers who under-assess their credit (i.e., believe their credit record is worse than it actually is) may pay too high a rate for the credit they receive. Most advocates of financial counseling believe, therefore, that consumers should develop accurate self-assessments of their credit situation as part of the process of improving their financial literacy.

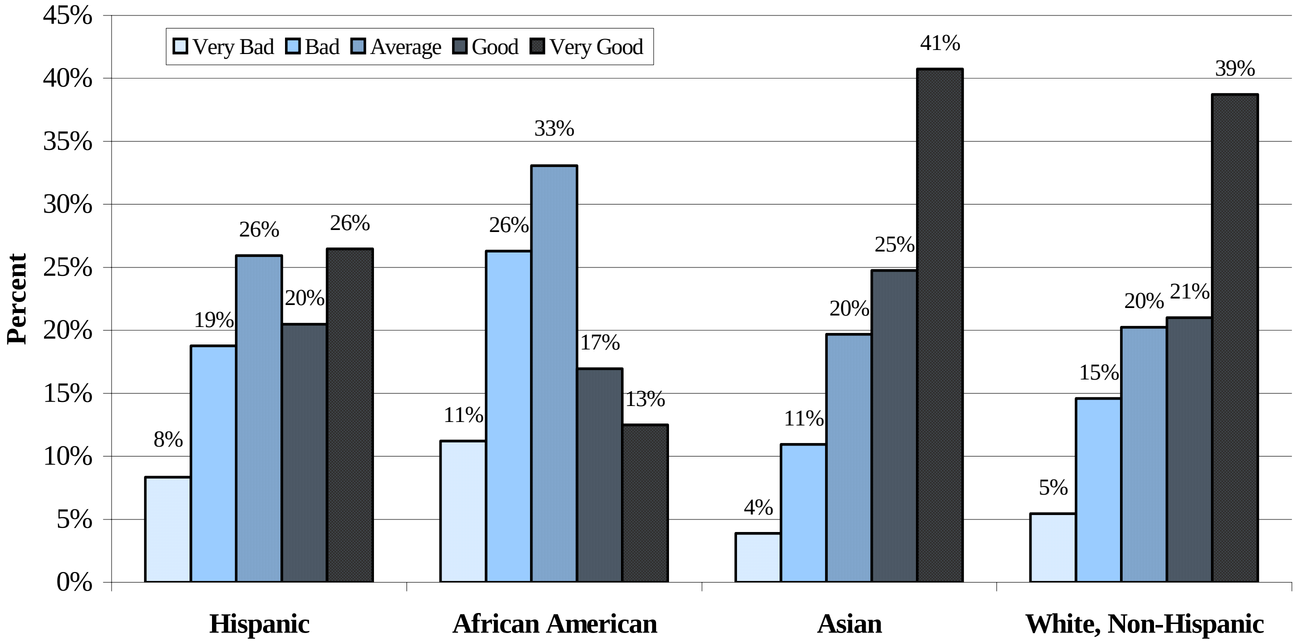
Little is known, however, about the prevalence of inaccurate credit self-assessments or the characteristics of consumers who inaccurately self-assess their credit. As a first step in our research, therefore, we measure the gaps between self-assessed and actual credit. Moreover, because of our interest in assessing the impact of these gaps on financial outcomes, combined with the public policy focus of reducing the minority homeownership gap, we explore the prevalence of inaccurate credit self-assessments separately by the race/ethnicity of consumers.

The data from our survey allow us to measure respondents’ self-assessment of their credit using answers to the question “How would you rate your current credit record?” Survey answers include “very bad,” “bad,” “average,” “good,” and “very good.”[1] Exhibit 1 provides distributions of the answers to this question, separately by the race/ethnicity of the respondent.

[1] See Courchane and Zorn (2005) for a description of the Freddie Mac survey data.

The distributions in Exhibit 1 clearly illustrate dramatic differences in respondents' self-assessment of credit across race/ethnicity. For example, 60 percent of white non-Hispanic respondents characterize their credit as "good" or "very good," while only 30 percent of African-American respondents do so.

Exhibit 1
Distribution of Self-Asessed Credit
Separately by Race/Ethnicity

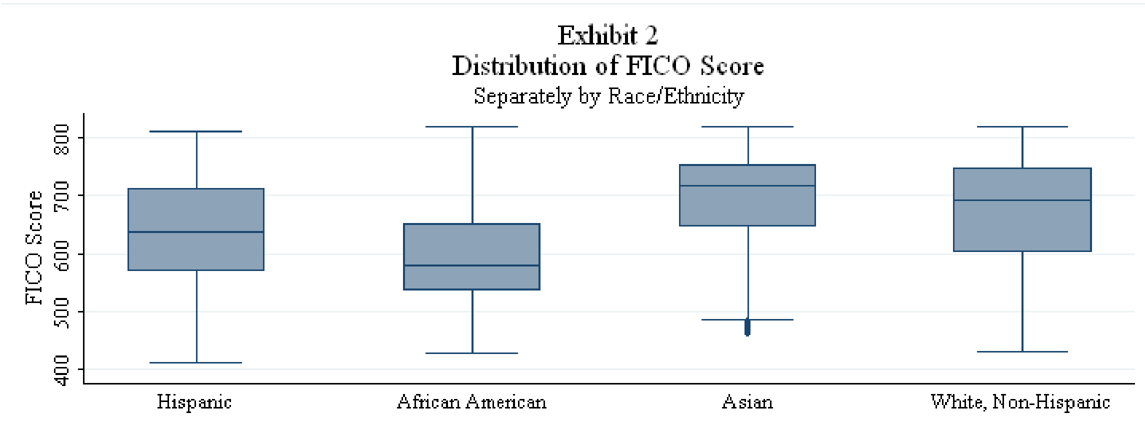


However, while differences in these distributions are intriguing, our focus is on the accuracy of credit self-assessment and this cannot be determined without recourse to some objective measure of consumers' credit records. In particular, it is possible that the dramatic differences in the distributions in Exhibit 1 reflect equally dramatic differences in the distributions of consumers' actual credit records. We use FICO scores, a proprietary measure of credit records created and marketed by Fair, Isaac Company, as a summary measure of consumers' credit records.[2] Box plots of the distributions of FICO scores are shown in Exhibit 2, separately by race/ethnicity of survey respondent.

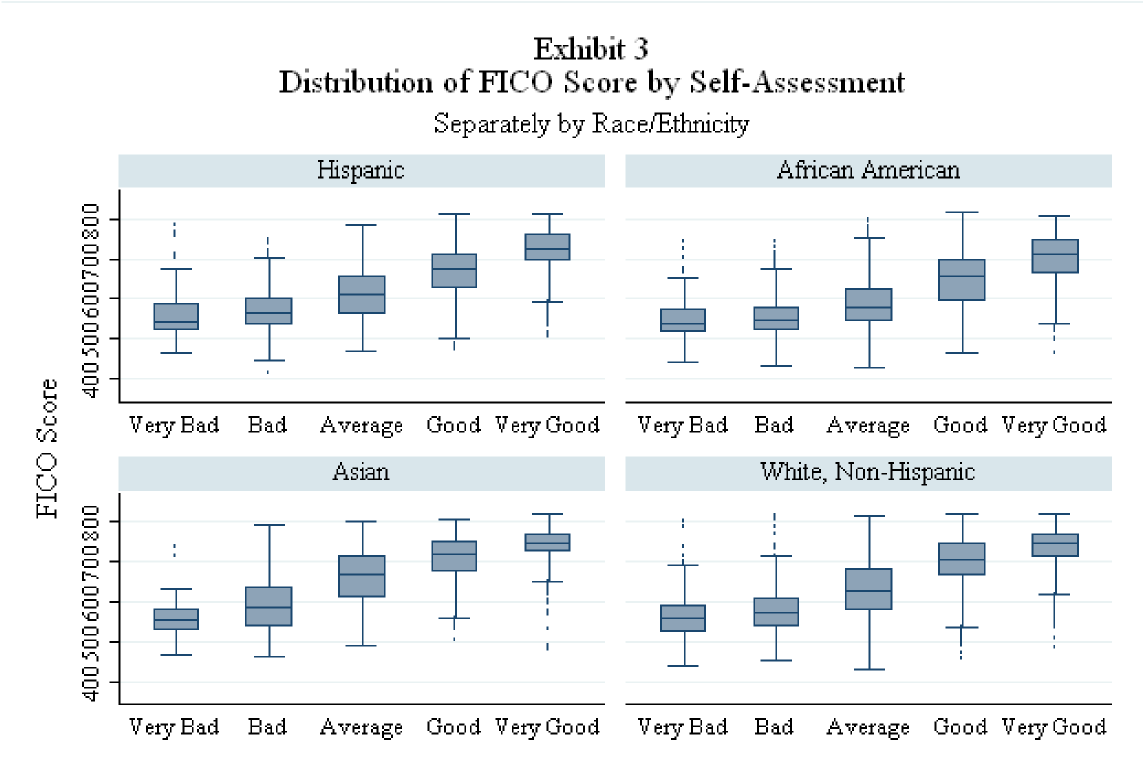
Exhibit 2 illustrates that FICO score distributions also vary substantially across race/ethnicity, and in ways that may explain much of the observed differences in consumers' self-assessments of their credit. For example, African-American respondents have the lowest distribution of FICO scores and the highest percentage of consumers who self-assess their credit records as "bad" or "very bad," while Asian respondents have the highest distribution of FICO

