Anatomy of the Credit Score

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This paper addresses the question of what determines a poor credit score. We compare estimated credit scores with measures of impulsivity, time preference, risk attitude and trustworthiness, in an effort to determine the preferences that underlie credit behavior. Data are collected using an incentivized decision making lab experiment, together with financial and psychological surveys. Credit scores are estimated using an online FICO credit score estimator based on survey data supplied by the participants. Preferences are assessed using a survey measure of impulsivity, with experimental measures of time and risk preferences, as well as trustworthiness. Controlling for income differences, we find that the credit score is correlated with measures of impulsivity, time preference, and trustworthiness.

Key words: credit score, time preference, risk attitude, trust, impulsivity

JEL codes: D14, C91

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1. Introduction

Credit scoring has become an increasingly popular topic in recent years—in the media, in business, and at the dinner table. In these days of easy access to information, a negative credit event such as a mortgage default or bankruptcy can haunt a consumer for a considerable period of time. A credit score is a number that represents an assessment of the creditworthiness of a person, or the likelihood that the person will repay his or her debts. Credit scores are generated based on the statistical analysis of a person's credit report; credit bureaus such as Experian, Equifax and TransUnion maintain a record of a person's borrowing and repaying activities.

The Fair Isaac Corporation (FICO) developed the formula used by all three major credit reporting agencies in the U.S. The algorithm is kept secret, but most believe that it is based upon the ratio of debt to available credit; this denominator, in most cases, is a direct function of income. The score is then adjusted for payment history, number of recent credit applications, and negative events such as bankruptcy/foreclosure, as well as changes in income caused by changes in employment or family status.

In addition to its original purpose, credit scores are also used to determine insurance rates and for pre-employment screening. Employers as well as lenders use credit reports and scores to gain insight into the records and tendencies of prospective employees, making the assumption that credit scores correlate with general trustworthiness. There is even a dating website, creditscoredating.com, that purports to match subscribers with high-score partners. With reports and scores available to the public for little or no cost, the FICO score has become a part of the dating and mating process: along with a criminal background check, a credit report reveals much about a person's personality and behavioral tendencies… or does it?

The repayment of debt is contingent upon two factors: the ability to pay the debt, and the borrower's willingness to pay. The first condition is largely determined by income, while the second is more psychological in nature. Debtors may choose to pay their balances and reduce funds available to spend on other items, or default on their loans and keep their current level of liquidity, accruing penalties and credit bruises in the process.

Our study seeks to find which, if any, underlying preferences or personality factors contribute to the credit score. We consider four factors: impatience, impulsiveness, risk tolerance, and trustworthiness. It seems reasonable to expect lower credit scores to be associated with greater discounting of future payoffs: that is, impatience is associated with a desire to move consumption toward the present from the future by borrowing, and higher borrowing implies a higher probability of default. Impulsive individuals are likely to have difficulty resisting the temptation to borrow for present consumption, and more likely to fail to pay their debts. Poor credit scores could also be caused by a lack of trustworthiness, as the less trustworthy fail to meet their obligations. And finally, credit scores could be impacted significantly by financial risk-taking, as those who gamble accumulate debt that they have difficulty repaying.

In this study we estimate credit scores using an online FICO estimator, based on information reported by the subjects. These estimated credit scores are compared with incentivized measures of risk attitudes, trustworthiness, and time preference, and a survey measure of impulsivity. Our purpose is to determine the behavioral correlates of credit behavior reflected by credit scores. We find that measures of impatience, trustworthiness and impulsivity have an impact on the credit score.

2. Related Literature

There is little prior research on the determinants of credit scores, and few studies explicitly link credit scores to the above mentioned correlates of behavior. A number of studies, however, examine the role of preferences in consumer financial decisions.

Preferences that are elicited using incentivized tasks are correlated with self-reported credit-related decisions by several researchers. Harrison et al. (2002) find no relationship between individual discount rates and borrowing behavior in a sample of Danish adults, while Dohment et al. (2006) find a significant relationship between present-biased preferences and self-reported financial difficulties. Both studies rely on self-reported financial information. Eckel et al. (2007) show that patience and risk tolerance are positively related to consumer decisions to borrow for the purpose of investing in post-secondary education. That study utilizes a sample of about 1000 Canadian adults, and elicits risk and time preferences along with information about the decision to borrow for post-secondary education.[1]

Meier and Sprenger (2010) show that individual time preference is a determining factor in credit card borrowing. They elicit time preferences from a sample of about 600 low- and moderate-income individuals, and (with their permission) directly access their credit reports and tax returns. Preference data are then correlated with administrative data, providing a distinct improvement on previous studies. They find that, while an individual's elicited discount factor is not significantly related to credit card borrowing, their present bias is an important explanatory factor, with stronger present bias associated with greater borrowing, controlling for a variety of demographic and situational variables. Our study is closely related to theirs, except that we add incentivized measures of risk attitudes and trustworthiness, but replace the incentivized present-bias measure with a survey assessment of impulsiveness.

Several studies have shown a relationship between trust or trustworthiness and credit

[1] In a related paper, Eckel et al. (2004) show that short-term elicited discount rates are highly correlated with long-term (five-year) discount rates, though the long term rates involve less discounting of future payoffs on average.

decisions. The earliest of these is Karlan (2005), who found that trustworthiness in the trust game (developed by Berg et al. 1995) predicts loan repayment in a Peruvian group lending microfinance program. (See also Karlan 2007). Cassar et al. (2007) examine the effect of various elements of social capital, including interpersonal trust and trustworthiness (in the trust game used here), on microfinance loan repayment (in a "microfinance game") among two groups of subjects in South Africa and Armenia. They fail to find a significant effect of trustworthiness in the game on loan repayment in South Africa, but observe a very strong positive relationship in Armenia.

