Cognitive Abilities and
Household Financial Decision Making[†]

By Sumit Agarwal and Bhashkar Mazumder*

We analyze the effects of cognitive abilities on two examples of consumer financial decisions where suboptimal behavior is well defined. The first example features the optimal use of credit cards for convenience transactions after a balance transfer and the second involves a financial mistake on a home equity loan application. We find that consumers with higher overall test scores, and specifically those with higher math scores, are substantially less likely to make a financial mistake. These mistakes are generally not associated with nonmath test scores. (*JEL* D14, G21)

Individuals commonly make financial decisions that would be considered suboptimal according to standard consumer finance theory (e.g., Agarwal et al. 2009; Bertrand and Morse 2011; Choi, Laibson, and Madrian 2011). Financial decision-making behavior has potentially wide ranging ramifications on society. For example, the boom and bust in US housing markets that helped precipitate the recent economic downturn was likely due in part to poor household decision making. Yet despite the growing salience of the issue, our current understanding of exactly what causes suboptimal financial decision making is limited.

The ability to process information and to make financial calculations appears to be an especially important aspects of sound financial decision making, and a growing literature has linked cognitive ability to financial behaviors and outcomes.[1] We present new empirical findings on the relationship between cognitive ability and financial decision making by focusing on two cases where suboptimal behavior is clearly defined. The first example features consumers who transfer their entire credit card balance from an existing account to a new card but decide to use the new card for "convenience" transactions—transactions that are fully paid for within the grace period. As we explain in the next section, it is never optimal to use the new

[1] There is growing evidence that cognitive ability is related to behavioral anomalies (e.g., Frederick 2005; Dohmen et al. 2010; Benjamin, Brown, and Shapiro forthcoming) and to financial market outcomes (e.g., Cole, Paulson, and Shastry 2012; McArdle, Smith, and Willis 2011; Grinblatt, Keloharju, and Linnainmaa 2011; Christelis, Jappelli, and Padula 2010).

card for such purchases, since it leads to finance charges that could be avoided by simply using the old card. We refer to this as a "balance transfer mistake," and describe the point at which a consumer discovers the optimal strategy as experiencing a "eureka" moment.

The second example features individuals who apply for a home equity loan or line of credit and who are provided with a pricing schedule that shows how the APR for their loan will depend on the loan-to-value ratio (LTV). Individuals are asked to estimate their home price, and the bank separately calculates an estimate of the value of the home. If the individual's estimated home price is sufficiently different from the bank's estimate, then the individual may be penalized by being offered a higher APR than what the initial pricing schedule would have determined based on the bank's estimate of the home value. We classify individuals who proceed to take out the loan at the higher APR (rather than simply decline the loan and reapply for a loan elsewhere) as having made a "rate-changing mistake," or RCM.

We construct a unique dataset that links members of the US military in 1993 to administrative data from a large financial institution containing retail credit data from 2000–2002. Our measures of cognitive skills are based on the Armed Forces Qualifying Test (AFQT) score which contains information on both math and verbal ability. We find that consumers with higher overall AFQT scores, and specifically those with higher math scores, are substantially less likely to make balance transfer and rate-changing mistakes. A 1 standard deviation increase in the composite AFQT score is associated with a 24 percentage point increase in the probability that a consumer will discover the optimal balance transfer strategy and an 11 percentage point decrease in the likelihood of making a rate-changing mistake in the home loan application process. Interestingly, we find that verbal scores are not at all associated with balance transfer mistakes and are much less strongly associated with rate-changing mistakes.

Our analysis improves upon the current literature in several respects. First, in contrast to studies that rely on broad outcomes, such as stock market participation, we use clearly defined examples of financial mistakes where there is little ambiguity about whether the behavior is suboptimal. Second, we use well-established measures of cognitive ability and do not rely on proxies, such as age or education. Third, we study very routine behaviors concerning debt management that cover a broad swath of the population. In combination, these three aspects of our analysis provide a novel contribution to the existing literature.

Since we do not have a random sample of the national population, strictly speaking, our inferences only pertain to the population we examine. However, we show that on many observable characteristics our matched samples are broadly similar to the universes from which they are drawn.[2]

The rest of the paper is organized as follows. Section I describes the data and our measures. In Section II, we present our main results. In Section III, we briefly

---

[2] We also note that other important contributions (e.g., Madrian and Shea 2001; Cullen et al. forthcoming) in the related literature have drawn inferences from the behavior of employees in a single firm. We also conduct a supplementary exercise using nationally representative data from the National Longitudinal Survey of Youth (NLSY) and find similar results when we link AFQT math scores to a measure of intertemporal decision making (see the online Appendix).

discuss the possible implications of our findings. Our conclusions are offered in Section IV.

I. Data and Measures

A. *Military Data*

We use all active duty military personnel in 1993 who entered the military beginning in September 1986 so that test scores are measured consistently. We use the Armed Forces Qualifying Test (AFQT) which combines two of the math scores with two of the verbal scores.[3] In addition to test scores, we have data on sex, age, education, service branch, race, ethnicity, marital status, and zip code of residence.

B. *Credit Card Data*

We use a proprietary panel dataset from a large financial institution that made balance transfer offers to credit card users nationally between January 2000 and December 2002.[4] The data includes the main billing information listed on each account's monthly statement as well as specific information on the balance transfer offer.[5] We also observe the FICO score as well as a proprietary (internal) credit "behavior" score. A higher score implies that the borrower has a lower probability of default. In addition, we have credit bureau data on the number of other credit cards, total credit card balances, mortgage balances, as well as age, gender, and self-reported income at the time of the account opening.