[2] See *www.myfico.com* for additional information on FICO scores, including an explanation of FICO scores and how to interpret them, a discussion of the different uses to which FICO scores are put, and a comparison of how loan rates vary by FICO scores in mortgage and auto lending.

scores and the highest percentage of consumers who self-assess their credit records as “good” or “very good.”



We further explore the relationship between actual and self-assessed credit records in Exhibit 3 through the use of box plots of FICO score distributions by self-assessed credit categories, again separately by race/ethnicity. If consumers each accurately self-assessed their credit, we would expect to see clearly separated FICO score distributions for each of the self-assessed credit categories and would also expect that the “breaks” in the FICO score distributions across self-assessed credit categories occur at the same points for each race/ethnicity subpopulation of consumers.



While Exhibit 3 clearly shows that FICO scores vary as expected across consumers who differentially self-assess their credit records, it also indicates that consumers do not perfectly accurately self-assess their credit. As one example, while the distribution of FICO scores increases with improvements in consumers' self-assessment of credit, there are substantially overlapping FICO score distributions across consumers who differentially self-assess their credit records. This overlap is especially large between consumers who self-assess their credit as "bad" or "very bad." In addition, similar FICO score distributions are associated with different self-assessment credit categories for consumers with different race/ethnicities. For example, the FICO score distribution for African-American consumers who self-assess their credit as "good" is almost identical to the FICO score distribution of Asian consumers who self-assess their credit as "average."

Our next step is to more systematically determine the accuracy of self-assessed credit by comparing, consumer by consumer, the "credit quality" of FICO scores to consumers' subjective judgments. This requires dividing FICO scores into the same five categories that consumers used to self-assess their credit (i.e., "very bad, " "bad, " "average, " "good,4" and "very good"). As noted previously, however, the FICO score distributions themselves do not neatly separate into five categories, nor will a single set of four FICO score category "cut points" equally separate credit across race/ethnicity.

We consider two approaches to categorizing FICO scores—an industry standard set of cut points that is consistent across all consumers and an "empirical" approach that finds cut points for each race/ethnicity subgroup that best fit the data (i.e., lead to the largest number of "correct" self-assessments of credit for consumers in each race/ethnicity subgroup). Both approaches have their merits. The industry standard approach is more consistent with a single frame of credit reference (e.g., mortgage lending) and more naturally allows comparisons across race/ethnicity. The empirical approach, on the other hand, allows for the possibility that consumers may differentially access credit markets. For example, consumers may differentially use credit cards, auto loans, and mortgages, all of which can have different standards for what makes "good" and "bad" credit records. Prime mortgage lenders, for example, use relatively strict standards in assessing credit, while subprime/nonprime 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. The empirical approach, however, makes comparisons of the accuracy of self-assessments across race/ethnicity more difficult.

We opt for the industry standard approach since our market outcome measures are biased towards a consistent product (mortgages), and we are interested in cross-race/ethnicity comparisons.[3] We base our FICO ranges on pricing guidelines implicit in mortgage rate sheets. In particular, we categorize "very bad" credit as FICO scores less than or equal to 580; "bad" credit as FICO scores between 581 and 620; "average" credit as FICO scores between 621 and 680; "good" credit as FICO scores between 681 and 720; and "very good" credit as FICO scores greater than or equal to 721.

Using these FICO score ranges, we can cross-categorize survey respondents by actual and self-assessed credit to assess the accuracy of their self-assessment. Exhibits 4A through 4D provide the distributions of this categorization, separately by the race/ethnicity of respondents.

Exhibit 4A
Summary of Credit Self-Assessment for Hispanic Respondents

Row Percent *Column Percent*	**Credit Self-Assessment**				
FICO Score	**Very Bad**	**Bad**	**Average**	**Good**	**Very Good**
0-580	20.95 73.65	39.83 62.21	30.34 34.29	7.10 10.17	1.78 1.97
581-620	9.80 16.85	24.73 18.88	40.05 22.13	17.03 11.92	8.39 4.54
621-680	1.82 4.29	13.67 14.36	33.11 25.17	33.04 31.81	18.37 13.68
681-720	1.35 2.56	4.44 3.74	17.05 10.38	34.08 26.28	43.07 25.69
721-850	1.06 2.65	0.73 0.81	9.99 8.03	19.47 19.82	68.75 54.13

[3] Subject comparisons are available from the authors on request.

Exhibit 4B
Summary of Credit Self-Assessment for African-American Respondents

Row Percent *Column Percent*	**Credit Self-Assessment**				
FICO Score	**Very Bad**	**Bad**	**Average**	**Good**	**Very Good**
0-580	18.12 81.41	39.47 75.67	33.42 50.93	7.02 20.88	1.97 7.92
581-620	8.57 11.98	26.45 15.79	45.41 21.54	14.46 13.39	5.11 6.41
621-680	4.17 5.98	11.37 6.97	40.13 19.55	32.03 30.47	12.31 15.86
681-720	0.27 0.19	4.36 1.36	22.96 5.69	37.48 18.12	34.94 22.88
721-850	0.51 0.44	0.57 0.21	7.85 2.29	30.14 17.14	60.93 46.93

Exhibit 4C **Summary of Credit Self-Assessment for Asian Respondents**					
Row Percent *Column Percent*	**Credit Self-Assessment**				
FICO Score	**Very Bad**	**Bad**	**Average**	**Good**	**Very Good**
0-580	22.21 70.93	42.33 48.01	25.55 16.08	6.77 3.39	3.15 0.96
581-620	10.66 18.22	22.93 13.92	39.32 13.25	22.88 6.13	4.21 0.69
621-680	0.82 3.35	20.44 29.62	33.36 26.84	30.55 19.55	14.82 5.77
681-720	0.63 2.76	1.40 2.17	23.72 20.51	34.47 23.71	39.79 16.64
721-850	0.38 4.73	1.43 6.29	9.55 23.31	24.31 47.21	64.33 75.95

Exhibit 4D **Summary of Credit Self-Assessment for White Non-Hispanic Respondents**					
Row Percent *Column Percent*	**Credit Self-Assessment**				
FICO Score	**Very Bad**	**Bad**	**Average**	**Good**	**Very Good**
0-580	20.03 70.91	42.09 55.65	28.82 27.45	7.00 6.43	2.06 1.03
581-620	9.12 17.15	33.40 23.48	37.82 19.14	14.18 6.92	5.48 1.45
621-680	2.67 7.99	14.88 16.65	32.68 26.34	27.37 21.28	22.41 9.44
681-720	0.27 0.76	2.34 2.50	19.25 14.78	32.45 24.04	45.69 18.34
721-850	0.45 3.18	0.65 1.72	6.44 12.28	22.47 41.33	69.99 69.74

Consider, for example, Exhibit 4A, which shows the distribution of Hispanic survey respondents across the 25 cells (five actual credit records categories times five self-assessed credit categories). Each cell in the exhibit contains two numbers—the top is the row percent and the bottom is the column percent. To illustrate, the upper-left cell shows that 20.95 percent of all Hispanic respondents with FICO scores less than or equal to 580 (i.e., “very bad” actual credit records) self-assess themselves as having “very bad” credit, and 73.65 percent of all Hispanic respondents that self-assess themselves as having “very bad” credit have FICO scores less than or equal to 580 (i.e., “very bad” actual credit records). Respondents who accurately self-assess their credit fall along the main diagonal, which is highlighted in yellow. The more accurate respondents are in self-assessing their credit, therefore, the higher the row and column percents on the main diagonal.