Ausubel (1999) reports the results of a large-scale field experiment testing the effects of different credit card offers. He draws three conclusions from the study. First, respondents to credit card solicitations were significantly higher credit risks than non-respondents. Secondly, solicitations offering inferior terms attracted higher-risk borrowers. Third, even after controlling for all of the information available to the credit card company, consumers who accepted such unfavorable terms exhibited a higher likelihood of default. This suggests that characteristics that are not considered by the credit card companies may play an important role in predicting those who will default on their credit commitments. We argue that these may consist of preferences and personality factors, such as time and risk preferences, trustworthiness and impulsiveness.

These variables may be related to each other: Martins et al. (2004) show that impulsivity is related to risk taking by gamblers. The study was conducted on seventy-eight female and male pathological gamblers who were compared on a profile of risk taking behaviors which included suicide attempts, illegal activities meant to finance gambling, sexual risky behavior, and alcohol abuse.

Taken together these studies provide some evidence of the impact of preferences on financial decision making. Time discounting, assessed using incentivized choice or valuation experiments, plays a role in several studies involving credit or savings, and time-inconsistency, in the form of present-biased decision making in similar incentivized games is also important and appears to play a separate role from time discounting alone. Present bias is akin to impulsiveness, so it is not surprising that impulsivity is also related to poor credit choices. Finally, trustworthiness, as measured by the second stage of the trust game, corresponds with good credit behavior, as represented by repayment and low default rates on microfinance loans.

3. Research Design and Procedure

The experiment contained modules used to assess credit scores, impulsivity, time and risk preferences, and trustworthiness. Each of these is explained in turn. The design consisted of a survey plus four incentivized tasks/games. The stakes for these tasks was set to be relatively high. At the end of the experiment, one of the tasks was selected randomly, and all subjects were paid in cash for their decisions on that task.

Credit scores were estimated using the FICO credit score estimator (www.myfico.com), an internet based tool that provides a credit score range based on self-reported financial information. We incorporated the questions from the online estimator into a survey that was completed by the subjects. These responses were then entered into the website by the researchers to obtain the credit score estimate. Two researchers separately made all website entries and recorded the resulting scores; discrepancies were then reconciled.[2]

Impulsivity was assessed using a widely-adopted psychological survey measure, the Barratt Impulsiveness Scale (BIS-11, Patton et al. 1995). This scale consists of several subscales,

[2] A more accurate approach would be to use the subjects' actual credit scores. However, this proved cumbersome and costly. In order to obtain an official credit score, an individual must register for – and provide credit card information to pay for – a firm's credit service. While this service can subsequently be cancelled at no net cost, we felt it was overly invasive and demanding to request that subjects complete such a procedure.

attention (5 items), motor (7 items), self-control (6 items), cognitive complexity (5 items), perseverance (4 items) and cognitive instability (3 items). We collected the full scale, and analysis was conducted using that as well as the self-control subscale, which, according to the original study, is most relevant to financial decision making.[3]

Risk preferences are elicited using the measure in Eckel and Grossman (2008). To complete this task, subjects choose the one they most prefer from among six possible 50/50 gambles. These gambles are shown in Figure 1 and described in Table 1. The first gamble earns the subject 20 with certainty. The gambles increase in risk and expected value through the fifth gamble. The sixth involves a possible loss, and consists of an increase in variance only, with the same expected value as the fifth gamble. The choice of gamble implies a level of risk tolerance; Table 1 also shows ranges for the coefficient of relative risk aversion (CRRA) associated with each choice, under the assumption that the subject's utility function is of that form. This measure has been used in a number of studies in the lab and the field, and is easily understood by subjects. If this task was chosen for payment, the subjects were asked to roll a six-sided die. A roll of 1,2,3 gave them the lower payoff for their chosen gamble, whereas a roll of 4,5,6 gave them the higher payoff.

Time preferences are elicited using a variation on the 'multiple price list' approach of Coller and Williams (1999), as modified for use in the field. Subjects make a sequence of seven choices between $100 in one week and larger amounts of money in six months plus a week; subjects also had the option to choose "indifferent", in which case the experimenter rolled a die to determine which of the alternatives to select. The decision screen is shown in Figure 2.

[3] Note that it would be possible to elicit impulsiveness using incentivized games, but to our knowledge, all such protocols tend to be complex and involve a large number of decisions. Our strategy was to focus on simple measures of preferences, and the psychological measure was appealing for its simplicity and ease of administration. Jorm et al 1997 explore its validity in a community sample. We are unaware of any studies that validate the measure in the context of an incentivized decision-making experiment.

Subjects typically choose the smaller, sooner payment for the first few decisions, and then switch at some point to the larger later amount. Care was taken to schedule the experiments so that students were likely to be on campus for the later payment date. If this task was chosen for payment the participants could choose to pick up their payment at the conveniently-located experiment lab at a designated time or provide a mailing address to which it could be sent. If this task was chosen for payment, participants rolled a seven-sided die to determine which decision they would be paid for. If they checked 'indifferent' in the decision they were to be paid for, then a coin was flipped in order to determine a sooner or later payoff date.

Trustworthiness was evaluated using the trust game task (Berg, Dickaut and McCabe 1995). In this game two persons are randomly and anonymously matched, and both are endowed with 20 tokens. The first mover can send any amount from 0 to 20 in increments of 2 to the second mover. The amount sent is multiplied by three on the way and then deposited in the second-mover's account. The second mover can then choose how many tokens (from the ones received and the initial endowment) to send back to the proposer. These tokens returned are not multiplied.

