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Cognitive Abilities and Household Financial Decision Making*

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Abstract

We analyze the impact of cognitive skills on two specific examples of consumer financial decisions where suboptimal behavior is well defined: first, the use of a credit card for a transaction after making a balance transfer on the account, and second, cases where individuals are penalized for inaccurate estimation of the value of one's home on home equity loan or line of credit application. We match individuals from the US military for whom we have detailed test scores from the Armed Services Vocational Aptitude Battery test (ASVAB), to administrative datasets of retail credit from a large financial institution. Our results show that consumers with higher overall composite test scores, and specifically those with higher math scores, are substantially less likely to make a financial mistake. Importantly no such effects are found for verbal or for most other component scores. We also examine the effect of these mistakes on the consumer cost of credit (APR and fee) payments. We show that our matched sample is reasonably representative of both universes from which it is drawn.

Keywords: Household finance, Credit Cards, Home Equity, AFQT Scores

JEL Classifications:

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1. Introduction

An emerging literature has shown that individuals commonly make financial decisions that would be considered suboptimal according to standard consumer finance theory. For example, individuals accept payday loans with astronomical APRs when other cheaper forms of credit are available (Agarwal, Skiba, and Tobacman, 2009; Bertrand and Morse, 2009), and consumers with multiple credit card offers fail to optimally choose the right credit card (Agarwal et. al., 2006). More broadly, it is puzzling that less than 30 percent of U.S. households directly participate in equity markets (Cole and Shastry, 2009; Li, 2009) and among those who do hold stocks, many have highly concentrated portfolios and trade excessively (Korniotis and Kumar, 2009a and b).

Suboptimal household financial decision-making behavior has important and potentially wide ranging ramifications for society. For example, the ability of families to adequately invest in their children's human capital or for older individuals to optimally secure retirement income is undoubtedly affected at least in part, by the quality of financial decision making. There is also heightened interest among policy makers in restraining excessive consumer debt that can lead to bankruptcy and home foreclosures. Recent economic events suggest that suboptimal financial behavior among households in the residential mortgage market may have contributed to large spillover effects on the aggregate economy. Despite the growing salience of the issue, our current understanding of exactly what factors might account for suboptimal financial behavior is limited.

One potential explanation is that high levels of very specific cognitive abilities may be a prerequisite for making optimal financial choices.[1] For instance, in choosing an investment portfolio, an investor must synthesize a wide range of information concerning economic conditions and the past performance of various assets, accounting for transactions costs, asset volatility, and covariance among asset returns. This task requires memory, computational ability, and financial sophistication. Cognitive limitations might also lead consumers to make suboptimal credit decisions, perhaps because they overestimate their

[1] Analytic cognitive function can be measured in many different ways, including tasks that evaluate working memory, reasoning, spatial visualization, and cognitive processing speed.

ability to repay loans or fail to translate monthly payment rates into annualized interest rates (Ausubel 1991, Agarwal et. al. 2006, and Bertrand and Morse, 2009). In general, there is now growing evidence that cognitive ability is an important predictor of financial outcomes (Benjamin, Brown, and Shapiro, 2006; Cole and Shastry, 2009; Frederick, 2005).

The evidence from the existing literature however, has some important shortcomings along several dimensions. First, among studies that have used precise measures of suboptimal financial behavior, direct measures of cognitive ability have been lacking. For example, Agarwal et. al. (2009) and Korniotis and Kumar (2009a) link the effects of cognitive ability on specific financial decisions only *indirectly*, through the correlation of cognitive skills with other variables such as age. Second, some of the studies that have used more direct measures of cognitive ability have relied on experimental outcomes rather than real world financial decisions. Third, several studies have relied on very broad outcomes such as measures of financial participation (e.g. stock market participation) and in some cases have not provided evidence on the intensive margin. Moreover, most studies of financial market participation have focused disproportionately on investment decisions, mainly because of data availability.

As a result of these limitations, there is thus far little compelling evidence that *directly* links detailed measures of cognitive ability to precisely defined examples of suboptimal financial behavior at the intensive margin. Moreover, previous studies have generally been unable to shed much light on the mechanisms through which cognitive ability influences the decision making process.[2] Finally, the use of broad financial outcomes such as stock market participation also raises the concern of omitted variable bias, as those with higher cognitive ability likely have higher levels of socio-economic status or other positive endowments and may have been more likely to invest irrespective of their cognitive ability. In the absence of a compelling research design it is difficult to assess whether the estimated relationships using such broad outcome measures are truly causal.

Our data and analysis address many of these shortcomings. We use scores from the Armed Services Vocational Aptitude Battery test (ASVAB) which is used by the military as a screening tool and as a measure of trainability. The ASVAB is especially useful for our analysis because in addition to testing subject matter knowledge in several specific areas, there are subtests that directly assess an individual's math, verbal and perceptual skills.[3] Since the ability to process and synthesize written mathematical information likely affects an individual's financial decision making ability, it is plausible that these tests would capture the relevant cognitive skills. Two of the math subtest scores and two of the verbal subtest scores are combined to create the composite Armed Forces Qualifying Test (AFQT) score which is used as part of the selection criteria for entrance into the military.

Frederick (2005) found that individuals who score higher on a cognitive reflection test are more patient and more forward looking. This suggests that those with higher cognitive skills may be more likely to invest in their own human capital and undertake healthier behaviors. In fact many previous studies have shown that cognitive skills, as measured specifically by the AFQT play an important role in determining one's educational attainment (e.g. Cascio and Lewis, 2006), future earnings (e.g. Neal and Johnson, 1996) and participation in crime and other risky behaviors (Heckman, Stixrud and Urzua, 2006). Warner and Pleeter (2001) evaluated a natural experiment during the downsizing of the US military where individuals were offered a choice between a lump-sum separation benefit or an annuity and used the results to infer personal discount rates. An ancillary finding in their study was that individuals with higher AFQT scores had lower discount rates.

We further improve upon the existing literature by linking this oft-used and well validated measure of cognitive ability, to two very specific but distinct types of financial decisions where suboptimal behavior is clearly defined. The first example is individuals who make purchases on a credit card after making a balance transfer to the account. As we explain in the next section, it is never optimal to use the card with the balance transfer given that another credit card is available. We refer to this as a "balance transfer mistake" and describe consumers who ultimately discover the optimal strategy as experiencing a "eureka"

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[2] Information constraints and a variety of behavioral biases are sometimes cited as possible causes.
[3] The ASVAB test for our sample consists of 10 subtests. We describe the test in further detail in section 2. The coding speed component of the test which is arguably a measure of perceptual skills has been dropped from the ASVAB.

moment. The second example is individuals who are penalized on their home equity loan application for inaccuracies in estimating the value of their home. We match a subset of the universe of active duty military personnel to an administrative datasets of retail credit from a large financial institution and run statistical models linking suboptimal financial behavior to ASVAB test scores.

Our results show that consumers with higher overall AFQT scores, and specifically those with higher math scores, are substantially less likely to make balance transfer and house price estimation mistakes. Specifically a one standard deviation increase in the AFQT score is associated with a 24 percent increase in the probability that a consumer will discover the optimal strategy and a 11 percent reduction in home equity loan mistakes. The fact that verbal scores are not at all associated with either of these mistakes provide a useful internal validity check and suggests that omitted variables bias is not of major concern. We also use a rich set of observable demographic characteristics and financial measures to show that our matched sample is reasonably representative of both the overall military sample and the administrative dataset from the financial institution. We further assess the external validity of our results by using a nationally representative sample, the National Longitudinal Survey of Youth (NLSY79) who were given the ASVAB in order to provide national norms. We demonstrate that a simple measure of patience is strongly associated with only the math component of the test providing a parallel set of supportive results that may shed light on one potential mechanism.

