Supporting Online Material for

Numerical Ability Predicts Mortgage Default

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Contents

I. Materials and Methods

This section provides a detailed discussion of the sample and survey design. First, the mortgage data and the pool of mortgage borrowers that the survey sample is drawn from is described, and potential sample selection biases are discussed. Then, the details of the survey procedure and the questions of interest are presented.

A. Mortgage Data and Sampling

In order to obtain objective measures of mortgage delinquency and default, the survey sample is constructed from data that combines two micro-level mortgage datasets. The first is a loan-level dataset constructed and maintained by Corelogic (formerly FirstAmerican LoanPerformance). Corelogic collects information on individual mortgages that are used as collateral for non-agency, mortgage-backed securities (MBS) and sold to investors on the secondary mortgage market. The sample comes from data that the Federal Reserve Bank of Boston purchased in mid-2007, which covers Massachusetts, Connecticut, and Rhode Island from the late-1990s through March 2009. The dataset contains extensive loan-level information on mortgage characteristics, including interest rates (initial levels and changes over time), documentation levels, payment histories, loan-to-value ratios, and various other lending terms. It also contains some information regarding borrower characteristics, such as the borrower's credit score and debt-to-income ratio at origination (borrower's monthly debt payment divided by his or her monthly income). Finally, the Corelogic dataset identifies the type of MBS each loan was packaged into — subprime, Alt-A, or prime.[1]

The second source of data used in this study was supplied by The Warren Group, a private Boston firm that has been tracking real estate transactions in New England for more than a century. The Warren Group collects publicly available real estate transaction records that are filed at Registry of Deeds offices throughout New England, and have maintained an electronic database of these records for the past twenty years. The data includes the universe of purchase-money mortgages, refinance mortgages, home equity loans, home equity lines of credit (only information on capacities and no information on utilization rates), and purchase deeds (including foreclosure deeds) transacted in Massachusetts, Connecticut, and Rhode Island. Unlike the Corelogic data, this dataset contains the precise location of each property and the exact names of the buyers and sellers of each property as well as the names of the mortgage borrowers. These data make it possible to construct a history of mortgage

[1]The sample of prime loans in the Corelogic dataset consists of mortgages with values above the GSE (Government Sponsored Enterprise) conforming loan limits. This segment of the prime market is often referred to as jumbo-prime.

transactions for a household in a given property. In other words, with the Warren Data it is possible to follow households in the same house across different mortgages. Since the data include information on all mortgage liens and the sale price for each property, it is also possible to construct a precise measure of the cumulative loan-to-value ratio at the time of purchase,[2] and to keep track of the total number of mortgages obtained by each homeowner.

The sample of first-lien mortgages contained in subprime MBS that were originated in 2006 and 2007 from the Corelogic dataset were matched to the Warren Group registry data. The match was based on the zip code of the property (Corelogic data contains only the identity of the zip code where the property is located), the date of mortgage origination, the amount of the mortgage, whether the mortgage was for purchase or refinance, and the identity of the institution that originated the mortgage. The match rate was approximately 45 percent, and left us with a sample of more than 74,000 mortgages.[3]

Mortgages from this matched dataset were randomly selected to construct the sample of borrowers for the survey. Two different strategies were used to contact borrowers: 1) *Cold-calls* involved calling borrowers by phone, which was possible as each borrower's name and address is contained in the Warren Group data. This information was then used as an input into an internet search engine (USAPeopleSearch.com) to find each borrower's phone number(s). 2) *Mail-ins* involved mailing invitations to participate in the survey to the addresses listed in the Warren Group data.

The *Cold-call* strategy, entailed calling a total of 3,523 borrowers[4] in the summer of 2008 (June - August). The borrower was positively identified in approximately one-third of the cases (1,087).[5] In half of those cases it proved impossible to speak to the actual borrower,

[2]The Corelogic data has only sporadic information on the presence of second liens, and thus does not allow for the construction of accurate cumulative loan-to-value ratios.

[3]The main issue that contributed to the low match rate was the inconsistent definition of dates between the two datesets. The date listed in Corelogic is the date of origination, while the date listed in the Warren Group data is the date that the mortgage document was recorded. It usually takes at least a few days for documents to be filed in the Registry of Deeds offices (sometimes a few weeks), and thus, these two dates do not match. Therefore, we were forced to use a date range in the matching algorithm, and consequently often found cases of multiple mortgages of the same amount, originated in the same zip code, in a given date range. We were forced to throw out these cases of multiple matches. The identity of the originating institution often helped in these cases, but unfortunately the Corelgoic data contain only sparse information on this variable. The matched sample of mortgages appears to be quite representative of both the Corelogic and Warren Group datasets based on observable mortgage, property and borrower characteristics.

[4]Often multiple phone numbers were found for each borrower in the data, so the actual number of phone numbers called was much larger than the number of borrowers.

[5]For another one-third the phone line was not working. For the last one-third, a working

and thus, a response to the interview request was never received.[6] In 296 cases the borrower was contacted, but he or she refused to participate in the survey,[7] and in 253 cases the borrower was contacted and he or she agreed to participate in the survey. Based on these statistics, two participation rates are reported for the *Cold-calls*: Of the borrowers that were directly contacted, 46.1 percent agreed to participate in the survey; of the borrowers that were matched to a correct phone number, 10.5 percent agreed to participate.

The *Mail-in* strategy entailed mailing almost 5,000 invitation letters to borrowers for whom phone contact information could not be obtained. The invitation letter was one page (two-sided) and contained a brief description of the survey and the survey conductors (and was signed by the president of the Federal Reserve Bank of Boston). A small response card was also included that contained a question asking if the borrower would be interested in participating in the survey, and included space for borrowers who agreed to participate to list working phone numbers and the best times of day to call. In addition, a response envelope and postage was included. In the vast majority of cases (98.3 percent), a response was not received. For the cases in which a response was received, an attempt was made to call the borrower to conduct the interview. Of the borrowers that were subsequently contacted, approximately 92 percent agreed to participate in the survey (70 percent of the borrowers for whom a correct address could be verified).

Sample selection bias is always a serious concern in surveys such as this one. Since information about observable mortgage and borrower characteristics for *all* of the borrowers is available in the Corelogic and Warren Group datasets, it is possible to test whether there is sample selection on those observable characteristics. According to sample statistics listed in Table S1, there is little evidence of sample selection on observable characteristics. The table compares average characteristics between the respondents and non-respondents for both the *Cold-Calls* sample and the *Mail-In* sample. Only the mortgage amount for the phone sample and initial interest rate for the mailing is statistically significant at the 10 percent level. All the other differences are not statistically significant at even the 10 percent level. Importantly, information about the foreclosure rate of *all* individuals is also available, and there is no difference in the probability of foreclosure after the mailing went out between

line was reached, but it was not possible to verify that the phone number corresponded to the borrower in the data either because nobody picked up the phone or because an answering machine was reached (it was not possible to identify the borrower from the answering machine message, and furthermore the borrower never responded to a message that was left on the machine).