In order to elicit responses in this game we employed the strategy method. This means that each player played as the proposer and responder. As the proposer they could choose what amount to send. Sending amounts in increments of two implies that they could send 0, 2, 4,6,8,10,12,14,16,18 and 20. For the responder we collected responses to each possible amount that he could receive: 0, 6, 12, 18, 24, 30, 36, 42, 48, 54 and 60. If this task was chosen for payment the participants were randomly divided into two groups, the proposers and the responders. They were then matched randomly and paid according to the decisions made for these respective roles. (Before starting the experiment we made sure we had an even number of participants).

The tasks and games were explained using experimental dollars, and at the end of the session one of these three tasks was randomly chosen for payment at a conversion rate of 1 experimental dollar =50 U.S. cents.

A total of 79 subjects were recruited from evening graduate courses and staff email lists in order to obtain data from older subjects who were more likely to have a job and a meaningful credit history. Of these, 66 gave responses that allowed us to estimate a credit score; the remaining observations were dropped due to missing credit information. Three additional outlier observations with estimated scores in the 500-550 range were dropped because of a very recent negative event (bankruptcy, foreclosure, divorce, etc.) This is explained further below.

Prior to making their respective decisions, the participants were informed of the confidentiality of the data. The experiment was conducted electronically and all the tasks and surveys were programmed in z-tree (Fishbacher 2007). The experiment started off with a financial survey, followed by the impulsivity survey. The subjects then completed the trust task, gamble task and time preference task. Before each task, the participants had to complete self-paced instructions and a short quiz in order to ensure their understanding of the tasks. This was followed by an exit demographic survey. One task was chosen randomly to determine payment for all subjects, and payment took place in private.

4. Data Analysis

4.1 Hypotheses

Our hypotheses about the effects of the variables on the FICO score are summarized here.

<u>Patience</u> is measured as the number of times the subject chooses the larger, later payment in the time preference task, and is expected to correlate positively with the FICO score. The more

patient an individual, the more likely it is that he/she will forgo present consumption to achieve an expected higher level of well-being in the future. Patient subjects may opt to borrow less, and rather save and make cash purchases to avoid paying interest. If and when they do borrow, patient subjects would be likely to look for favorable interest rates, and spend carefully in order to have funds available to repay the loan, thereby generating a high credit score.

Impulsiveness implies a lack of self-control and discipline, and this measure is expected to correlate negatively with the estimated FICO score. Impulsivity is measured using the Barratt Impulsiveness Scale (BIS-11). Impulsive financial decisions could lead to excessive debt without available means to pay it off. Let us take a moment to delineate the difference between impatient and impulsive behavior. Essentially, the impatient decision is a calculated one, in which, for the decision maker, the benefit obtained from imminent consumption outweighs the benefit obtained by waiting to consume later, even if the future benefit is ultimately more valuable than the imminent one. (See the survey in Frederick and Loewenstein 2002.) Impulsive consumers are more likely to make purchases on a whim without any consideration of future obligations. This behavior can be distinguished even in young children (Shoda and Mischel 1990). Economists have suggested the prevalence of present bias (hyperbolic discounting) in many consumers, which seems related to impulsivity (Angletos et al. 2001).

Risk Preference is defined as a subject's level of risk-tolerance, as measured by an incentivized choice task. Here a subject chooses their most preferred from six gambles that vary in expected value and variance, and range from a sure thing to a 50/50 gamble with a possibility of losses. We expect a positive relationship between willingness to take financial risks in this context and credit behavior, leading to a positive correlation with the FICO score. This is perhaps clearest when imagining gamblers, who are likely to make decisions that lead to poor credit scores. While modest risk-taking can increase income and credit scores, more extreme risk-taking is likely to be harmful.

Trustworthiness is measured using the second mover decision in the Trust Game, and is expected to have significant positive correlation with the estimated FICO score. Untrustworthy behavior could play a role in producing an unfavorable credit score, and paying debt in a timely manner is imperative to maintaining a healthy credit score. We are particularly interested in the behavior of subjects when they are trusted with a large fraction of the first-mover's endowment. In this situation second movers are left holding a large amount of money, and the temptation to keep it is highest.

Income is an important control variable: Higher income should directly correlate with a high FICO score. Income is the basis for credit limit which is central in calculating the score.

4.2 Results

We first discuss each of the preference measures and their correlation with the credit score. Table 2 contains descriptive statistics and Figures 3-8 show histograms of the key variables in the study. Table 3 contains correlations among the variables. Two-tailed significance tests are reported in this table; given the hypotheses above, one-tailed tests arguably are appropriate and would strengthen the statistical significance of the results.

A histogram of estimated FICO scores is shown in Figure 3, revealing a distribution with a mean of 708, and a range of about 600 to 800. FICO credit scores are calculated on a scale from 300 - 850, with 850 the maximum possible score. Since we draw from a sample of university students and employees, the average is somewhat above the national average of 680. In general, a good credit score is anything above 700.

The patience task was presented as a series of choices between a smaller, sooner payoff versus a larger, later payoff. Recall that the sooner payoff was a week from the date of the experiment and the later payoff was a week and six months from that day. Subjects could check the second column if they were indifferent between the two choices. The patience score was calculated as the number of patient (larger, later) choices, with indifferent scored as 0.5 of a patient response. Figure 4 shows the patience histogram, which ranges from 0-7 with a mode at 4. As shown in Table 3, this variable is positively correlated with the FICO score ($p<.10$).