The rest of the paper is organized as follows. Section 2 provides an overview of the current literature on financial decision making and cognitive ability. Section 3 describes the data. Section 4 discusses the empirical estimation and presents results. Finally section 5 concludes.

2. Literature Review

We describe some of the relevant literature linking cognitive ability to behavioral differences that may be relevant to our study. One major reason why cognitive ability might matter is because of the importance of information. In a seminal paper Tversky and Kahneman (1981) demonstrated that the way in which information is presented can affect an individuals' decision making. Several recent studies have specifically emphasized that information may be an important factor influencing financial behaviors. Stango and Zinman (2009) find that U.S. consumers regularly underestimate the APR of a loan if they are given only the loan principal and repayment stream. They further find that mistake-prone consumers hold loans with higher interest rates when borrowing from non bank lenders who are may be more likely to suppress interest rate information and emphasize monthly payment rates. Bertrand and Morse (2009) find that payday loan borrowers who are shown information on the aggregate cost of their loan or the time to repayment frequencies, borrow significantly less per pay cycle. Korniotis and Kumar (2009a) present evidence that some deviations from standard portfolio choice theory are due to access to superior information among high cognitive ability investors. Finally, Li (2009) finds that information sharing may explain the correlation in financial market participation among family members.

Other studies have emphasized psychological biases in financial decision making. Heaton (1997) showed that managers tend to be overly optimistic about their firms' prospects which leads them make managerial decisions that might not have been chosen in the absence of emotional influences. Korniotis and Kumar (2009a) suggest that low cognitive ability investors have lower risk-adjusted performance due to overconfidence and familiarity. Firms tend to keep prices stable or even below marginal costs in part to avoid anger or regret from consumers (Rotemberg, 2007).

Several papers have found that individuals with higher cognitive ability demonstrate fewer and less extreme cognitive biases that may lead to suboptimal behavior. Benjamin, Brown, and Shapiro (2006) found that Chilean high school students with higher standardized test scores were less likely to exhibit small stakes risk aversion and short run discounting in a laboratory setting. Preference anomalies were greater when the complexity, or "cognitive load," of the choices increased, but smaller when subjects were asked to explain their decisions. Though financial decisions are made with larger stakes and over a longer time frame, these results suggest that cognitive limitations might be related to similar behavioral biases that influence financial decisions. Frederick (2005) documents similar phenomena with college students using a different measure of intelligence called the Cognitive Reflection Test (CRT), which evaluates an individual's ability to override initial but incorrect cognitive impulses. Subjects with high CRT scores were more patient with short term tradeoffs but not significantly more patient with long term tradeoffs, suggesting that these differences may be due to differences in cognitive reflection rather than underlying preferences.

It is clear that one important objective of future studies should be to distinguish the relative importance of information channels, psychological biases and other forms of cognitive bias. One potential avenue for investigating this is to use distinct measures of separate cognitive skills simultaneously. One study that does attempt to distinguish between the information channel and other biases is Korniotis and Kumar (2009a). However, a major caveat to the analysis is that the study uses other characteristics (e.g. age, education, income, and wealth) to impute cognitive ability. Consequently, unlike many of the other studies which hold the effects of other key covariates constant, Korniotis and Kumar estimate the effect of cognitive ability on financial outcomes through its relationship with these control variables. Any separate effect of cognitive ability is *not* captured in their analysis.

A second relevant literature is concerned with the general importance of cognitive ability on economic outcomes and financial market outcomes. Several studies have shown that individuals with greater cognitive ability as measured by ASVAB scores have higher educational attainment (Neal and Johnson 1996, Hansen, Heckman, and Mullen 2004, Cascio and Lewis 2006), higher earnings (Neal and Johnson 1996) and are less likely to engage in criminal or other socially deviant behaviors (Heckman, Stixrud and Urzua, 2006). A few studies have utilized ASVAB scores from the NLSY to analyze financial market participation. Benjamin, Brown, and Shapiro (2006) found that individuals with higher AFQT scores were significantly more likely to own stocks, bonds or mutual funds. Cole and Shastry (2009) using the same data also find effects of AFQT scores on the intensive margin (e.g. amounts of stock ownership).

Grinblatt, Keloharju, and Linnainmaa (2009) use very detailed data on the daily portfolios and trades of Finnish households matched to test scores from the Finnish Armed Forces Intelligence Assessment taken by all males in Finland. They find a positive monotonic relationship between intervals of this score and stock market participation, for both the entire population and for a subsample of more affluent Finns. They further find that only 60% of this relationship can be explained by IQ's correlation with other control variables and that the results are also robust to household fixed effects. While Benjamin, Brown, and Shapiro (2006), Cole and Shastry (2009) and Grinblatt, Keloharju, and Linnainmaa (2009) all use family or household fixed effects, there still may be lingering concerns that sibling specific characteristics that could be correlated with cognitive ability (e.g. motivation, or other sibling specific endowments) may have an independent effect on financial market participation. This helps motivate the need for a much narrower measure of suboptimal financial decision making that would be more tightly related only to cognitive skills.

To our knowledge, the only paper that attempts to study the relationship between cognitive ability and credit decisions is Agarwal et. al. (2009). Similar to Korniotis and Kumar (2009b), Agarwal et al. use an indirect approach by analyzing how credit decisions vary with age. They find that middle aged borrowers pay lower interest rates and fees than their younger and older counterparts, creating a U-shaped age-price curve. This curve is consistent across ten financial products including home equity loans, auto loans, mortgages, and several credit card services, and is not explained by cohort effects, selection effects, or differences in borrower risk. Most interestingly, the authors find mechanisms related to experience and cognitive ability for the two forms of financial decision making mistakes also used in this paper –opitmal use of credit card balance transfer offers, and the ability to correctly assess the values of one's home. They find that the combined effects of increasing experience and declining cognitive ability drive the U-shape of the age-price curve (Agarwal et. al., 2009).

3. Data and Methodology

Our primary analysis combines information from three distinct datasets: U.S. military data, credit card data, and data on home equity loan/lines. We describe each of these datasets below. We also discuss the two samples that are formed based on the merging of the the military records with the two sets of financial records. We also describe the two forms of suboptimal behavior and our basic estimation strategy.

3.1 Military data

We begin with a universe of approximately 1.4 million active duty military personnel in 1993. Since the Armed Services Vocational Aptitude Battery test (ASVAB) has changed over time, we limited our sample to individuals who entered the military beginning in September 1986 and whose test form is between 35 and 47 so that the scores are measured on a consistent basis. This gives us a sample of approximately 840,000 individuals.

For our sample, the ASVAB consists of a total 10 different subtests including: numerical operations, word knowledge, arithmetic reasoning, math knowledge, electronics information, mechanical comprehension, general science, paragraph comprehension, coding speed and automotive and shop. The armed forces qualifying test (AFQT) is constructed by combining two of the math scores with the two of the verbal scores.[4] The AFQT is used for enlistment screening and various subscores of the ASVAB are used for assigning jobs within the military. The ASVAB has undergone exhaustive analysis including a 1991 National Academy of Science study establishing the validity of the test as apredictor of job performance (Wigdor and Green, 1991). In addition to test scores, we have information on gender, age, education levels, branch of service, race, ethnicity, marital status and zipcode of residence. Summary statistics for this sample are shown in Appendix Table A1.

