Sustainable Homeownership and Numerical Ability*

Kristopher Gerardi[†] FRB Atlanta

Lorenz Goette[‡] University of Lausanne

Stephan Meier[§] Columbia University

October 22, 2009

VERY PRELIMINARY DRAFT. PLEASE DO NOT DISTRIBUTE OR QUOTE.

ABSTRACT

The recent decreases of house prices has lead to a dramatic increase in delinquencies and foreclosures of subprime mortgages. The resulting subprime mortgage crisis lead to the biggest financial crisis since the Great Depression. What triggered the massive defaults in the subprime sector is still unclear.

This paper investigates whether borrowers limited numerical abilities are associated with mortgage delinquencies and defaults. We measure numerical and cognitive ability among subprime homeowners in a survey and match the measures to objective loan performance data. The results show a large and significant effect of numerical ability on delinquencies and foreclosures. The result is robust to controlling for a broad set of socio-demographic control variables and is not driven by financial literacy, cognitive abilities or specifics of the mortgage contracts.

*We thank Chris Foote, Jeff Fuhrer, John Leahy, Robert Shiller and seminar audiences at FRB Boston, the ASSA meetings 2009, Columbia University and ... We are especially grateful to the FRB Boston, where the authors were all employed at the time the survey was conducted, and which provided the funding for the survey. The views expressed in this paper are, however, those of the authors and not necessarily those of the Federal Reserve System or the Federal Reserve Bank of Boston.

[†]kristopher.gerardi@atl.frb.org, Federal Reserve Bank of Atlanta, Research Department, 1000 Peachtree Street N.E., Atlanta, GA 30309, USA.

[‡]lorenz.goette@unil.ch, University of Lausanne, Department of Economics, Internef, 1015 Lausanne-Dorigny, Switzerland.

[§]sm3087@columbia.edu, Columbia University, Graduate School of Business, 3022 Broadway, New York, NY 10027, USA; Phone: +1(212)851-1801.

I. Introduction

One of the goals of policymakers in the U.S. over the past half century has been to encourage homeownership. However, the presence of substantial borrowing constraints in the mortgage market like downpayment requirements and debt-to-income constraints served as a big barrier to this goal. Consequently, numerous policies have been enacted over the years to relax these borrowing constraints and achieve the goal of a higher homeownership rate. Such policies include, but are not limited to, the deductibility of mortgage interest (Tax Reform Act of 1986), the Federal Housing Administration (FHA) lending program, the Community Reinvestment Act (CRA), and the affordable housing goals applied to the Government Sponsored Enterprises (GSEs). These policies promoted homeownership by lowering financing costs for the average borrower, and opening housing finance markets to more low income and minority households. The standard model in economics implies that agents are rational and fully understand their environment. In such a model, making credit available to more individuals will unambiguously increase welfare, and so from that perspective these policies were viewed by many as welfare-enhancing. However, the onset of the housing crisis has called this view into serious question, as many of these same low-income and minority borrowers have lost their homes to foreclosure

The subprime mortgage crisis that began in the second half of 2007 in most areas of the United States has been well documented in the literature. In addition to fueling a nationwide foreclosure crisis that is still adversely impacting the U.S. housing market today, it spilled over into the broader macroeconomy, and caused the worst global financial crisis since the Great Depression. The combination of increasingly complex mortgage instruments and the expanded access of credit to low income and minority borrowers over the past decade, has naturally led many market observers to conclude that a lack of financial sophistication on the part of mortgage borrowers may have played an important role in the housing bust. While there have been many theories proposed to explain the causes of the subprime mortgage crisis[1], the role of irrationality on the part of individuals has not received much attention in the academic literature. Many market observers, including Akerlof and Shiller (2009), believe that departures from full rationality are an important factor in explaining the decline of the subprime mortgage market and the subsequent foreclosure crisis. While these authors point to "irrational exuberance" or "animal spirits" corresponding to the widely-held belief at the peak of the housing market that house prices would continue rising, others including Boeri and Guiso (2007) have focused on the lack of financial literacy that seemingly characterized subprime mortgage borrowers as an important contributor.

This paper begins to fill in this gap in the literature. We present evidence that a lack of financial literacy did in fact play a role in the adverse outcomes of subprime mortgage borrowers. We conducted a survey in the summer of 2008 of a sample of subprime borrowers in the states of Connecticut, Massachusetts, and Rhode Island who obtained mortgages in 2006 and 2007, and measured their numerical and cognitive ability using methods standard in the literature. Our sample of subprime borrowers is taken from a dataset on privately securitized subprime mortgages that the Federal Reserve Bank of Boston purchased from First American LoanPerformance. This dataset contains detailed information regarding mortgage terms and performance, which allows us to track the sample over time and follow their subsequent mortgage outcomes. Conditional on a broad set of control variables we find a large and statistically significant effect of numerical ability on mortgage delinquency and default. This finding is robust to the inclusion of controls for income, education, risk aversion, time preferences, and even the extent of prior experience in mortgage markets, leading us to conclude that the effect is highly specific to numerical ability.

While the consequences of limited numerical ability have not been previously studied in mortgage markets, they have in other contexts. Recent research by Banks and Oldfield

[1] These explanations include falling house prices that occurred from the deflation of the housing bubble in the U.S. (Gerardi et al., 2009), the relaxation of mortgage underwriting standards that may have fueled the housing bubble (Mian and Sufi, 2009; Demyanyk and Hemert, 2009, add more references), predatory lending on the part of housing finance institutions (Congressional Oversight Panel of the Troubled Assets Recovery Program , COP, add more references), and various others.

(2007) and Lusardi and Mitchell (2009) suggests that limited numerical ability is associated with worse consumption and savings outcomes. Our results are broadly consistent with the findings of these studies, and point to the importance of addressing limited financial literacy in the post-crisis reformation of mortgage markets.

II. Literature Review (to be completed)

Strong presumption that departures from full rationality are an important factor in explaining abysmal performance of subprime mortgages (Akerlof and Shiller, 2009).

However, no direct evidence on this mechanism.

- Evidence on determinants of mortgage performance, but little information on individuals.

- Evidence on the association between limitations in numerical ability and savings / consumption outcomes, but no evidence on mortgages.

A large number of studies show that decline in house prices lead to a strong increase in mortgage defaults (Gerardi, Shapiro and Willen, 2008; Mayer and Pence, 2009; Foote et al, 2008, 2009)

- Many defaults come after a long period of delinquencies, which is difficult to reconcile with "ruthless default" model (Foote et al., 2009).
- Higher local unemployment also increases defaults (Gerardi, Shapiro and Willen, 2008).

▷ No evidence on how individual characteristics affect defaults.

▷ Only indirect evidence on motives for defaults.

A burgeoning literature documents that individuals have very limited numerical abilities.

- Make mistakes in most basic calculations (Banks and Oldfield, 2007; Lusardi and Mitchell, 2007; Lusardi, 2006)

Strong evidence that limited numerical ability is associated with significantly lower savings (Banks and Oldfield, 2007; Lusardi and Mitchell, 2009)

- Effect is significant even after controlling for other aspects of cognitive skills.

- Effect is quantitatively large.

▷ Provides a testable hypothesis for mortgage defaults: Are individuals with limited numerical ability more likely to default?

III. Survey Design

In this section we provide a detailed discussion of the sample and survey design of our analysis. First, we describe the pool of mortgage borrowers that we chose to draw our survey sample from. Then, we discuss the survey, focussing on both the questions as well as an analysis of potential sample selection bias.

A. The Sample

We combine two micro-level datasets that contain information on mortgages to construct our survey sample. The first is a loan-level dataset constructed and maintained by FirstAmerican LoanPerformance (LP). LP 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. We use LP data that the Boston Fed purchased in mid-2007. This dataset covers Massachusetts, Connecticut, and Rhode Island from the early-1990s through March 2009. The LP 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 (borrowers monthly debt payment divided by his monthly income). Finally, the LP dataset identifies the type of MBS each loan was packaged into — subprime, Alt-A, or prime.[2] Unfortunately, the LP dataset does not include demographic information such as race, education, or gender.