[6] In most of these cases either a message was left on an answering machine, or another member of the household answered, but the actual borrower was not available.

[7] This includes cases in which the borrower agreed to participate at a later date, but never followed through on that agreement.

respondents and non-respondents. Furthermore, a more formal statistical test of sample selection is conducted, and the results support the findings from Table S1.[8]

While it does not appear that selection into the survey sample is an issue, the timing of the survey raises some important issues. The survey was conducted in the summer of 2008 between June and August, while the borrowers chosen for the survey obtained their mortgages in 2006 and 2007. August 2007 is the last month that a mortgage was originated in the survey sample, quite simply because the subprime mortgage market had completely shut down at that point and no new mortgages were originated. This means that the subprime borrowers taking the survey had been paying their respective mortgages for at least 10 months and up to 32 months (for mortgages originated in January 2006). In addition, one of the requirements imposed for inclusion into the sample was that each borrower not be in the foreclosure process at the time that the survey was conducted. This requirement was made because of the increased difficulty in contacting borrowers in foreclosure. Many of those borrowers are either likely not living in the home anymore, or if they are, will likely refuse to answer phone calls or mail requests. Because of this design feature, the results in this study are not necessarily representative of all subprime mortgage borrowers. Many subprime borrowers defaulted on their loans and experienced foreclosure within the first year of origination. The average number of months to default for all subprime mortgages originated in 2006 and 2007 in the LP dataset for which the servicer has initiated foreclosure proceedings is slightly less than 18. More than one-quarter of the defaults occurred within one year of origination.

In the end, 339 individuals responded to the survey and constitute the main sample. The last two columns in Table S1 display summary statistics of the detailed information in the Corelogic data on respondents' mortgage characteristics. The statistics are consistent with what one might expect in a sample of subprime mortgage borrowers. The average FICO score of 632 is relatively low, the majority of borrowers have adjustable-rate mortgages

[8]To test for potential sample selection bias on observables we estimate for each observable outcome measure k (see Table S1), the equation

$$y_i^k = \alpha_k + \gamma_k R_i + \beta_k CC_i + \epsilon_i^k \tag{1}$$

where α_k is the constant for outcome k, γ_k is the difference in the outcome if the individual was a respondent (and $R_i = 1$), and β_k is the difference in the outcome if individual i was a cold call (and $CC_i = 1$). Finally, ϵ_i^k is the residual for outcome k. The k equations in (1) are estimated by seemingly unrelated variables, thus allowing the residuals ϵ_i^k to be correlated across outcomes within individuals. The hypothesis $\gamma_k = 0$ is then tested for all k outcome measures. The p-value of the corresponding χ^2-test is $p = 0.51$, which suggests little to no evidence of selectivity into the survey on these 10 important variables.

(two-thirds), and the average debt-to-income ratio (ratio of the summation of all monthly debt payments to the monthly mortgage payment) of 0.42 is relatively high, which suggests that this group of borrowers is characterized by heavy debt burdens.

Table S1
Summary Statistics of Mortgage Data

	t-test of Differences NR vs. R				Summary Statistics	
	Cold Calls		Mail-Ins		Respondents	
	NR-R	p-value	*NR-R*	p-value	Means	Std. Dev.
FICO Score	-4.99	0.201	6.025	0.340	632	61.4
Fixed-Rate Mortage (=1)	-0.010	0.760	-0.026	0.523	0.339	.
Interest-Only (=1)	-0.011	0.516	0.020	0.483	0.083	.
Balloon Payment (=1)	-0.014	0.613	-0.035	0.490	0.257	.
Refinance (=1)	0.021	0.517	0.002	0.973	0.555	.
Loan-to-Value Ratio	0.814	0.324	0.147	0.899	78.6	12.7
Amount of Mortgage ($ thousands)	-14.5	0.068	20.6	0.119	245	130
Initial interest rate	0.118	0.123	0.243	0.053	7.94	1.19
Debt-to-Income Ratio	0.437	0.473	-1.48	0.136	42.0	8.18
Full-Doc Status (=1)	-0.018	0.532	0.060	0.245	0.699	.
Foreclosure after mailing went out (=1)	0.019	0.326	-0.004	0.901	0.094	.

Notes: The first part of the table shows differences of various mortgage characteristics between R and NR (NR-R) and p-values of t-tests of whether the differences are statistically significant. The information is based on 3,615 observations for the Cold Calls and 4,995 observations for the Mail-Ins. The information about *Debt-to-Income Ratio* is missing for a few observations in the Warren Group data. To compare *Foreclosure after mailing went out* we focus on individuals who were never in foreclosure between the origination and the date we contacted them. For some of the borrowers who were "current" on their mortgage when we contacted them, a foreclosure petition had been filed before and they may have already been in the process of moving out. The last two columns show summary statistics of all respondents (N= 339).

B. The Survey

The survey contains four important parts: 1) Measures of two aspects of individuals' financial literacy, numerical ability and basic economic literacy, and a measure of general cognitive ability. 2) Measures of time and risk preferences. 3) Questions about the details of the mortgage contract (we already know much of this information from the micro datasets) and the experience of shopping for the mortgage. 4) An extensive list of socio-demographic characteristics that complements information from the Corelogic and Warren Group datasets.

On average, the survey took about 20 minutes to complete, and individuals were compensated $20 for their participation.

B.1. Financial Literacy and Cognitive Ability

The first measure of financial literacy, which is the primary focus of this study, determines the proficiency of a respondent for solving basic mathematical calculations. Participants were asked the following five questions originally developed by (1). The questions are as follows:

1. *In a sale, a shop is selling all items at half price. Before the sale, a sofa costs $300. How much will it cost in the sale?*

2. *If the chance of getting a disease is 10 per cent, how many people out of 1,000 would be expected to get the disease?*

3. *A second hand car dealer is selling a car for $6,000. This is two-thirds of what it cost new. How much did the car cost new?*

4. *If 5 people all have the winning numbers in the lottery and the prize is $2 million, how much will each of them get?*

5. *Let's say you have $200 in a savings account. The account earns ten per cent interest per year. How much will you have in the account at the end of two years?*

To construct an index of numerical ability, (1) suggest dividing individuals into four separate groups based on the responses to the five questions. A borrower is placed into the first group corresponding to the lowest level of numerical ability if he answers questions 1, 2, and 3 incorrectly *or* answers question 1 correctly, but answers questions 2, 3, and 4 incorrectly. The second group is made up of borrowers who answer at least one of the first four questions incorrectly (the outcome of the fifth question is not considered for the first or second groups).