3.1 Credit Card Data

We use a proprietary panel data set from a large financial institution that made balance transfer offers to credit card users nationally.[5] Our universe consists of 14,798 individuals who accepted the offers between January 2000 and December 2002. The data includes the main billing information listed on each account's monthly statement including total payment, spending, credit limit, balance, debt, purchases, cash advance annual percentage rates (APRs), and fees paid. We also observe the amount of the balance

[4] The 1980 metric of the test combined the scores from the arithmetic reasoning, numerical operations, word knowledge and paragraph comprehension subtests. The 1989 metric replaced the numerical operations score with the mathematical knowledge score. In the current draft we use the 1980 metric. The current version of the ASVAB uses only 8 subtests.

transfer, the start date of the balance transfer teaser rate offer, the initial teaser APR on the balance transfer, and the end date of the balance transfer APR offer.[6] At a quarterly frequency, we observe each customer's credit bureau rating (FICO) and a proprietary (internal) credit `behavior' score. In addition, we have credit bureau data on the number of other credit cards held by the account holder, total credit card balances, mortgage balances as well as age, gender, and self-reported income at the time of account opening.

We merge the credit card data with the military data using a unique identifier and obtain a sample of 541 borrowers who transferred balances and for whom we have a full set of non-missing information on the military variables. Appendix Table A1 presents summary statistics of the resulting sample and compares a common set of covariates to the full military sample in Panel A. The comparison shows that there are no significant differences in any of the test scores. The mean AFQT is just slightly lower in the matched sample (60.2 versus 61.3). For eight of the ten subtests the matched sample has slightly lower scores, the two exceptions are word knowledge and general science where the scores are slightly higher in the matched sample. On the other hand, average years of education are slightly higher in the matched sample (12.1 vs. 12.0), a difference which though tiny is nonetheless statistically significant. The average age at entry into the military is also quite similar (19.7 versus 19.8). The share of males is a bit higher in the matched sample (88.9% vs. 87.6%). The most noticeable difference is with respect to race, where we find that our matched sample overrepresents blacks (25.3% vs. 19.8%) and slightly underrepresents whites (67.3% vs. 69.8%) and other racial groups (7.4% vs. 10.4%) compared to the full military sample. Overall, however, for the key dimension of our analysis --cognitive skills-- our sample is reasonably representative of the full military.

Panel B of Table A1 compares this matched sample to the full sample of borrowers. The average matched sample borrower is riskier as reflected by the FICO and behavior scores – they are 23 and 63 points lower respectively. Surprisingly, the income of the matched sample borrowers is $14,242 higher.

[5]The offers were not made conditional on closing the old credit card account.
[6] In this sample, borrowers did not pay fees for the balance transfer.

The balance transfer APR for the matched sample borrowers is 77 basis points higher than the full sample of borrowers, while this is statistically significantly different, but it is economically not significant. Surprisingly, the purchase APR for matched sample borrowers is 649 basis points lower. Potentially, this is because the account age of these borrowers is less than half of the full sample borrowers and so they still have favorable lending terms.

3.2 Home Equity Loans and Lines Data

Similarly, for home equity loans and lines of credit, we use a proprietary panel dataset obtained from a national financial institution.[7] Between March and December 2002, the lender offered a menu of standardized contracts for home equity loans or lines of credit. Consumers chose the following: (a) either a loan or a credit line; (b) either a first or second lien; and (c) an incremental loan amount and an estimate of her property value, corresponding to a loan-to-value (LTV) ratio of less than 80 percent, between 80 and 90 percent, or between 90 and 100 percent. In effect, the lender offered twelve different contract choices. In the results below, we run regressions for home equity loans and lines of credit together, but have a dummy variable for home equity loans, not having a first mortgage and LTV bucket; hence we control for contract type. All loans have the same five-year maturity.

For 75,000 out of 1.4 million such contracts, we observe the contract terms, borrower demographic information (years at current job, home tenure), financial information (income and debt-to-income ratio), and risk characteristics (credit (FICO) score, and LTV).[8] 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 1393 borrowers who took out a home equity loan or line of credit and for whose home we have non-missing value on the key variables.

Panel A of Table A2 presents summary statistics comparing the matched sample to the overall military sample. Unlike with the credit card match, we find that test scores are generally higher in our matched sample and although the differences are not very large, they are statistically significant. We

[7] The lender did not specialized in subprime loans or other market segments.

suspect that this is primarily driven by the fact that our matched sample is selected on home ownership status which likely reflects higher levels of socioeconomic status. We also find that unlike our credit card sample, our matched home equity sample contains a larger share of whites and a smaller share of males, although neither difference is statistically significant.

In panel B of the table, we compare the matched home equity sample to the full home equity sample. Borrowers in the matched sample are less risky, have higher income, and pay lower APR. Additionally, the FICO score in the matched group is 10 points higher , the APR is 196 basis points lower and the debt-to-income ratio is 6.5% lower than for the full sample. Finally, borrowers in the matched sample have been on their jobs 2.4 years longer and the appraised value of their homes is $21,040 higher than the full sample borrowers.

3.3 Balance Transfer Mistake

Credit card holders frequently receive offers to transfer account balances on their current cards to a new card. Borrowers 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 have high APRs. The catch is that *payments* on the new card *first* pay down the (low interest) transferred balances, and only subsequently pay down the (high interest) debt accumulated from new purchases.

The optimal strategy during the teaser-rate period, is for the borrower to only make new purchases on the *old* credit card and to make all payments to the old card. To be clear, this implies that 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).[9] 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

[8] We do not have internal behavior scores (a supplementary credit risk score) for these borrowers. Such scores are performance-based, and are thus not available at loan origination.

have what we refer to as a “eureka” moment, after which they will implement the optimal strategy. Some borrowers will never identify the optimal strategy.

This allows to categorize account holders in several ways including: whether they ever make a balance transfer mistake or not; or if they do make a balance transfer mistake, how long it takes them to adopt the optimal strategy and stop using the balance transfer card for new purchases. To operationalize this we track use of the balance transfer card for a six month period for consumers who continue to use at least one card for a purchase. Our main dependent variable “eureka” will be defined as those who either never make the mistake during the six month period or if they do make a mistake at some point, whether they cease to make the mistake for the remainder of the sixth month window. Our second measure of eureka tracks how loan it takes for the consumer to adopt the optimal strategy and stop using the balance transfer card for new purchases.

About one third of all customers who make a balance transfer do no spending on the new card, thus implementing the optimal strategy immediately. Slightly more than one third of customers who make a balance transfer spend on the new card every month during the promotional period, thus never experiencing a eureka moment. The remaining third of customers experience a eureka moment at some point between the first and sixth months.

In section 4 we will estimate the effect of overall AFQT scores as well as specific math and verbal subtests on the likelihood that a borrower will have a eureka moment. We run linear probility regressions where we include a variety of demographic and financial control variables. Figure 1 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 scores above 70, everybody ultimately identifies the optimal strategy. In contrast, among those with an AFQT score below 50, the majority will not identify the optimal strategy. A full set of differences in the mean characteristics of those who experience eureka versus those that don’t are shown in Table A3. Of particular note is that blacks comprise a much

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[9] This is true even if the interest rate for purchases on the old card is higher than the interest rate for purchases on the new card because our measure of eureka is strictly for those consumers who always pay off the entire purchase on

larger fraction of the "no eureka" subsample. As we show later our results are insensitive to dropping blacks.