Figure 5 illustrates the Self-Control subscale of the Barratt Impulsivity Scale, where a high score indicates a low level of self-control. The full scale consists of a set of 30 questions (items) that measure general impulsivity. The 30 questions can be sub-divided into six subscales. We were most interested in self-control since it relates most closely to the event of acquiring debt. People who cannot control their desires and who seek immediate gratification are more likely to build unsustainable debt levels. In Table 3, we see that the correlation between the self-control subscale and the FICO score is negative and statistically significant ($p<.05$), consistent with our hypothesis.

Elicited risk preferences are illustrated in Figure 6. The histogram shows the percentage of participants that chose each gamble. Recall that the risk task presented a choice between six 50/50 gambles with a low and high payoff. A choice of a higher gamble number indicates a lower level of risk aversion or greater willingness to take risks. A risk-neutral person would choose Gamble 5, and only risk-takers should prefer Gamble 6. The modal gamble chosen is 3, which has a modest level of risk. Using the gamble number as a scale of risk tolerance, we see that this is negatively, but not significantly, correlated with the FICO score in Table 3 ($p=.83$), which is not consistent with the hypothesis above.

As a proxy for trustworthiness, we use the percent returned by the subject in the second mover role at the maximum level of trust, focusing on the decision made when the amount sent was the maximum amount of 20. In our analysis we explored several ways of coding the strategy-method data, and settled on the range of amounts sent that represent the most tempting situation for the responder, the most extreme decision – the amount sent of 20 tokens. This meant that the responder had 20*3=60 tokens ($30) deposited in their account. (Similar results are obtained when we use the slope of the second mover's response function, or the average response for amounts sent above 10 tokens.) The distribution of this variable is shown in Figure 7. Trustworthiness when trust is highest is strongly positively correlated with the FICO score, as shown in Table 3 ($p<.005$).

Finally, Figure 8 illustrates the income distribution of the subjects. The subjects were asked what income bracket they fell into. The choices were as follows; -$0 to $5000; $5001 to $10000; $10001-$20000; $20001-$40000; above $40000. As we can see, since many of the recruits were college students, a high proportion of subjects fell into the $0-$5000 income bracket, although subjects are represented in each of the categories. Income is also strongly correlated with the FICO score ($p<.005$).

4.3 Regression Analysis

In order to further test our hypotheses, we conduct OLS regressions, reported in Table 4. The dependent variable is the FICO score and the independent variables are patience (denoted as time preference in the model), self-control from the BIS-11(coded as No Self-Control), risk attitude (denoted as risk), trustworthiness, income, age, and gender. Model 1 includes the experimental variables and income. As predicted, all the signs are in the hypothesized direction. Patience and impulsivity (as measured by lack of self-control) are significant at $p<.10$ (two-tailed test). Income and trustworthiness are significant with $p<.05$ (two-tailed test).[4]

The second model adds age and gender to the regression. Refer Table 2. The qualitative results are robust to these additions, except that adding age causes income to lose statistical significance. This is due to the fact that income and age are highly correlated. Gender does not have a significant effect on the FICO score.

The model is also robust to alternative specifications. Dropping risk aversion leaves the remaining coefficients relatively unchanged.[5] A further consideration is that income may be seen as endogenous to preferences. We conduct two additional tests to explore this possibility. First, dropping income from the regressions lowers the significance level of time preference in Model 1 (to $p=0.12$), but increases the significance of the other variables. Dropping both risk and income leaves the remaining coefficients at similar magnitudes and significance levels. In a second test, we regress income on the preference measures. Risk, time, and impulsivity are unrelated to income ($p>.5$). However, trustworthiness is positive and significant at $p<0.01$, confirming the correlations in Table 3. Dropping it from the regression does not affect the magnitude or significance of the other variables. While in our data the complex effect of income cannot be fully isolated, nevertheless, whether or not we control for income, there is substantial evidence of the importance of the preference variables.

5. CONCLUSION AND DISCUSSION

The results suggest that, in addition to the important effect of income, there are certain behavioral factors that are correlates of credit scores. These behaviors include impulsivity, time preference (or future orientation), and trustworthiness. Risk attitude was not statistically

[4] Recall that three outliers in the FICO scores in the range of 510-550 were dropped from the analysis. Similar results are obtained if these three observations are included, but including them introduces heteroskedasticity in the model, making statistical inference problematic.
[5] Note the coefficients and significance on the remaining variables are unaffected by dropping the risk variable from the analysis. Additional specifications discussed in this paragraph are available from the authors on request.

significantly related to credit score, suggesting that a preference for risk-taking is not an important source of variability in credit scores, and dropping it from the regression does not affect the magnitude or significance of the other variables. Our results build upon those of Meier and Sprenger (2010), but add the key measures of impulsivity and trustworthiness. These two variables are significantly correlated with the credit score, and add additional explanatory power to the model. We believe that with more observations, a more varied sample, and the more precise measure provided by actual (instead of estimated) FICO scores, these relationships can be explored in more detail. That is, more precise measures will reduce “noise” in the credit score measure, and a larger more variable sample will enhance variability in both credit history and demographics.

The FICO score captures elements of preferences or personality that affect credit behavior, apart from the obvious effect of income. It is not too much of a stretch to say that the use of FICO scores for employment screening or on dating websites might after all be a useful technique for selecting applicants (or potential partners) who are likely to be less impulsive, more trustworthy, and more future-oriented. However, further study is needed to show whether credit score adds additional information over and above income for predicting impatient, impulsive, or untrustworthy behavior in other domains.

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Figure 1: Risk Measure: Subjects are asked to choose one from among the six gambles shown below, and the chosen gamble is played out to determine payoffs. These 50/50 gambles vary in risk and expected value, from 20 with certainty to a 50/50 chance of gaining 59 or losing 2.