Table S2
Distribution of Numerical Ability Index

	Numerical Ability Group			
	1	2	3	4
This study:	15.6%	53.9%	17.1%	13.3%
Banks and Oldfield (2007):	16.2%	46.6%	26.8%	11.1%

The third group contains borrowers who answered questions 1, 2, 3, and 4 correctly, but answered question 5 incorrectly. Finally, borrowers who answered all five questions correctly are placed into the fourth group. Table S2 shows the distribution of the numerical ability index in the survey sample as well as the distribution from the Banks and Oldfield paper. Approximately 16 percent of borrowers fall into the lowest group, 54 percent into the second group, 17 percent into the third group, and 13 percent into the highest group. Despite being characterized by a very different group of individuals, the distribution of the index in the Banks and Oldfield study is very similar to the distribution in the survey sample.

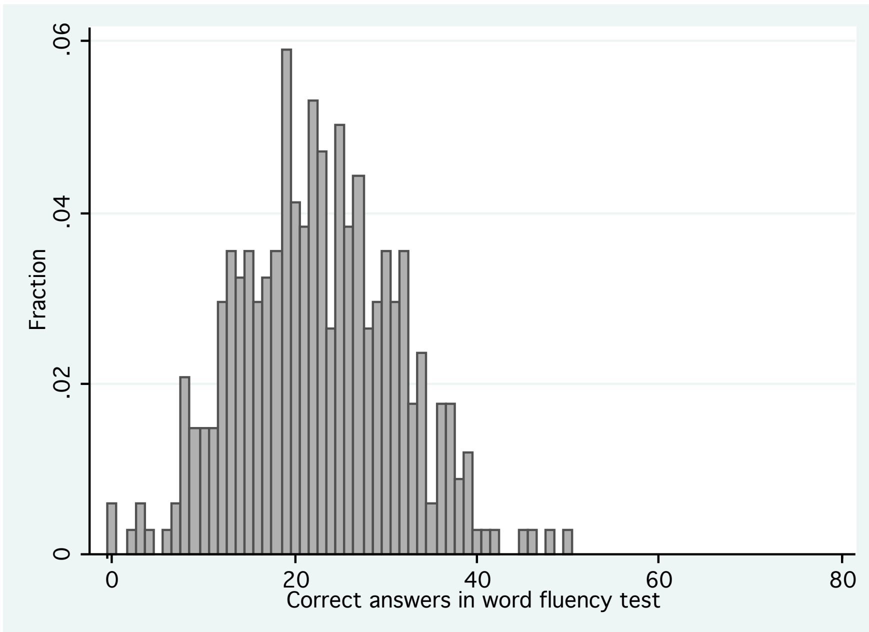
It is important in this context to distinguish between the effects of financial literacy and the more general notion of cognitive ability. To do so, we use a verbal fluency measure first introduced by (2). Participants were asked: *" In the next 90 seconds, name as many animals as you can think of. The time starts now."* The number of animals named is highly correlated with IQ (e.g. 2). The reason for this is that intelligence is highly correlated with the ability to retrieve known information. As most people know hundreds, if not thousands of animals, the question reveals how easy it is to retrieve that information. Obviously, the ability to name animals in English also depends on individuals' English language skills, which is elicited separately (see below). In the economics literature, (3) also use this question to measure cognitive ability. Figure S1 compares the distribution of responses in the survey sample to the distribution in their study, which used a representative sample of the German population. The shape of the distributions is very similar.[9]

In addition to the measure of financial literacy that focuses on respondents' numerical ability, we measure respondents' basic understanding of economic mechanisms using two questions from (4). (4) refer to these as "basic financial literacy" questions, but in our opinion they measure an individual's understanding of basic economic concepts, and thus

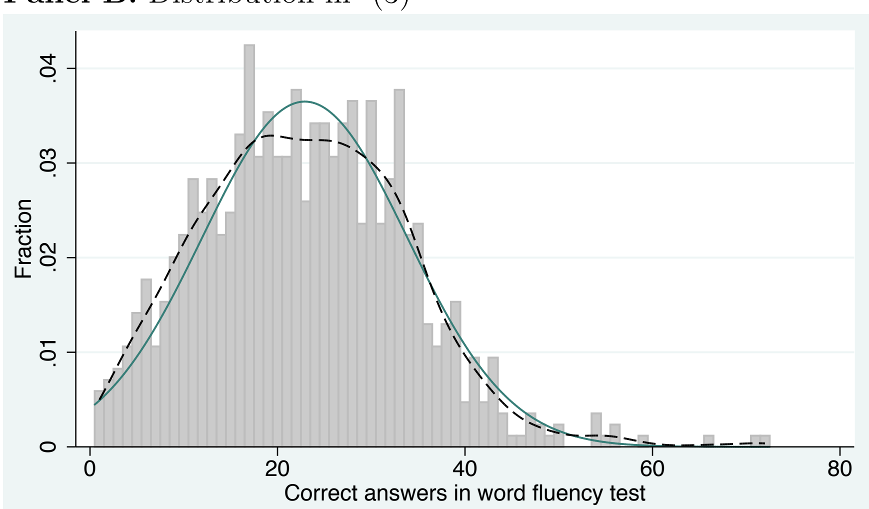
[9]This is quite interesting in its own right, as a priori, we did not expect a sample of U.S. subprime mortgage borrowers to have a similar distribution of cognitive ability as a representative sample of German borrowers.

Figure S1. Distribution of Verbal IQ Scores

Panel A: Distribution in this study



Panel B: Distribution in (3)



we refer to them as questions that measure “economic literacy.”

1. *Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? More than today, exactly the same as today, or less than today?*

2. *Suppose that in the year 2020, your income has doubled and prices of all goods have doubled too. In 2020, how much will you be able to buy with your income? More than today, exactly the same as today, or less than today?*

In the survey sample, approximately 79 percent of borrowers answered the first question correctly, and 74 percent answered the second question correctly, while 60 percent answered both questions correctly. These results are very similar to those obtained by (4).

