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# Consumer credit literacy: What price perception?

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## Abstract

This paper considers the question of 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 some support for our hypothesis that inaccurate self-assessments lead to increased probabilities of being denied credit, experiencing a “bad” financial event, or having a higher annual percentage rate on a mortgage. © 2007 Elsevier Inc. All rights reserved.

*Keywords:* Credit score; Financial literacy; Mortgage

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## 1. Introduction

Consumers, researchers, and policy analysts all recognize the increasingly important role played by credit history, and in particular credit scores, in today's financial and non-financial 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 underway to reduce the minority homeownership gap. There has been, however, little empirical research suggesting that a poor alignment between self-assessed credit and credit scores 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 and credit outcomes, as well as data gathered from credit repositories on

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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).

Our hypothesis is that poor alignment between consumers' self-assessments of credit and their credit scores ("inaccurate self-assessments") lead to less desirable financial outcomes. 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 declaring bankruptcy.

We find a relationship between consumers' self-assessments of credit scores and undesirable financial outcomes. For example, we find that self-assessing credit lower than is reflected by credit scores tends to be associated with worse 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 financial outcome. So, for example, consumers have better outcomes when they assess their credit as better than their credit scores reflect, suggesting that inaccurately over-assessing credit actually improves outcomes.

We have, however a concern about the direction of causality in the analysis of our survey data. In particular, consumers' self-assessments are measured at best contemporaneously with, 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. We do not find a strong effect, and where we do find one it is consistent with the view that optimism has a more important impact than accuracy.

A potential alternative explanation for these empirical results is that consumers are correct—consumers that appear to under-assess their credit relative to their credit 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 credit 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 credit 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 credit 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.

## **2. Previous research**

The past years have witnessed significant interest in credit scores, credit worthiness 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-priced mortgages (see for example, Avery, Canner, & 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, Avery, Calem, & Canner, 2004; Consumer Federation of America, 2002). 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, Hartarska & Gonzalez-Vega, 2005; Hiraad & Zorn, 2001 and for studies of the effectiveness of counseling in mitigating mortgage delinquency and default, and Haurin & Morrow-Jones, in press for the impact of financial knowledge on homeownership).

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 credit scores indicate), and the 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 previous studies in two important ways. First, we more fully explore the issue of how to subdivide credit scores in a way that best correlates with consumers' self-assessment of their credit as "very bad", "bad", "average", "good" or "very good". And second, we empirically test whether inaccurate self-assessment of credit scores disproportionately is associated with undesirable financial outcomes.

### 3. 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 score is higher than it actually is) may disproportionately experience denials of credit while borrowers who under-assess their credit (i.e., believe their credit score is lower than it actually is) may pay too high a rate for the credit they receive. Most advocates of financial counseling believe, therefore, that as part of the process of improving financial literacy, consumers must develop accurate self-assessments of their credit situation.

The first step in our research is to measure consumers' accuracy in their self-assessment of credit. 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."<sup>1</sup> We measure actual credit records with FICO scores, a proprietary summary measure of credit records created and marketed by Fair, Isaac Company.<sup>2</sup>

Measuring the alignment between consumers' self-assessments and FICO scores requires dividing FICO scores into the same five categories to which consumers self-assessed their credit

<sup>1</sup> See Courchane and Zorn (2005) for a description and longer discussion of the Freddie Mac survey data.

<sup>2</sup> See <http://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.

Table 1  
Distribution of respondent accuracy

Variable value	Population (%)
Wrong-low	6
Close-low	19
Correct	46
Close-high	21
Wrong-high	8
Total	100

(“very bad”, “bad”, “average”, “good”, and “very good”). We consider two approaches to categorizing FICO scores—an “objective” approach that relies on industry standard categories (or “cut points”) and is consistent across all consumers, and a “subjective” 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 objective approach is more consistent with a single frame of credit reference (e.g., mortgage lending). The subjective approach, on the other hand, allows for the possibility that consumers may differentially access credit markets, all of which can have different standards of what makes “good” and “bad” FICO scores. 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.

We opt for the objective approach since our market outcome measures are biased towards a consistent product (mortgages).<sup>3</sup> We base our FICO ranges on industry standards and consultation of pricing guidelines implicit in mortgage rate sheets. In particular, we categorize “very bad” FICO scores as less than or equal to 580, “bad” FICO scores as between 581 and 620, “average” FICO scores as between 621 and 680, “good” FICO scores as between 681 and 720, and “very good” FICO scores as greater than or equal to 721. Using these FICO score ranges, we cross-categorize survey respondents by FICO score bucket and self-assessed credit to assess the accuracy of consumers’ self-assessments.