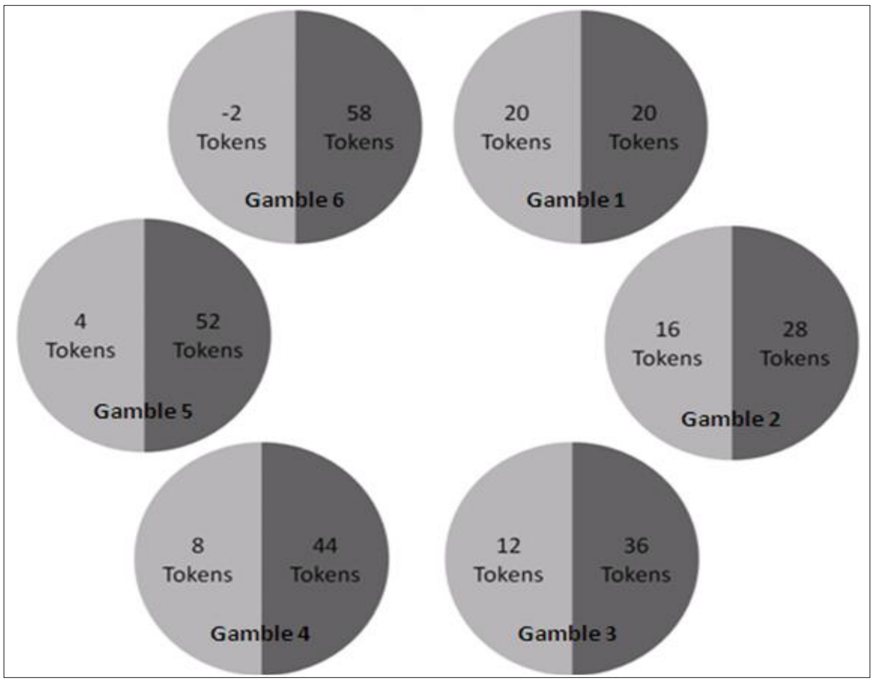


Figure 2: Time Preference Measure: Subjects were asked to check the desired box corresponding to payment sooner vs. payment later for each of the 7 choices. One was selected randomly for payment.

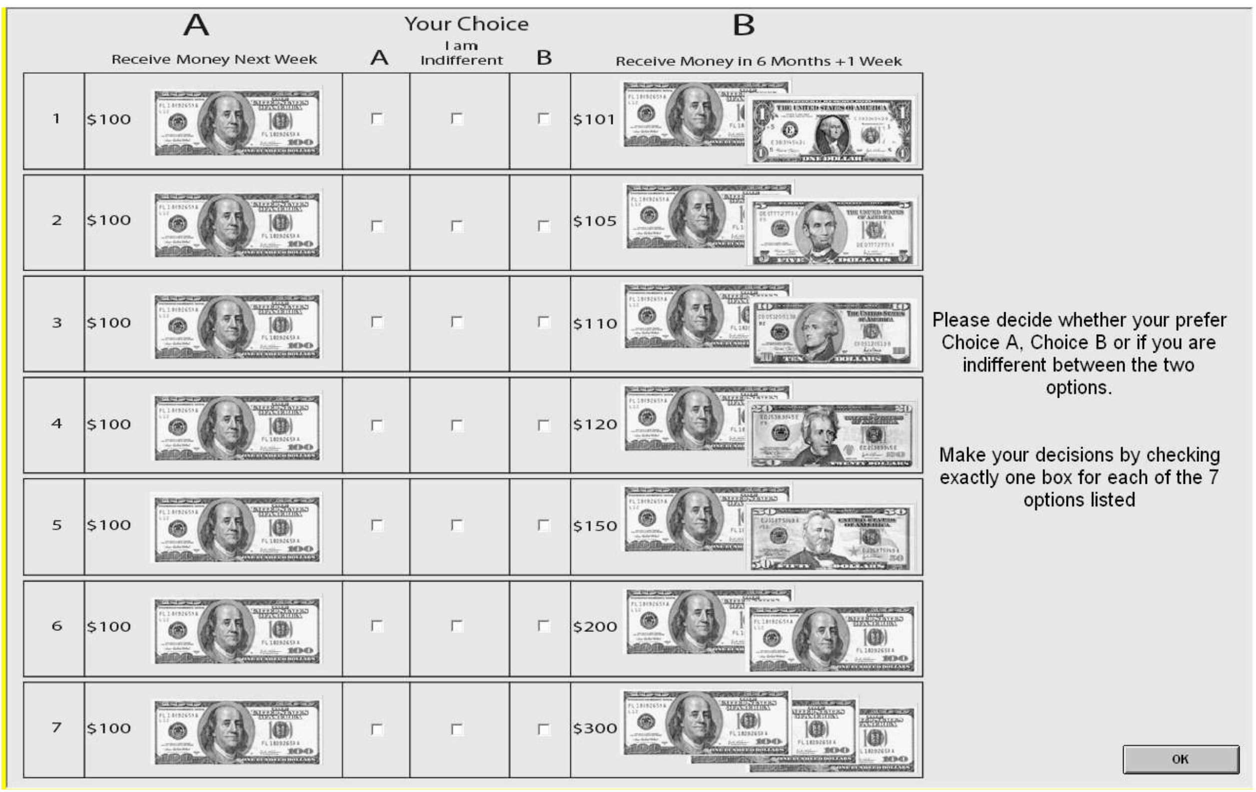


Figure 3: Histogram Estimated FICO Scores (n=63)