We merge the credit card data with the military data using a unique identifier. We restrict the sample to individuals who transferred their entire balance out of the existing card and who only made convenience transactions on either the new or the old card after completing the balance transfer. Convenience transactions are those that are fully paid for during the grace period. Balance transfer amounts exceeded $2,000 on average. Our sample includes a total of 480 individuals who were matched to the military data and who had nonmissing data on the key variables of interest. Online Appendix Table A1 presents summary statistics and compares a common set of covariates to the full military sample in panel A. The comparison shows that for the most part our sample is reasonably representative of the full military.[6] Panel B of Table A1 compares

---

[3] There are a total of 10 different subtests, which cover numerical operations, word knowledge, arithmetic reasoning, mathematical knowledge, electronics information, mechanical comprehension, general science, paragraph comprehension, coding speed, and automotive and shop. We use the 1989 metric of the AFQT. A 1991 National Academy of Science study established the validity of the test as a predictor of job performance (Wigdor and Green 1991). The test is used for enlistment screening and for assigning jobs within the military. Many previous studies have used the AFQT to measure cognitive ability (e.g., Neal and Johnson 1996; Heckman, Stixrud, and Urzua 2006; Warner and Pleeter 2001).

[4] A total of 14,798 accepted the offer. Balance transfer offers were not made conditional on closing the old credit card account and in our sample, borrowers did not pay fees for the balance transfer.

[5] The monthly billing information includes total payment, spending, credit limit, balance, debt, purchases, cash advance APRs, and fees paid. The balance transfer data includes the amount of the balance transfer, the start date of the teaser rate, the initial teaser APR, and the end date of the balance transfer APR offer.

[6] For example, test scores, education, and age at entry are very similar. The most noticeable difference is with respect to race. The matched sample overrepresents blacks (25.3 percent versus 19.8 percent) compared to the full military sample.

this matched sample to the full sample of borrowers, and here we find differences that in some cases are due to differences in the age distribution of the samples.[7]

C. *Balance Transfer Mistake*

When a borrower makes a balance transfer to a new card they pay substantially lower APRs on the balances transferred to the new card for a six- to nine-month period (a "teaser" rate). However, *new* purchases on the new card typically have high APRs. The catch is that payments on the new card first paid down the (low interest) transferred balances, and only subsequently paid down the (high interest) debt accumulated from new purchases. The CARD Act of 2009 now requires card issuers to apply payments above the minimum to the balance with the highest rate first. For borrowers who have transferred the entire balance from an existing credit card, and who subsequently only make "convenience" transactions, that is trans-actions that the consumer intends to pay off in full within the grace period, the optimal strategy during the teaser-rate period is for the borrower to only make new purchases on the *old* credit card.[8] The borrower should make no new purchases with the new card to which balances have been transferred (unless she has already repaid her transferred balances on that card). This ensures that the borrower will pay no interest irrespective of the interest rates on each account.

Some borrowers will identify this optimal strategy immediately and will not make any new purchases using the new card. Some borrowers may not initially identify the optimal strategy, but will discover it after one or more pay cycles, as they observe their (surprisingly) high interest charges. Those borrowers will make purchases for one or more months, then experience what we refer to as a "eureka" moment, after which they will implement the optimal strategy. Some will never identify the optimal strategy.

We track the use of the balance transfer card for a six-month period for consum-ers who continue to use at least one card for a convenience purchase. Our main dependent variable is an indicator variable that is equal to one if a person discovers the optimal strategy at some point during the six-month period. That is, if they either never make the mistake, or, if they do make the mistake at some point in this period, they cease to make the mistake for the remainder of the sixth-month window. A sec-ond outcome tracks how many months it takes for the consumer to adopt the optimal strategy and to stop using the balance transfer card for new purchases.[9] Figure 1,

---

[7] The majority of our matched sample are in their 30s in the 2000–2002 period, when the balance transfer occurred, compared with an older sample in the general population of borrowers. The average matched sample borrower has higher income but is also riskier as reflected by lower FICO and behavior scores. The balance transfer APR for the matched sample of borrowers is slightly higher (77 basis points) than for the full sample, but the pur-chase APR for matched sample borrowers is much lower (649 basis points). This is most likely due to the fact that the account age of these borrowers is less than half of the full sample borrowers, and so they still have favorable lending terms. It is also possible that individuals could have received more favorable terms if they were still in the military in 2000-2002.

[8] We restrict the sample to individuals who transfer their *entire* balance because we want to ensure that they have the ability to use the old card for convenience use and incur no finance charges. This allows us to unambiguously identify cases where the optimal strategy is to use the old card.

[9] About one-third implement the optimal strategy immediately, slightly more than one-third never implement the optimal strategy, and the remaining third implement the optimal strategy at some point after the first month.
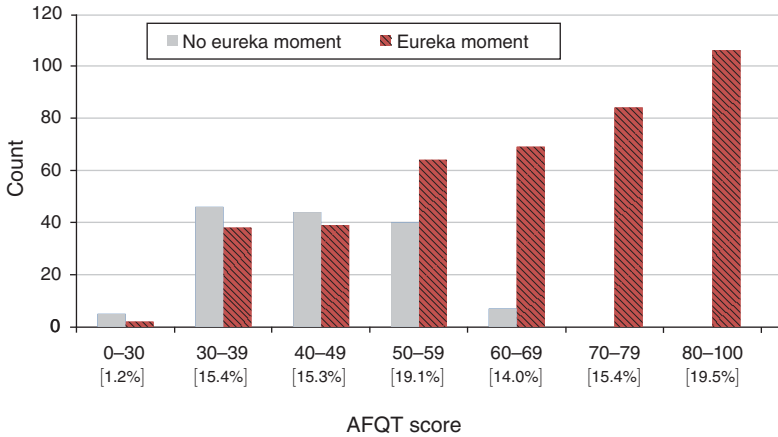
FIGURE 1. DISTRIBUTION OF AFQT SCORES BY WHETHER A CREDIT CARD HOLDER
HAS A "EUREKA" MOMENT