Looking at the main diagonal across the four exhibits reveals a common trend—the only cells with values consistently above 50 percent are for respondents who correctly self-assess their credit as “very good” (i.e., the lower-right cell). Interestingly, it is also consistently the case that 70 percent or more of respondents who self-assess their credit as “very bad” actually have FICO scores in that range. Put another way, respondents who self-assess their credit at the two extremes (either “very bad” or “very good”) are consistently far more accurate in their self-assessment than respondents who place themselves in the middle ranges. This is not symmetric, however. While respondents with “very good” FICO scores (721-850) also consistently self-assess their credit as “very good,” respondents with “very bad” FICO scores (0-580) are more likely to over-assess their credit as “bad” rather than accurately assess it as “very bad.”

If accurate self-assessment places respondents on the main diagonals of Exhibits 4A through 4D, then inaccurate self-assessment puts them either above or below the main diagonal. Respondents above the main diagonal self-assess their credit as better than is reflected in their actual FICO scores (i.e., over-assess their credit), and respondents below the main diagonal self-assess their credit as worse than is reflected in their actual FICO scores (i.e., under-assess their credit). We classify as “close,” respondents who incorrectly self-assess their credit by only one category (for example, have “bad” FICO scores but categorize their credit record as “average”), and we classify as “wrong,” respondents who incorrectly self-assess their credit by two or more categories (for example, have “bad” FICO scores but categorize their credit record as “good” or “very good”). We highlight in light blue respondents who are “close-high” and in dark blue respondents that are “wrong-high.” We highlight in light green respondents who are “close-low” and in dark green respondents that are “wrong-low.” As can be seen by the exhibits, by construction there is an asymmetry in how respondents can incorrectly self-assess their credit. Specifically, respondents with the lowest FICO scores cannot under-assess their credit, and respondents with the highest FICO scores cannot over-assess their credit.

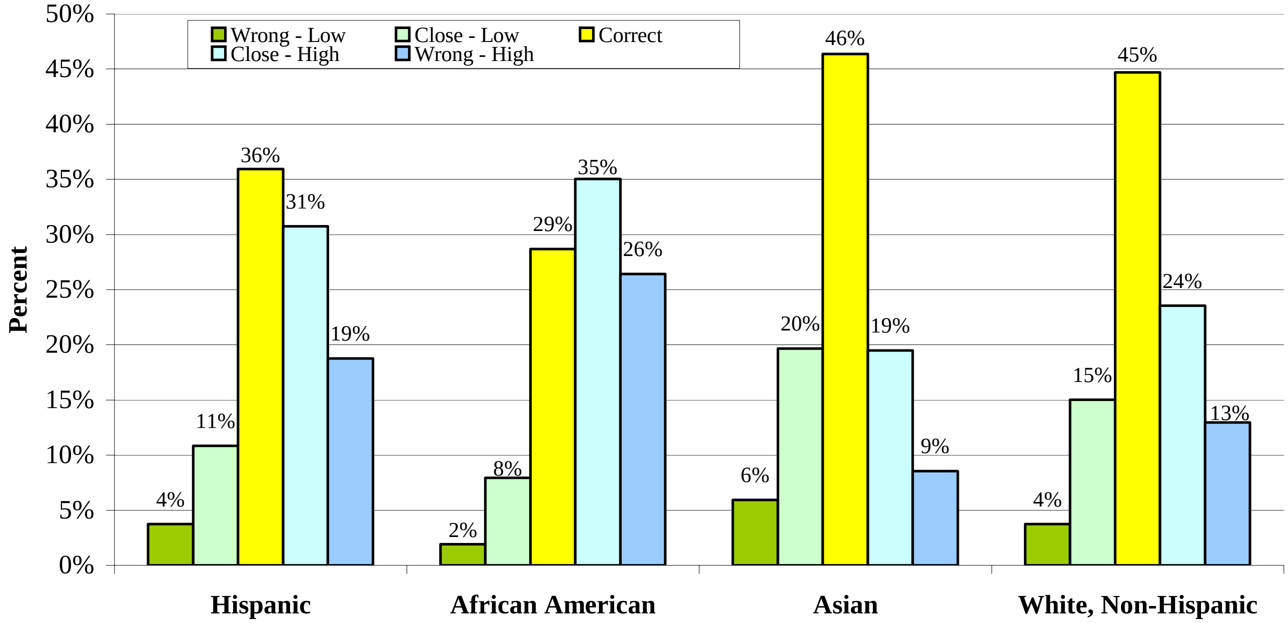
A perusal of the full set of cells in Exhibits 4A through 4D reveals the same characteristic that was highlighted in the FICO score box plots of Exhibit 3. Specifically, there is a large overlap in how respondents with lower FICO scores self-categorize their credit records. For example, we see that column percents for FICO scores less than or equal to 580 are all relatively high for respondents who self-assess as “very bad,” “bad” and “average.” Obviously, there is a significant tendency for respondents with low FICO scores to over-assess their credit. On the other hand, respondents with high FICO scores (greater than 720) are much more accurate in their credit assessment, showing relatively little tendency to under-assess their credit.

To more clearly illustrate this point, and to more broadly assess respondents’ accuracy of self-assessment, we provide in Exhibit 5 the distribution of respondents across our self-assessment accuracy categories.

Exhibit 5

Distribution of Self-Asessed Credit Accuracy

Separately by Race/Ethnicity



We use in Exhibit 5 the same color assignments as we did in Exhibits 4A through 4D—dark green is “wrong-low,” light green is “close-low,” yellow is “correct,” light blue is “close-high” and dark blue is “wrong-high.” Clearly, at least using our “objective” mortgage-based criteria for defining FICO score categories, there are large differences in the accuracy with which respondents self-assess their credit. Asian respondents in particular appear the most accurate in their assessments—fully 46 percent of Asian respondents are “correct,” and only 15 percent are “wrong” (either high or low). The other three groups of respondents disproportionately over-assess their credit, and increasingly so as you move from White non-Hispanic to Hispanic to African-American respondents. At the extreme, among African-American respondents, 61 percent are either “close-high” or “wrong-high” while only 10 percent are “close-low” or “wrong-low.”

The differences in the distributions of respondent self-assessment across race/ethnicity are not, therefore, significantly reduced by transforming the distributions to reflect the *accuracy* of respondent self-assessment. That is, the distributions within Exhibit 1 are roughly equally dissimilar across race/ethnicity as the distributions within Exhibit 5. We turn in our next section to an examination of the factors associated with self-assessment accuracy.

IV. An Examination of Inaccurate Self-Assessment

The first step in our examination is to understand why there are such large differences in the distribution of self-assessment accuracy across the race/ethnicity of survey respondents. The answer turns out to be quite simple; the differences arise almost entirely because of differences in the distributions of FICO scores. In particular, as noted in our discussion of Exhibits 4A through 4D, consumers with low FICO scores are far less accurate in self-assessing their credit records than are consumers with higher FICO scores. Moreover, there are significant differences in the distribution of FICO scores across race/ethnicity, with white non-Hispanic, Hispanic and African-American respondents all having a greater proportion of respondents with low FICO scores than is the case for Asians.