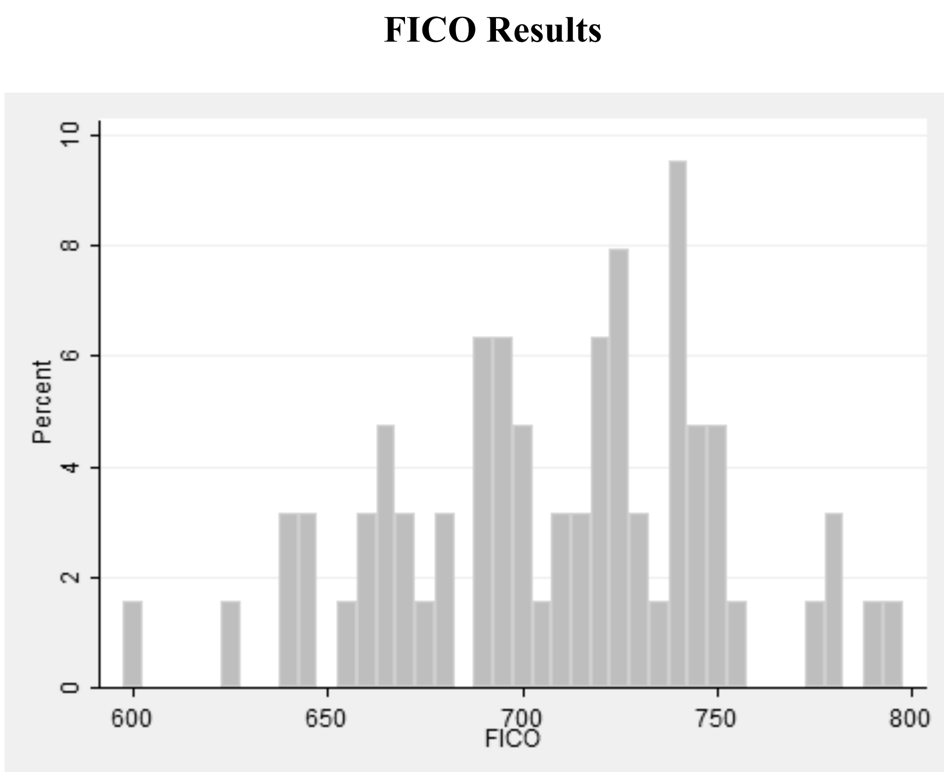


Figure 4: Histogram and Summary of Time Preference Task

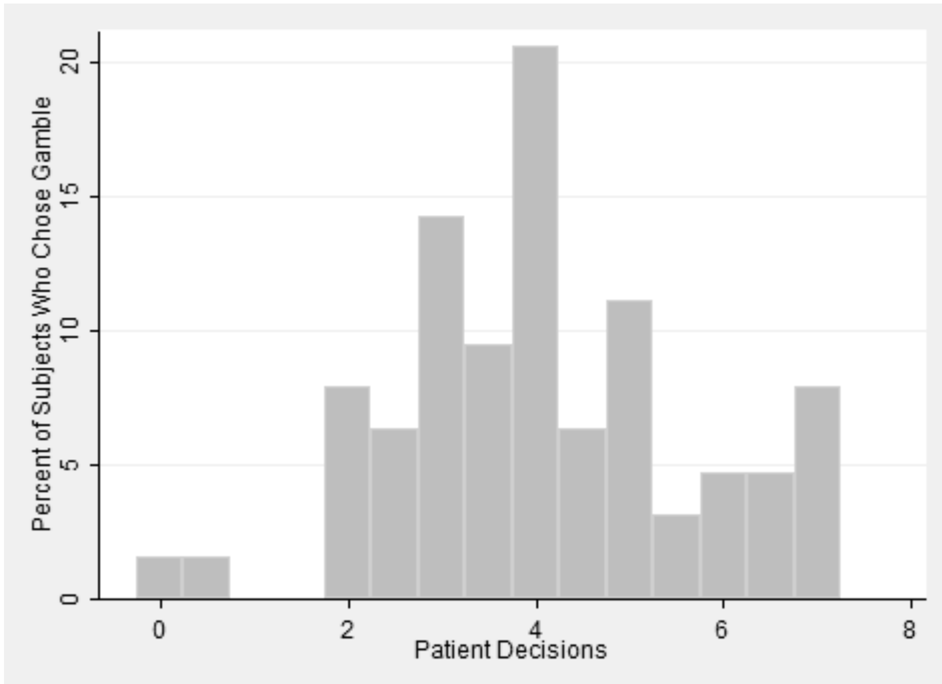


Figure 5: Histogram of Barratt Impulsivity Scale (Self Control Subscale)