The second dataset we use 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 dataset 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 that we use 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 LP data, this data 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 mortgage borrowers. This data allows us to construct a history of mortgage transactions for a household in a given property. In other words, with the Warren Data we are able 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, we are able to construct a precise measure of the cumulative loan-to-value ratio at the time of purchase,[3] and to keep track of the total number of mortgages obtained by each homeowner.

[2]The sample of prime loans in the LP 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.

[3]The LP 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.

We matched data from the LP dataset to data from the Warren Group, registry of deeds dataset. We used only the sample of first-lien mortgages contained in subprime MBS from the LP dataset that were originated in 2006 and 2007. The match was based on the zip code of the property (LP 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.[4]

We randomly selected mortgages from this matched dataset to construct our sample of borrowers for the survey. We used two different strategies to contact the borrowers. One strategy involved calling borrowers, which was possible because we have borrower names and addresses from the Warren dataset. We used an internet search engine to find phone numbers[5]. The second strategy that we used was to mail invitations to participate in the survey to the addresses listed in the Warren data.

Table I displays summary statistics for these two strategies. In the summer of 2008 (June - August), we called a total of 3,523 borrowers.[6] For approximately one-third (1,043), we were unable to reach a working phone line, while for a little more than one-third (1,366), we were able reach a working line, but unable to verify that the phone number corresponded to the borrower in the data.[7]. Finally, we were able to positively identify the borrower in slightly less than one-third of the cases. In half of those cases (559) we were unable to speak

[4]The main issue that contributed to the low match rate was the inconsistent definition of dates between the two datesets. The date listed in LP is the date of origination, while the date listed in the Warren 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 our matching algorithm, and consequently often found cases of multiple mortgages of the same amount, originated in the same zip code, in a given data range. We were forced to throw out these cases of multiple matches. The identity of the originating institution often helped us in these cases, but unfortunately the LP data contain only sparse information on this variable.

[5]The search engine we use is USAPeopleSearch.com

[6]We often found multiple possible phone numbers for each borrower in the data, so the actual number of phone numbers that we called was much larger than the number of borrowers.

[7]This included cases in which nobody picked up the phone and cases in which we reached an answering machine and left a message, but received no response (and could not identify the borrower from the answering machine message)

to the actual borrower, and thus never received a response to our interview request.[8] In 296 cases we reached the borrower, but he or she refused to participate in the survey,[9] and in 259 cases we reached the borrower and he or she agreed to participate in the survey. Based on these statistics, we report two participation rates for the phone contact portion of our study in the first column of Table I. Of the borrowers that we actually spoke to directly, 46.6 percent agreed to participate in the survey, while 10.4 percent of the borrowers for whom we were able to verify a correct phone number agreed to participate.

We also mailed almost 5,000 invitation letters out to borrowers for whom we could not find phone contact information. The invitation letter was one page (two-sided) and contained a brief description of the survey and the survey conductors. We also included a small response card that contained a question asking if the borrower would be interested in participating in the survey, and space for the borrowers who agreed to participate to list working phone numbers and times of the day that were best to contact them. We included a response envelope and postage. In the vast majority of cases (97.5 percent), we never received a response. When we did receive a response, we attempted to call the borrower to conduct the interview. Of the borrowers that we were able to reach (93), approximately 97 percent agreed to participate in the survey (74 percent of the borrowers for whom we could verify a correct phone number).

Sample selection bias is always a serious concern in surveys such as this one. Table II contains detailed information on the presence of sample selection in observable mortgage and borrower characteristics. The table compares average characteristics between the responders and non-responders for both the phone call sample (top panel) and the mailing sample (bottom panel). There is no evidence of sample selection in the phone call sample, as the difference in averages for all variables is never statistically significant at even the 10 percent level. Furthermore, there is very little evidence of sample selection in the mailing sample.

[8] In most of these cases we either left a message on an answering machine and never heard back, or spoke to another member of the household, but were not able to reach the actual borrower.

[9] We include cases in which the borrower agreed to participate at a later date, but never followed through on that agreement.

The only difference that is statistically significant (at the 10 percent level) is the average mortgage size.

While it does not appear that selection into the survey sample is an issue, there is an important attrition bias present in the survey by construction. 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) 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 that we imposed for inclusion into the sample was that each borrower not be in the foreclosure process at the time that the survey was conducted. Because of this design, 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. Table III displays the distribution of the time to default for all subprime mortgages originated in 2006 and 2007 in the LP dataset for which the servicer has initiated foreclosure proceedings. The average number of months to default is slightly less than 18, while more than one-quarter of the defaults occurred within one year of origination. We discuss this issue at greater length below, where we argue that the effects we find of financial literacy on delinquency and default in this analysis are likely lower bounds, as the attrition bias present in our sample likely means that the most financially illiterate subprime mortgage borrowers defaulted before we conducted the survey, and thus did not make it into our sample.

B. The Survey

On average, the survey took about 20 minutes to complete, and individuals were compensated $20 for their participation. The survey contains four important segments: measures of cognitive skills including cognitive ability and numerical ability, measures of time and risk preferences, questions about the mortgage contract and the experience in shopping for the mortgage, and finally, socio-demographic questions.

B.1. Financial literacy and cognitive ability

We measure numerical ability using five questions developed by Banks and Oldfield (2007). 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?

Banks and Oldfield (2007) suggest constructing an index of numerical ability comprised of four separate groups from the responses of these 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 gets questions 2, 3, and 4 incorrect. 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 this group). 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 IV shows the distribution of the numerical ability index in our sample as well as the distribution from Banks and Oldfield. 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.

We also measure another component of financial literacy relating to an individual's basic understanding of economic mechanisms. We use two questions from Lusardi and Mitchell (2009) that have to do with money illusion. They are as follows:

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 our sample, approximately 79 percent of borrowers answered the first question correctly, and 74 percent answered the second question correctly.

In order to try to separate the effects of financial literacy from those of intelligence more broadly, we attempt to measure cognitive ability. We use a verbal fluency measure that was introduced by Lang et al. (2005) and shown to be highly correlated with IQ. The question is

In the next 90 seconds, name as many animals as you can think of. The time starts now.

Dohmen et al. (2009) also use this question to measure cognitive ability, and Figure 1 compares the distribution of responses in our survey to their study. The shape and first few moments of the distributions are very similar.

B.2. Preferences

We ask a series of hypothetical questions that allow us to calculate discount factors (see for similar approaches Meier and Sprenger, 2009a,b) and risk preferences (e.g., Burks et al., 2009). In addition, we ask participants to assess their levels of impatience and risk tolerance on a scale from 0 to 10 as in Dohmen et al. (2005).

B.3. Mortgages

The survey contains numerous questions about the characteristics of the mortgage contracts including questions about the size of the mortgage, initial interest rate, whether the mortgage is an adjustable-rate or fixed-rate instrument, whether the mortgage was for the purchase of the home or a refinance of a previous loan, and the existence of a prepayment penalty. In addition to all of these characteristics the combined LoanPerfomance and Warren dataset also contains information on the credit score of the borrower, the initial cumulative loan-to-value ratio, the extent of the documentation provided to the lender, and the monthly debt-to-income ratio of the borrower (including other forms of debt).

We also asked participants whether they were first-time homebuyers, and questions about their experience in purchasing the home and obtaining the mortgage. For example, we asked each participant if they obtained information about mortgage pricing before obtaining their loan, and how they obtained the information (internet, relative, friend, etc.). We also asked whether they had taken a home buying class or had received counseling. We are also able to use the dataset to obtain information on previous experience in mortgage markets. The Warren Data has information on all mortgages obtained since the house purchase (going back to January 1987), which allows us to calculate the number of mortgages taken out by each household before the current one.[10]

B.4. Socio-demographics

Finally, the survey contains detailed questions about socio-demographic characteristics and information regarding household income and employment status. We asked participants 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 to 10). We included questions regarding the amount of household income, the number of family members that contribute to household income,

[10]We only see mortgage information for the current property, and do not have any information on previous residences.

and the variability of household income. Finally, we asked participants about their current employment status and the number of times that they had been out of work over the previous five years.