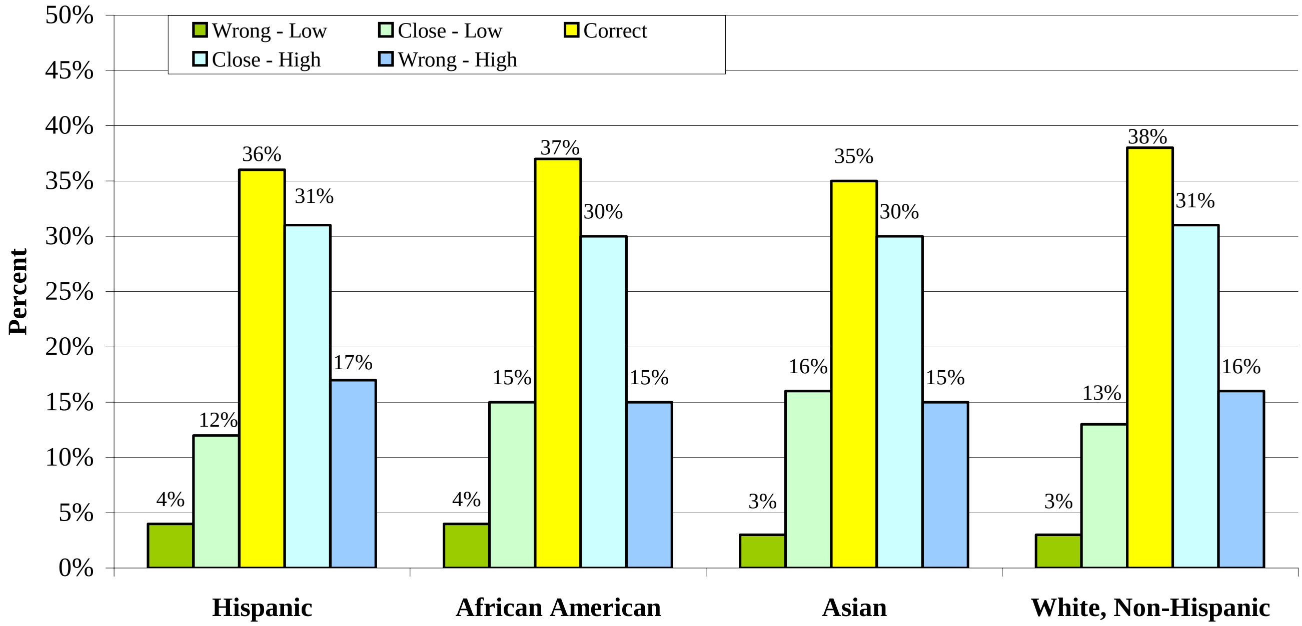
Exhibit 6 again provides the distributions of self-assessment accuracy that were provided in Exhibit 5, but in this instance after adjusting the FICO score distributions to be uniform across the "very bad," "bad," "average," "good" and "very good" categories for Hispanic, African-American, Asian, and white non-Hispanic respondents.[4]

Exhibit 6 clearly illustrates the important role that FICO score distributions play in explaining assessment errors across the subpopulations—the error distributions are very similar across race/ethnicity after accounting for distributional differences in FICO scores. In particular, African-American respondents are only very slightly differently distributed than White non-Hispanic respondents. Given this similarity, we combine respondents across race/ethnicity for the remaining analyses in this paper.

Exhibit 6

Distribution of Self-Asessed Credit Accuracy Adjusted for FICO Score

Separately by Race/Ethnicity



We turn now to examining why respondents, conditional on their FICO scores, are more or less likely to inaccurately assess their credit. Credit record information is relatively arcane, inaccessible, and difficult to interpret, and the factors observable to credit grantors that

[4] Specifically, for each of the race/ethnicity subpopulations we weight the data so 20 percent of each subpopulation's set of respondents fall into each of the five FICO score categories ("very bad," "bad," "average," "good," "very good").

statistically are linked to default performance often appear unintuitive 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. Moreover, until relatively recently, the importance to consumers of accurately knowing their credit histories has been, arguably, broadly underappreciated.

We expect accurate self-assessment to be driven by several factors. Specifically, we expect that respondents will be more accurate in assessing their credit the greater their education and financial literacy. We measure knowledge across several dimensions including 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. This 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 argue that respondents are more likely to accurately assess their credit the more they "invest" in learning about their credit. We measure the incentive to invest in information about credit from several dimensions. Specifically, we postulate that because they expect to get little return from their investment, risk-takers are less likely to invest in credit knowledge, as are respondents who are pessimistic about the future, worry little about money matters, or have an external locus of control (i.e., believe that the primary drivers of their life events are largely beyond their ability to influence).

As noted above, FICO score is a clear determinant of accuracy, and we include it as a control variable in our estimations. 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 race/ethnicity, whether or not they were born in the United States, and their age and presence of children.[5]

We explore these broad hypotheses through the use of ordered probit estimations. There is a natural ranking of respondents' divergence from "correct" self-assessment to close ("close-high" and "close-low") to wrong ("wrong-high" and "wrong-low"); however there is no clear ranking between equally diverging high and low self-assessments. Moreover, experimentation with separate estimates for "high" and "low" errors indicates substantial differences in the estimated coefficients. As a consequence, we separately estimate ordered probits for "correct," "close-low" and "wrong-low" and for "correct," "close-high" and "wrong-high." In the over-assessment estimations, we limit our observations to respondents with FICO scores in the range of 400 to 680 because respondents with FICO scores above 680 cannot be "wrong-high." In the under-assessment estimations we limit our observations to respondents with FICO scores in the range of 621 to 850, because respondents with FICO scores below 621 cannot be "wrong-low."

Our ordered probit results are presented in Exhibit 7. In both estimations, the dependent variables are structured so that positive coefficients indicate an increased likelihood of accurately self-assessing credit. Turning to the coefficients themselves, we find that the coefficients in the

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[5] We measure respondents' economic safety net by their answers to the questions "If you (and your spouse) faced a major unexpected loss in income, how likely or unlikely is it that you could (a) pay your bills for the next three months without borrowing, (b) get significant help from family or friends, and (c) borrow enough money from a financial institution such as a bank or a credit union to pay all your bills on time."

under-assess estimations are generally significant and of the expected sign, while the coefficients in the over-assess estimation are generally significant and of an unexpected sign.

We expect, for example, that increased knowledge will be associated with increased accuracy, and we find some evidence in support of our hypothesis. As expected, the higher the percent of households in a tract with mortgages (and presumably, therefore, the greater the knowledge base in the neighborhood), the greater the likelihood of accurately rather than over-assessing credit. On the other hand, while respondents with "very little" credit knowledge are more likely to accurately than to under-assess their credit, respondents with very little credit knowledge are more likely to over-assess than to accurately assess their credit.

In addition, we expect that respondents with a longer time horizon will be more willing to invest in financial knowledge, and, therefore, be more likely to accurately assess their credit. We find no support for this hypothesis. We also expect greater accuracy from respondents who are less likely to take risks, more optimistic about their future, have had money worries, and have an internal locus of control. This is true in the under-assessment estimation, but we find significant and unexpected signs on these variables in the over-assessment estimation.

As noted earlier, lower FICO scores are associated with over-assessment of credit, and higher FICO scores are associated with under-assessment of credit. Similarly, respondents with lower income, less net worth, and a worse economic safety net all are more likely to under-asses their credit, although they are less likely to over-assess their credit. Race/ethnicity is not an important determinant of self-assessment accuracy—holding constant for FICO score and other variables, the coefficients on race/ethnicity are, as expected, insignificant in both estimations. Finally, female respondents and respondents born in the United States are less likely to over-assess their credit.