As an additional measure of cognitive ability, the average time it took the participants to respond to the (1) numerical ability questions was calculated. The time was measured from the moment the interviewer had finished reading the question to the moment an answer was given by the respondent. Table S3 displays the correlations between all of the measures of cognitive ability and financial literacy. There is a strong, positive correlation between the measures of financial literacy and cognitive ability as measured by the verbal fluency question. There is also a strong, negative correlation between the measures of financial literacy and verbal fluency with the response times to the numerical ability questions. Individuals who responded more quickly to these questions achieved higher scores.[10]

A more formal factor analysis reveals one common factor among the five variables. Only the first eigenvalue is greater than one, while all others are almost exactly equal to zero. Finding one common component to different measures of intelligence is quite common, and has been found in many other studies (See, e.g., 5; 6).

B.2. Time and Risk Preferences

To measure time and risk preferences, respondents were asked to make a number of hypothetical choices that made it possible to calculate their discount factors and risk aversion parameters.

[10] A skeptic may argue that differences in the measure of cognitive ability instead may simply measure different styles in which individuals answer questions. Some may take the time to think about the question and then answer, while others may just blurt out the first thing that comes to their mind. The negative correlation between response times and the measures of financial literacy and cognitive ability provides some evidence against this interpretation, as it shows that individuals who struggled to answer in a timely manner, also were more likely to get the answer wrong.

Table S3
Correlation Between Measures of Cognitive Ability

	NA group	Verbal IQ measure	Savings scenario	Inflation scenario
Verbal IQ measure	0.356 (0.000)	1		
Savings scenario correct (DV)	0.236 (0.000)	0.153 (0.005)	1	
Inflation scenario correct (DV)	0.273 (0.000)	0.251 (0.000)	0.093 (0.087)	1
Reaction time in NA questions	-0.279 (0.000)	-0.303 (0.000)	-0.157 (0.004)	-0.207 (0.000)

Notes: $N = 339$. p-values in parentheses. A factor analysis performed on these correlations reveals one common factor ($\lambda = 1.17$), while all other eigenvalues are less than 0.005.

Similar to experimental measures of time preferences (see, e.g., 7; 8), individuals were asked to decide on a monetary amount that makes them indifferent between receiving the amount immediately versus waiting x months for a larger monetary amount. The answers to these questions allows for the calculation of individual discount factors. Individuals were asked to make such intertemporal trade-offs for the present versus both $x = 6$ months and $x = 12$ months. The two different time frames make it possible to construct a measure of whether individuals have dynamically inconsistent time preferences (e.g., 9). As can be seen in panel A in Table S4, which displays summary statistics of key variables from the survey, the average discount factor in our sample is 0.96 (over one month) and 80 percent of our sample exhibits dynamically consistent time preferences, similar to (7). In addition, the borrowers were asked to assess their own level of impatience on a 11-point scale from 0 corresponding to "very impatient" to 10 corresponding to "very patient." The measure of impatience that is based on the set of hypothetical choices is primarily used in the empirical work, but the results are largely unchanged if the subjective scale is used instead.

The measure of risk aversion also follows standard experimental strategies (e.g., 10). Participants were asked to hypothetically choose between a certain payoff and a 50-50 chance of receiving a good or bad payoff:

Which would you prefer: A mortgage for which you paid $1000 per month for the next thirty years, or a mortgage, in which, after two years the payment is either $500 or $1100 with equal chance?

If the participant accepted the uncertain lottery, the high payment of the uncertain mortgage was raised by increments of \$100. The payoff at which the participant switches to the safe mortgage is used as the measure of risk tolerance. The mean switching amount (see Table S4) was \$ 1184, revealing a substantial degree of risk aversion. In addition, participants were asked to assess their own level of risk tolerance on a scale from 0 to 10 as in (11). As with the self-assessed impatience measure, the second risk measure does not require any numerical skills. Nevertheless, the risk measure based on the set of hypothetical choices (most related to experimental risk measures) is primarily used in the empirical work, but the results are robust to using the self-reported scale measure.

B.3. Socio-demographics

The survey contains a number of detailed questions about socio-demographic characteristics and information about household income and employment status. Participants were asked about their race and ethnicity, gender, age, place of birth, amount of time spent in the United States, marital status, number of children, education level, and proficiency with the English language (scale from 0 corresponding to a "beginner" to 10 corresponding to a "native speaker"). In addition, questions were included to measure the amount of household income, the number of family members that contribute to household income, and the volatility of household income (on a three-point scale with 1 signifying that "it's been pretty stable"; 2 signifying "it has gone up and down a little over the last few years"; and 3 indicating that "it has gone up and down a lot over the last few years"). Finally, participants were asked about their current employment status and the number of times that they had been out of work over the previous five years.

Panel B in Table S4 presents summary statistics of the socio-demographic information. Approximately one-third of the respondents are minority (defined here as not white), and the split between males and females is about 50-50. The average age of respondents is 47 and their average household income is \$80 thousand, which is surprisingly high for a sample of subprime borrowers.[11] Almost 84% of respondents were born in the United States, and almost three-quarters have more than a high school education.

B.4. Mortgage Experience

As we discussed above it is possible to obtain information on respondents' previous experience in mortgage markets. The Warren Group data allows one to calculate the number

[11]The high average and huge standard deviation of income in the sample supports the idea that the subprime mortgage market was used by a diverse group of borrowers.

Table S4
Summary Statistics of Survey Questions

	Dummy?	Mean	Std. Dev.
Panel A: Time and Risk Preferences			
Discount Factor	No	0.964	0.026
Present Bias	Yes	0.201	.
Risk tolerance	No	1184.971	157.996
Panel B: Socio-Demographics			
Asian	Yes	0.012	.
African American	Yes	0.192	.
Hispanic	Yes	0.074	.
Native American	Yes	0.027	.
Other Ethnicity	Yes	0.027	.
Male	Yes	0.487	.
Age	No	46.6	10.3
Born in USA	Yes	0.838	.
# of Years lived in US	No	43.1	13.7
Married	Yes	0.631	.
Separated	Yes	0.029	.
Divorced	Yes	0.112	.
Single	Yes	0.192	.
Widowed	Yes	0.035	.
# of Children	No	2.09	1.49
No High School	Yes	0.032	.
Some High School	Yes	0.044	.
High School Degree	Yes	0.180	.
Some College	Yes	0.333	.
College Degree	Yes	0.271	.
Higher Degree	Yes	0.139	.
Fluency in English	No	9.74	1.05
Income ($ thousands)	No	80.0	57.4
Income Volatility	No	1.87	0.791
Employment Status	Yes	0.841	.
# of Years out of Work	No	0.730	1.54
Panel C: Mortgage Characteristics / Search Behavior			
First-time Homebuyer	Yes	0.552	.
Home counseling	Yes	0.091	.
Shop around	Yes	0.602	.