Table V displays sample means and standard deviations of the survey variables for each of the four financial literacy groups discussed above. The patterns for each variable across the different financial literacy groups accord well with intuition. Proficiency with the English language, the percent of households born in the United States, cognitive ability, and household income is monotonically increasing in the level of numerical ability as measured by the four groups. In contrast, income volatility, the percentage of black and hispanic households, the percentage of households with a high school diploma or less, the level of the initial contract interest rate, and the percentage of low documentation mortgages is monotonically decreasing in the level of numerical ability. The pattern for the two variables that summarize a household's experience in mortgage markets is very interesting. The percentage of first-time homebuyers is monotonically decreasing in the level of numerical ability, as 70 percent of households in the lowest numerical ability group are first-time homebuyers, while only 33 percent of households in the highest group are first-time homebuyers. This pattern suggests that the least experienced households with respect to buying a home are also the most financially illiterate (as measured by numerical ability). But, the average number of previous mortgages obtained by a household is also monotonically decreasing in the level of numerical ability. This implies that on average, households with the most experience in mortgage markets are the most financially illiterate, and seems to contradict the relationship between financial literacy and experience in housing markets. These two observations can be reconciled by noting that a much lower percentage of mortgage originations were for the purchase of a home for the lower financial literacy groups as compared with the higher financial literacy groups. In addition, the lower financial literacy groups are characterized by a disproportionate of households that have frequently refinanced. We conjecture that this is a result of a greater amount of cash-out refinancing activity on the part of households characterized by lower financial literacy. There are a few other interesting patterns that are worth discussing. Average credit scores (as measured by FICO) are much higher for the most financially literate group of borrowers as compared to the three lower groups, but there is very little difference in average credit scores across groups 1, 2, and 3. The correlation between financial literacy and higher education appears puzzling in the table, but that reflects the manner in which we constructed the education groups. We constructed the groups to be mutually exclusive, so for example a household that obtained an undergraduate college degree as well as a professional degree would be given a value of 1 in the "Higher degree" group, but a value of 0 in the "College" group (even though that household also obtained an undergraduate college degree). This is the reason for the significant decrease in the "College" variable percentage when moving from the second most financially literate group of households to the most financially literate group. The highest group is characterized by a large percentage of households that obtained a graduate degree (about 40 percent), and by only a small percentage of households that obtained an undergraduate college degree without a graduate degree (25 percent).

IV. Empirical Design

A. Measures of Mortgage Delinquency

We use three different measures of mortgage delinquency in the empirical analysis. First, we construct a variable that measures the amount of time a borrower is behind on his mortgage payments. To be precise, it measures the percent of months that a borrower is delinquent on his mortgage. This variable does not reflect the extent of delinquency. For example, it would not distinguish between a borrower who is only 1 payment behind for 5 months from a borrower who is 1 payment behind for 1 month, 2 payments behind for 1 month, and 3 payments behind for 3 months. In both of these cases the variable would take the same value (as long as both borrowers have held the mortgage for the same amount of time).

The second measure of mortgage delinquency is the percent 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.[11]

Our third 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 his mortgage (or equivalently is 4 payments behind).[12]

Table VI contains information on the distributions of the three delinquency measures in our sample. The average borrower in our sample is in delinquency 11 percent of the time, and has missed 20 percent of his mortgage payments. Half of the borrowers in our sample are delinquent more than 5 percent of the time and have missed more than 7 percent of their mortgage payments, while 10 percent of the borrowers are delinquent more than 30 percent of the time and have missed more than 60 percent of their payments. Almost 20 percent of the borrowers in our sample have been in the state of foreclosure at some point in their mortgage experience.

Figure 2 displays histograms that show the average delinquency value for each numerical literacy group (with standard error bars). There are three histograms corresponding to each of the three delinquency measures. There is a monotonically decreasing relationship between the percent of time delinquent and financial literacy (Panel A). Borrowers in the lowest

[11]This variable differs substantially from our first measure since it does not take into account the amount of time spent in delinquency. A borrower who makes 6 consecutive mortgage payments after missing 3 mortgage payments in a row, but who does not make up for the missed payments would be assigned the same value of percent of payments missed (33 percent) as a borrower who misses 3 consecutive payments, repays those missed payments immediately, and then makes 6 consecutive payments. In contrast, we would assign the first borrower a value of 100 percent for the percent of time spent in delinquency and the second borrower a value of 33 percent.

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

financial literacy group on average spend almost 25 percent of the time in delinquency, while those in the highest group spend on average only 12 percent of the time in delinquency. In Panel B we also see a similar relationship between the percent of missed mortgage payments and financial literacy. The lowest group has missed almost 15 percent of mortgage payments on average, while the highest group has missed only 6 percent of payments on average. Foreclosure also appears to be negatively related to financial literacy (Panel C). While there is a small difference in the percentage of foreclosure between the first and second financial literacy group (the lowest group actually has a lower percentage of foreclosures than the second group), the third group is characterized by a significantly lower percentage of foreclosures than the first two groups (15 percent versus more than 20 percent), while the fourth and highest group is characterized by a significantly lower percentage of foreclosures than the third group (7 percent versus 15 percent).

B. Empirical Specification

Our main empirical specification takes the following form:

$$D_i = \gamma NA_i + x_i\beta + e_i \tag{1}$$

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 literacy group of household i, x_i represents a vector of control variables, and e_i is the residual. We estimate the equation by ordinary least squares (OLS), accounting for possible heteroskedasticity in the standard errors.

For our third measure of delinquency, the initiation of foreclosure proceedings, we estimate a probit model,

$$Pr[F_i = 1|NA_i, x_i] = \Phi(\gamma NA_i + x_i\beta) \tag{2}$$

where F_i takes the value of one if foreclosures proceedings have been initiated on the borrower and zero otherwise.

We employ two different specifications for numerical ability in the regressions. Our preferred specification is to include the index with four possible values (1, 2, 3, and 4) corresponding to each of the four numerical literacy groups. This specification assumes a linear relationship between delinquency and the groups. For example, it assumes that the effect of being in group 1 versus group 2 is the same as the effect of being in group 3 versus group 4. In order to allow for differential effects between the groupings, we estimate a second specification in which we include a dichotomous variable for each numerical literacy group (except for the group 1, which is taken to be the reference group). We use a baseline vector of controls that includes largely mortgage-related and demographic variables. The variable set includes English proficiency (index from 0 - 10), volatility of household income (on a 3-point scale 1 "It's been pretty stable"; 2 "It has gone up and down a little over the last few years"; 3 "it has gone up and down a lot over the last few years"), indicator variable for whether the household head was born in the United States, number of years spent in the United States, indicator variables for the racial composition of the household head (asian, black, hispanic, Native American, other), a set of mutually exclusive education dummy variables (less than high school diploma, high school diploma, less than undergraduate college degree, college degree, professional or graduate degree), employment status (at the time of interview), age, number of children, FICO score (at the time of mortgage origination), an indicator variable for whether the purpose of the mortgage was for the purchase of the home, risk tolerance (index from 0 - 10), discount factor, indicator variable for dynamically inconsistent time preferences (i.e. present-bias), the number of months since origination, the number of months since the purchase of the home, and an indicator variable for whether the property is an investment or vacation home. We also include an indicator variable for the year of mortgage origination (2006 is the reference group) and a constant.

In addition to this baseline set of control variables, we also perform a series of robustness checks in which we include additional controls. The idea behind this exercise is to try and identify the channel through which numerical ability is affecting mortgage payment behavior. It is possible that our measure of numerical ability is correlated with some other borrower attribute or choice that is itself a determinant of mortgage delinquency and default. Possible candidates are cognitive ability, financial literacy more generally, the extent of experience in mortgage and housing markets, and the choice of certain types of mortgage contracts like low documentation mortgages, high loan-to-value ratio mortgages, etc.

