ALL THE TIME IN THE WORLD:
AN EXAMINATION OF TIME PREFERENCES USING MONETARY DELAY DISCOUNT RATES

by

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Abstract

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Contents

1 Introduction

Decision-making, either over a set of options offered during the same period or with an intertemporal element, is a fundamental issue in economics. This is especially pertinent for adolescents, who make a wide variety of decisions that have ambiguous long-term consequences. Understanding how people make decisions and what governs the process is important to ensure that economic models and theories reflect actual human behaviour. As a result, there is a large literature on time preferences in behavioural economics.[1]

Recent studies in behavioural economics have found that risk and time preferences are good predictors of field behaviour (e.g. Sutter et al., 2013). People with higher discount rates or who are more impatient are typically connected with risky behaviours, such as smoking and alcohol consumption. Non-cognitive skills may also be an important predictor of outcomes (e.g. Heckman and Rubinstein, 2002). This branch of research commonly assumes that time preferences are stable, which is reinforced by findings of stable within-subject time preferences over a test-retest interval that is a year or shorter in length (e.g. Ohmura et al., 2006; Kirby, 2009; Meier & Sprenger, 2010). If unstable, then time-varying behaviour could be affected by both changing time preferences and responses to economic incentives (Meier & Sprenger, 2010).

Given the connection between time preferences and risky behaviours, researchers have tried to find exogenous factors that explain variation in these time preferences. Advances in genetics have led researchers to investigate whether genes that control the brain's reward pathways represent primitives of behaviour (e.g. Carpenter, Garcia, & Lum, 2011). Research on financial risk preferences using twin design studies estimate that genetic effects account for 20% of the variation in risk-taking for lottery choices (Cesarini et al., 2009). In order to identify the specific genes responsible for this connection, most studies in this area have focused on the dopamine and serotonin reward systems in the brain and found some genotype correlates of time preferences (e.g. Carpenter, Garcia, & Lum, 2011; Kuhnen &

[1] A seminal review of research on intertemporal choice is presented in Frederick, Loewenstein & O'Donoghue (2002). A more recent review of discount rate functional forms and experimental issues when measuring discount rates is presented in Andersen, et al. (2011). Economists have typically measured time preferences in monetary terms, though recent studies suggest that time and risk preferences are not stable across contexts (e.g. Barseghyan, Prince, and Teitelbaum, 2011; Einav et al., 2012; Weatherly, Terrell, & Derenne, 2010).

Chiao, 2009). It is important to replicate these results to verify that these associations are not false positives (Chabris et al., 2012).

While the literature on decision-making in behavioural economics and psychology has evolved separately, a related concept in psychology is the delay discount rate (DDR). In these tasks, the subject is offered a choice between a hypothetical immediate reward and a hypothetical larger reward offered at a later time. Studies suggest that the discount curve can be modelled using the hyperbolic function:

$$V = \frac{A}{1 + kD} \tag{1}$$

where V is the present value of the reward A given with a delay D, and k is the DDR. The parameter k is typically normalized by taking the natural logarithm (ln(k)). This parameter only measures time preferences and not risk preferences as the hypothetical rewards are offered with certainty.

This concept has been studied extensively in psychology, usually through laboratory experiments (e.g. Madden, Petry, Badger, & Bickel, 1997; Businelle, McVay, Kendzor, & Copeland, 2010; Johnson, Bickel, & Baker, 2007). These laboratory experiments ask the subject to repeatedly choose between an immediate reward and a delayed reward until an indifference point is reached. In contrast, survey-based methods use a number of standardized questions to infer an approximate indifference point. While it identifies the indifference point precisely and hence has greater internal validity, laboratory experiments are also more equipment intensive and therefore base their conclusions on much smaller sample sizes.

The survey-based Georgetown Adolescent Tobacco Research (GATOR) and Adolescent Longitudinal Outcomes Health Assessment (ALOHA) studies follow a group of adolescents from grade 9 to four years after high school. With three observations of the monetary delay discount rate (MDDR) or ln(k) collected using a monetary choice questionnaire, an initial cohort of over a thousand students, and a much richer set of variables than those typically collected in other studies, this dataset can be used to expand the literature on time preferences in a number of ways.

First, this analysis finds that within-subject MDDR is unstable over a period of three to four years, from adolescence to young adulthood. Modelling how within-subject time preferences evolve over a lifetime or relaxing the assumption of stable time preferences may be important for empirical analysis of decision-making. Second, given that the person had never smoked before, adolescent MDDR is positively correlated to the decision to begin smoking in a manner that is robust to the inclusion of different variables. It is therefore important to understand to what extent time preferences are pre-determined and what are the main factors that determine time preferences. Finally, given the lack of stability in the MDDR, it is not surprising that there is only a weak connection between the genes examined in this paper and the MDDR.

This paper is organized as follows. Section 2 presents background information on DDR and a model of intertemporal decision-making using DDR. Section 3 contains background information on the GATOR/ALOHA dataset and sample characteristics. Sections 4, 5, and 6 analyze ln(k) from the perspective of within-subject stability, risky behaviours, and correlates respectively. Section 7 addresses selective attrition as a potential threat to external validity, Section 8 discusses the results, and Section 9 concludes.[2]

2 Theoretical Overview

2.1 Overview of the Delay Discount Rate

The concept of delay discounting in psychology is typically measured as the extent to which a person will forego an immediate reward in exchange for a larger reward at a later time. This reward could be in terms of money, health-years, or other dimensions. The key variable of interest is the DDR: if a larger, delayed reward is discounted enough that its present value is smaller than the immediate reward, a more impulsive decision will be made. The inclination to postpone gratification could be important when choosing whether to indulge in risky behaviours that promise immediate rewards in exchange for later costs.