Notes: Based on 339 observations.

of mortgages obtained since the home purchase (going back to January 1987), which allows one to calculate the number of mortgages taken out by each household before their current subprime loan.[12] This information is supplemented with additional proxies for borrowers' experience with mortgages and their search behavior prior to obtaining their current mortgage. The survey asks participants whether they were first-time homebuyers, whether they had taken a home buying class or had received counseling, if they obtained information about mortgage pricing before obtaining their loan, and if they had, how they obtained the information (internet, relative, friend, etc.). According to panel C of Table S4, more than half (55%) of the sample are first-time homebuyers, less than 10% took a home counseling class before purchasing their house, while 60% reported that they shopped around for a mortgage.

C. Measures of Mortgage Delinquency

Using the Corelogic mortgage performance data, three different measures of mortgage delinquency were created (two are reported in the main text). All measures incorporate delinquency from the origination of the mortgage until March 2009 (the latest update provided by Corelogic).[13] The first measure of delinquency measures the fraction of time a borrower is behind by at least one mortgage payment. This measure captures the amount of time during which a household is unable or unwilling to meet the promised mortgage payments. For example, if a household missed its very first payment and made all future payments on time, this measure would consider that the household was behind in each period until that first payment is made.

The second measure of mortgage delinquency is the fraction of mortgage payments missed. This variable is an explicit measure of the extent of delinquency. For example, a borrower who has had a mortgage for 12 months and who has missed 6 payments would be assigned a value of 50 percent for this measure, while a borrower who has had the mortgage for the same amount of time, but who has only missed 3 payments, would be assigned a value of 25 percent.

The thirs measure is a dichotomous variable that takes a value of one if foreclosure proceedings have been initiated by the lender. Normally, foreclosure proceedings are initiated when a borrower is 120 days delinquent on their mortgage (or equivalently is 4 payments behind).[14]

[12] Mortgage information is only available for the current property.

[13] Restricting the time period until summer 2008 when we conducted the survey does not materially affect the results.

[14] One of the participation criteria was not being in foreclosure at the time of the survey.

Table S5
Distribution of Delinquency Measures

			Percentiles				
	Mean	Std. Dev.	10	25	50	75	90
Fraction of periods during which household is behind on at least one payment	0.198	0.247	0	0	0.077	0.367	0.621
Fraction of missed payments	0.110	0.143	0	0	0.056	0.167	0.304
Foreclosure	0.192	.	.	.	.	.	.

Notes: $N = 339$ observations.

Table S5 contains information on the distributions of the three delinquency measures. The average borrower in the sample was behind on their payments 20 percent of the time. Half of the borrowers in the sample were delinquent more than 7 percent of the time while 10 percent of the borrowers were delinquent more than 60 percent of the time. Almost 20 percent of the borrowers in the sample had been in the state of foreclosure at some point in their mortgage experience.

But, there are a few instances in which a borrower had been in foreclosure in the period before the survey was administered, but then had recovered by the time of the survey. These borrowers were included in the survey sample.

II. Empirical Specification

The primary empirical specification takes the following form:

$$D_i = \gamma NA_i + \mathbf{x_i}'\beta + \epsilon_i \quad (2)$$

where D_i corresponds to the first two measures of delinquency discussed above, the percent of time spent in delinquency and the percent of mortgage payments missed, for household i. The term NA_i represents the numerical ability group of household i, $\mathbf{x_i}$ represents a vector of control variables, and ϵ_i is the residual. The equation is estimated by ordinary least squares (OLS)[15], and potential heteroskedasticity in the standard errors is taken into account by estimating robust standard errors.

A probit specification is estimated for the second measure of delinquency, the initiation of foreclosure proceedings,

$$Pr[F_i = 1|NA_i, \mathbf{x_i}] = \Phi(\gamma NA_i + \mathbf{x_i}'\beta) \quad (3)$$

where F_i takes the value of one if foreclosure proceedings have been initiated on the borrower and zero otherwise, and $\Phi()$ is the cumulative distribution function of the standard normal distribution.

III. Supportive Empirical Analysis

A. Table S6 and Table S7: Main Findings With and Without Control Variables

In the paper we discuss the following results which relate to Figure 1 in the main text:

- Table S6 shows that the extent of delinquency and foreclosure is monotonically increasing in numerical ability when a specification that includes a separate dichotomous variable for each numerical ability group is employed as in Figure 1.

- Table S7 displays the coefficient estimates from the linear regressions (columns (1)) and the estimated marginal effects from the probit model of foreclosure starts (column (3)). They indicate that, as suggested by the figure, the correlations between numerical ability and the delinquency measures are positive and statistically significant.

[15]The results are robust to using a Tobit specification instead of OLS (see Table **??** in the appendix).

- In columns (2), (3), (5), (6), (8) and (9) of Table S6 and in Table S7 we stepwise add age, gender, ethnicity, education, marital status, the size of the household, time and risk preference parameters, labor market status over the previous five years, the household's income, the subjective measure of income volatility, FICO score, and dummy variables for whether the borrower is an investor (owner occupant as the reference group), as well as whether the mortgage is for a home purchase (refinance is the reference group left out of the regression). The coefficient estimates are unaffected, and remain statistically significant in all specifications. The inclusion of these controls significantly increases the R^2 of the regression from around 2 percent to approximately 25 percent. The FICO score, in particular, is an important determinant of delinquency and default. The fact that the correlation between numerical ability and delinquency does not change when the FICO score at origination is included is an important finding.[16] It implies that the measure of numerical ability is not just capturing the fact that borrowers who have defaulted on previous debts are more likely to default on their mortgage compared to borrowers with good credit histories. Therefore, initial creditworthiness, i.e. the ability to borrow to smooth out shocks, doesn't drive the effect of numerical ability.[17]

- All the conclusions with respect to the impact of numerical ability are independent of the specific measure of mortgage delinquency. We use the fraction of time spent in delinquency, the fraction of payments missed or the filing of a foreclosure petition, and always arrive at the same conclusion.

[16]Notice also that the inclusion of the FICO score renders most labor market controls that were significant in columns (2), (5), and (8), insignificant, with the exception of the volatility of income. Since the FICO score is constructed to be a catch-all predictor for delinquency, this is not entirely surprising.

[17]The estimated correlation between numerical ability and delinquency is not affected by the inclusion of debt-to-income ratios at origination, which capture other types of debt in addition to mortgage debt (see the discussion below and Table S11).