V. Results

A. Baseline Findings

The results from the estimation of equations (1) and (2) are displayed in Table VII. The table contains three panels corresponding to the three different measures of mortgage delinquency. There are three columns of results in each panel. The first column displays the unconditional correlation between the mortgage delinquency measures and the numerical ability index (without any controls); the second column includes the baseline set of control variables; and the third column also includes the baseline control set, but contains the alternative specification for numerical ability discussed above (separate dummy variables for each group). The results of the estimation show a statistically significant, negative correlation between the numerical ability index and mortgage delinquency measures. The magnitude of the coefficient estimates is relatively large, and is robust to the inclusion of the set of control variables. For example, a unit increase in the numerical ability index (moving from group 1 to 2, 2 to 3, or 3 to 4) is associated with a 4.3 percentage point decrease in the percent of time spent in delinquency (column (1)). On average, borrowers in our sample have had their mortgage for about 29 months (Table V) and have spent 11 percent of the time behind on their payments (Table VI), which corresponds to just over 3 months. Thus, on average, a borrower with slightly more numerical ability, is estimated to spend approximately 1 less month behind on his mortgage ($0.043 * 29$ months). The absolute value of the coefficient estimate increases to 0.047 with the addition of the control variables (column (2)).

The results for the fraction of mortgage payments missed are similar. A unit increase in the numerical ability index is associated with a 2.4 percentage point decrease in the percent of mortgage payments missed (2.6 percentage point decrease with controls). On average, borrowers in our sample have missed 20 percent of their mortgage payments (Table V), so this estimate suggests that for the average borrower, slightly higher numerical ability corresponds to a decrease in missed mortgage payments of about 0.7. Finally, a one unit increase in the numerical ability index is associated with an approximately 6 percentage point decrease in the probability of foreclosure (6.5 percentage points with controls).

Results reported in columns (3), (6), and (9) provide some further insight into the relationship between mortgage delinquency and the numerical ability index, as this more flexible specification allows for a different effect for each numerical ability group. The columns show a monotonically decreasing relationship between the measures of mortgage delinquency and the numerical ability index, and generally seem to support the linear specification assumed in the other columns.

Do we want to discuss the other covariate estimates here or not?

B. The Effect of Cognitive Ability and Economic Literacy

A very plausible explanation for the results reported in Table VII is that mortgage delinquency is determined, in part, by the ability or intellect of a borrower, which is in turn correlated with our index of numerical ability. To address this possibility, we attempted to measure cognitive ability (discussed in section B.1. The positive correlation between our measure of cognitive ability and the numerical ability index is clear in Table V. The group with the lowest level of numerical ability scored the lowest on the cognitive ability question, while the two highest numerical ability groups scored the best. To test the hypothesis that the correlation between numerical ability and mortgage delinquency is actually being driven by the effect of cognitive ability on mortgage payment behavior, we included the cognitive ability measure as a separate control variable in the estimation of equations (1) and (2). The results are reported in columns (1), (3), and (5) in Table VIII. Cognitive ability does not have an effect on the percent of time spent in delinquency or the percent of mortgage payments missed, and its inclusion does not significantly effect the coefficient estimate associated with the numerical ability index. It does have a small, statistically significant, negative impact on the probability of foreclosure, and its inclusion in equation (2) decreases the absolute value of the coefficient estimate associated with numerical ability by almost 25 percent (from 0.065 to 0.049).

It is also possible that our measure of numerical ability is really picking up the effect of economic and financial literacy on mortgage payment behavior more generally. To address this possibility, we include in the estimation the results of the two questions from Lusardi and Mitchell (2009) discussed above in section B.1. The results are displayed in columns (2), (4), and (6) in Table VIII. The estimates associated with the answers to the two questions are not statistically significant, and do not affect the estimates of the numerical ability index or the cognitive ability measure.

C. The Effect of Mortgage Characteristics

Another potential explanation for the results is that borrowers with lower numerical ability are more likely to obtain riskier mortgages, characterized by either fluctuating payments or higher payments, which result in higher default and delinquency rates. For example, mortgages characterized by high debt-to-income ratios and high initial interest rates may be indicative of borrowers who have taken out a significant amount of debt relative to their income and wealth, which could lead to a higher incidence of delinquency and default in the event of financial distress. Adjustable-rate mortgages with their fluctuating payment schedules may also contribute to higher default rates.[13] Borrowers who provided small

[13] There are several recent papers in the literature that dismiss the idea that interest rate resets contributed significantly to the foreclosure crisis. Examples include Mayer et al. (2009), Foote et al. (2008),

downpayments (high initial loan-to-value ratios) are also more likely to default, all else equal, as they are more likely to find themselves in a position of negative equity in the event of a housing price decline.[14] Finally, mortgages characterized by low or zero documentation of income and assets may be signals of higher default risk.

The estimation results with these controls included are displayed in Table IX. Columns (1), (3), and (5) add the initial interest rate and indicator variables for fixed-rate mortgages and low documentation mortgages to the control set, and columns (2), (4), and (6) include these variables as well as the debt-to-income ratio and loan-to-value ratio at origination (we lose almost 30 observations because of incomplete reporting of debt-to-income ratios in the LoanPerformance data). The addition of these variables do not substantially effect the magnitude or statistical significance of the numerical ability estimates in the specifications corresponding to the percent of time spent in delinquency and the percent of missed payment (except in column (2), in which the estimate decreases by about 1 percentage point and is statistically significant at the 10 percent level instead of the 1 percent level). However, the addition of LTV in the estimation of equation 2 does decrease the numerical ability estimate by about 25 percent. The result that LTV is significantly, positively correlated with the probability of foreclosure, but not our other delinquency measures is not surprising, and is supported by theory (see Foote et al. (2008) for a detailed discussion).

D. The Effect of Experience in Mortgage and Housing Markets

Experience in housing and mortgage markets may also provide an explanation and channel by which financial literacy and numerical ability affects mortgage payment behavior. It may very well be the case that borrowers with prior experience in making housing purchase and mortgage decisions may have developed more financial budgeting and numerical skills, which has helped them in achieving successful mortgage outcomes. We can test this hypothesis since the survey contains questions about the amount of research that borrowers performed

and Demyanyk and Hemert (2009).

[14] See Gerardi et al. (2009) for an analysis of the relationship between negative equity and foreclosure.

before purchasing their homes and obtaining their mortgages, as well as a question about whether participants were first-time homebuyers or repeat homebuyers. In addition, the unique structure of our data enables us to measure the number of previous mortgages obtained by borrowers on their current home. This allows us to measure variation in the extent of mortgage market experience for the group of first-time homebuyers.

Estimation results including controls for prior experience in housing and mortgage markets are contained in Table IX. The coefficient parameter associated with the first-time homebuyer indicator is positive and significant at the 10 percent level in column (1) and is significant at the 5 percent level in column (3). However, the inclusion of these controls does not affect the correlation between numerical ability and mortgage delinquency and default, which suggests that the effect of experience on mortgage payment behavior is not operating through the numerical ability index.

E. Robustness Checks

We perform a few robustness checks to make sure that model misspecification is not playing a role in the estimation results. Our first robustness exercise is to estimate a Tobit model rather than a least-squares specification for the cases in which the dependent variable is the percent of time spent in delinquency and the percent of payments missed. By definition, these variables are truncated at the value of zero (you can never do better than never missing a mortgage payment), so a truncation bias may be impacting the results reported above. Table XI contains the estimated marginal effects of a Tobit specification (both with controls and without controls). In all cases, the coefficient estimates are actually larger in magnitude than those obtained from least-squares estimation.

We also estimate equations (1) and (2) including a set of town, lender, and servicer fixed effects. Table XII contains the results. Even though we lose some observations (due to the instances in which we do not have multiple loans located in the same town, originated by the same lender, and serviced by the same servicer), the estimates of numerical ability retain their statistical significance and are larger in magnitude in basically all of the fixed-effects specifications.

VI. Conclusion

This paper investigates whether subprime borrowers with limited cognitive abilities are more likely to be delinquent on their mortgage and more likely to default. We conduct an extensive survey to measure subprime borrowers' numerical and cognitive abilities and match the individual-level measures to mortgage information and payment data from LoanPerformance. The results show a significant and quantitatively large association between numerical ability and mortgage delinquency. Foreclosures are two-thirds lower in the top-numeracy group compared to the bottom numeracy group. The effect is robust to several measures of delinquency and to the inclusion of a wide set of socio-economic and demographic control variables. The effect is specific to numerical ability and not driven by general cognitive skills or economic literacy. Our results therefore show that limitations in numerical ability are common and that there is a strong link to mortgage defaults.