3.4 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 loan-to-value (LTV) ratio, is an important 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 categories depending on the implied borrower-generated LTV estimate. The categories correspond to LTVs of 80 percent or less (80-); LTVs of between 80 and 90 percent (80+); and LTVs of 90 percent or greater (90+). The financial institution then independently verifies the house value using an industry-standard methodology and constructs an LTV measure. The institution's LTV can therefore differ from the borrower's LTV.[10]

Loan pricing (APR) depends on the LTV category that the borrower falls into and not on the specific LTV value within that category.[11] If the borrower has overestimated the value of the house, so that the financial institution's LTV (80+) is higher than the borrower's LTV (80-), the institution will direct the buyer to a different loan with a higher interest rate corresponding to the higher LTV (80+). In such circumstances, the loan officer is also given some discretion to depart from the financial institution's normal pricing schedule to offer a higher interest rate than the officer would have offered to a borrower who had correctly estimated her LTV. If the borrower has underestimated the value of the house (e.g. the borrowers' LTV category is 80+ while the banks LTV category, 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

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the card every month. Hence, they will not incur any interest payment on the purchase.

[10]Agarwal (2007) provides evidence that younger households are more likely to overstate their house value and older households are more likely to understate their house values. Bucks and Pence (2008) present evidence that borrowers do not generally have accurate estimates of their house value or know their mortgage terms.

[11]We have verified this practice in our dataset by regressing the APR on both the level of the bank-LTV and dummy variables for whether the bank-LTV falls into one of the three categories. Only the coefficients on the dummy variables were statistically and economically significant. Ben-David (2007) also shows that there are discrete jumps in lending rates at LTV cutoff points.

loan officer may simply choose to offer the higher interest rate associated with the borrower's LTV (80+), instead of lowering the rate to reflect the lower financial institution's LTV (80-).[12]

We define a Rate-Changing Mistake (RCM) to have occurred when the borrower-LTV category differs from the bank-LTV category (conditional on the bank LTV being greater than 80) — for instance, when the borrower estimates an LTV of 85 but the bank calculates an LTV of 75 (or vice versa).[13] We find that, on average, making a RCM increases the APR by 269 basis points for home equity loans and lines. In the next section, we will estimate the effect of math and verbal AFQT test scores in a borrower's ability to not make the RCM.

Table A4, Panel B highlights the significant differences between the borrowers with and without a RCM. The FICO score for the RCM borrowers is 24 points lower, the income is $20,360 lower and the debt-to-income is 5% higher. However, to highlight the importance of RCMs, we estimated the effect of AFQT on the APR for consumers who do not make a Rate-Changing Mistake and found no statistically significant or quantitatively meaningful effect. When coupled with our findings below, this suggests that AFQT only affects the pricing of the loan through the rate changing mistake.

As with balance transfer mistakes, we find stark differences in rate changing mistakes by AFQT. Figure 2 shows that there are no cases of rate changing mistakes among those with scores above 60. Although rate changing mistakes are still relatively uncommon even among those with lower test scores they are concentrated in the lower half of the AFQT distribution. Table A4 provides more detailed summary statistics separately for those who experience an RCM versus those who don't. In section 4 we control for these demographic and financial factors using a linear probability model. We estimate the effect of AFQT scores and specific math and verbal subtests on the likelihood that a borrower will make a rate changing mistake.

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[12]Even if the financial institution's estimate of the true house value is inaccurate, that misestimation will not matter for the borrower as long as other institutions use the same methodology.

[13] An example where misestimation does not lead to a higher APR is if the borrower's estimated LTV is 60, but the true LTV is 70. 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.

4. Results

4.1 Balance Transfer Mistakes and AFQT Scores

In Table 1 we show the results of our first set of estimates that use overall 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 one 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. Further, we find that most of the financial controls (e.g. FICO score, income) have no effect on the probability of a eureka moment. The one exception is the behavior score. The behavior score is a measure of the borrowers payment and purchase behavior. Hence, it is not surprising that the behavior score is predictive in explaining the credit card purchases subsequent to balance transfers.

In column (3) we find the effect rises slightly to 0.24 when we include our demographic controls. Perhaps surprisingly, there is no effect of years of education. Further, we find that the effect for blacks is positive (0.064) once we control for AFQT scores, though this is not statistically significant. Those that were married at the time they were in the military are significantly less likely to have a eureka moment. In column (4) we include both sets of controls and again find that it has no effect on our main finding.

In columns (5) through (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 0. For example, the largest point estimate for a verbal score suggests that a one 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.

In other specifications (not shown) we also estimated the effect of AFQT on whether a borrower *immediately* adopts the optimal strategy. In these cases the coefficient on AFQT 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 immediate effect and about a third of the effect is due to borrowers who learned the optimal strategy subsequent to 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 how AFQT influences the speed at which individuals learn, in Figure 3 we plot 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 one standard deviation increase in AFQTis associated with a 1.5 month reduction in the number of months it takes to achieve optimal behavior speed. This analysis is akin to showing that cognitive skills also affects the "intensive" margin of optimal financial decision making behavior.

4.2 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 (RCM) for home equity loans or lines. The first four columns use the overall AFQT score and utilize: 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 one standard deviation increase in AFQT lowers the probability that a borrower will make a rate changing mistake by between 10 and 11 percentage points. The unconditional average probability of making a rate-changing mistake is 14 percent in our sample so the effect size is over 70 percent.

Among the financial covariates, taking out a loan versus a line raises the likelihood of an RCM by about 10 percentage points as does an increase in the APR. The debt to income ratio has a small but perceptible effect. The FICO score also has a small effect but not economically significant. Education has virtually no effect once we condition on financial variables. Interestingly, blacks are actually significantly less likely to make an RCM controlling for AFQT while women are slightly more likely to (not shown).

When we use the four subtests that comprise the AFQT (columns 5 to 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 one standard deviation increase in word knowledge lowers the probability of an RCM by about 2 to 3 percentage points.

Given the large costs associated with an RCM, one might ask why borrowers do not make greater effort to more accurately estimate their house values. One possibility is that potential borrowers may not be aware that credit terms will differ by LTV category; or, even if they are aware of this fact, they may not know how much the terms differ by category. This particular aspect of loan pricing may thus be a shrouded attribute, in the sense of Gabaix and Laibson (2006).

4.3 Robustness Checks

An important finding is that it is specifically quantitiative skills, as opposed to other dimensions of cognitive ability or measures of general knowledge, that appear to matter for financial decision making. To reinforce this, we also show results that include the other 6 subtests from the ASVAB in Table 3. Columns (1) to (4) use the same specifications from the previous tables to examine the effect of the scores on eureka moments using the credit card data. Columns (5) to (8) estimate the effects on a rate changing mistake using the home equity borrower sample. For the credit card results, we find that the effects from two main math scores from Table 1 are unaffected by the inclusion of the other scores. For example, the results in column (4) imply that a one standard deviation increase in either of the main math scores alone, would raise the probability of a eureka moment by about 13 percent. We also find that a test called "coding speed" which measures how quickly and accurately individuals can recognize numerical patterns is statistically significant.

A third test of math skills called numerical operations enters *negatively* controlling for the other two math scores. However, the raw correlation between eureka moments 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) suggesting that numerical operations is picking up some factor that is orthogonal to the other two math scores.[14]

With our home equity borrowers we find that in addition to the arithmetic reasoning, math knowledge and word knowledge, that numerical operations has the correct sign and is marginally significant. We do not find that coding speed has any effect on rate changing mistakes. Overall, though not every effect is perfectly consistent across the two outcomes the two main math tests are highly significant while most other subtests are insignificant. Our results are insensitive to using state fixed effects or limiting the sample to only whites. Finally, the results are also robust to controls for contract type (loan interacted with LTV category).