Respondents’ self-assessments are categorized as “correct” if their self-assessed credit and FICO score buckets are identical (e.g., self-assessment and FICO score both are “good”). Respondents are categorized as “close-high” if their self-assessment is one level above their FICO score bucket (e.g., they self-assess as “very good” but their FICO score bucket is only “good”), and “close-low” if their self-assessment is one level below their FICO score bucket (e.g., they self-assess as only “good” but their FICO score bucket is “very good”). Respondents are categorized as “wrong-high” if their self-assessment is two or more levels above their FICO score bucket (e.g., they self-assess as “very good” or “good” but their FICO score bucket is only “bad”), and “wrong-low” if their self-assessment is two or more levels below their FICO score bucket (e.g., they self-assess as only “very bad” or “bad” but their FICO score bucket is “good”).

Table 1 provides the distribution of respondent accuracy. By our calculations, arguably, respondents are reasonably accurate in their self-assessments of their FICO scores. Specifically, 46%

<sup>3</sup> Subject comparisons are available from the authors on request.

are “correct” by our definition, and 86% are either “correct” or close. Two other points are worthy of note. First, even with this relatively accurate self-assessment of credit, 15% of respondents are either “wrong-low” or “wrong-high.” Our interest is in whether these consumers are more likely to experience undesirable financial outcomes because of their inaccurate self-assessments. Second, the distributions show a slight tendency for respondents to over-optimistically assess their FICO scores—29% of respondents are either “close-high” or “wrong-high,” while a lower 25% of respondents are “close-low” or “wrong-low.”

#### 4. 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 2 years. Respondents are also asked if in the last 2 years they have experienced “eviction notice for non-payment”, “utilities turned off for non-payment”, “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 addressing this hypothesis with the Freddie Mac survey data raise questions regarding the direction of causality. Specifically, our hypothesis is that inaccurate self-assessment for FICO scores “causes” undesirable market outcomes, but, in fact, the causality may be reversed and undesirable market outcomes may “cause” inaccurate self-assessment. Conceivably, respondents may learn through the “school of hard knocks” that it is important for them to accurately assess their FICO scores. This concern is especially relevant because the undesirable market outcome could have happened any time in the 2 years prior to respondents 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 (also known as LOWESS) regressions 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.<sup>4</sup> Our hypothesis is that, holding constant for FICO score, respondents who assess their credit either wrong-low or wrong-high should be more likely to be denied credit or have had a bad financial event than respondents who correctly self-assess their credit.

Figs. 1 and 2 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% to 30%. This basic relationship is true regardless of respondents’ accuracy of self-assessment, and regardless of outcome measure.

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<sup>4</sup> LOWESS techniques are a semi-parametric approach to data fitting. Specifically, they fit each data point using a locally weighted polynomial regression that is then “smoothed” to form a continuous function. For a discussion of LOWESS, see the Engineering Statistics Handbook. (<http://www.itl.nist.gov/div898/handbook/pmd/section1/pmd144.htm>).