The results suggest that numerical ability does not act through attributes of the mortgages on delinquencies. Controlling for details of the mortgage contract leaves the association between numerical ability and delinquencies unchanged. This suggests that limited numerical abilities might lead to other mistakes, e.g. too much spending, too little savings or inappropriate reaction to income / consumption shocks. However, the current data does not allow answering this question conclusively. This result would suggest that borrowers with limited numerical abilities were unlikely to have been steered into unfavorable contract terms. But, our results also do not rule out completely that limitations in numerical abilities lead to unfavorable mortgage terms or contracts, which can cause defaults. We survey individuals approximately 2 years after the mortgage had been originated. Many subprime defaults (about 60 percent) happen before that and those defaults might have been caused by unfavorable mortgage terms.

The results show that a normally unobservable characteristic/ability can explain part of the heterogeneity in defaulting. This finding provides insights to lending firms on designing contract terms and default reduction strategies. Individuals who have difficulties dealing with numbers seem to be more risky, controlling for usual indicators like FICO scores. In order to select a less-risky costumer pool, lending institutions might want to make application procedures more complicated. Making credit applications slightly harder to fill out for numerically challenged costumers should result in a more creditworthy pool of borrowers.

References

Akerlof, George and Robert Shiller, *Animal spirits: how human psychology drives the economy, and why it matters for global capitalism*, Princeton University Press, 2009.

Banks, J. and Z. Oldfield, "Understanding Pensions: Cognitive Function, Numerical Ability and Retirement Saving," *Fiscal Studies*, 2007, *28* (2), 143170.

Boeri, T. and L. Guiso, "Subprime crisis: Greenspan's Legacy," *VoxEU.org* 2007.

Burks, Stephen, Jeffrey Carpenter, Lorenz Goette, and Aldo Rustichini, "Cognitive skills affect economic preferences, strategic behavior, and job attachment," *Proceedings of the National Academy of Science*, 2009, *106* (19), 7745–7750.

Congressional Oversight Panel of the Troubled Assets Recovery Program (COP), "*Foreclosure Crisis: Working Toward A Solution*," 2009.

Demyanyk, Y. and O. Van Hemert, "Understanding the Subprime Mortgage Crisis," *Review of Financial Studies*, 2009, p. forthcoming.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde, "Are Risk Aversion and Impatience Related to Cognitive Ability?," *American Economic Review*, 2009, p. forthcoming.

_ , _ , _ , _ , Juergen Schupp, and Gert G. Wagner, "Individual risk attitudes: New evidence from a large, representative, experimentally-validated survey," *Journal of the European Economic Association*, 2005, p. Forthcoming.

Foote, Christopher, Kris Gerardi, Lorenz Goette, and Paul Willen, "Reducing foreclosures: No easy answers," *NBER working paper*, 2009.

Foote, Christopher L., Kris Gerardi, Lorenz Goette, and Paul S. Willen, "Just the facts: An initial analysis of subprimes role in the housing crisis," *Journal of Housing Economics*, 2008, *17* (4), 291–305.

Gerardi, Kris, Adam Shapiro, and Paul Willen, "Decomposing the Foreclosure Crisis: House Price Depreciation versus Bad Underwriting," *Federal Reserve Bank of Atlanta Working Paper 2009-25*, 2009.

Lang, F., D. Hahne, S. Gymbel, S. Schropper, and K. Lutsch, "Erfassung des kognitiven Leistungspotenzials und der Big Five" mit Computer-Assited-Personal-Interviewing (CAPI): Zur Reliabilitat und Validitat zweier ultrakurzer Tests und des BFI-S," *DIW Research Notes, Berlin* 2005.

Lusardi, Anemaria and Oivia Mitchell, "How Ordinary Consumers Make Complex Economic Decisions: Financial Literacy and Retirement Readiness," *NBER Working Paper No. 15350*, 2009.

Lusardi, Annamaria, "Financial Literacy and Financial Education: Review and Policy Implications," *NFI Policy Brief No. 2006-PB-11*, 2006.

_ **and Olivia S. Mitchell**, "Baby boomer retirement security: The roles of planning, financial literacy, and housing wealth," *Journal of Monetary Economics*, 2007, *54* (1), 205–224.

Mayer, Christopher, Karen Pence, and S.M. Sherlund, "The rise in mortgage defaults," *Journal of Economic Perspectives*, 2009, *23* (1), 27–50.

Meier, Stephan and Charles Sprenger, "Present-Biased Preferences and Credit Card Borrowing," *American Economic Journal: Applied Economics*, 2009, p. Forthcoming.

_ **and** _ , "Stability of Time Preferences," *Working Paper*, 2009.

Mian, Atif and Amir Sufi, "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis," *Quarterly Journal of Economics*, 2009, (124).

Table I
Individuals contacted

	Cold-calls	Mail-Ins
Dead	1,043	3
Unknown	1,366	4,871
ID	559	29
Refuse	296	3
Respond	259	90
Response Rate		
of working phone #s	10.4 %	–
of individuals answering phone	46.6 %	96.7 %
Total	3,523	4,996

Notes: **Dead** means that none of the phone numbers were working. **Unknown** means that a phone was ringing, but the subject could not be identified. **ID** means that the phone number did belong to the target subject, but could never be reached in person. **Refuse** means that the subject was reached, but refused to participate. **Respond** means that the subject was reached and participated in the survey.

Table II
Comparing Characteristics of Responders and Non-Responders

Variable	Number of Observations *NR*	*R*	Means *NR*	*R*	Diff *NR-R*	*p*-value	*t*-value
Cold-Calls							
FICO Score	2,346	242	632.3	638.7	-6.4	0.116	-1.571
Fixed-Rate Mortage (=1)	2,346	242	0.410	0.397	0.014	0.678	0.415
Interest-Only (=1)	2,346	242	0.082	0.095	-0.013	0.479	-0.708
Balloon Payment (=1)	2,346	242	0.203	0.227	-0.024	0.372	-0.894
Refinance (=1)	2,346	242	0.529	0.492	0.037	0.275	1.092
Loan-to-Value Ratio	2,346	242	78.264	77.706	0.559	0.520	0.643
Amount of Mortgage	2,346	242	237,215	250,294	-13,079	0.124	-1.538
Initial interest rate	2,346	242	8.003	7.938	0.065	0.408	0.827
Debt-to-Income Ratio	2,153	227	41.666	41.348	0.318	0.619	0.497
Full-Doc Status (=1)	2,346	242	0.725	0.723	0.002	0.949	0.064
Foreclosure after mailing went out (=1)	2,017	217	0.105	0.092	0.013	0.553	0.594
Mail-Ins							
FICO Score	4,902	90	621.3	612.9	8.4	0.173	1.363
Fixed-Rate Mortage (=1)	4,902	90	0.161	0.178	-0.017	0.659	-0.441
Interest-Only (=1)	4,902	90	0.079	0.056	0.023	0.421	0.805
Balloon Payment (=1)	4,902	90	0.303	0.344	-0.042	0.394	-0.853
Refinance (=1)	4,902	90	0.781	0.778	0.003	0.943	0.071
Loan-to-Value Ratio	4,902	90	81.200	80.530	0.670	0.556	0.589
Amount of Mortgage	4,902	90	257,982	235,381	22,601	0.080	1.752
Initial interest rate	4,902	90	8.201	8.000	0.200	0.103	1.631
Debt-to-Income Ratio	4,537	86	42.226	43.756	-1.530	0.116	-1.574
Full-Doc Status (=1)	4,902	90	0.653	0.600	0.053	0.294	1.050
Foreclosure after mailing went out (=1)	3,779	76	0.160	0.145	0.015	0.718	0.362

Table III
Time to Default

	# Months to Default
Mean	17.7
10th percentile	8
25th percentile	11
Median	17
75th percentile	23
90th percentile	29
# Subprime Defaults	22,472

Notes:. We defined default to be the initiation of foreclosure proceedings. Data is from First American Loan Performance and covers the states of Massachusetts, Connecticut, and Rhode Island. The sample is limited to subprime mortgages that were originated in 2006 and 2007.