Note: Numbers in brackets represent the fraction of the sample in each AFQT bin.

which plots the distribution of AFQT scores by whether the consumer ever has a eureka moment, provides a preview of the main results. We find that among those with AFQT percentile scores above 70, everybody ultimately identifies the optimal strategy. In contrast, the majority of cases with a score below 50 will not identify the optimal strategy.[10] In Section II, we estimate the effects using a linear probability model while including demographic and financial controls.

D. *Home Equity Loans and Lines Data*

We also use a proprietary panel dataset obtained from a national financial institution to study financial mistakes with respect to home equity loans and lines of credit.[11] Between March and December of 2002, the lender offered a menu of standardized contracts for home equity loans or lines of credit with five-year maturities. Consumers chose the following: either a loan or a credit line; either a first or second lien; and an incremental loan amount corresponding to an LTV of less than 80 percent (80–), between 80 and 90 percent (80–90), or 90 percent and greater (90+). In essence, the lender offered 12 different contract choices, each having an associated APR.

For 75,000 out of 1.4 million such contracts who took up the loan or line of credit, we observe the contract terms, borrower demographic information (job and home tenure), financial information (income and debt-to-income ratio), and risk characteristics (FICO score and LTV). We also observe borrower estimates of their property values and the loan amount requested. We merge this data with the military dataset using a unique identifier producing a sample of 1,393 borrowers who took

---

[10] A full set of differences in the mean characteristics of those who experience eureka versus those who don't are shown in online Appendix Table A3. Of particular note is that blacks make up a much larger fraction of the "no eureka" subsample. As we show later, however, our results are robust to dropping blacks.

[11] This company did not specialize in subprime loans or any other segment of the market.

out a home equity loan or line of credit and for whose home we have nonmissing values on the key variables.

Panel A of Table A2 in the online Appendix presents summary statistics comparing the matched sample to the overall military sample. In this case, we find that test scores are generally a little bit higher in our matched sample. This is likely due to the fact that our matched sample is selected on those who own homes.[12] Panel B of Table A2 compares the matched sample to the full home loan sample. Borrowers in the matched sample have higher FICO scores, have longer job tenure, have higher income, have higher home values and loan amounts, and pay a lower APR.

E. Rate-Changing Mistake

In determining the APR for a home equity loan or line of credit, the amount of collateral offered by the borrower, as measured by the LTV, is a key determinant. Higher LTVs imply higher APRs, since the fraction of collateral is lower. At the financial institution that provided our data, borrowers first estimate their home values, and ask for a credit loan or credit line falling into one of three implied borrower-generated LTV categories described earlier (80−, 80–90, 90+). The financial institution then independently verifies the house value using an industry-standard methodology and determines their own estimate of the LTV. The institution's LTV can therefore differ from the borrower's LTV.[13]

Loan pricing (APR) depends on the LTV *category* that the borrower falls into and not on the specific LTV within that category.[14] If the borrower has overestimated the value of the house, so that the financial institution's LTV is higher than the borrower's LTV (e.g., the borrowers' LTV category is 80−, while the bank's LTV category is 80–90), the institution will direct the buyer to a different loan with a higher interest rate corresponding to the higher LTV. In such circumstances, the loan officer is also given discretion to depart from the financial institution's normal pricing schedule to offer *an even higher* interest rate than the officer would have offered to a borrower who had correctly estimated her LTV.[15] If the borrower has underestimated the value of the house (e.g., the borrowers' LTV category is 80–90, while the banks LTV category is 80−), the financial institution need not direct the buyer to a loan with a lower interest rate corresponding to the financial institution's LTV; the loan officer may simply choose to offer the higher interest rate associated with the borrower's LTV (80–90), instead of lowering the rate to reflect the financial institution's lower LTV (80−).[16]

We define a rate-changing mistake to have occurred when the borrower LTV category differs from the bank LTV category *and the borrower proceeds with the loan*—for instance, when the borrower estimates an LTV of 85 percent but the bank

---

[12] Our matched home equity sample contains a larger share of whites and a smaller share of males, although neither difference is statistically significant.

[13] Agarwal (2007) and Bucks and Pence (2008) present evidence showing that borrowers often do not know their house value or mortgage terms.

[14] We have verified this empirically in our data.

[15] We have verified that this occurs by talking to loan officers.