4.4 Additional Evidence from the NLSY: Cognitive Ability and Patience

In order to better understand the underlying mechanisms behind the link between cognitive ability and optimal financial decision-making we conduct a similar analysis using the 1979 National Longitudinal Survey of Youth (NLSY). The NLSY followed a nationally representative smaple of who were born between the ages of 14 and 21 as of January 1979 into adulthood. One hypothesis that we can test is whether cognitive skills are associated with lower discount rates reflecting greater patience. In the 2006 survey, respondents were asked an experimental question designed to elicit their implicit personal discount rates. Specifically, the question read as follows: *Suppose you have won a prize of $1000, which you can claim immediately. However, you can choose to wait one month to claim the prize. If you do wait, you will receive more than $1000. What is the smallest amount of money in addition to the $1000 you would have to receive one month from now to convince you to wait rather than claim the prize now?* A

[14] Numerical operations had been included in the 1980 metric of the AFQT before it was replaced with math knowledge.

response of $100, for example, would imply an annual discount rate of over 200%. We use a subset of responses that lie within the range of $1 to $500.[15] The mean value in this range is ___.

We link responses to this question to respondent test scores as well as a number of other controls. Individuals in the NLSY were given the ASVAB in 1980 and their scores were used to norm the test. The use of the same scores for a nationally representative sample also may help alleviate any lingering concerns that our results on suboptimal financial behavior are driven by unrepresentative samples. Previous work by Warner and Pleater (2001) showed that AFQT scores are associated with lower discount rates as implied by a real world experiment where military personell were offered a choice of either a lump-sum payment or an anuuity during separation. However, their analysis was limited to four broad intervals of the composite AFQT and could not distinguish between specific subtest scores. .

In Table 4 we present the results of this analysis. In column (1) we show that a one standard deviation increase in AFQT is associated with 44 dollar decline in the amount an individual would require to be compensated. This implies a decline in the monthly subjective discout rate of 4.4 percent. This estimate controls for several demographic characteristics including gender, race, Hispanic status and education that are all at least marginally significant. As a point of comparion for our AFQT results, even four additional years of schooling would only lower the discount rate by 0.8 percentage points. In column (2) we include the scores from the other 6 ASVAB subtests not incorporated into the composite AFQT. In column (3) we also add one's own annual earnings in 2005. These have a limited effect on our main estimates. In column (4) we utilize the fact that the NLSY contains many multiple sibling families and include family fixed effects. This raises the standard errors considerably, but we still estimate a significant negative effect of about 55 dollars. In this case we have arguably greatly reduced the potential scope for omitted variables bias since we only utilize differences in cognitive ability between siblings and sweep away all variation that is across families.

[15] Many respondents provided answers that were clearly unreasonable with implied discount rates of __% or more. We also have experimented with a parallel question that asks the same thing over a 1 year range.

In columns (5) through (8) we run the same specifications but now show the effects of the four main math and verbal subtests of the ASVAB on our measure of patience. In all four specifications the effects are highly concentrated in the arithmetic reasoning subtest with coefficients ranging from to -27 to -44. The other main subtests also generally have negative coefficients but are never statistically significant.

5. Conclusion

Several recent papers have shown that individuals commonly make financial decisions that would be considered suboptimal according to standard consumer finance theory. Suboptimal household financial decision-making behavior has important and potentially wide ranging ramifications for society. For example, the ability of families to adequately invest in their children's human capital or for older individuals to optimally secure retirement income is undoubtedly affected at least in part, by the quality of financial decision making. There is also heightened interest among policy makers in restraining excessive consumer debt that can lead to bankruptcy and home foreclosures.

In this paper, we analyze the impact of cognitive skills on two specific examples of consumer financial decisions where suboptimal behavior is well defined: first, the use of a credit card for a transaction after making a balance transfer on the account, and second, cases where individuals are penalized for inaccurate estimation of the value of one's home on home equity loan or line of credit application. We match individuals from the US military for whom we have detailed test scores from the Armed Services Vocational Aptitude Battery test (ASVAB), to administrative datasets of retail credit from a large financial institution.

Our results show that consumers with higher overall AFQT scores, and specifically those with higher math scores, are substantially less likely to make balance transfer and house price estimation mistakes. Specifically a one standard deviation increase in the AFQT score is associated with a 24 percent increase in the probability that a consumer will discover the optimal strategy and a 11 percent reduction in home equity loan mistakes. The fact that verbal scores are not at all associated with either of these mistakes provide a useful internal validity check and suggests that omitted variables bias is not of major concern.

We also use a rich set of observable demographic characteristics and financial measures to show that our matched sample is reasonably representative of both the overall military sample and the administrative dataset from the financial institution. We further assess the external validity of our results by using a nationally representative sample, the National Longitudinal Survey of Youth (NLSY79) who were given the ASVAB in order to provide national norms. We demonstrate that a simple measure of patience is strongly associated with only the math component of the test providing a parallel set of supportive results that may shed light on one potential mechanism.

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Table 1: Effects of AFQT on optimal behavior ("Eureka") by consumer borrowers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFQT Score	0.233***	0.232***	0.245***	0.242***				
	(0.019)	(0.017)	(0.020)	(0.018)				
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		-0.001		-0.001		-0.000		-0.000
		(0.003)		(0.003)		(0.003)		(0.003)
Behavior Score		-0.570***		-0.562***		-0.558***		-0.552***
		(0.085)		(0.086)		(0.082)		(0.082)
Behavior Score Sq.		0.081***		0.081***		0.081***		0.080***
		(0.010)		(0.010)		(0.009)		(0.010)
Fico Score		-0.057		-0.046		-0.033		-0.025
		(0.081)		(0.082)		(0.077)		(0.079)
Fico Score Squared		-0.001		-0.001		-0.003		-0.003
		(0.008)		(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			0.008	0.019			0.008	0.020
			(0.028)	(0.026)			(0.027)	(0.025)
Black			0.064	0.058			0.052	0.044
			(0.043)	(0.039)			(0.043)	(0.039)
Other			0.044	0.096			0.034	0.083
			(0.071)	(0.064)			(0.070)	(0.062)
Female			-0.007	-0.007			0.030	0.026
			(0.056)	(0.050)			(0.055)	(0.049)
Married			-0.082**	-0.065*			-0.062*	-0.043
			(0.037)	(0.033)			(0.036)	(0.032)
Observations	480	480	480	480	480	480	480	480
R-squared	0.245	0.407	0.256	0.417	0.295	0.461	0.302	0.467

*** p<0.01, ** p<0.05, * p<0.1

Table 2: Effects of AFQT on rate changing mistakes (RCM) by home equity borrowers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFQT Score	0.101***	-0.105***	-0.113***	-0.113***				
	(0.011)	(0.009)	(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 Knowl.					-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		0.027		0.025		0.026		0.025
		(0.018)		(0.018)		(0.018)		(0.018)
Refinancing		0.016		0.017		0.018		0.019
		(0.016)		(0.016)		(0.016)		(0.016)
Equity Loan		0.099***		0.102***		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		-0.028*		-0.028*		-0.024		-0.024
		(0.015)		(0.015)		(0.015)		(0.015)
APR		0.100***		0.098***		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			0.023*	0.007			0.020	0.005
			(0.013)	(0.010)			(0.013)	(0.010)
Black			-0.062***	-0.042**			-0.061***	-0.042**
			(0.022)	(0.017)			(0.022)	(0.018)
Other			-0.123***	-0.057**			-0.117***	-0.050*
			(0.035)	(0.029)			(0.036)	(0.029)
Observations	1380	1380	1380	1380	1380	1380	1380	1380
R-squared	0.061	0.408	0.077	0.414	0.069	0.411	0.082	0.416

Notes: Due to space limitations, coefficients on self employment , married and female are suppressed.