Table S6
Dummy Variables of NA Categories Instead of Linear Term

	Fraction of Time in Delinquency		Fraction of Payments Missed		Foreclosure Initiated (=1)	
	(1)	(2)	(3)	(4)	(5)	(6)
NA Index = 2 (DV)	− 0.025	− 0.037	− 0.031	− 0.040	0.020	− 0.016
	(0.042)	(0.042)	(0.027)	(0.027)	(0.058)	(0.054)
NA Index = 3 (DV)	− 0.070	− 0.108**	− 0.033	− 0.056	− 0.050	− 0.084*
	(0.050)	(0.053)	(0.033)	(0.035)	(0.065)	(0.048)
NA Index = 4 (DV)	− 0.125***	− 0.142**	− 0.084***	− 0.104***	− 0.142***	− 0.145***
	(0.048)	(0.060)	(0.029)	(0.034)	(0.052)	(0.032)
Control variables?	No	Yes	No	Yes	No	Yes
F-Test: all coefficients of NA are zero	$p = 0.01$	$p = 0.04$	$p < 0.01$	$p = 0.01$	$p = 0.07$	$p = 0.02$
F-Test: Relationship is linear	$p = 0.86$	$p = 0.81$	$p = 0.6$	$p = 0.7$	$p = 0.28$	$p = 0.31$
R^2	0.024	0.261	0.026	0.247		
N	339	322	339	322	339	318

Notes: Regression coefficients are reported in columns (1) - (4). Marginal effects from probit models are reported in columns (5) - (6). Robust standard errors in parentheses in columns (1) - (4). All specifications contain the full set of control variables as in Table S7.
Level of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table S7: The Baseline Result

	Fraction of Time in Delinquency			Fraction of Payments Missed			Foreclosure Initiated (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Numerical Ability Index	–0.043***	–0.038*	–0.052***	–0.024***	–0.024**	–0.032***	–0.059**	–0.067**	–0.085***
	(0.014)	(0.020)	(0.019)	(0.009)	(0.011)	(0.010)	(0.026)	(0.030)	(0.028)
Log (Household Income)		–0.056**	–0.025		–0.022	–0.006		–0.062	–0.043
		(0.027)	(0.028)		(0.017)	(0.017)		(0.046)	(0.042)
Volatility of HH Income		0.038**	0.039**		0.022**	0.023**		0.048*	0.043
		(0.018)	(0.016)		(0.010)	(0.009)		(0.029)	(0.026)
Employed (DV) (d)		–0.001	–0.003		–0.002	–0.002		0.034	0.044
		(0.046)	(0.045)		(0.026)	(0.026)		(0.056)	(0.046)
# of times out of work in past		0.018**	0.009		0.006	0.002		–0.020	–0.026*
		(0.008)	(0.008)		(0.004)	(0.004)		(0.016)	(0.015)
Age		–0.003	–0.003		–0.001	–0.001		0.000	–0.000
		(0.003)	(0.003)		(0.002)	(0.002)		(0.005)	(0.005)
Male (DV) (d)		0.017	0.049		0.019	0.035**		0.120**	0.146***
		(0.032)	(0.031)		(0.018)	(0.017)		(0.049)	(0.046)
Asian (DV)		–0.162**	–0.285***		–0.108**	–0.171***			
		(0.077)	(0.087)		(0.049)	(0.050)			
African American (DV) (d)		0.116***	0.098**		0.077**	0.068**		0.177**	0.153**
		(0.044)	(0.040)		(0.030)	(0.027)		(0.076)	(0.074)
Hispanic (DV) (d)		0.003	0.015		0.007	0.011		–0.010	–0.016
		(0.056)	(0.055)		(0.029)	(0.027)		(0.093)	(0.081)
Native American (DV) (d)		–0.050	–0.031		–0.031	–0.024		0.036	0.005
		(0.110)	(0.100)		(0.054)	(0.040)		(0.185)	(0.180)
Other Ethnicity (DV) (d)		0.108	0.100		0.082	0.078		0.147	0.166
		(0.137)	(0.106)		(0.097)	(0.085)		(0.220)	(0.222)
Born in USA (DV) (d)		–0.038	–0.058		–0.023	–0.030		–0.152	–0.159
		(0.072)	(0.079)		(0.044)	(0.046)		(0.165)	(0.165)
Years lived in US		0.004	0.005		0.003	0.003		0.004	0.004
		(0.003)	(0.003)		(0.002)	(0.002)		(0.005)	(0.005)
Fluency in English		0.002	0.007		0.005	0.008		0.018	0.019
		(0.017)	(0.015)		(0.008)	(0.008)		(0.029)	(0.026)
Some High School (DV) (d)		–0.106	–0.072		–0.035	–0.016		–0.001	0.017
		(0.096)	(0.099)		(0.052)	(0.051)		(0.182)	(0.177)
High School Degree (DV) (d)		–0.073	–0.057		–0.013	–0.004		0.111	0.123
		(0.074)	(0.075)		(0.044)	(0.043)		(0.202)	(0.196)
Some College (DV) (d)		–0.024	0.002		0.010	0.024		0.244	0.260

Table S7: (continued)

	Fraction of Time in Delinquency			Fraction of Payments Missed			Foreclosure Initiated (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		(0.074)	(0.075)		(0.043)	(0.042)		(0.195)	(0.189)
College Degree (DV) (d)		0.022	0.042		0.025	0.038		0.230	0.257
		(0.078)	(0.078)		(0.044)	(0.042)		(0.209)	(0.208)
Professional Degree (DV) (d)		0.020	0.048		0.019	0.039		0.311	0.384
		(0.080)	(0.079)		(0.045)	(0.044)		(0.255)	(0.266)
Married (DV) (d)		–0.036	–0.048		–0.053	–0.057		–0.166	–0.139
		(0.082)	(0.061)		(0.049)	(0.038)		(0.132)	(0.127)
Separated (DV) (d)		0.005	–0.001		0.015	0.017		0.021	0.030
		(0.113)	(0.091)		(0.083)	(0.070)		(0.160)	(0.160)
Divorced (DV) (d)		–0.080	–0.106		–0.093*	–0.106***		–0.158***	–0.135***
		(0.086)	(0.065)		(0.050)	(0.038)		(0.044)	(0.036)
Single (DV) (d)		–0.049	–0.044		–0.066	–0.064		–0.128*	–0.110*
		(0.090)	(0.067)		(0.052)	(0.040)		(0.074)	(0.064)
Number of Children		0.008	0.001		0.000	–0.003		0.017	0.015
		(0.011)	(0.010)		(0.006)	(0.006)		(0.016)	(0.014)
Estimated δ		–0.643	–0.298		–0.416	–0.251		–0.941	–0.562
		(0.548)	(0.529)		(0.313)	(0.298)		(0.816)	(0.734)
Present-Biased (DV) (d)		–0.026	–0.023		–0.007	–0.004		–0.065	–0.059
		(0.034)	(0.033)		(0.019)	(0.018)		(0.046)	(0.039)
Risk preferences		0.000	0.000		0.000	0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
FICO Score / 10			–0.015***			–0.009***			–0.020***
			(0.002)			(0.001)			(0.004)
Home Purchase (DV) (d)			–0.036			–0.009			0.049
			(0.036)			(0.019)			(0.061)
Months since home purchased			–0.000			–0.000**			–0.000
			(0.000)			(0.000)			(0.000)
Originated in 2007 (DV) (d)			–0.050			–0.021			–0.032
			(0.035)			(0.019)			(0.044)
Investor (DV) (d)			–0.009			0.001			0.010
			(0.057)			(0.032)			(0.106)
Constant	0.296***	0.881	1.452***	0.164***	0.498	0.857***			
	(0.037)	(0.598)	(0.547)	(0.023)	(0.323)	(0.306)			