Overall then, the results of the ordered probit estimations provide some support for our hypothesis that knowledge and appropriate psychological motivation encourage accuracy of self-assessment. At the same time, however, these same factors appear to encourage a more "optimistic" assessment by respondents of their credit. In the next section, we focus on the question of whether inaccurately assessing credit is associated with "bad" outcomes.

Exhibit 7
Ordered Probit Estimations of Self-Assessment Error

Variable name	Variable value	Under-Assessment		Over-Assessment	
		Estimate	Prob (ChiSq)	Estimate	Prob (ChiSq)
Intercept		0.3699	0.1611	-1.1604	<.0001
Intercept 1		1.1823	<.0001	1.1733	<.0001
Credit Knowledge	*Very Little*	-0.5284	<.0001	0.4133	<.0001
	Some	-0.3026	<.0001	0.3559	<.0001
	A Fair Amount	0	.	0	.
Education	*Some School*	-0.0071	0.9649	-0.1719	0.044
	Finished High School	0.104	0.1273	0.0628	0.2461
	Some College	-0.0039	0.9473	0.1079	0.0285
	Associates Degree	0.0019	0.9808	0.0633	0.3473
	Finished College	0	.	0	.
Percent in tract with mortgage		0.1944	0.2122	0.3058	0.0052
Wait For Money	*<= 1 Month*	0.1985	0.1748	0.0254	0.8208
	2-6 Months	0.2111	0.1457	0.0433	0.7015
	7-12 Months	0.1527	0.305	0.003	0.9798
	1-2 Years	0.1754	0.2911	-0.003	0.9822
	>2 Years	0	.	0	.
Take Risks	*Slightly*	0.2491	0.0024	-0.188	0.0003
	Somewhat	0.196	0.0209	-0.113	0.0356
	Well	0	.	0	.
Optimistic	*Slightly*	-0.1401	0.0585	0.0902	0.0742
	Somewhat	-0.0465	0.3913	-0.0694	0.0772
	Well	0	.	0	.
Money Worries	*Very Little*	0.3293	0.0001	-0.2604	0.0003
	Some	0.1578	0.009	-0.2672	<.0001
	A Fair Amount	0	.	0	.
Locus of Control	*Internal*	0.1945	0.0223	-0.1852	0.0012
	Neutral	0.0926	0.2496	-0.1868	0.0005
	External	0	.	0	.
FICO Score buckets	*400-580*	-	-	-0.8576	<.0001
	581-620	-	-	-0.2296	<.0001
	621-680	0.497	<.0001	0	.
	681-720	0.1213	0.0554	-	-
	721-850	0	.	-	-
Income	*Under $35,000*	-0.3925	0.0002	0.276	0.004
	$35,000 - $74,999	-0.2013	0.0453	0.257	0.0059
	$75,000 or more	0	.	0	.
Net Worth	*Under $10,000*	-0.4407	<.0001	0.2994	<.0001
	$10,000 - $49,999	-0.1786	0.0088	0.1285	0.0428
	$50,000 or more	0	.	0	.
Adequate Safety Net	*Unlikely*	-0.6151	<.0001	0.6006	<.0001
	Neutral	-0.2928	<.0001	0.3103	<.0001
	Likely	0	.	0	.
Race/ethnicity	*Hispanic*	0.0252	0.7588	-0.0211	0.6787
	African-American	-0.0194	0.8448	0.013	0.7774
	Asian	-0.1876	0.1097	0.1123	0.3373
	White non-Hispanic	0	.	0	.
Born in USA	*Yes*	-0.0103	0.9181	0.2254	0.0035
	No	0	.	0	.
Gender	*Male*	0.0509	0.278	-0.0963	0.0052
	Female	0	.	0	.
Age	*< 30 years old*	0.0237	0.6508	-0.0042	0.9062
	>= 30 years old	0	.	0	.
Kids	*No Kids*	0.0804	0.1055	0.03	0.4231
	Kids	0	.	0	.
Number of Observations		3201		4726	
Log Likelihood		-2344.23		-4702.27	

V. Self-Assessment Accuracy and Market Outcomes

Our first attempt to see if self-assessment accuracy is associated with market outcomes uses the Freddie Mac survey data. Included in the survey is a question asking if respondents have been denied credit in the past two years. Respondents are also asked if in the last two years they have experienced "eviction notice for nonpayment," "utilities turned off for nonpayment," "calls or letters from creditors about late payments," or "repossession of furniture, appliances, or vehicle." If any of these latter four events has occurred, respondents are categorized as having had a "bad financial event."

Our hypothesis is that respondents who inaccurately assess their credit are more likely to experience undesirable market outcomes such as the denial of credit or experiencing a bad financial event. It is important to note, however, that assessing this hypothesis with the Freddie Mac survey data raise questions regarding the direction of causality. Specifically, our hypothesis is that inaccurate self-assessment "causes" undesirable market outcomes, but, in fact, the causality may be reversed and undesirable market outcomes may "cause" inaccurate self-assessment. Conceivably, for example, respondents may learn through the "school of hard knocks" that it is important for them to accurately assess their credit records. This concern is especially relevant because the undesirable market outcome could have happened any time in the two years *prior* to respondents self-assessing their credit. We directly address the causality issue latter in this section by using entirely separate data.

Our first step is to take a relatively simplistic look at the relationship between outcomes and credit assessment. FICO scores are widely used to predict undesirable market outcomes, so almost certainly they are highly correlated with being denied credit or having a bad financial event. We begin our analysis, therefore, by computing locally weighted polynomial regressions (also known as LOWESS) of the percent of respondents experiencing a bad market outcome on FICO score, separately for respondents who self-assess their credit "correctly," are "wrong-high" and are "wrong-low."[6] Our hypothesis is that, holding constant for FICO score, respondents who assess their credit either "wrong-low" or "wrong-high" are more likely to be denied credit or have a bad financial event than respondents who "correctly" self-assess their credit.

Exhibits 8A and 8B display the LOWESS plots for denied credit and bad financial event, respectively. The first thing to notice is the very strong relationship between FICO scores and our outcome measures. For example, for respondents correctly assessing their credit, moving from a FICO score of 600 to one of 700 reduces the probability of experiencing a credit denial from 75 percent to 30 percent. This basic relationship is true for both outcome measures regardless of respondents' accuracy of self-assessment.

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[6] For a discussion of LOWESS regressions, see, for example, the *Engineering Statistic Handbook* (*http://www.itl.nist.gov/div898/handbook/pmd/section1/pmd144.htm*).

Exhbit 8A
Denied Credit by Self-Assessment Accuracy

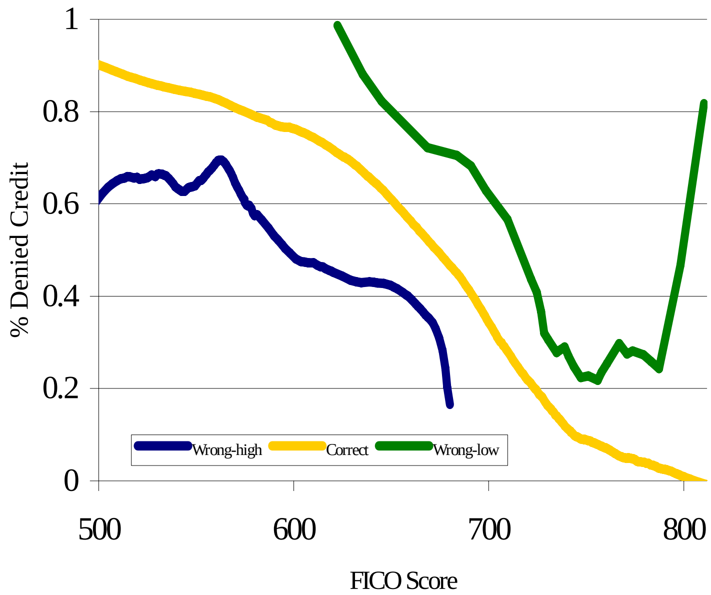
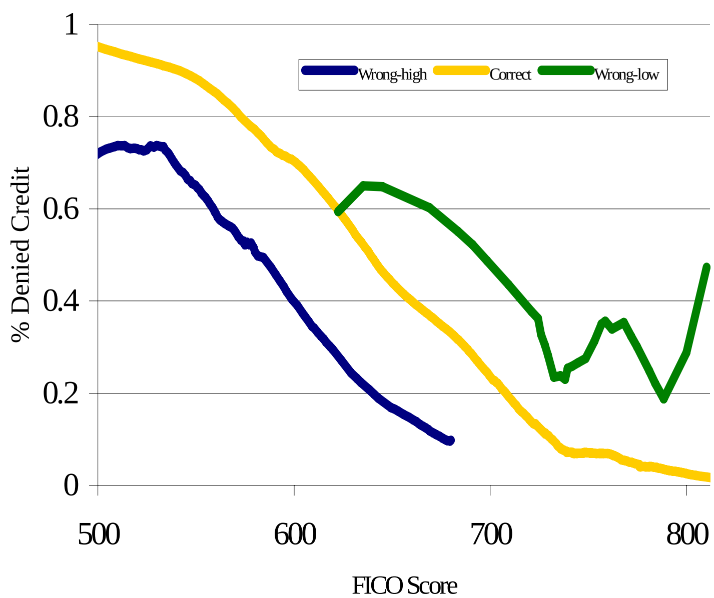