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	N	Y	N	Y	N	Y	N	Y
Demog. Controls	N	N	Y	Y	N	N	Y	Y
Observations	480	480	480	480	1380	1380	1380	1380
R-squared	0.312	0.471	0.318	0.476	0.074	0.413	0.087	0.417

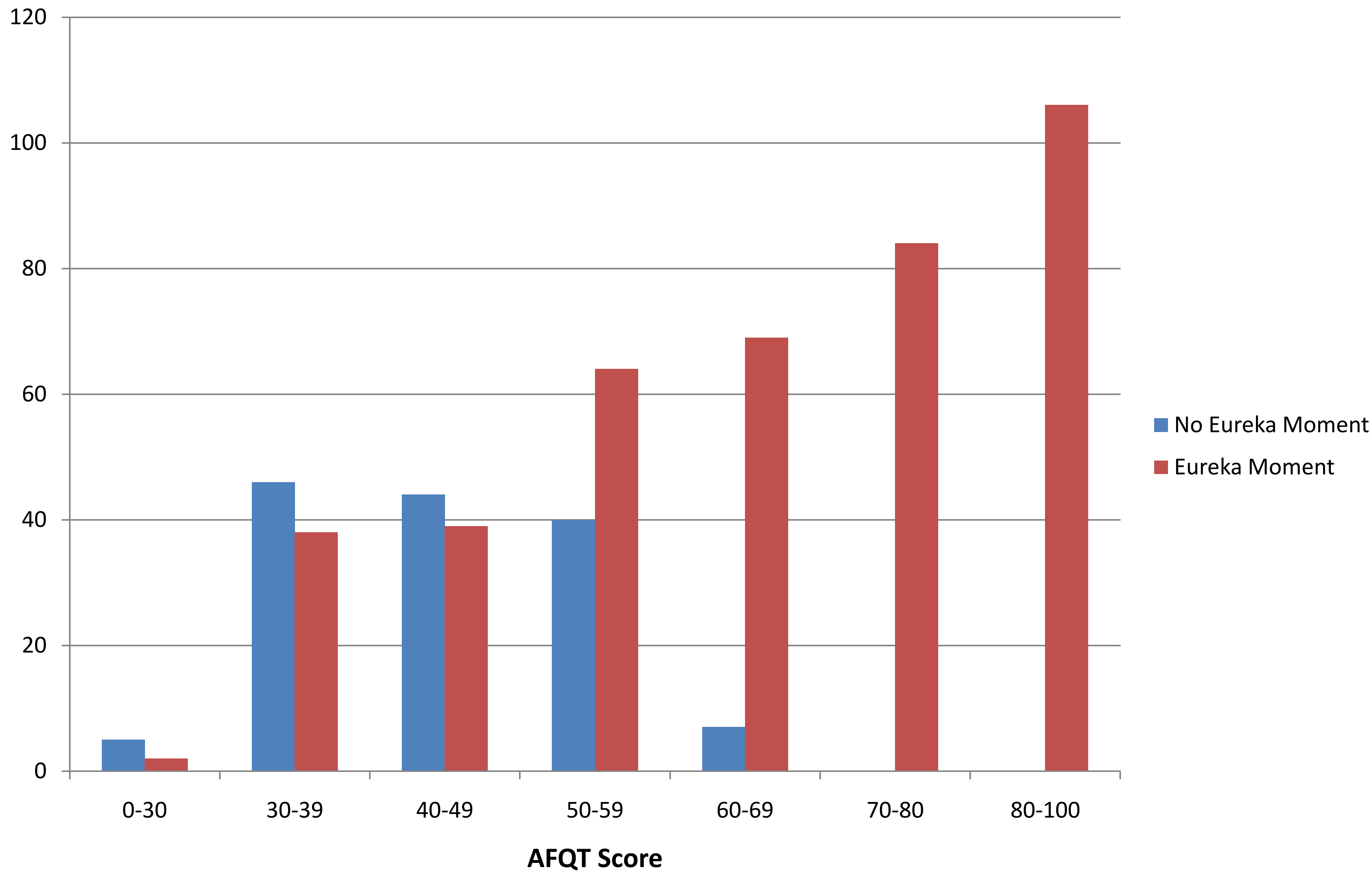
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Effects of AFQT on implied discount rates using NLSY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFQT Score	-44.066**	-38.781**	-40.574**	-51.871**				
	[3.703]	[6.146]	[7.810]	[20.878]				
Arithmetic Reas.					-28.026**	-26.297**	-32.258**	-44.483**
					[5.428]	[5.694]	[7.360]	[20.923]
Math Knowledge					-7.664	-6.201	-1.134	4.86
					[5.178]	[5.318]	[6.843]	[17.580]
Paragraph Comp.					-6.351	-1.596	1.953	-28.62
					[5.290]	[6.155]	[7.971]	[21.684]
Word Knowl.					-5.102	-4.437	-7.248	-0.104
					[5.038]	[5.142]	[6.523]	[15.242]
Female	18.551***	16.411**	9.556	60.619**	15.739***	12.498*	4.378	61.006**
	[5.315]	[6.917]	[8.995]	[24.199]	[5.504]	[7.123]	[9.246]	[24.784]
Black	65.282***	62.458***	55.858***		65.506***	62.755***	54.898***	
	[7.329]	[7.683]	[10.352]		[7.429]	[7.696]	[10.374]	
Hispanic	18.056**	16.877**	11.153		18.543**	16.976**	10.234	
	[7.677]	[7.807]	[9.990]		[7.677]	[7.794]	[9.990]	
Education	-2.046*	-1.997*	-1.435	-2.425	-2.354**	-2.296*	-1.858	-2.465
	[1.142]	[1.164]	[1.386]	[2.569]	[1.159]	[1.176]	[1.391]	[2.562]
Log Earnings			-9.033**	10.063			-9.083**	9.077
			[3.933]	[9.487]			[3.934]	[9.491]
Other 6 ASVAB Tests	N	Y	Y	Y	N	Y	Y	Y
Childhood Family Inc.	N	N	Y	N	N	N	Y	N
Family Fixed Effects	N	N	N	Y	N	N	N	Y
Observations	4158	4158	2476	2476	4167	4167	2480	2480
R-squared								

*** p<0.01, ** p<0.05, * p<0.1

Figure1: Distribution of AFQT scores by whether a credit card holder has a "Eureka" moment