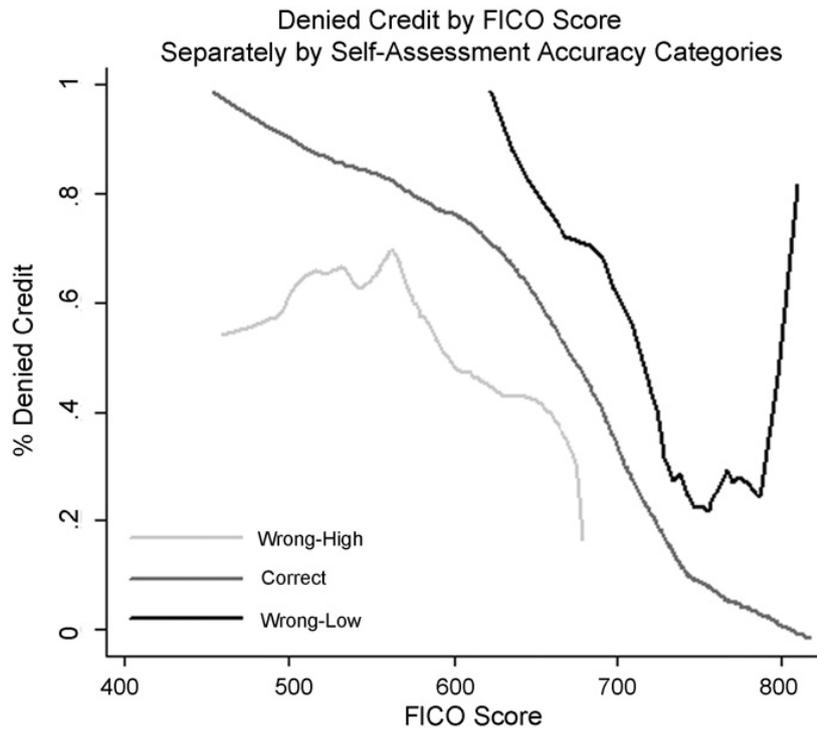


Fig. 1. Denied credit by FICO score.

The second thing to note, however, is that our hypothesis is only inconsistently supported. Respondents who under-assess their FICO scores and are “wrong-low” are more likely to experience being denied credit or having a bad financial event, as hypothesized. However, respondents who over-assess their credit and are “wrong-high” are less likely than respondents

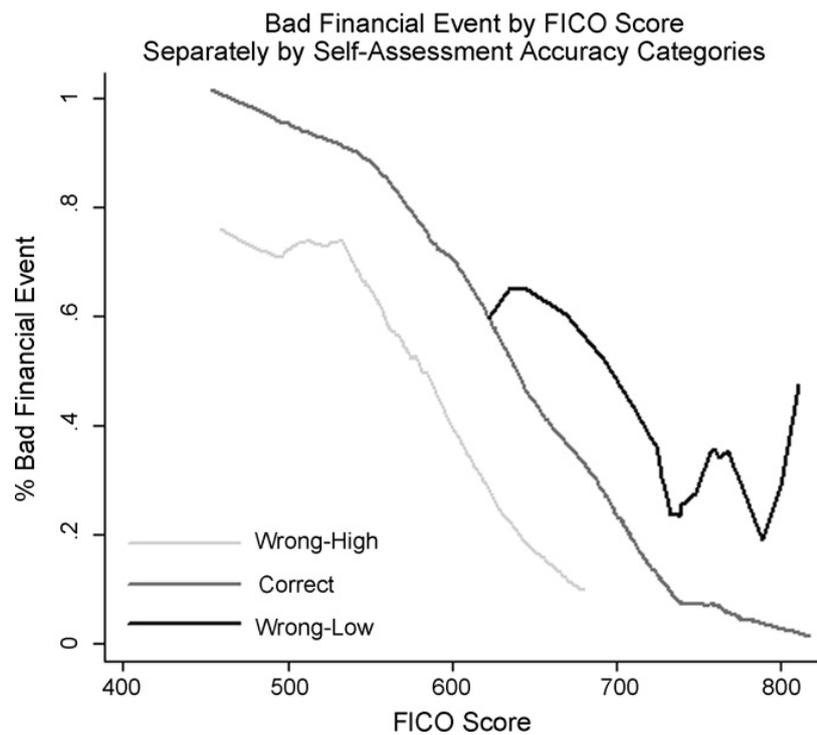


Fig. 2. Bad financial event by FICO score.

who accurately self-assess to experience a denial of credit or 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 score.

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 Table 2.

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 a denial of credit or 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 a denial of credit or 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. These results raise potential concerns about the efficacy and fairness of the financial markets in which these respondents participate. Fully exploring these findings, however, is beyond the scope of this study.

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 Figs. 1 and 2 is unchanged by the inclusion of additional control variables. Specifically, we see that respondents self-assessing as “wrong-low” are more likely to experience being denied credit or having a bad financial event than those self-assessing “correct,” but that respondents self-assessing “wrong-high” have the least likelihood of experiencing bad outcomes. Again we find that accuracy is very 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 FICO score.

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 annual percentage rate (APR).<sup>5</sup> 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 50 states and use both wholesale and retail channels for loan origination purposes.

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

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<sup>5</sup> 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.