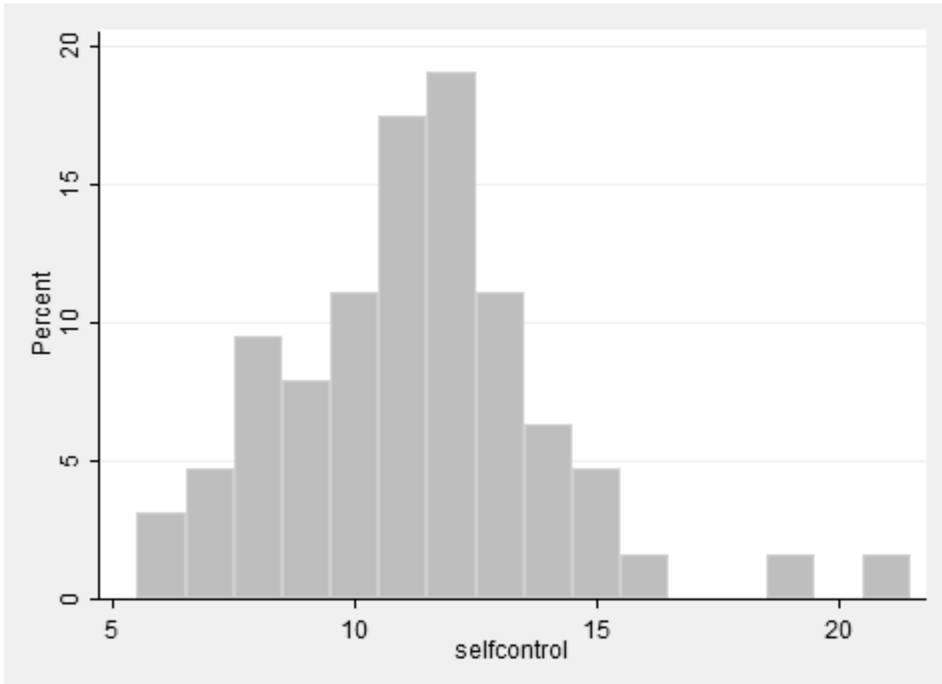


Figure 6: Histogram of Risk Task

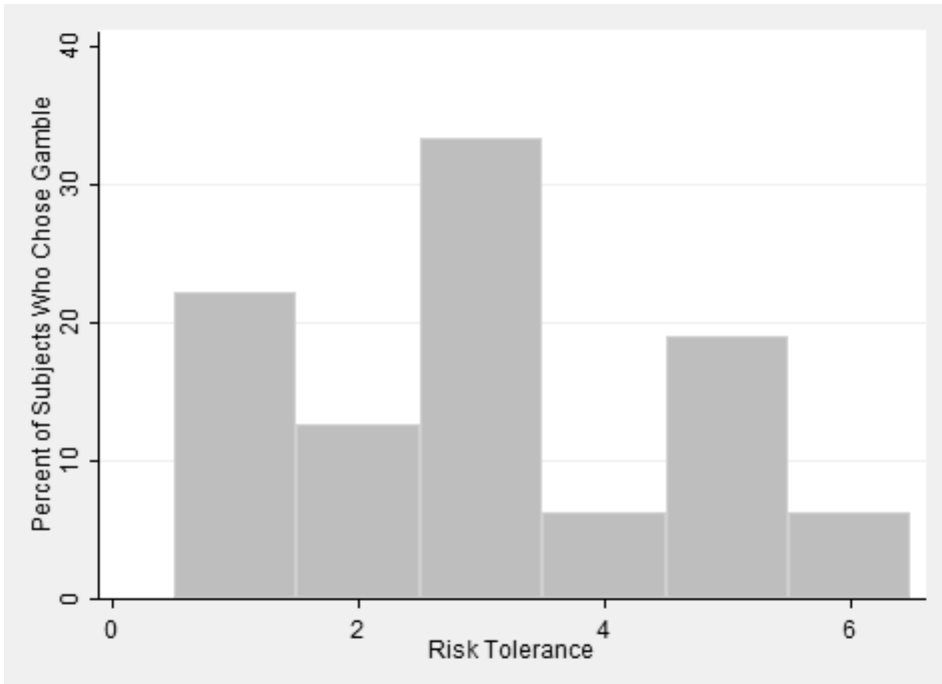


Figure 7: Histogram and Summary of Trustworthiness When 20 Tokens Were Sent

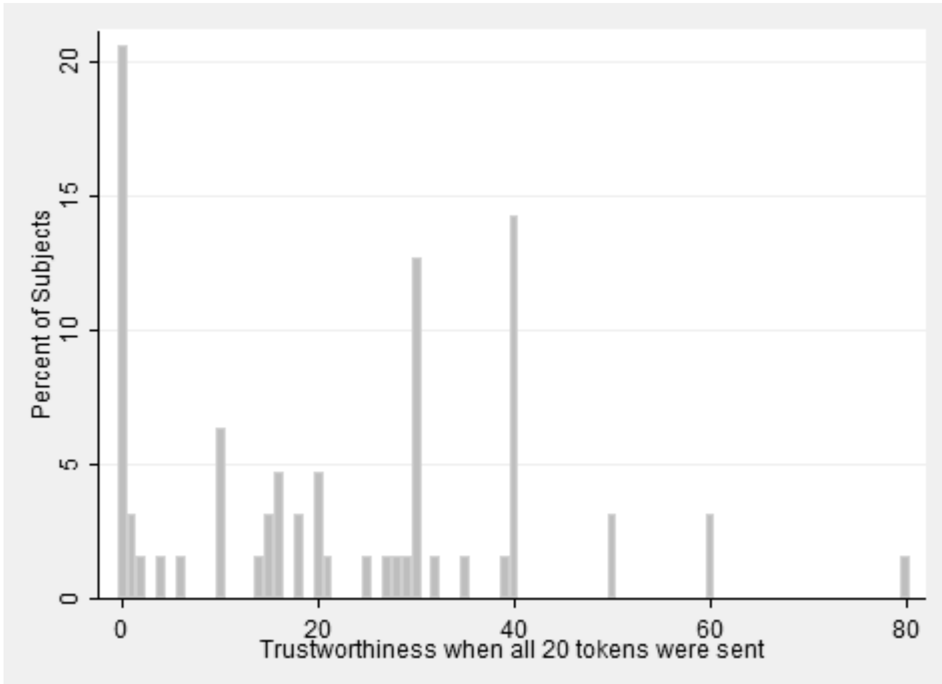
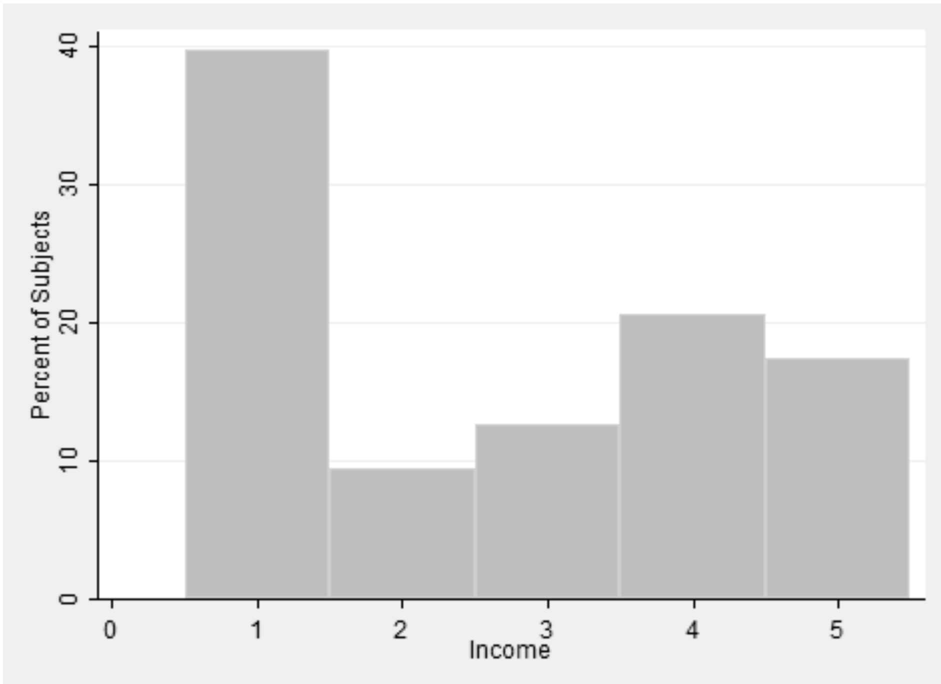