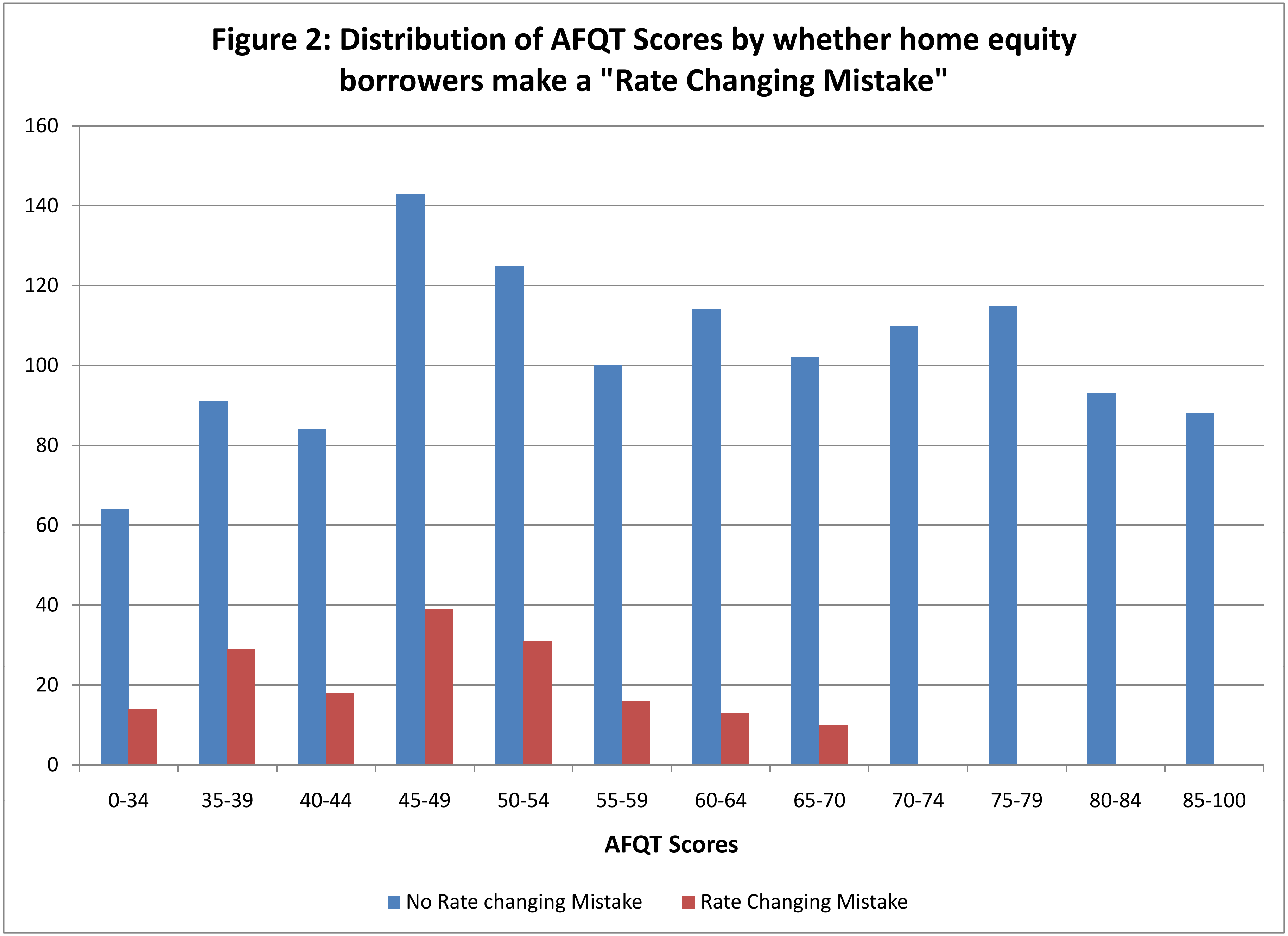


Figure 2: Distribution of AFQT Scores by whether home equity borrowers make a "Rate Changing Mistake"
160
140
120
100
80
60
40
20
0
0-34
35-39
40-44
45-49
50-54
55-59
60-64
65-70
70-74
75-79
80-84
85-100
AFQT Scores
No Rate changing Mistake
Rate Changing Mistake


Figure 3: Mean AFQT Scores by Months it Takes Consumers to Discover Optimal Strategy
100
90
80
70
60
50
40
30
20
10
0
AFQT Score
0
1
2
3
4
5
Months

Table A1: Summary Statistics of Credit Card Samples

Panel A: Comparison of Matched Credit Card Sample to Full Military Sample

	Matched CC Sample			Military Sample				T-Stat
	Mean	s.d	N	Mean	s.d.	N	Diff.	of diff
Variables from Military Sample								
Enlistment Age	19.7	2.31	541	19.8	2.54	828314	-0.06	-0.60
Education	12.1	0.62	541	12.0	1.26	829999	0.10	3.59
Black	25.3%	0.44	541	19.8%	0.40	829999	0.055	2.94
White	67.3%	0.47	541	69.8%	0.46	829999	-0.025	-1.24
Other	7.4%	0.26	541	10.4%	0.31	829999	-0.030	-2.66
Male	88.9%	0.31	541	87.6%	0.33	829999	0.013	0.95
Female	11.1%	0.31	541	12.4%	0.33	829999	-0.013	-0.94
Married	34.2%	0.47	541	33.9%	0.47	829999	0.00	0.14
AFQT Score	60.2	18.74	541	61.3	18.64	829999	-1.12	-1.39
Word Knowl.	28.4	4.42	541	28.4	4.46	829999	-0.07	-0.36
Arithmetic Reas.	20.9	5.23	541	21.1	5.19	829999	-0.12	-0.54
Math Knowledge	16.2	4.94	541	16.5	4.86	829999	-0.27	-1.27
Paragraph Comp.	12.5	2.00	541	12.6	2.00	829999	-0.11	-1.27
Numerical Oper.	41.0	7.30	541	41.4	7.28	829969	-0.41	-1.32
Electronic Info.	12.6	3.44	541	12.6	3.46	829797	-0.03	-0.19
Mechanical Comp.	16.7	4.28	541	16.9	4.10	829963	-0.19	-1.01
General Science	17.8	4.03	541	17.8	3.94	829994	0.01	0.06
Coding Speed	53.5	11.39	541	54.1	11.74	829983	-0.60	-1.23
Automotive/Shop	15.4	5.14	541	15.5	5.06	829935	-0.18	-0.80

Panel B: Comparison of Matched Credit Card Sample to Full Credit Card Sample

	Matched CC Sample			Full Credit Card Sample				T-Stat
	Mean	s.d	N	Mean	s.d.	N	Diff.	of diff
Variables from Credit Card Sample								
Bal. Transfer APR	7.16	2.84	541	6.38	3.93	14798	0.77	6.14
Purchase APR	7.91	5.11	541	14.40	2.44	14798	-6.49	-29.41
Account Age	15.19	9.80	541	34.83	23.02	14798	-19.63	-42.51
Behavior Score	663.09	157.54	541	727	81	14798	-63.91	-9.39
Fico Score	707.16	64.09	508	731	76	14798	-23.84	-8.19
Income	71363	70797	511	57121	114375	10227	14242	4.28

Table A2: Summary Statistics of Home Equity Samples

Panel A: Comparison of Matched Home Equity Sample to Full Military Sample

	Matched HE Sample			Military Sample				T-Stat
	Mean	s.d	N	Mean	s.d.	N	Diff.	of diff
Variables from Military Sample								
Enlistment Age	19.6	2.4	1380	19.8	2.54	828314	-0.12	-1.86
Education	12.1	0.68	1383	12.0	1.26	829999	0.12	6.71
Black	22.4%	0.42	1393	19.8%	0.40	829999	0.03	2.30
White	71.4%	0.45	1393	69.8%	0.46	829999	0.02	1.29
Other	6.2%	0.24	1393	10.4%	0.31	829999	-0.04	-6.38
Male	86.6%	0.34	1393	87.6%	0.33	829999	-0.01	-1.08
Female	13.4%	0.34	1393	12.4%	0.33	829999	0.01	1.08
Married	35.2%	0.48	1393	33.9%	0.47	829999	0.01	1.05
AFQT Score	63.6	16.01	1393	61.3	18.64	829999	2.21	5.15
Word Knowl.	28.9	3.91	1393	28.4	4.46	829999	0.46	4.37
Arithmetic Reas.	21.5	4.71	1393	21.1	5.19	829999	0.45	3.58
Math Knowledge	17.0	4.52	1393	16.5	4.86	829999	0.48	3.95
Paragraph Comp.	12.8	1.82	1393	12.6	2.00	829999	0.20	4.07
Numerical Oper.	41.4	7.16	1393	41.4	7.28	829969	0.03	0.13
Electronic Info.	12.9	3.45	1393	12.6	3.46	829797	0.29	3.12
Mechanical Comp.	16.9	4.01	1393	16.9	4.10	829963	0.06	0.54
General Science	18.2	3.77	1393	17.8	3.94	829994	0.40	3.93
Coding Speed	54.4	11.56	1393	54.1	11.74	829983	0.33	1.05
Automotive/Shop	15.7	5.07	1393	15.5	5.06	829935	0.19	1.36