Exhibit 8B
Bad Financial Event by Self-Assessment Accuracy



Note also that there is some support for our hypothesis. In particular, respondents who under-assess their credit and are "wrong-low" are more likely to experience being denied credit or having a bad financial event. Contrary to our hypothesis, however, respondents who over-assess their credit and are "wrong-high" are less likely than respondents who accurately self-assess to experience being denied credit or having a bad financial event. There is a clear trend, apparently, for respondents to experience better market outcomes the more optimistically they assess their credit relative to their FICO scores and to experience worse market outcomes the more pessimistically they assess their credit relative to their FICO scores.

Our next step is to see how robust this relationship is to the inclusion of other control variables. In particular, we run probit estimations for denied credit and bad financial events as a function of FICO score, self-assessment accuracy, and other control variables to see if the LOWESS pattern between market outcomes and self-assessment continues to hold.

We hypothesize that respondents who evidence greater financial self-control and respondents with greater knowledge will be less likely to experience bad market outcomes. We also include a standard array of socio-economic variables, including income, net worth, economic safety net, respondent race/ethnicity, age, and presence of children. The results of these estimations are presented in Exhibit 9.

As was the case in the LOWESS plots, FICO score is strongly related to market outcomes. In addition, and as hypothesized, respondents evidencing "poor" financial self-control are significantly more likely to experience being denied credit and having a bad financial event. We do not see, however, a strong impact of education or the percent of households in a tract with a mortgage (the latter variable has an unexpected sign in the denied credit estimation). Not unexpectedly, there is some evidence that having lower net worth and a less adequate safety net are associated with being denied credit and having a bad financial event.

These estimations also show that Asian respondents are more likely to experience being denied credit, all things equal, and that African-American respondents are more likely to experience both being denied credit and having bad financial events. Fully exploring these findings is beyond the scope of this study. These results certainly raise potential concerns, however, about the efficacy and fairness of the financial markets in which these respondents participate.

Turning now to the specific variable of interest, we see that the relationship between credit assessment accuracy and market outcome shown in the LOWESS plots of Exhibits 8A and 8B is unchanged by the inclusion of additional control variables. Specifically, we see that accuracy is significantly related to being denied credit or having bad financial outcomes, but that it is not inaccurately assessing credit that is related to bad outcomes, rather it is pessimistically assessing credit conditional on the FICO score.

Exhibit 9
Probit Estimations of Undesirable Market Outcomes

Variable name	Variable value	Denied Credit		Bad Financial Event	
		Estimate	**Prob (ChiSq)**	**Estimate**	**Prob (ChiSq)**
Intercept		4.196	<.0001	5.4904	<.0001
Self Assessment Accuracy	*Wrong-Low*	0.5847	<.0001	0.6854	<.0001
	Close-Low	0.2051	<.0001	0.2122	<.0001
	Correct	0	.	0	.
	Close-High	-0.0768	<.0001	-0.1308	<.0001
	Wrong-High	-0.3289	<.0001	-0.6208	<.0001
FICO score		-0.0084	<.0001	-0.0106	<.0001
Financial Self Control	*Poor*	0.3719	<.0001	0.8421	<.0001
	Okay	0.1915	0.0021	0.5475	<.0001
	Good	0.1505	0.0108	0.3022	<.0001
	Very Good	0	.	0	.
Education	*Some School*	0.0822	0.3814	0.4028	<.0001
	Finished High School	0.0863	0.0896	0.0392	0.4723
	Some College	0.0862	0.0596	-0.0020	0.9679
	Associates Degree	0.0342	0.5914	0.1149	0.0929
	Finished College	0	.	0	.
Percent in tract with mortgage		0.2391	0.0339	-0.0484	0.6854
Income	*Under $35,000*	-0.0628	0.4418	-0.0032	0.9719
	$35,000 - $74,999	-0.0865	0.2648	-0.0259	0.7624
	$75,000 or more	0	.	0	.
Net Worth	*Under $10,000*	0.1671	0.0034	0.0816	0.1867
	$10,000 - $49,999	0.0663	0.2393	0.0393	0.5199
	$50,000 or more	0	.	0	.
Adequate Safety Net	*Unlikely*	0.4043	<.0001	0.2115	0.0001
	Neutral	0.3600	<.0001	0.1156	0.0121
	Likely	0	.	0	.
Race/ethnicity	*Hispanic*	0.0763	0.1464	0.0355	0.5222
	African-American	0.1276	0.0201	0.2514	<.0001
	Asian	0.2132	0.021	0.0906	0.3659
	White non-Hispanic	0	.	0	.
Gender	*Male*	-0.0468	0.1748	-0.1174	0.0014
	Female	0	.	0	.
Age	*< 30 years old*	0.0952	0.009	0.0046	0.9057
	>= 30 years old	0	.	0	.
Kids	*No Kids*	0.0922	0.0128	-0.0677	0.0879
	Kids	0	.	0	.
Number of Observations		7215		7256	
Log Likelihood		-3635.85		-3123.61	

For the final stage of our analysis we use an entirely different set of data—mortgage loan level "pricing" information made available to us by prime and subprime lenders—to see if credit self-assessment accuracy affects the price paid for the mortgage as measured by APR.[7] Our lender data include the geographic and demographic variables included in HMDA, as well as loan level characteristics used by lenders in pricing and underwriting decisions (such as FICO score, loan-to-value ratio (LTV) and debt-to-income ratio (DTI)). The lenders in our sample originate loans across all fifty states and use both wholesale and retail channels for loan origination purposes.[8]

What the lender data do not include is information on borrowers' self-assessments of their credit records. We add this to the lender data through an imputation process that takes advantage of observed relationships between race/ethnicity, FICO score, and income on respondents' self-assessment of credit in the Freddie Mac survey.[9] Finally, to match the Freddie Mac survey, we restrict borrowers in our lender data to incomes of $100,000 or less.

There are several advantages to these data and this approach. First and foremost, it directly addresses the causality issue raised previously. In this instance, credit self-assessment is imputed on the basis of race/ethnicity, which is exogenous, and FICO score and income at the time of application. This arguably places the credit assessment prior to the setting of the mortgage APR. In addition, APR is an excellent measure of all-in mortgage costs, and so is a good market outcome measure for assessing the impact of credit assessment accuracy.

On the negative side, however, these data do not contain borrowers' self-assessment of their credit records, and so we must rely on the imputation process outlined in footnote 9. This imputation undoubtedly introduces some error, and may bias coefficients on the self-assessment probabilities towards zero. Moreover, the Freddie survey was taken in 2000, while the lender data are of loans originated in 2004. Arguably there has been a significant increase in awareness by consumers of the importance of knowing and understanding their credit records, so 2004 borrowers likely are more accurate in their self-assessment than implied imputations based on 2000 data, which therefore adds additional error.