Table IV
Distribution of Financial Literacy Index

	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%

Table V
Summary Statistics by Financial Literacy Group

	Financial Literacy Group					Financial Literacy Group			
	1	2	3	4		1	2	3	4
English Fluency	9.30	9.78	9.81	9.98	Risk tolerance	1157	1171	1202	1256
	1.87	0.92	0.66	0.15		119	146	168	208
Income Volatility	1.98	1.87	1.84	1.80	Discount Factor	0.97	0.96	0.96	0.97
	0.77	0.81	0.77	0.79		0.03	0.03	0.03	0.03
Born in U.S. (dv)	0.74	0.84	0.86	0.91	Present Bias (dv)	0.19	0.21	0.14	0.24
# Years spent in U.S.	43.5	43.1	41.1	45.2	Duration of mortgage	28.4	28.6	29.4	28.3
	15.8	14.0	11.8	12.6		4.2	4.9	5.0	4.7
Asian (dv)	0.02	0.02	0.00	0.00	# Months previously in home	50.7	52.6	38.1	35.8
						57.9	61.3	58.6	55.4
Black (dv)	0.32	0.20	0.14	0.07	2007 cohort (dv)	0.19	0.19	0.16	0.20
Hispanic (dv)	0.17	0.06	0.05	0.04	Owner non-occupant (dv)	0.04	0.04	0.02	0.04
Native American (dv)	0.04	0.02	0.00	0.07	Cognitive ability score	17.5	21.5	26.9	27.1
						7.9	8.2	8.6	7.6
Other race (dv)	0.00	0.04	0.00	0.04	Fixed-rate loan (dv)	0.36	0.31	0.38	0.38
High school or less (dv)	0.49	0.29	0.10	0.04	Initial interest rate	8.2	8.0	7.9	7.8
						1.1	1.1	1.1	1.2
Some college (dv)	0.34	0.36	0.28	0.31	Low documentation (dv)	1.40	1.33	1.22	1.22
College (dv)	0.11	0.25	0.52	0.24	Cumulative LTV	0.86	0.83	0.85	0.85
						0.17	0.16	0.15	0.17
Higher degree (dv)	0.06	0.11	0.10	0.40	Back-end DTI ratio	43.1	42.5	39.9	41.3
						6.8	8.1	9.3	8.6
Employment status (dv)	0.75	0.86	0.84	0.87	# Previous mortgages	2.1	1.9	1.5	1.3
						2.6	2.2	2.2	2.0
Age of borrower	50	46	44	47	First-time Homebuyer (dv)	0.70	0.58	0.50	0.33
	10	11	8	10					
# Children	2.5	2.1	1.8	1.8	Home counseling (dv)	0.06	0.11	0.05	0.09
	1.5	1.5	1.3	1.4					
Credit score (FICO)	625	632	624	650	Shop around (dv)	0.47	0.56	0.76	0.71
	49	62	59	72					
Purchase mortgage (dv)	0.40	0.39	0.53	0.62	Income ($ thousands)	51.6	69.4	100.6	127.1
						29.9	33.3	63.3	98.9

Table VI
Distribution of Delinquency Measures

				Percentiles				
	# observations	Mean	Std. Dev.	10	25	50	75	90
Fraction of Periods Behind	339	0.110	0.143	0	0	0.056	0.167	0.304
Fraction of Missed Payments	339	0.198	0.247	0	0	0.077	0.367	0.621
Foreclosure	339	0.192	.	.	.	.	.	.

Table VII: 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***	-0.047***		-0.024***	-0.026***		-0.059**	-0.065**	
	(0.014)	(0.016)		(0.009)	(0.009)		(0.026)	(0.028)	
Numerical Ability Index = 2 (DV)			-0.032			-0.035			0.007
			(0.042)			(0.026)			(0.056)
Numerical Ability Index = 3 (DV)			-0.107**			-0.05			-0.072
			(0.050)			(0.033)			(0.056)
Numerical Ability Index = 4 (DV)			-0.123**			-0.087***			-0.130***
			(0.053)			(0.031)			(0.043)
Fluency in English		0.003	0.002		0.005	0.005		0.007	0.006
		(0.014)	(0.014)		(0.007)	(0.007)		(0.025)	(0.025)
Volatility of HH Income		0.053***	0.053***		0.031***	0.031***		0.066**	0.066**
		(0.016)	(0.016)		(0.009)	(0.009)		(0.027)	(0.026)
HH Income		0	0		0	0		0	0
		(0.000)	(0.000)		(0.000)	(0.000)		(0.001)	(0.001)
Born in USA (DV)		-0.029	-0.031		-0.01	-0.009		-0.053	-0.044
		(0.078)	(0.077)		(0.043)	(0.044)		(0.139)	(0.135)
Years lived in US		0.003	0.003		0.002	0.002		0	0
		(0.003)	(0.003)		(0.002)	(0.002)		(0.005)	(0.005)
Asian (DV)		-0.293***	-0.295***		-0.170***	-0.169***		0.096	0.095
		(0.087)	(0.085)		(0.046)	(0.047)		(0.064)	(0.064)
African American (DV)		0.092**	0.092**		0.060**	0.060**		-0.016	-0.002
		(0.039)	(0.039)		(0.026)	(0.026)		(0.083)	(0.088)
Hispanic (DV)		0.033	0.035		0.023	0.022		0.007	0.01
		(0.053)	(0.053)		(0.027)	(0.027)		(0.167)	(0.173)
Native American (DV)		0.01	0.007		-0.007	-0.007		0.149	0.143
		(0.087)	(0.086)		(0.036)	(0.038)		(0.226)	(0.230)
Other Ethnicity (DV)		0.084	0.074		0.077	0.081		0.155**	0.149**

Table VII: (continued)

	Fraction of Time in Delinquency			Fraction of Payments Missed			Foreclosure Initiated (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		(0.094)	(0.095)		(0.075)	(0.075)		(0.068)	(0.067)
Some College (DV)		0.053	0.053		0.029	0.029		0.154*	0.143*
		(0.035)	(0.035)		(0.021)	(0.021)		(0.081)	(0.080)
College Degree (DV)		0.089**	0.093**		0.042*	0.040*		0.261**	0.263**
		(0.038)	(0.039)		(0.021)	(0.022)		(0.119)	(0.120)
Professional Degree (DV)		0.105**	0.102**		0.048**	0.049**		0.055	0.056
		(0.043)	(0.043)		(0.024)	(0.024)		(0.046)	(0.045)
Employed (DV)		-0.008	-0.009		0.001	0.002		0.005	0.005
		(0.042)	(0.042)		(0.024)	(0.024)		(0.005)	(0.005)
Age		-0.002	-0.002		0	0		0.021	0.02
		(0.003)	(0.003)		(0.002)	(0.002)		(0.014)	(0.014)
Number of Children		0.002	0.002		0	0		-0.002***	-0.002***
		(0.010)	(0.010)		(0.006)	(0.006)		(0.000)	(0.000)
FICO Score		-0.001***	-0.001***		-0.001***	-0.001***		0.046	0.049
		(0.000)	(0.000)		(0.000)	(0.000)		(0.064)	(0.063)
Home Purchase (DV)		-0.038	-0.038		-0.01	-0.011		0	0
		(0.036)	(0.036)		(0.019)	(0.019)		(0.000)	(0.000)
Risk Tolerance		0	0		0	0		-0.391	-0.449
		(0.000)	(0.000)		(0.000)	(0.000)		(0.775)	(0.774)
Estimated δ		-0.309	-0.344		-0.248	-0.235		-0.062	-0.061
		(0.513)	(0.514)		(0.293)	(0.295)		(0.042)	(0.042)
Present-Biased (DV)		-0.018	-0.02		-0.003	-0.002		0.008	0.008
		(0.031)	(0.031)		(0.018)	(0.018)		(0.006)	(0.005)
Months since origination		0.002	0.002		0.002	0.002		-0.001	-0.001
		(0.003)	(0.003)		(0.002)	(0.002)		(0.001)	(0.001)
Months since home purchased		0	0		-0.000*	-0.000*		0.041	0.034
		(0.000)	(0.000)		(0.000)	(0.000)		(0.076)	(0.074)

Table VII: (continued)

	Fraction of Time in Delinquency			Fraction of Payments Missed			Foreclosure Initiated (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2007 (DV)		-0.033	-0.033		-0.005	-0.005		-0.003	-0.005
		(0.041)	(0.041)		(0.023)	(0.023)		(0.110)	(0.108)
Investor (DV)		-0.003	-0.005		0.001	0.002			0.007
		(0.055)	(0.054)		(0.031)	(0.031)			(0.056)
constant	0.296***	1.197**	1.199**	0.164***	0.658**	0.617*			
	(0.037)	(0.545)	(0.552)	(0.023)	(0.318)	(0.324)			
R^2	0.023	0.239	0.241	0.022	0.224	0.225			
F-test on all coefficients (p)	0.003	0.000	0.000	0.006	0.000	0.000	0.021	0.000	0.000
N	339	336	336	339	336	336	339	332	332

Notes: Robust standard errors in columns (1) - (6). ***, **, * indicate significance at the 1, 5, 10 percent level, respectively.