[16] Even if the financial institution's estimate of the true house value is inaccurate, that misestimation will not matter for the borrower's decision to accept the loan as long as other institutions use the same methodology.
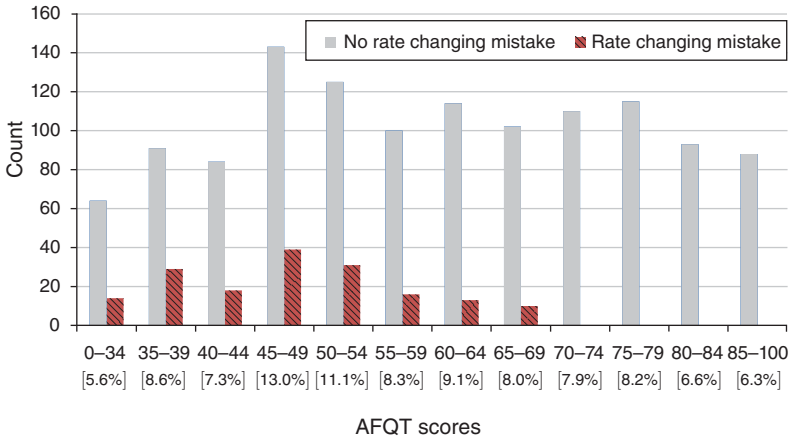
Figure 2. Distribution of AFQT Scores by whether Home Equity Borrowers Make a "Rate Changing Mistake"

Note: Numbers in brackets represent the fraction of the sample in each AFQT bin.

calculates an LTV of 95 percent (or vice versa).[17] It is important to note that borrowers who make RCMs (regardless of whether it is due to overestimating or underestimating) are presented with sufficient information to make them aware of their mistake at the time that they are presented with the APR for the loan and before they agree to the loan. These individuals are given both the full menu of prices for each LTV category (in the absence of a mistake) as well as their actual offered APR. For borrowers who have been penalized, it is suboptimal to proceed with the loan, since they can simply reapply for a loan from the same lender or a different lender armed with an accurate estimate of their home value that would allow them to avoid such a penalty.[18] We find that, on average, making an RCM increases the APR by 269 basis points, which is clearly a costly mistake. Online Appendix Table A4, panel B, highlights the significant differences between the borrowers with and without an RCM. The FICO score for the RCM borrowers is 25 points lower, their income is $20,357 lower, and their debt-to-income ratio is 6 percentage points higher.

To preview our results with respect to the effects of cognitive ability on making an RCM, Figure 2 shows that there are no cases of rate-changing mistakes among those with percentile scores above 69. In contrast, RCMs are concentrated in the lower half of the AFQT distribution.[19] We present more detailed statistical results based on estimating linear probability models in Section II.

---

[17] An example in which misestimation does not lead to a higher APR is if the borrower's estimated LTV is 60 percent but the true LTV is 70 percent. In this case, the borrower would still qualify for the highest quality loan category (LTV < 80) and would not suffer an effective interest rate penalty.

[18] We have no information on the subsequent behavior of borrowers who choose not to accept a loan. Therefore, we cannot distinguish the reasons why a borrower declined a loan or determine if they received a loan elsewhere. There are also no pecuniary costs if the borrower decides to decline the loan.

[19] Online Appendix Table A4 provides more detailed summary statistics separately for those who experience an RCM versus those who do not.

II. Results

A. *Balance Transfer Mistakes and AFQT Scores*

In Table 1, we show the results of our first set of estimates that use the composite AFQT test score to predict whether consumers learn the optimal behavior after a balance transfer, i.e., experience a eureka moment. In all of our estimations, we have standardized all the test score variables to have a mean of zero and a standard deviation of one. In column 1, where we don't include any controls, the estimated effect of a 1 standard deviation increase in AFQT scores is to raise the probability of a eureka moment by about 23 percentage points. The effect is highly significant with a *t*-statistic over 12. In column 2, we add financial controls from our credit card dataset and find that this has almost an imperceptible effect on the AFQT score coefficient. Further, we find that most of the financial controls have no effect on the probability of a eureka moment. Perhaps not surprisingly, the one exception is the behavior score—where higher values indicate greater credit worthiness based on the borrower's payment and purchase behavior.

In column 3, the effect rises slightly to 0.24 when we include our demographic controls. Perhaps surprisingly, there is no effect of education, though this may be an imperfect measure since it may only capture completed schooling by the time of enlistment or early in one's military career. Those that were married at the time they were in the military are significantly less likely to have a eureka moment. Interestingly, we find that the effect on being black is actually positive conditional on AFQT scores and education. This finding is interesting in light of the theoretical model developed by Lang and Manove (2011) who argue that blacks of similar ability to whites may need to signal their productivity to employers by acquiring more education.[20] They cite studies suggesting that blacks are not rewarded the same as whites in the labor market for equivalent AFQT scores. It is possible that the increased likelihood of discovering the optimal balance transfer strategy among blacks who have the same measured ability as whites, reflects their greater investments along other dimensions of human capital.

In column 4, we include both sets of controls and again find that doing this has no effect on our main finding. In columns 5–8, we use the four component scores (arithmetic reasoning, math knowledge, paragraph comprehension, and word knowledge) that are used to calculate the AFQT score. In all four specifications, the two math scores are both highly significant, suggesting that quantitative skills are critical for avoiding suboptimal behavior. In contrast, we estimate that the effects of the two verbal test scores are a fairly precisely estimated zero. For example, the largest point estimate for a verbal score suggests that a 1 standard deviation increase in word knowledge would only increase the incidence of eureka moments by a little more than a tenth of a percentage point. We also find that once we include all of the covariates using this specification, we no longer find any of the demographic controls to be significant.

---

[20] Lang and Manove (2011) find that there are significant black-white wage differences conditional on education and AFQT, suggesting the possibility of labor market discrimination.