Figure 8: Histogram and Summary of Income



Categories are as follows: 1-$0 to $5000; 2- $5001 to $10000; 3-$10001-$20000; 4-$20001-$40000; 5-above $40000.

Table 1: Gamble Options

(Subjects choose one of the six gambles represented below to play)

Choice (50/50 Gamble)	Low Payoff	High Payoff	Expected Return	Standard Deviation	Implied CRRA* Range	Fraction of Subjects (%)
Gamble 1	20	20	20	0	2< r	22.22
Gamble 2	16	28	22	6	.67 < r < 2	12.70
Gamble 3	12	36	24	12	0.38< r < 0.67	33.33
Gamble 4	8	44	26	18	0.20< r < 0.38	6.35
Gamble 5	4	52	28	24	0 < r < 0.20	19.05
Gamble 6	-2	58	28	30	r < 0	6.35

*Coefficient of relative risk aversion, assuming the subject's utility function takes this form.

Table 2: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
FICO	63	708.49	41.57	600	795
Time Preference	63	4.08	1.58	0	7
Risk	63	3.06	1.56	1	6
No Self-Control	63	11.25	2.81	6	21
Income*	63	2.67	1.59	1	5
Trustworthiness	63	21.87	18.39	0	80
Age	63	27.30	8.75	18	60
Male	63	0.40	0.49	0	1
Female	63	0.60	0.49	0	1

*Categories are as follows: 1-$0 to $5000; 2- $5000 to $10000; 3-$10000-$20000; 4-$20000-$40000; 5- above $40000.

Table 3: Pair-wise Correlations (p-values in parentheses)

.

	Est. FICO score	Time Pref.	Gamble Choice	No Self Control	Income	Trust-worthiness	Age
Time Preference	0.210†	1.000					
	(0.099)						
Risk	-0.027	0.109	1.000				
	(0.834)	(0.397)					
No Self-Control	-0.279*	-0.092	0.088	1.000			
	(0.027)	(0.475)	(0.492)				
Income	0.387**	-0.034	-0.056	-0.100	1.000		
	(0.002)	(0.790)	(0.661)	(0.434)			
Trustworthiness	0.369**	-0.001	-0.288**	-0.134	0.359**	1.000	
(for sent = 20)	(0.003)	(0.994)	(0.022)	(0.296)	(0.004)		
Age	0.381**	0.032	-0.137	-0.030	0.594**	0.247†	1.000
	(0.002)	(0.804)	(0.285)	(0.819)	0.000	(0.052)	
Female	0.136	0.042	-0.180	0.008	0.151	0.185	0.077
	(0.288)	(0.746)	(0.159)	(0.953)	(0.237)	(0.146)	(0.551)

Significance: †, p ≤ .10; *, p ≤ .05, **, p≤.0 1

Table 4: Credit Score Determinants, OLS Regression
(standard errors in parentheses)

FICO Score	MODEL I		MODEL II	
Time Preference	5.114	†	4.584	
	(2.942)		(2.934)	
Risk	1.592		2.545	
	(3.103)		(3.141)	
No Self-Control	-3.011	†	-3.223	†
	(1.669)		(1.660)	
Income	7.459	*	3.667	
	(3.121)		(3.789)	
Trustworthiness	0.582	*	0.563	*
	(0.281)		(0.280)	
Age			1.105	†
			(0.657)	
Female			5.257	
			(9.589)	
Constant	684.00	**	663.90	**
	(27.210)		(29.340)	
N	63		63	
R2	0.301		0.338	
Adjusted R2	0.240		0.254	

Significance: †, p ≤ .10; *, p ≤ .05, **, p≤.0 1