Table 2  
 Probit estimations of undesirable market outcomes

Variable name	Variable value	Denied credit		Bad financial event	
		Estimate	Prob (ChiSq)	Estimate	Prob (ChiSq)
Intercept		4.196	<0.0001	5.4904	<0.0001
	Wrong-low	0.9136	<0.0001	1.3062	<0.0001
	Close-low	0.5340	<0.0001	0.8330	<0.0001
Self-assessment accuracy	Correct	0.3289	<0.0001	0.6208	<0.0001
	Close-high	0.2521	<0.0001	0.4900	<0.0001
	Wrong-high	0	–	0	–
FICO score		–0.0084	<0.0001	–0.0106	<0.0001
	Poor	0.3719	<0.0001	0.8421	<0.0001
Financial self control	Okay	0.1915	0.0021	0.5475	<0.0001
	Good	0.1505	0.0108	0.3022	<0.0001
	Very good	0	–	0	–
Education	Some school	0.0822	0.3814	0.4028	<0.0001
	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	<0.0001	0.2115	0.0001
	Neutral	0.3600	<0.0001	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	<0.0001
	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	

advantage of observed relationships between race/ethnicity, FICO score and income on respondents' self-assessment of credit in the Freddie Mac survey.<sup>6</sup> Finally, to match the Freddie Mac survey population 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 a reasonable 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 above. 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 consumers have become increasingly aware 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.

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 are "correct" in their assessment of their FICO scores as well as those that are "wrong-high" and "wrong-low".<sup>7</sup> These plots are provided in Fig. 3.<sup>8</sup>

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% to 6%). As was the case in the Freddie Mac survey data, the relationship between market outcome and self-assessment accuracy in the lender data only weakly supports our hypothesis. Specifically, we find that, consistent with our hypothesis, inaccurately under-assessing credit

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<sup>6</sup> 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 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.

<sup>7</sup> In this instance we use random assignment of discrete credit assessment outcomes rather than the process of assigning probabilities as previously outlined. Specifically, for each observation in the lender data we randomly assign credit assessments based on the probabilities associated with its race/ethnicity, FICO score, and income cell. This process is repeated 10 times per lender observation.

<sup>8</sup> LOWESS techniques are data intensive, and thus cannot be performed on the full (10×) 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, 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 data set we perform LOWESS estimations of APR against actual FICO by self-assessment accuracy categories ("correct", "wrong-high" and "wrong-low"), using a 10% bandwidth.

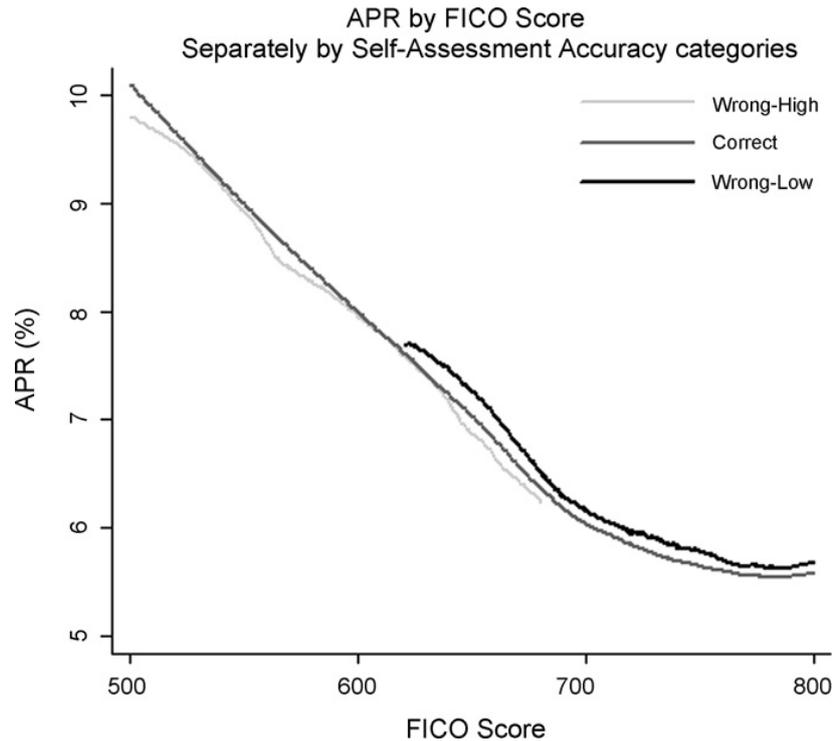


Fig. 3. APR by FICO score.

(“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.

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.<sup>9</sup>

The results of our OLS estimation of APR on the above explanatory variables are provided in Table 3. The estimated coefficients can be interpreted as basis points of APR. The fit of the estimation is reasonably good, with an  $R^2$  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 (non-owner-occupants), loans on manufactured or multi-family homes, and loans with no prepayment penalties. The effect 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

<sup>9</sup> Lenders contributing data to our analysis are classified as prime or subprime based on their own self-assessments.