Table VIII
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	-0.045***	-0.047***	-0.027***	-0.029***	-0.049*	-0.048*
	(0.017)	(0.017)	(0.010)	(0.010)	(0.028)	(0.029)
Verbal IQ measure	-0.001	-0.001	0	0	-0.006**	-0.006**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Savings Scenario correct (DV)		0.016		0.011		-0.025
		(0.035)		(0.019)		(0.054)
Inflation scenario correct (DV)		0.01		0.012		0.003
		(0.033)		(0.017)		(0.047)
R^2	0.253	0.254	0.239	0.241		
p	0	0	0	0	0	0
N	326	326	326	326	322	322

Notes: All specifications contain the same control variables as in Table VII. Robust standard errors in columns (1) - (6). ***, **, * indicate significance at the 1, 5, 10 percent level, respectively.

Table IX
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**	-0.033*	-0.025***	-0.022**	-0.060**	-0.045*
	(0.017)	(0.017)	(0.010)	(0.010)	(0.027)	(0.024)
Fixed-Rate Mortgage	0.031	0.041	0.012	0.018	0.022	0.028
	(0.028)	(0.029)	(0.016)	(0.017)	(0.045)	(0.042)
Initial Interest Rate	0.026*	0.028*	0.01	0.01	0.033	0.015
	(0.016)	(0.017)	(0.009)	(0.009)	(0.022)	(0.020)
Low-Doc Loan (DV)	0.024	0.015	0.005	0.001	0.012	0.024
	(0.033)	(0.033)	(0.018)	(0.018)	(0.050)	(0.047)
Loan-to-Value Ratio		0.109		0.088*		0.645***
		(0.098)		(0.053)		(0.158)
Debt-to-Income Ratio		0.003		0.001		0.003
		(0.002)		(0.001)		(0.002)
R^2	0.266	0.278	0.244	0.252		
p	0	0	0	0	0	0
N	325	297	325	297	321	295

Notes: All specifications contain the same control variables as in Table VII. Robust standard errors in columns (1) - (6). ***, **, * indicate significance at the 1, 5, 10 percent level, respectively.

Table X
Controlling for Previous Home-Ownership Experience

	(1)	(2)	(3)
Numerical Ability Index	-0.045***	-0.026***	-0.056**
	(0.016)	(0.009)	(0.028)
Number of Previous Mortgages	0.002	0.005	0.025*
	(0.009)	(0.005)	(0.015)
First-time Home Buyer (DV)	0.051*	0.025	0.103**
	(0.030)	(0.016)	(0.043)
Took Home-Owner Counseling (DV)	-0.021	0	0.042
	(0.046)	(0.028)	(0.078)
Shopped around for Mortgages (DV)	0.027	0.016	-0.003
	(0.028)	(0.016)	(0.042)
R^2	0.262	0.248	
p	0	0	0
N	326	326	322

Notes: All specifications contain the same control variables as in Table VII. Robust standard errors in columns (1) - (6). ***, **, * indicate significance at the 1, 5, 10 percent level, respectively.

Table XI: Tobit Specifications of Baseline Regressions

	Fraction of Time in Delinquency		Fraction of Payments Missed	
	(1)	(2)	(3)	(4)
Numerical Ability Index	-0.063***	-0.057**	-0.035***	-0.033**
	(0.023)	(0.024)	(0.013)	(0.014)
Fluency in English		-0.002		0.003
		(0.020)		(0.012)
Volatility of HH Income		0.077***		0.045***
		(0.024)		(0.014)
HH Income		-0.001		0
		(0.000)		(0.000)
Born in USA (DV)		0		0.01
		(0.115)		(0.067)
Years lived in US		0.005		0.003
		(0.005)		(0.003)
Asian (DV)		-0.587***		-0.342***
		(0.225)		(0.131)
African American (DV)		0.136***		0.087***
		(0.049)		(0.028)
Hispanic (DV)		0.062		0.039
		(0.076)		(0.044)
Native American (DV)		0.027		0.001
		(0.125)		(0.073)
Other Ethnicity (DV)		0.065		0.075
		(0.141)		(0.081)
Some College (DV)		0.065		0.036
		(0.050)		(0.029)
College Degree (DV)		0.137**		0.068**
		(0.055)		(0.032)
Professional Degree (DV)		0.158**		0.076*
		(0.067)		(0.039)
Employed (DV)		0.026		0.021
		(0.053)		(0.031)
Age		-0.004		-0.001
		(0.005)		(0.003)
Number of Children		0.013		0.006
		(0.013)		(0.008)
FICO Score		-0.002***		-0.001***
		(0.000)		(0.000)
Home Purchase (DV)		-0.077		-0.031
		(0.054)		(0.031)
Risk Tolerance		0		0

Table XI: (continued)

	Fraction of Time in Delinquency		Fraction of Payments Missed	
	(1)	(2)	(3)	(4)
		(0.000)		(0.000)
Estimated δ		-0.506		-0.389
		(0.703)		(0.407)
Present-Biased (DV)		-0.034		-0.01
		(0.046)		(0.027)
Months since origination		0.003		0.003
		(0.005)		(0.003)
Months since home purchased		-0.001		-0.001*
		(0.000)		(0.000)
2007 (DV)		-0.036		-0.005
		(0.059)		(0.034)
Investor (DV)		0.021		0.016
		(0.098)		(0.056)
constant	0.249***	1.784**	0.137***	1.004**
	(0.056)	(0.769)	(0.032)	(0.446)
σ	0.350***	0.295***	0.201***	0.171***
	(0.018)	(0.015)	(0.011)	(0.009)
Pseudo R^2	0.02	0.291	0.054	0.8
p	0.007	0	0.008	0
N	339	326	339	326

Notes: ***, **, * indicate significance at the 1, 5, 10 percent level, respectively.