TABLE 1—EFFECTS OF AFQT ON OPTIMAL BEHAVIOR ("EUREKA") BY CONSUMER BORROWERS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFQT score	0.228***	0.228***	0.244***	0.241***				
	(0.018)	(0.016)	(0.019)	(0.017)				
Arithmetic reas.					0.121***	0.116***	0.133***	0.125***
					(0.022)	(0.020)	(0.023)	(0.020)
Math knowledge					0.134***	0.141***	0.126***	0.134***
					(0.021)	(0.019)	(0.022)	(0.019)
Paragraph comp.					0.006	−0.000	0.009	0.002
					(0.021)	(0.019)	(0.021)	(0.019)
Word knowl.					0.008	0.008	0.014	0.013
					(0.022)	(0.020)	(0.023)	(0.020)
Financial controls								
Bal transfer APR		0.002		0.002		0.003		0.003
		(0.006)		(0.006)		(0.005)		(0.006)
Purchase APR		−0.004		−0.004		−0.005		−0.005
		(0.004)		(0.004)		(0.004)		(0.004)
Account age		−0.002		−0.002		−0.000		−0.000
		(0.003)		(0.003)		(0.003)		(0.003)
Behavior score		−0.572***		−0.560***		−0.558***		−0.552***
		(0.084)		(0.084)		(0.082)		(0.082)
Behavior score ^{2}		0.081***		0.080***		0.081***		0.080***
		(0.010)		(0.010)		(0.009)		(0.010)
Fico score		−0.045		−0.037		−0.033		−0.025
		(0.080)		(0.080)		(0.077)		(0.079)
Fico score ^{2}		−0.001		−0.002		−0.003		−0.003
		(0.007)		(0.008)		(0.007)		(0.007)
Income		−0.000		−0.000		−0.000		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Demographic controls								
Education			0.011	0.023			0.008	0.020
			(0.028)	(0.025)			(0.027)	(0.025)
Black			0.086**	0.079**			0.052	0.044
			(0.043)	(0.039)			(0.043)	(0.039)
Other			0.050	0.102			0.034	0.083
			(0.071)	(0.063)			(0.070)	(0.062)
Female			0.007	0.007			0.030	0.026
			(0.055)	(0.049)			(0.055)	(0.049)
Married			−0.078**	−0.062*			−0.062*	−0.043
			(0.037)	(0.033)			(0.036)	(0.032)
Observations	480	480	480	480	480	480	480	480
R^2	0.261	0.424	0.274	0.436	0.295	0.461	0.302	0.467

Note: See text for further details.
   ***Significant at the 1 percent level.
   **Significant at the 5 percent level.
   *Significant at the 10 percent level.

In other specifications (not shown), we also estimated the effect of AFQT scores on whether a borrower *immediately* adopts the optimal strategy. In these cases, the coefficient on the AFQT score is consistently around 0.18. This suggests that about two-thirds of the 0.24 effect of cognitive skills shown in Table 1 is due to an
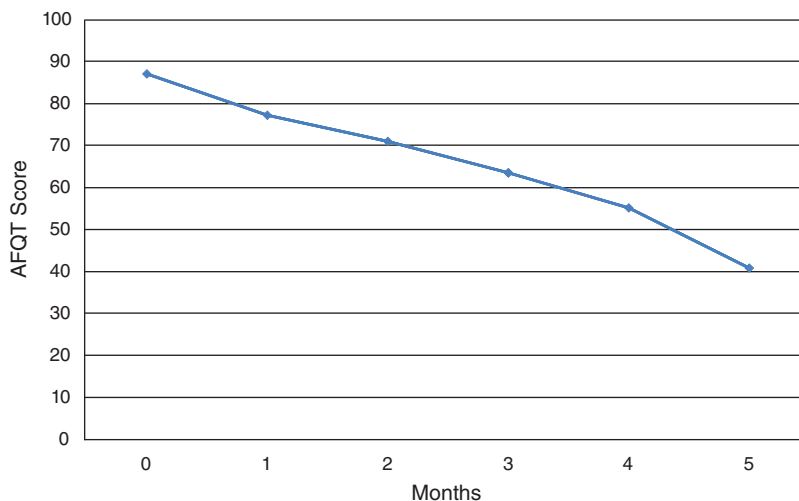
FIGURE 3. MEAN AFQT SCORES BY MONTHS IT TAKES CONSUMERS
TO DISCOVER OPTIMAL STRATEGY

immediate effect and about one-third of the effect is due to borrowers who learned the optimal strategy after initially making a financial mistake. We also found that when we used this dependent variable, that none of the financial or demographic controls were ever significant.

To illustrate the effects of AFQT scores on the speed at which individuals learn, we plot in Figure 3 the unadjusted mean AFQT scores for borrowers based on how many months it took them to discover the optimal strategy. The chart shows that AFQT is monotonically decreasing in the number of months it takes borrowers to learn. We estimate that a 1 standard deviation increase in AFQT scores is associated with a 1.5 month reduction in the time it takes to achieve optimal behavior speed. This analysis suggests that cognitive skills also affect the "intensive" margin of optimal financial decision-making behavior.

B. *Rate-Changing Mistakes and AFQT Scores*

In Table 2, we report the effects of AFQT scores on the probability of making a rate-changing mistake for home equity loans or lines.[21] The first four columns use the overall AFQT score and utilize the following: no controls in column 1, financial controls from the home equity data in column 2, demographic controls from the military data in column 3, and both sets of controls in column 4. The key finding is that a 1 standard deviation increase in AFQT lowers the probability that a borrower will make a rate-changing mistake by between 10 and 11 percentage points. Since the average probability of making a rate-changing mistake is 14 percent in our sample, the implied effect size is over 70 percent.

---

[21] For these regressions we pool home equity loans and lines of credit together, but include a dummy variable for home equity loans. We also control for not having a first mortgage and LTV bucket.