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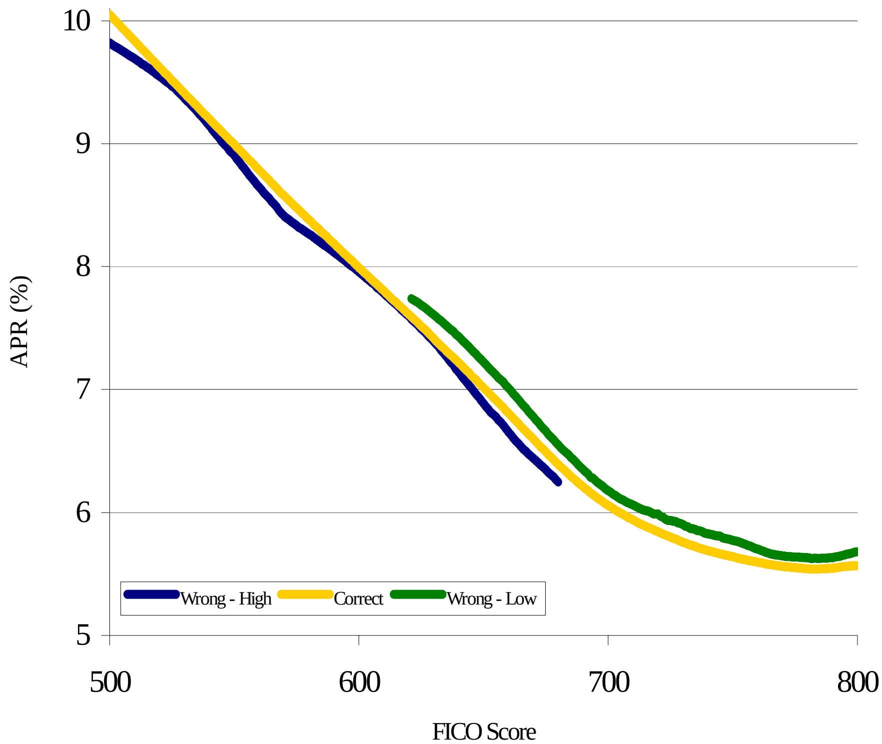
[7] The loan level data used in this paper is being used with the permission of lenders. The data was pooled across many lenders and has been completely de-identified as to borrower or lender except for a designation that the lender was a prime or nonprime lender according to our specific definition.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

[8] We provide some summary statistics for our full sample and for our selected sample in the Appendix.

[9] Specifically, in the lender and Freddie Mac survey data, separately for each of the four race/ethnicity subgroups, we divide FICO score in up to eight categories and income into up to four categories, creating a maximum of up to 32 cells for each race/ethnicity subgroup. For all the Freddie Mac survey respondents in a race/ethnicity by FICO score by income cell, we compute the percent that self-assess their credit as "very bad," "bad," "average," "good," or "very good." For our APR regressions we then simply take all the loans in the equivalent race/ethnicity by FICO score by income cell in our lender data, and assign to each of them the probabilities from the Freddie Mac survey respondents. In this manner we impute for each loan in our lender data a probability that the borrower will self-assess their credit as "very bad," "bad," "average," "good," or "very good." However for our LOWESS plots we need to assign discrete credit assessments, not probabilities, in order to separately plot relationships by self-assessment accuracy. In this instance, therefore, for each observation in the lender data we randomly assign credit assessments based on the probabilities associated with its race/ethnicity by FICO score by income cell. This random assignment is repeated 10 times per lender observation, affectively doubling the number of observations in the LOWESS analysis.

We turn now to the results of our analysis. As with the Freddie survey market outcomes, we expect APR to be closely related to FICO score. We start, therefore, with LOWESS plots of APR on FICO score, separately for borrowers who "correctly" assess their credit as well as those that are "wrong-high" and "wrong-low." These plots are provided in Exhibit 10.[10]

Exhibit 10
APR by Self-Assessment Accuracy



As expected, the LOWESS plots show a clear relationship between APR and FICO score. For example, as FICO score increases from 600 to 700, APR declines by roughly two percentage points (from 8 percent to 6 percent). As was the case in the Freddie Mac survey data, the relationship between market outcome and self-assessment accuracy in the lender data provides some support for our hypothesis. Specifically, we find that, consistent with our hypothesis, inaccurately under-assessing credit ("wrong-low") is associated with higher APRs, holding FICO score constant. On the other hand, however, we also find that inaccurately over-assessing credit ("wrong-high") is associated with lower APRs, which is inconsistent with our hypothesis.

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[10] LOWESS techniques are data intensive, and thus cannot be performed on the full (10x) dataset. 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, self-assessment, and race/ethnicity. The data are 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. We assign to each grouping the average APR for the group. With this collapsed dataset, we perform LOWESS estimations of APR against actual FICO by self-assessment accuracy categories ("correct," "wrong-high" and "wrong-low"), using a 10 percent bandwidth.

Our next step is to see whether controlling for other observable factors that may influence APR affects its relationship with self-assessment accuracy. In addition to FICO score, our lender data include a wide variety of variables included in mortgage pricing sheets that traditionally are expected to affect APR. Specifically, we include LTV, DTI, amortization type (fixed or adjustable), loan purpose (purchase, refinance or home improvement), occupancy status (owner-occupied or investor), documentation status, loan amount, the existence of a prepayment penalty, loan term and structure type (1-4 family, multifamily or manufactured home). We also include as explanatory variables in our estimation the market channel (prime or subprime) and the race/ethnicity of the borrower.[11]

The results of our OLS estimation of APR on the above explanatory variables are provided in Exhibit 11. The estimated coefficients are basis points of APR. The fit of the estimation is reasonably good, with an R-square of 0.76, and coefficient estimates of the additional control variables are quite reasonable. For example, APR is found to increase with increases in LTV, DTI, and loan term, and to decrease with increases in loan amount. We also find that APR is higher for fixed-rate mortgages, home improvement loans, loans to investors (nonowner-occupants), loans on manufactured or multifamily homes, and loans with no prepayment penalties. The affect of documentation type is somewhat surprising, but likely reflects the fact that low-doc loans in the prime market largely are a perk given to very low-risk borrowers, while low-doc loans in the subprime and Alt-A markets are more consistently associated with higher credit risk. The market channel variable is also hard to interpret because both FICO score and loan amount splines are separately estimated for the prime and subprime channels.

The coefficients on the African-American and Hispanic dummy variables suggest that these borrowers have APRs that are, respectively, 14 basis points and 10 basis points higher than white non-Hispanic borrowers, all things equal. The exploration of this finding forms a focus of an additional research paper.[12]

Turning now to the specific variables of interest—the probabilities of accurately self-assessing credit—we find mixed support for our hypotheses. We expect that incorrectly self-assessing credit will be associated with higher APRs, holding constant other factors. This is the case for borrowers who only slightly over-assess their credit (“close-high”); but borrowers who more significantly over-assess their credit (“wrong-high”) and borrowers who only slightly under-assess their credit (“close-low”) both have lower APRs, holding constant other factors. Moreover, borrowers who more significantly under-assess their credit (“wrong-low”) appear to have no significant difference in their APRs than borrowers who accurately self-assess.

[11] Lenders contributing data to our analysis are classified as prime or subprime based on their own self-assessments.

[12] Interested readers are directed to Courchane and Zorn (2007) where this issue is more fully explored.