Panel B: Comparison of Matched Home Equity Sample to Full Home Equity Sample

	Matched HE Sample			Full HE Sample				T-Stat
	Mean	s.d	N	Mean	s.d	N	Diff.	of diff
Variables from Home Equity Sample								
Years on the Job	9.1	7.2	1393	6.66	8.38	75927	2.42	12.40
Appraised Value	249350	134852	1393	228310	148717	75927	21040	5.76
Self Employed	7.2%	25.8%	1393	7.87%	27.00%	75927	-0.01	-0.99
Improvement	22.0%	41.5%	1393	19.96%	40.40%	75927	0.02	1.85
Refinancing	40.4%	49.1%	1393	58.44%	47.56%	75927	-0.18	-13.59
Equity Loan	18.2%	38.6%	1393	24.82%	42.82%	75927	-0.07	-6.30
Income	108768	114758	1393	82012	132044	75927	26756	8.60
First Mortgage Bal.	116489	83738	1393	100481	91801	75927	16008	7.06
FICO Score	728.02	48.80	1393	718.6	53.32	75927	9.42	7.12
APR	5.06	1.53	1393	7.0192	1.0816	75927	-1.96	-47.63
DTI ratio	33.69	17.26	1393	40.28	18.28	75927	-6.59	-14.10

Table A3: Summary Statistics by "Eureka" Moments among credit card borrowers

Panel A: Comparison of Demographic Characteristics and Test Scores

	Eureka Sample			Non-Eureka Sample				T-Stat
	Mean	s.d.	N	Mean	s.d	N	Diff.	of diff
Enlistment Age	19.67	2.33	399	19.80	2.25	142	-0.12	-0.559
Education	12.14	0.71	399	12.01	0.17	142	0.12	3.225
Black	21.8%	0.41	399	35.2%	0.48	142	-0.13	-2.964
White	71.4%	0.45	399	55.6%	0.50	142	0.16	3.320
Other	6.8%	0.25	399	9.2%	0.29	142	-0.02	-0.873
Male	89.5%	0.31	399	87.3%	0.33	142	0.02	0.673
Female	10.5%	0.31	399	12.7%	0.33	142	-0.02	-0.673
Married	33.3%	0.47	399	36.6%	0.48	142	-0.03	-0.700
AFQT Score	65.93	17.93	399	44.20	9.37	142	21.73	18.212
Word Knowl.	29.11	4.29	399	26.24	4.10	142	2.87	7.060
Arithmetic Reas.	22.50	4.96	399	16.57	3.04	142	5.93	16.658
Math Knowledge	17.66	4.56	399	12.23	3.59	142	5.43	14.371
Paragraph Comp.	12.77	1.95	399	11.68	1.92	142	1.08	5.757
Numerical Oper.	41.74	7.10	399	38.83	7.46	142	2.91	4.047
Electronic Info.	13.04	3.39	399	11.27	3.25	142	1.76	5.484
Mechanical Comp.	17.45	4.06	399	14.46	4.11	142	2.99	7.475
General Science	18.60	3.96	399	15.69	3.40	142	2.91	8.362
Coding Speed	54.98	10.95	399	49.20	11.55	142	5.78	5.192
Automotive/Shop	15.78	5.09	399	14.22	5.15	142	1.559	3.108

Panel B: Comparison of Financial Variables

	Eureka Sample			Non-Eureka Sample				T-Stat
	Mean	s.d.	N	Mean	s.d	N	Diff.	of diff
Bal. Transfer APR	7.22	2.80	399	6.97	2.92	142	0.25	0.883
Purchase APR	7.43	5.12	399	9.26	4.86	142	-1.83	-3.805
Account Age	14.65	9.73	399	16.71	9.88	142	-2.06	-2.142
Behavior Score	685.39	123.35	399	600.45	216.20	142	84.94	4.432
Fico Score	708.39	68.91	375	703.71	48.03	133	4.68	0.855
Income	72613	72836	376	67883	64911	135	4730	0.703

Table A4: Summary Statistics by "Rate Changing Mistakes" among home equity borrowers

Panel A: Comparison of Demographic Characteristics and Test Scores

	No RCM			Rate Changing Mistake				T-Stat
	Mean	s.d	N	Mean	s.d.	N	Diff.	of diff
Enlistment Age	19.65	2.44	1211	19.57	2.31	169	0.08	0.410
Education	12.13	0.66	1214	12.15	0.79	169	-0.02	-0.391
Black	22.1%	0.41	1214	25.4%	0.44	169	-0.03	-0.945
White	71.1%	0.45	1214	72.8%	0.45	169	-0.02	-0.461
Other	6.8%	0.25	1214	1.8%	0.13	169	0.05	4.049
Male	87.3%	0.33	1214	81.1%	0.39	169	0.06	1.971
Female	12.7%	0.33	1214	18.9%	0.39	169	-0.06	-1.971
Married	34.9%	0.48	1214	37.9%	0.49	169	-0.03	-0.739
AFQT Score	65.03	16.18	1214	52.88	9.58	169	12.15	13.953
Word Knowl.	29.09	3.85	1214	27.32	4.01	169	1.77	5.416
Arithmetic Reas.	21.90	4.73	1214	18.74	3.55	169	3.16	10.365
Math Knowledge	17.39	4.52	1214	14.05	3.28	169	3.34	11.792
Paragraph Comp.	12.84	1.80	1214	12.40	1.92	167	0.44	2.798
Numerical Oper.	41.65	7.13	1214	39.84	7.26	169	1.81	3.051
Electronic Info.	13.03	3.44	1213	11.81	3.32	169	1.22	4.468
Mechanical Comp.	17.11	3.98	1213	15.40	3.87	169	1.71	5.363
General Science	18.39	3.78	1214	16.96	3.48	169	1.43	4.942
Coding Speed	54.55	11.53	1214	53.48	11.94	167	1.07	1.094
Automotive/Shop	15.88	5.07	1214	14.62	5.01	167	1.267	3.060

Panel B: Comparison of Financial Variables

	No RCM			Rate Changing Mistake				T-Stat
	Mean	s.d	N	Mean	s.d.	N	Diff.	of diff
Years on the Job	9.3	7.3	1214	7.22	6.27	169	2.12	4.03
Appraised Value	257974	137881	1214	183962	86684	169	74013	9.55
Self Employed	7.4%	26.2%	1214	4.7%	21.3%	169	0.03	1.49
Improvement	21.6%	41.2%	1214	24.9%	43.3%	169	-0.03	-0.92
Refinancing	38.3%	48.6%	1214	56.8%	49.7%	169	-0.19	-4.55
Equity Loan	11.0%	31.2%	1214	70.4%	45.8%	169	-0.59	-16.36
Income	111105	115325	1214	90748	107109	169	20357	2.29
First Mortgage Bal.	118351	86024	1214	102545	63556	169	15807	2.89
FICO Score	731.01	48.23	1214	706.35	47.14	169	24.66	6.35
APR	4.73	1.28	1214	7.42	1.00	169	-2.69	-31.60
DTI ratio	33.02	17.21	1214	38.69	16.99	169	-5.67	-4.06