TABLE 2—EFFECTS OF AFQT ON RATE CHANGING MISTAKES (RCM) BY HOME LOAN BORROWERS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFQT score	−0.096***	−0.100***	−0.107***	−0.107***				
	(0.010)	(0.008)	(0.011)	(0.009)				
Arithmetic reas.					−0.039***	−0.044***	−0.047***	−0.049***
					(0.012)	(0.009)	(0.012)	(0.010)
Math knowledge					−0.056***	−0.050***	−0.053***	−0.048***
					(0.011)	(0.009)	(0.011)	(0.009)
Paragraph comp.					0.007	−0.005	0.005	−0.006
					(0.011)	(0.009)	(0.011)	(0.009)
Word knowledge					−0.026**	−0.023**	−0.034***	−0.027***
					(0.012)	(0.009)	(0.012)	(0.009)
Financial controls								
Years on the job		−0.001		−0.001		−0.001		−0.001
		(0.001)		(0.001)		(0.001)		(0.001)
Appraised value		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Improvement		0.026		0.025		0.026		0.025
		(0.018)		(0.018)		(0.018)		(0.018)
Refinancing		0.017		0.018		0.018		0.019
		(0.016)		(0.016)		(0.016)		(0.016)
Equity loan		0.103***		0.105***		0.107***		0.109***
		(0.032)		(0.032)		(0.032)		(0.032)
Income		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
First mortgage bal.		−0.000		−0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
FICO score		−0.025*		−0.025*		−0.024		−0.024
		(0.015)		(0.015)		(0.015)		(0.015)
APR		0.098***		0.097***		0.097***		0.096***
		(0.008)		(0.008)		(0.008)		(0.008)
DTI ratio		0.001**		0.001*		0.001**		0.001*
		(0.000)		(0.000)		(0.000)		(0.000)
Demographic controls								
Education			0.022*	0.006			0.020	0.005
			(0.013)	(0.010)			(0.013)	(0.010)
Black			−0.066***	−0.046***			−0.061***	−0.042**
			(0.022)	(0.018)			(0.022)	(0.018)
Other			−0.119***	−0.053*			−0.117***	−0.050*
			(0.035)	(0.029)			(0.036)	(0.029)
Observations	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380
R^2	0.062	0.408	0.078	0.414	0.069	0.411	0.082	0.416

Notes: Coefficients on self employment, married and female are suppressed. See text for further details.

Among the financial covariates, taking out a loan versus a line raises the likelihood of an RCM by about 10 percentage points, as does a 1 percentage point increase in the APR. The debt-to-income ratio has a small but perceptible effect. The FICO score also has a small effect, but it is not economically meaningful. Turning to demographic controls, education actually has a positive sign, but the effect is reduced once we condition on financial variables. As before, blacks are significantly

less likely to make an RCM conditional on AFQT scores, while women are slightly more likely to make one (not shown).

When we use the four subtests that make up the AFQT (columns 5–8), we again find that both math scores have large and significant negative effects on RCM. Among the verbal scores, paragraph comprehension has no effect, but we do see a negative statistically significant effect of word knowledge. A 1 standard deviation increase in word knowledge lowers the probability of an RCM by about 2 to 3 percentage points.

Finally, to highlight the importance of RCMs, we estimated the effect of AFQT scores on the APR for consumers who *do not make an RCM,* and found no statistically significant or quantitatively meaningful effect. When coupled with our main findings, this suggests that cognitive ability only affects loan pricing through the rate-changing mistake.

C. *Robustness Checks*

To reinforce that it is specifically mathematical skills that seem to matter for financial decision making, we also include the other six subtests from the military entrance exam in Table 3. We find that the effects from the two math scores from Table 1 are unaffected by the inclusion of the other scores and continue to find few effects from nonmath scores.[22] In other results (not shown), we find that our results are insensitive to using state code or zip code fixed effects, or to limiting the sample to only whites.[23]

We also conduct a supplementary exercise using the Health and Retirement Survey (see online Appendix) to show that while mathematical ability predicts later life financial success, it is *not* predictive of suboptimal behavior in other aspects of life, such as failure to take medication. We further show that other forms of cognitive ability are, in fact, critically predictive of suboptimal nonfinancial behaviors. This suggests that there is a correspondence in the kinds of cognitive abilities that are relevant for particular outcomes and strengthens the notion that there is something inherent in mathematical ability that lessens the likelihood of an individual making poor financial decisions.

III. Discussion

An intriguing question is why exactly math ability appears to matter for financial mistakes. While we are limited in our ability to investigate this in any definitive way, we speculate on some possibilities. In a supplementary exercise using data from the nationally representative National Longitudinal Survey of Youth

---

[22] "Coding speed," which measures how quickly and accurately individuals can recognize numerical patterns, is statistically significant for eureka, but not for RCM. A third math test, "numerical operations," reduces the probability of a eureka moment, controlling for the other two math scores. However, the raw correlation between eureka and numerical operations is positive (0.18), but much lower than the raw correlations of eureka moments with arithmetic reasoning (0.50) or math knowledge (0.48). This relatively lower correlation suggests that numerical operations is picking up some factor that is orthogonal to the other two math scores. With RCM, we find no effect of coding speed and that numerical operations has the correct sign and is marginally significant.

[23] The RCM results are also robust to controls for contract type (loan type interacted with LTV category).