Table XII: Robustness Checks: 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	-0.083**	-0.053***	-0.060***	-0.045**	-0.032***	-0.034***	-0.117**	-0.085***	-0.072**
	(0.032)	(0.016)	(0.018)	(0.020)	(0.010)	(0.011)	(0.057)	(0.029)	(0.030)
Fluency in English	-0.008	0.009	0.009	0.005	0.006	0.009	-0.001	0.017	0.02
	(0.037)	(0.015)	(0.015)	(0.018)	(0.008)	(0.008)	(0.060)	(0.022)	(0.024)
Volatility of HH Income	0.060*	0.061***	0.060***	0.043**	0.037***	0.031***	0.096	0.093***	0.070**
	(0.033)	(0.018)	(0.018)	(0.021)	(0.011)	(0.010)	(0.060)	(0.032)	(0.030)
HH Income	0	0	0	0	0	0	0.001	0	0
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Born in USA (DV)	-0.077	0.015	-0.048	-0.021	0.001	-0.031	-0.139	-0.108	-0.124
	(0.159)	(0.104)	(0.081)	(0.093)	(0.050)	(0.046)	(0.278)	(0.155)	(0.145)
Years lived in US	0.007	0.002	0.003	0.002	0.001	0.002	0.003	0.001	-0.001
	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.012)	(0.007)	(0.005)
Asian (DV)	-0.524**	-0.469***	-0.427***	-0.265**	-0.220***	-0.245***	-0.415	-0.259	-0.436**
	(0.246)	(0.129)	(0.092)	(0.127)	(0.062)	(0.052)	(0.311)	(0.185)	(0.182)
African American (DV)	0.057	0.095**	0.083*	0.041	0.058*	0.044	-0.006	0.091	0.081
	(0.074)	(0.045)	(0.042)	(0.048)	(0.030)	(0.029)	(0.133)	(0.076)	(0.074)
Hispanic (DV)	0.029	0.046	0.034	0.023	0.021	0.019	-0.07	-0.043	-0.072
	(0.118)	(0.063)	(0.058)	(0.067)	(0.031)	(0.027)	(0.238)	(0.098)	(0.093)
Native American (DV)	0.084	0.01	0.026	0.003	0.005	0.016	0.056	-0.021	0.043
	(0.134)	(0.077)	(0.084)	(0.081)	(0.039)	(0.038)	(0.224)	(0.118)	(0.140)
Other Ethnicity (DV)	0.13	0.025	0.065	0.093	0.022	0.054	0.119	0.017	-0.013
	(0.127)	(0.081)	(0.087)	(0.092)	(0.056)	(0.076)	(0.250)	(0.182)	(0.155)
Some College (DV)	0.043	0.031	0.068*	0.023	0.023	0.029	0.109	0.109	0.120*
	(0.061)	(0.041)	(0.040)	(0.039)	(0.025)	(0.025)	(0.118)	(0.067)	(0.072)
College Degree (DV)	0.072	0.061	0.088**	0.053	0.033	0.03	0.149	0.113	0.099
	(0.073)	(0.045)	(0.043)	(0.044)	(0.026)	(0.025)	(0.140)	(0.079)	(0.073)
Professional Degree (DV)	0.123	0.069	0.112**	0.067	0.044	0.050*	0.148	0.194**	0.181**

Table XII: (continued)

	Fraction of Time in Delinquency			Fraction of Payments Missed			Foreclosure Initiated (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(0.080)	(0.053)	(0.052)	(0.046)	(0.030)	(0.029)	(0.175)	(0.089)	(0.088)
Employed (DV)	-0.062	-0.032	-0.014	-0.027	-0.012	-0.001	0.053	0.011	0.039
	(0.074)	(0.043)	(0.045)	(0.043)	(0.025)	(0.026)	(0.137)	(0.070)	(0.074)
Age	-0.005	-0.001	-0.001	-0.001	-0.001	0	0	0.002	0.007
	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.011)	(0.007)	(0.005)
Number of Children	0.006	0.008	-0.002	0.001	0.004	-0.005	0.019	0.024	0.005
	(0.021)	(0.012)	(0.011)	(0.012)	(0.006)	(0.006)	(0.037)	(0.020)	(0.019)
FICO Score	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***	-0.001***	-0.002*	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Home Purchase (DV)	-0.035	-0.044	-0.038	0.027	-0.006	-0.009	0.12	0.049	0.04
	(0.075)	(0.042)	(0.042)	(0.047)	(0.023)	(0.023)	(0.129)	(0.067)	(0.067)
Risk Tolerance	0	0	0	0	0	0	0	0	0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Estimated δ	-0.439	-0.105	0.008	-0.28	-0.274	-0.145	-0.237	-0.48	0.015
	(0.958)	(0.566)	(0.604)	(0.562)	(0.335)	(0.344)	(1.730)	(0.982)	(1.013)
Present-Biased (DV)	0.025	-0.016	-0.018	0.016	0.003	-0.001	0.005	-0.046	-0.065
	(0.061)	(0.036)	(0.035)	(0.036)	(0.021)	(0.020)	(0.108)	(0.062)	(0.057)
Months since origination	0.002	-0.001	-0.001	0.001	0.001	-0.001	0.004	0.005	0.001
	(0.006)	(0.004)	(0.005)	(0.004)	(0.002)	(0.003)	(0.011)	(0.007)	(0.008)
Months since home purchased	-0.001	-0.001	0	0	-0.000*	0	0	0	0
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
2007 (DV)	0.011	-0.06	-0.036	0.02	-0.019	-0.011	0.029	-0.036	0.019
	(0.082)	(0.050)	(0.051)	(0.051)	(0.030)	(0.030)	(0.172)	(0.082)	(0.076)
Investor (DV)	-0.126	0.018	0.043	-0.058	-0.003	0.024	-0.04	0.036	0.053
	(0.142)	(0.071)	(0.071)	(0.120)	(0.039)	(0.040)	(0.309)	(0.137)	(0.149)
constant	1.923*	1.144*	1.131*	0.997	0.786**	0.761**	1.552	1.538	0.97
	(1.130)	(0.614)	(0.616)	(0.632)	(0.365)	(0.370)	(1.943)	(1.044)	(1.060)

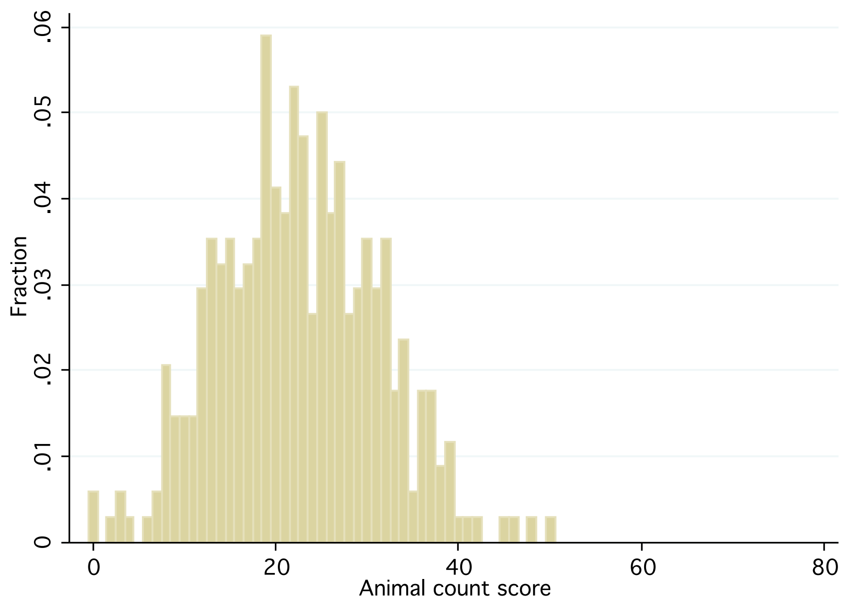
Table XII: (continued)

	Fraction of Time in Delinquency			Fraction of Payments Missed			Foreclosure Initiated (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R^2	0.719	0.356	0.344	0.686	0.351	0.324	0.65	0.3	0.268
p	0.012	0	0	0.104	0	0	0.834	0	0.001
N	323	311	295	323	311	295	323	311	295

Notes: Columns (1), (4), and (7) include town-level fixed effects. Columns (2), (5), and (8) include originator fixed effects. Columns (3), (6), and (9) include servicer fixed effects. ***, **, * indicate significance at the 1, 5, 10 percent level, respectively.

Figure 1. Distribution of Cognitive Ability Scores

This study



Dohmen et al. (2007) *AER*

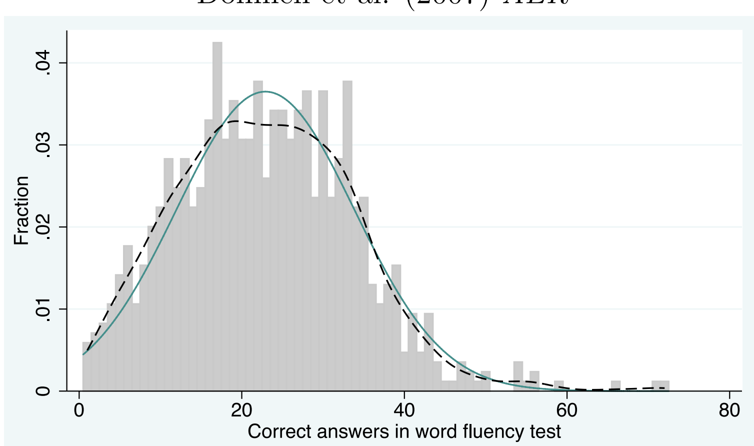


Figure 2. Delinquency and Financial Literacy Histograms