Table S7: (continued)

	Fraction of Time in Delinquency			Fraction of Payments Missed			Foreclosure Initiated (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R^2	0.023	0.153	0.268	0.021	0.153	0.265			
F-test of H_0: All coefficients are equal to zero	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
N	339	322	322	339	322	322	339	318	318

Notes: Robust standard errors in columns (1) - (6). ***, **, * indicate significance at the 1, 5, 10 percent level, respectively. Regression coefficients are reported in columns (1) - (6). Marginal effects from probit model are reported in columns (7) - (9).

B. Robustness Table S8: Prior Experience in Mortgage Markets

Experience in mortgage markets may also impact mortgage repayment behavior. A borrower who has obtained numerous previous mortgages may have a better idea of the type of product that best fits their financial situation. In the paper, we discuss the following results:

- Table S8 adds the number of previous mortgages obtained by the borrower to the control set. In addition an indicator for first-time homebuyers, as well as a number of variables collected in the survey pertaining to the amount of information the individual collected before signing the mortgage contract are included as control variables.
- Results in Table S8 show that the correlation between numerical ability and mortgage delinquency and default is not affected. This holds for all three measures of mortgage delinquency.

Table S8
Controlling for Previous Mortgage Market Experience

	Fraction of Time in Delinquency	Fraction of Payments Missed	Foreclosure Initiated (=1)
Numerical Ability Index	– 0.049***	– 0.030***	– 0.075***
	(0.019)	(0.010)	(0.028)
Number of prev. mortgages	0.001	0.005	0.019
	(0.009)	(0.005)	(0.014)
First home purchase (DV)	0.046	0.023	0.089**
	(0.031)	(0.017)	(0.043)
Shopped around before getting mortgage (DV)	0.029	0.017	0.017
	(0.029)	(0.016)	(0.040)
Sought counceling for home buyers (DV)	– 0.026	– 0.003	– 0.068
	(0.050)	(0.029)	(0.053)
Attended home owner classes (DV)	– 0.009	– 0.010	0.127
	(0.047)	(0.024)	(0.102)
Control variables?	Yes	Yes	Yes
R^2	0.270	0.255	
F-test of H_0: All coefficients are equal to zero.	$p < 0.01$	$p < 0.01$	$p < 0.01$
N	322	322	318

Notes: Regression coefficients are reported in columns (1) and (2). Marginal effects from probit models are reported in column (3). Robust standard errors in parentheses in columns (1) and (2). All specifications contain the full set of control variables as in Table S7.
Level of significance: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

C. Robustness Table S9: Geographic Area and Mortgage Lenders

In the paper we mention two further robustness tests that deal with that our measure of numerical ability could be correlated with (1) with some neighborhood characteristic like income or education that impacted mortgage default rates when house prices began to fall. For example, one of the stylized facts of the housing crisis is that house prices were more volatile (on both the upside and downside) in poorer neighborhoods with more subprime lending, and thus greater mortgage defaults and foreclosures. (2) Individuals with low numerical ability might choose mortgage companies that provide poor support for their mortgage borrowers. It is therefore important to control for mortgage lender or servicer treatment effects.

Table S9 shows that the results are robust to ...

- including a full set of town/city fixed effects into our specifications. The results are displayed in columns (1), (4), and (7) for each of the measures of delinquency, respectively. The inclusion leads to a large increase in the R^2, confirming that regional variation is important in explaining variation in mortgage delinquency, as found in many other studies (12; 13; 14). However, with 175 town fixed effects, the large increase likely also reflects the fact that in many towns, we observe few borrowers. But, the correlation between numerical ability and delinquency remains significant and the point estimate increases.[18]

- including originator (42) and servicer (27) fixed effects to the baseline specification in the remaining Columns. The additional controls increase the R^2, but again leave the coefficient estimate associated with numerical ability unchanged.

- All of these conclusions hold for all three of our measures of mortgage delinquency.

[18] We also estimated a specification in which we included the cumulative amount of house price appreciation experienced between the time the mortgage was originated and the time the survey was conducted. This controls for some of the cross-sectional dispersion in house prices that had developed over the course of the financial crisis. The results are robust to such a specification.

Table S9
Including Town, Servicer, and Originator Fixed Effects

	Fraction of Time in Delinquency			Fraction of Payments Missed			Foreclosure Initiated (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Numerical Ability Index	– 0.081**	– 0.055***	– 0.044***	– 0.045**	– 0.037***	– 0.026***	– 0.105*	– 0.106***	– 0.065**
	(0.033)	(0.020)	(0.015)	(0.022)	(0.011)	(0.009)	(0.056)	(0.032)	(0.025)
Town Fixed Effects?	Yes	No	No	Yes	No	No	Yes	No	No
Originator Effects?	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Servicer Effects?	No	No	Yes	No	No	Yes	No	No	Yes
Control Variables?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.735	0.361	0.350	0.690	0.358	0.337	0.668	0.318	0.298
F-test of H_0: All coefficients are equal to zero	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
N	319	307	293	319	307	293	319	307	293

Notes: Regression coefficients are reported in columns (1) - (6). Marginal effects from probit models are reported in columns (7) - (9). Robust standard errors in parentheses in columns (1) - (6). All specifications contain the full set of control variables as in Table S7.
Level of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

D. Table S10: Numerical Ability or Cognitive Ability?

In the paper we discuss the following results:

- In columns (1), (3), and (5) of Table S10, the verbal IQ measure is included in the estimation. Its inclusion does not affect the magnitude or statistical significance of the estimated coefficient associated with financial literacy. The verbal IQ measure, conditional on the numerical ability measure, is not correlated with the first two measures of delinquency (percent of time behind, and percent of payments behind). However, it does enter significantly into the probit model for the initiation of the foreclosure process. An increase of one standard deviation in the verbal IQ measure (8 points), is associated with a 4.8 percentage point decrease in the foreclosure rate. An important difference between foreclosure and the other two delinquency measures is that foreclosure is initiated by the lender. One possible interpretation of this finding is that lenders may be less likely to foreclose on an intelligent person who is behind, and that this is picked up by our measure of IQ.
- Columns (2), (4), and (6) display the results when the measures of economic literacy and the response times are included in the set of control variables. They are not correlated with any of the three measures of delinquency, and do not affect the point estimate of the numerical ability measure.
- All of these conclusions hold for all three of our measures of mortgage delinquency.