Table 3  
Regression estimations of APR

Variable name	Variable value	Estimate (bps)	Prob ( <i>t</i> )	
Intercept		2254.92	0.00	
	Probability of wrong-low	−2.51	0.44	
	Probability of close-low	−8.29	0.00	
Self-assessed credit accuracy	Probability of correct	0.00	–	
	Probability of close-high	4.31	0.00	
	Probability of wrong-high	−17.71	0.00	
FICO score splines	FICO < 600	−2.69	0.00	
	Prime	600 ≤ FICO < 700	−0.48	0.00
		700 ≤ FICO	−0.02	0.00
	Subprime	FICO < 600	−1.58	0.00
		600 ≤ FICO < 700	−0.92	0.00
		700 ≤ FICO	−0.95	0.00
	Loan-to-value	LTV ≤ 70	−5.63	0.00
		70 < LTV ≤ 80	0.00	–
80 < LTV ≤ 85		24.89	0.00	
85 < LTV ≤ 90		51.14	0.00	
90 < LTV ≤ 95		62.36	0.00	
95 < LTV ≤ 100		104.02	0.00	
100 < LTV		114.38	0.00	
LTV unknown		19.74	0.00	
Debt-to-income	DTI ≤ 28	0.00	–	
	28 < DTI ≤ 36	4.77	0.00	
	36 < DTI ≤ 50	9.05	0.00	
	50 < DTI	7.76	0.00	
	DTI unknown	−0.68	0.54	
Market channel	Subprime	−335.80	0.00	
	Prime	0.00	–	
Amortization type	Fixed	65.78	0.00	
	Arm	0.00	–	
	Unknown amortization type	31.13	0.00	
Purpose	Purchase money	0.00	–	
	Home improvement	13.73	0.00	
	Refinance	−5.23	0.00	
Occupancy status	Investor	40.93	0.00	
	Owner occupancy unknown	31.72	0.25	
	Owner occupied	0.00	–	
Documentation type	Not full doc	−1.40	0.00	
	Full doc	0.00	–	
	Unknown documentation type	76.09	0.00	
Loan amount splines	Loan amount < 100,000	−0.86	0.00	
	Prime	100,000 ≤ loan amount < 334,000	−0.11	0.00
		334,000 ≤ loan amount < 500,000	−0.06	0.00
		500,000 ≤ loan amount	−0.08	0.00

Table 3 (Continued)

Variable name	Variable value	Estimate (bps)	Prob ( <i>t</i> )
Subprime	Loan amount < 100,000	−1.73	0.00
	100,000 ≤ loan amount < 334,000	−0.42	0.00
	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	0.00
	Prepayment penalty unknown	−47.53	0.00
Loan term	Loan term ≤ 5	−66.13	0.00
	5 < loan term ≤ 15	−32.24	0.00
	15 < loan term ≤ 20	−7.92	0.00
	20 < loan term ≤ 30	0.00	–
	30 < loan term ≤ 40	125.52	0.00
	Unknown loan term	86.82	0.01
Structure	1–4 family	0.00	–
	Manufactured housing	18.71	0.00
	Multi-family	130.98	0.00
Race/ethnicity	African American	14.39	0.00
	Hispanic	9.60	0.00
	Asian	−5.57	0.00
	White non-Hispanic	0.00	–
Number of observations		527,466	
$R^2$		0.76	

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 the focus of a separate research paper.<sup>10</sup>

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.

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 self-assessing credit leads to better outcomes, holding constant other factors including FICO scores, than that accuracy per se leads to better market outcomes.

<sup>10</sup> Interested readers are directed to Courchane (in press) where this issue is more fully explored.

## 5. 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 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 FICO score.

Given the importance of credit and financial literacy, there has been surprisingly little research on the question of whether having an inaccurate FICO score self-assessment results in any undesirable outcomes. We find in our research that consumers' self-assessments of their credit records affect their financial market outcomes, although it is generally the case that it is optimistic self-assessments, not accurate ones, which lead to better 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. Loan-to-value and debt-to-income 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.<sup>11</sup> 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 consumers who apparently are overly optimistic and overly pessimistic may, in fact, be accurately assessing their overall credit

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<sup>11</sup> 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, loan-to-value ratio, debt-to-income ratio and occupancy status, and use predicted APR as our alternative credit score.

records. This suggests that financial literacy programs should focus on more than 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, but rather 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.

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