TABLE 3—EFFECTS OF ALL ASVAB TESTS ON "EUREKA" MOMENTS AND RATE CHANGING MISTAKES

	Effects on eureka				Effects on RCM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Arithmetic reas.	0.128***	0.129***	0.132***	0.131***	−0.038***	−0.046***	−0.044***	−0.049***
	(0.024)	(0.022)	(0.025)	(0.022)	(0.013)	(0.010)	(0.013)	(0.010)
Math knowledge	0.118***	0.137***	0.113***	0.133***	−0.057***	−0.049***	−0.053***	−0.047***
	(0.023)	(0.021)	(0.024)	(0.021)	(0.012)	(0.010)	(0.012)	(0.010)
Paragraph comp.	0.000	−0.002	0.002	−0.000	0.004	−0.007	0.003	−0.008
	(0.021)	(0.019)	(0.021)	(0.019)	(0.011)	(0.009)	(0.011)	(0.009)
Word knowl.	−0.003	0.003	−0.000	0.004	−0.032**	−0.028***	−0.039***	−0.033***
	(0.025)	(0.022)	(0.026)	(0.023)	(0.013)	(0.010)	(0.013)	(0.011)
Numerical oper.	−0.040*	−0.046**	−0.041*	−0.048**	−0.018*	−0.012	−0.019*	−0.012
	(0.022)	(0.020)	(0.022)	(0.020)	(0.011)	(0.009)	(0.011)	(0.009)
Electronic info	0.012	0.005	0.010	0.005	−0.020*	−0.010	−0.015	−0.007
	(0.024)	(0.021)	(0.024)	(0.021)	(0.012)	(0.009)	(0.012)	(0.010)
Mechanical comp.	0.026	0.003	0.030	0.008	−0.001	0.002	−0.003	0.002
	(0.024)	(0.021)	(0.024)	(0.022)	(0.012)	(0.010)	(0.012)	(0.010)
General science	0.012	0.003	0.016	0.005	0.025*	0.013	0.021	0.011
	(0.025)	(0.023)	(0.026)	(0.023)	(0.013)	(0.011)	(0.013)	(0.011)
Coding speed	0.060***	0.045**	0.063***	0.046**	0.014	0.008	0.011	0.005
	(0.022)	(0.020)	(0.022)	(0.020)	(0.010)	(0.008)	(0.010)	(0.008)
Automotive/ shop	−0.046**	−0.028	−0.031	−0.016	−0.001	0.003	−0.008	0.001
	(0.023)	(0.021)	(0.026)	(0.023)	(0.012)	(0.009)	(0.012)	(0.010)
Financial controls	No	Yes	No	Yes	No	Yes	No	Yes
Demographic controls	No	No	Yes	Yes	No	No	Yes	Yes
Observations	480	480	480	480	1,380	1,380	1,380	1,380
R^2	0.312	0.471	0.318	0.476	0.074	0.413	0.087	0.417

Note: See text for further details.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

(see online Appendix), we find that a simple survey-based measure of patience based on an intertemporal decision-making problem is also strongly associated with AFQT scores, but once again, only with the math component of the test. One interpretation of this finding is that those with greater math ability are more patient and therefore less likely to make financial mistakes when there is an element of a time tradeoff in a financial decision, such as in our examples.[24] An alternative view is that math ability is directly related to the ability to understand financial concepts, to analyze intertemporal tradeoffs and to make relevant financial calculations—all of which are arguably very important for financial decision making. However, further research is needed to better understand and interpret our empirical findings.

---

[24] In the balance transfer case, the optimal strategy works when individuals can plan which card they will use for their *future* expenditures and stick with that plan. In the home loan case, it may be those that who are more patient would be willing to decline the loan and to simply reapply for the loan in the *future* armed with better knowledge of how to estimate their home price in order to avoid a penalty.

Since our primary aim is to demonstrate how financial mistakes are linked to cognitive ability, we have deliberately targeted very "clean" examples of suboptimal behavior, irrespective of the dollar values of the costs of such mistakes. While the costs of balance transfer mistakes are relatively small, in the case of home equity loans, since an RCM increases the APR by 269 basis points, this implies an increase in nearly $4,000 over the life of a typical loan.[25] In any case, we think that our analysis likely only touches the tip of the iceberg in terms of the effects of poor financial decision making, due to low cognitive ability, on individual and social welfare. It is highly plausible that similar types of financial mistakes have played a role in explaining loan default, foreclosures, and bankruptcies. In a highly complementary paper to ours, Gerardi, Goette, and Meier (2010) find a strong association between numerical ability and mortgage delinquency and default during the recent financial crisis.[26] Future research may shed more light on the quantitative importance of cognitive ability.

Finally, it is natural to consider whether our results have implications for current efforts to improve financial literacy. To the extent that our findings represent *causal* effects of math ability on financial mistakes, and to the extent that policies exist that can affect math test scores, our results could provide support for certain interventions.[27] However, we remain cautious in interpreting the relevance of our findings for policy, since we do not yet have a definitive understanding of exactly why math scores are correlated with financial mistakes.

IV. Conclusion

In the wake of the recent financial crisis, there is a clear desire among policymakers to improve the quality of household financial decision making. We add new empirical evidence to an emerging literature that has begun to link financial market behaviors to measures of cognitive abilty. Specifically, we use two clearly defined examples of suboptimal behavior on the part of households concerning management of debt. Our results show that consumers with higher overall AFQT scores, and specifically those with higher math scores, are substantially less likely to make financial mistakes in their usage of credit card balance transfer offers and on home equity loan applications. While our findings improve the quality of empirical evidence linking cognitive abilities to financial decision making, we argue that further research is needed to better elucidate the mechanisms underlying this association and to better understand the relevance of these findings for efforts to improve financial literacy in the population.