Exhibit 11
Regression Estimations of APR

Variable Name		Variable Value	Estimate (bps)	Prob (t)
Intercept			2254.92	<.0001
Self-Assessed Credit Accuracy		*Probability of Wrong-Low*	-2.51	0.44
		Probability of Close-Low	-8.29	<.0001
		Probability of Correct	0.00	.
		Probability of Close-High	4.31	<.0001
		Probability of Wrong-High	-17.71	<.0001
FICO Score Splines	Prime	*FICO < 600*	-2.69	<.0001
		600 <= FICO < 700	-0.48	<.0001
		700 <= FICO	-0.02	<.0001
	Subprime	*FICO < 600*	-1.58	<.0001
		600 <= FICO < 700	-0.92	<.0001
		700 <= FICO	-0.95	<.0001
Loan-to-Value		*LTV <= 70*	-5.63	<.0001
		70 < LTV <= 80	0.00	.
		80 < LTV <= 85	24.89	<.0001
		85 < LTV <= 90	51.14	<.0001
		90 < LTV <= 95	62.36	<.0001
		95 < LTV <= 100	104.02	<.0001
		100 < LTV	114.38	<.0001
		LTV Unknown	19.74	<.0001
Debt-to-Income		*DTI <= 28*	0.00	.
		28 < DTI <= 36	4.77	<.0001
		36 < DTI <= 50	9.05	<.0001
		50 < DTI	7.76	<.0001
		DTI Unknown	-0.68	0.54
Market Channel		*Subprime*	-335.80	<.0001
		Prime	0.00	.
Amortization Type		*Fixed*	65.78	<.0001
		Arm	0.00	.
		Unknown Amortization Type	31.13	<.0001
Purpose		*Purchase Money*	0.00	.
		Home Improvement	13.73	<.0001
		Refinance	-5.23	<.0001
Occupancy status		*Investor*	40.93	<.0001
		Owner Occupancy unknown	31.72	0.25
		Owner Occupied	0.00	.
Documentation Type		*Not Full Doc*	-1.40	<.0001
		Full Doc	0.00	.
		Unknown Documentation Type	76.09	<.0001
Loan Amount Splines	Prime	*Loan Amount < 100,000*	-0.86	<.0001
		100,000 <= Loan Amount < 334,000	-0.11	<.0001
		334,000 <= Loan Amount < 500,000	-0.06	<.0001
		500,000 <= Loan Amount	-0.08	<.0001
	Subprime	*Loan Amount < 100,000*	-1.73	<.0001
		100,000 <= Loan Amount < 334,000	-0.42	<.0001
		334,000 <= Loan Amount < 500,000	0.02	0.39
		500,000 <= Loan Amount	-0.08	0.44
Prepayment Penalty		*No Prepayment Penalty*	0.00	.
		Has Prepayment Penalty	-16.65	<.0001
		Prepayment Penalty Unknown	-47.53	<.0001
Loan Term		*Loan Term <= 5*	-66.13	<.0001
		5 < Loan Term <= 15	-32.24	<.0001
		15 < Loan Term <= 20	-7.92	<.0001
		20 < Loan Term <= 30	0.00	.
		30 < Loan Term <= 40	125.52	<.0001
		Unknown Loan Term	86.82	<.0001
Structure		*1-4 Family*	0.00	.
		Manufactured Housing	18.71	<.0001
		Multi-Family	130.98	<.0001
Race/Ethnicity		*African-American*	14.39	<.0001
		Hispanic	9.60	<.0001
		Asian	-5.57	<.0001
		White non-Hispanic	0.00	.
Number of Observations			527,466	
R^2			0.76	

In summary, then, the lender data provided no stronger support for our hypotheses than did the Freddie Mac survey data. It did provide support for the importance of borrowers' self-assessments on market outcomes (APR), but it is more consistent with the view that optimistically or pessimistically self-assessing credit leads to better or worse outcomes, holding constant other factors including FICO scores.

VI. Implications and Conclusions

The importance of good credit in applying for home mortgages cannot be overstated. Nearly every lender relies, at least in part, on credit bureau scores (such as FICO scores) in making underwriting and pricing decisions. 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 conclude that improving financial literacy is important to improving access to credit for home mortgages. It is equally natural to conclude that an important goal of financial literacy training should be participants' knowledge of the credit reporting process, the components of credit scores and their own credit record.

Given the importance of credit and financial literacy, there has been surprisingly little research on the question of whether or not consumers have an accurate assessment of their credit records, and whether having an inaccurate assessment results in any undesirable outcomes.

We find in our research that consumers generally tend to over-assess their credit records (believe their credit is better than it actually is) and that errors in self-assessment vary importantly with economic, psychographic, and demographic characteristics of potential mortgage market participants. We find that African-American and Hispanic consumers in particular are more likely to over-assess their credit, but that this differential is almost entirely explained by differences in FICO score distributions across race/ethnicity.

To our surprise, however, consumers with more financial knowledge and more incentive to invest in knowing about their credit records are not consistently more likely to accurately assess their credit. Rather, these consumers appear more likely to over-optimistically assess their credit, while consumers without these characteristics appear more likely to over-pessimistically assess their credit. Moreover, while we do find that consumers' self-assessments of their credit records affect their financial market outcomes, it is generally the case that it is optimistic self-assessments lead to better financial outcomes while pessimistic self-assessments lead to worse financial outcomes.

A potential reconciliation of this finding is that consumers may be correctly self-assessing their credit. In particular, consumers with more financial knowledge and more incentive to invest in knowing about their credit records may accurately assess that their credit records are better than suggested by their FICO scores alone, and as a consequence experience better financial outcomes.

Certainly it is widely recognized that more than FICO scores affect credit risk. LTV and DTI ratios, for example, long have been considered key variables in the mortgage underwriting process. Consumers and lenders both may perceive credit in a relatively broad manner, therefore, and assess credit records in terms of FICO scores and other directly observable characteristics. For example, apparently overly pessimistic consumers may accurately recognize that their overall credit record is worse than suggested by their FICO score, while apparently overly optimistic consumers may accurately recognize that their overall credit record is better than suggested by their FICO score. If this is the case, it would not be surprising to find that apparently overly pessimistic (wrong-low) borrowers experience worse financial outcomes while apparently overly optimistic (wrong-high) borrowers experience better financial outcomes.

We run a simple experiment to assess whether there is any empirical support for the above argument. Specifically, for each of the financial outcome measures we create an alternative credit score by estimating the outcome measure as a function of FICO score and other directly observable, credit-related control variables.[13] We then regress these alternative credit scores on FICO score and self-assessment accuracy ("wrong-low," "close-low," "correct," "close-high" and "wrong-high"). Holding constant for FICO score, in all three regressions we find that "wrong-low" consumers are associated with higher-risk values of our alternative credit scores, and in two of the three regressions we find that "wrong-high" consumers are associated with lower-risk values of our alternative credit scores. We take this as support for our hypothesis that credit records include more information than is captured by FICO scores alone, and that apparently overly optimistic and overly pessimistic consumers may in fact be accurately assessing their overall credit records. This suggests that financial literacy programs should focus on more that just FICO scores, and include as well a broader understanding of credit risk related factors.

Finally, we do not interpret our results as questioning the value of financial literacy, just the opposite. First and foremost, financial literacy plays a far broader role than simply providing participants an accurate assessment of their credit record. For example, our estimations clearly show the important role that loan characteristics play in determining APR, and educating borrowers about the particulars of mortgage choice attributes is an important component of many financial literacy programs. Moreover, previous studies such as Hirad and Zorn (2001) and Hartarska and Gonzalez-Vega (2005) have clearly demonstrated that financial counseling can have positive impacts on borrowers.

Second, while our data are unusually rich, they are not ideal. In particular, we do not have data that combine consumers' subjective assessments of their financial records with observed financial market outcomes in a later period. The definitive analysis of whether or not accurate self-assessment of credit improves financial outcomes likely awaits such data.

[13] For the financial outcome measures "denied credit" and "bad financial event" we create alternative credit scores by running probit estimations of observed outcomes on FICO score, income, net wealth, employment status, and whether or not the consumer declared bankruptcy, had an recent period of extended unemployment and/or recently experienced a significant reduction in income. We use the predicted probabilities from these probit estimations as our alternative credit scores. For APR we regress APR on FICO score, LTV ratio, DTI ratio, and occupancy status, and use predicted APR as our alternative credit score.

VII. References

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