Table S10
Controlling for General Cognitive Skills and Economic Literacy

	Fraction of Time in Delinquency		Fraction of Payments Missed		Foreclosure Initiated (=1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Numerical Ability Index	– 0.047**	– 0.051***	– 0.031***	– 0.033***	– 0.065**	– 0.061**
	(0.019)	(0.019)	(0.011)	(0.011)	(0.027)	(0.028)
Verbal IQ measure	– 0.001	– 0.002	0.000	0.000	– 0.006**	– 0.006**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Savings Scenario correct (DV)		0.002		– 0.000		– 0.051
		(0.036)		(0.021)		(0.058)
Inflation scenario correct (DV)		0.006		0.011		– 0.016
		(0.033)		(0.018)		(0.047)
Reaction time in NA questions		– 0.003		– 0.000		– 0.001
		(0.002)		(0.001)		(0.003)
Control variables?	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.262	0.268	0.242	0.244		
F-test of H_0: All coefficients are equal to zero.	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
N	322	322	322	322	318	318

Notes: Regression coefficients are reported in columns (1) - (4). Marginal effects from probit models are reported in columns (5) - (6). Robust standard errors in parentheses in columns (1) - (4). All specifications contain the full set of control variables as in Table S7.
Level of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

E. Table S11: Control for Mortgage Terms

In the text we mention the following regressions and results:

- Table S11 contains estimation results when mortgage and borrower characteristics are included in the set of control variables. Columns (1), (3), and (5) display the results when differences in contract terms are included. The control variables do not add to the explanatory power of the baseline specification and, consequently, leave the point estimate of the numerical ability index and its standard error, essentially unchanged.
- In columns (2), (4) and (6), LTV and DTI ratios at origination are added to the set of controls. The two variables are not correlated with the delinquency measure, but are correlated with the foreclosure measure. But, more importantly, the inclusion of both variables does not affect the magnitude or statistical significance of the correlation between numerical ability and mortgage delinquency and default.
- All of these conclusions hold for all three of our measures of mortgage delinquency.

Table S11
Controlling for Mortgage Attributes

	Fraction of Time in Delinquency		Fraction of Payments Missed		Foreclosure Initiated (=1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Numerical Ability Index	– 0.042**	– 0.032*	– 0.028***	– 0.026**	– 0.073***	– 0.043**
	(0.019)	(0.020)	(0.011)	(0.011)	(0.028)	(0.023)
Fixed-Rate Mortgage (DV)	0.036	0.033	0.015	0.011	0.028	0.028
	(0.029)	(0.029)	(0.017)	(0.017)	(0.047)	(0.037)
Initial Interest Rate	0.022	0.035*	0.006	0.012	0.016	0.008
	(0.017)	(0.018)	(0.009)	(0.009)	(0.021)	(0.015)
Low-Doc Loan (DV)	0.029	– 0.001	0.011	– 0.008	0.029	0.005
	(0.032)	(0.035)	(0.019)	(0.020)	(0.044)	(0.034)
Prepayment Penalty (DV)	– 0.005	0.032	0.008	0.031*	0.033	0.056
	(0.027)	(0.030)	(0.016)	(0.017)	(0.042)	(0.037)
Log (origination amount)		0.115***		0.070***		0.093**
		(0.037)		(0.023)		(0.044)
Loan-to-value ratio		– 0.009		0.018		0.517***
		(0.088)		(0.052)		(0.143)
Debt-to-income ratio		0.002		0.001		0.003*
		(0.002)		(0.001)		(0.002)
Control variables?	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.302	0.335	0.288	0.331		
F-test of H_0: All coefficients are equal to zero.	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
N	315	288	315	288	311	286

Notes: Regression coefficients are reported in columns (1) - (4). Marginal effects from probit models are reported in columns (5) - (6). Robust standard errors in parentheses in columns (1) - (4). All specifications contain the full set of control variables as in Table S7.
Level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

F. Table S12: The estimation partialing out the mortgage conditions for Figure 2

- In Table S12, we display the coefficient estimates on which we base the profile displayed in Figure 2 in the main text. The results display the same overall pattern as in Table S11.

Table S12
Controlling for Mortgage Attributes

	Fraction of Time in Delinquency (1)	Fraction of Payments Missed (2)	Foreclosure Initiated (=1) (3)
Numerical Ability Index = 2	0.002	– 0.028	0.027
	(0.043)	(0.027)	(0.069)
Numerical Ability Index = 3	– 0.055	– 0.032	– 0.070
	(0.056)	(0.036)	(0.089)
Numerical Ability Index = 4	– 0.080	– 0.089*	– 0.196*
	(0.064)	(0.036)	(0.098)
Fixed-Rate Mortgage	0.028	0.006	0.030
	(0.029)	(0.017)	(0.048)
Initial Interest Rate	0.038*	0.014	0.025
	(0.018)	(0.009)	(0.029)
Low-Doc Loan (DV)	– 0.009	– 0.013	– 0.040
	(0.035)	(0.020)	(0.058)
Pre-payment penalty (=1)	0.031	0.031	0.094
	(0.030)	(0.017)	(0.049)
Log(mortgage amount)	0.127**	0.068**	0.143*
	(0.039)	(0.024)	(0.064)
Loan-to-value Ratio	0.018	0.029	0.289
	(0.091)	(0.054)	(0.147)
Debt-to-Income Ratio	0.002	0.001	0.002
	(0.002)	(0.001)	(0.003)
F-test that Numerical ability has no impact	$p = 0.26$	$p = 0.04$	$p = 0.01$
R^2	0.332	0.329	0.289
p	0.000	0.000	0.000
N	288	288	288

Notes: Regression coefficients are reported in columns (1) - (3). Robust standard errors in parentheses specifications contain the full set of control variables as in Table S11, columns (2), (4) and (6), respectively.

Level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

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