---

[25] The increase in costs is $3,771 for a 5 year $50,000 loan, assuming a change in the APR from 5 percent to 7.69 percent.

[26] We also note that our HRS results, shown in the online Appendix, also suggest that there are potentially very large ramifications for having poor mathematical cognitive ability on savings behavior and accumulated wealth.

[27] It is worth noting that a number of studies (e.g., Neal and Johnson 1996; Hansen, Heckman, and Mullen 2004; Cascio and Lewis 2006; and Chay, Guryan, and Mazumder 2009) suggest that AFQT scores are not immutable and do not simply reflect innate intelligence.

REFERENCES

Agarwal, Sumit. 2007. "The Impact of Homeowners' Housing Wealth Misestimation on Consumption and Saving Decisions." *Real Estate Economics* 35 (2): 135–54.

Agarwal, Sumit, and Bhashkar Mazumder. 2013. "Cognitive Abilities and Household Financial Decision Making: Dataset." *American Economic Journal: Applied Economics*. http://dx.doi.org/10.1257/app.5.1.193.

Agarwal, Sumit, John Driscoll, Xavier Gabaix, and David Laibson. 2009. "The Age of Reason: Financial Decisions over the Life Cycle with Implications for Regulation." *Brookings Papers on Economic Activity* 39 (2): 51–117.

Benjamin, Daniel J., Sebastian A. Brown, and Jesse M. Shapiro. Forthcoming. "Who is 'Behavioral'? Cognitive Ability and Anomalous Preferences." *Journal of the European Economics Association*.

Bertrand, Marianne, and Adair Morse. 2011. "Information Disclosure, Cognitive Biases, and Payday Borrowing." *Journal of Finance* 66 (6): 1865–93.

Bucks, Brian, and Karen Pence. 2008. "Do Borrowers Know Their Mortgage Terms?" *Journal of Urban Economics* 64 (2): 218–33.

Cascio, Elizabeth U., and Ethan G. Lewis. 2006. "Schooling and the Armed Forces Qualifying Test: Evidence from School-Entry Laws." *Journal of Human Resources* 41 (2): 294–318.

Chay, Kenneth, Jonathan Guryan, and Bhashkar Mazumder. 2009. "Birth Cohort and the Black-White Achievement Gap: The Roles of Access and Health Soon after Birth." National Bureau of Economic Research (NBER) Working Paper 15078.

Choi, James J., David Laibson, and Brigitte C. Madrian. 2011. "$100 Bills on the Sidewalk: Suboptimal Investment in 401(k) Plans." *Review of Economics and Statistics* 93 (3): 748–63.

Christelis, Dimitris, Tullio Jappelli, and Mario Padula. 2010. "Cognitive Abilities and Portfolio Choice." *European Economic Review* 54 (1): 18–38.

Cole, Shawn, Anna Paulson, and Gauri K. Shastry. 2012. "Smart Money: The Effect of Education, on Financial Behavior." http://www.wellesley.edu/Economics/gshastry/cole-paulson-shastry-financial%20behavior.pdf. (accessed October 17, 2012).

Cullen, Mark, Liran Einav, Amy Finkelstein, and Iuliana Pascu. Forthcoming. "How General Are Risk Preferences? Choices under Uncertainty in Different Domains." *American Economic Review*.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde. 2010. "Are Risk Aversion and Impatience Related to Cognitive Ability?" *American Economic Review* 100 (3): 1238–60.

Frederick, Shane. 2005. "Cognitive Reflection and Decision Making." *Journal of Economic Perspectives* 19 (4): 25–42.

Gerardi, Kristopher, Lorenz Goette, and Stephan Meier. 2010. "Financial Literacy and Subprime Mortgage Delinquency: Evidence from a Survey Matched to Admministrative Data." Federal Reserve Bank of Atlanta Working Paper 2010–10.

Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa. 2011. "IQ and Stock Market Participation." *Journal of Finance* 66 (6): 2119–64.

Hansen, Karsten T., James J. Heckman, and Kathleen J. Mullen. 2004. "The Effect of Schooling and Ability on Achievement Test Scores." *Journal of Econometrics* 121 (1–2): 39–98.

Heckman, James J., Jora S. Stixrud, and Sergio Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." National Bureau of Economic Research (NBER) Working Paper 12006.

Lang, Kevin, and Michael Manove. 2011. "Education and Labor Market Discrimination." *American Economic Review* 101 (4): 1467–96.

Madrian, Brigitte C., and Dennis F. Shea. 2001. "The Power of Suggestion: Inertia in 401(K) Participation and Savings Behavior." *Quarterly Journal of Economics* 116 (4): 1149–87.

McArdle, John J., James P. Smith, and Robert Willis. 2011. "Cognition and Economic Outcomes in the Health and Retirement Survey." In *Explorations in the Economics of Aging*, edited by David A. Wise, 209–33. Chicago: University of Chicago Press.

Neal, Derek A., and William R. Johnson. 1996. "The Role of Pre-Market Factors in Black-White Wage Differences." *Journal of Political Economy* 104 (5): 869–95.

Warner, John T., and Saul Pleeter. 2001. "The Personal Discount Rate: Evidence from Military Downsizing Programs." *American Economic Review* 91 (1): 33–53.

Wigdor, Alexandra K., and Bert F. Green, Jr., eds. 1991. *Performance Assessment for the Workplace, Vol. II: Technical Issues*. Washington, DC: National Academies Press.