Early models of time discounting used an exponential representation of the discount

[2] Appendix A contains a mathematical interpretation for changes in ln(k). Appendix B contains an example of the monetary choice questionnaire. While brief highlights of the related literature will be presented in each section, Appendix C contains a more detailed literature review of past MDDR literature on the topics covered in this paper. Appendix D contains selected Figures and Tables using inverse probability weights to account for selective attrition.

rate. This had the advantage of time consistency in choices, though experimental studies suggested that this did not reflect actual choices. These studies indicated that the relationship between the subjective value of the reward and the time delay more closely resembled the hyperbolic function described in Equation 1, which has since been used in a number of papers (Kirby & Marakovic, 1995; Johnson & Bickel, 2002; Wileyto & Audrain-McGovern, 2004; Mazur, 1987; Navarick, 2004).[3] Small values of k (e.g. 0.001) suggest that the person has a general preference for delayed rewards, while large values (e.g. 0.1) indicate a preference for immediate rewards (Wileyto & Audrain-McGovern, 2004).

Graphically, k determines how steeply the present value decreases as the delay increases, with smaller values of k associated with steeper slopes of the present value curve. While V or A are typically given in dollar amounts, they can also be expressed in terms of food or other dimensions. The parameter k is frequently normalized and reported in terms of the natural logarithm. Figure 1 illustrates the difference in the evolution of the present value of 100 units over 100 days when the k =0.1 or 0.01.

There are a number of different methods that can be used to determine k.[4] A straightforward laboratory task is to ask the subject whether they would prefer V dollars immediately, or A dollars D days in the future. The question is then asked repeatedly with the variables slightly changed until an indifference value of k is identified. However, it can take over 100 questions to arrive at a well-defined value for k and can be cumbersome for large samples (Wileyto & Audrain-McGovern, 2004). As a result, surveys have often derived k using a series of questionnaires, such as the widely used monetary choice questionnaire. In this questionnaire, choices related to small ($25-35), medium ($50-60), and large ($75-85) rewards are presented in alternating order over a delay of 7 to 186 days.[5]

Two methods are commonly used to derive the value of k from the monetary choice questionnaire answers. If the person has a well-defined indifference point, then k can be approximately identified by recognizing at what point the person switches from the immediate reward to the larger, delayed reward. Kirby (2000) provides tables and instructions

[3]See Appendix A for a discussion of how to interpret differences in ln(k).

[4]The MDDR specifically refers to the DDR revealed by a person's intertemporal monetary choices. The DDR is a broader concept that can be applied to different types of rewards.

[5]See Appendix B for an example of the monetary choice questionnaire.

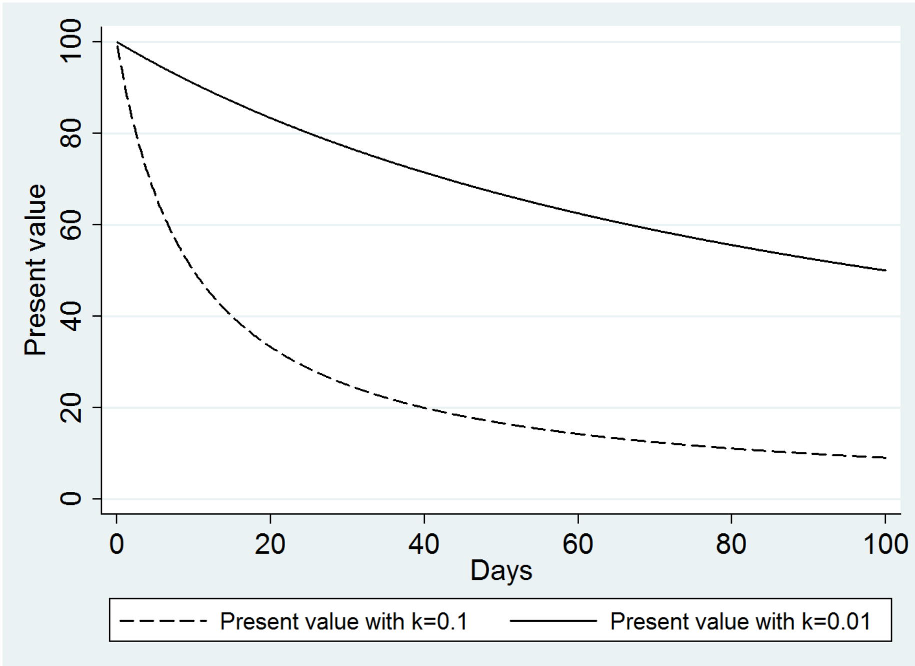
for this procedure. An alternative is to use logistic regression to estimate the delay discounting function. This has the advantage of simplifying the analysis while providing a better account for people who do not have a well-defined indifference point (Wileyto & Audrain-McGovern, 2004). Results from this process were found to have a high coefficient of determination with the k calculated manually.

A potential concern is that decision processes linked to hypothetical rewards might differ from decision processes linked to real rewards. Navarick (2004) noted that DDR derived using questionnaires are too low to explain impulsive choices in experiments, and that the DDR derived from experiments and questionnaires were significantly different. The author's hypothesis was that this may be due to the lack of consumption and reinforcement processes. On the other hand, Kirby (1997) suggested that rewards must be relatively small to be credibly rewarded to the participants. Therefore, the main reason for the difference between hypothetical and real reward DDR could be due to a magnitude effect, or that larger rewards are discounted at a lower rate than smaller rewards.

Other studies have investigated the link between DDR based on reward type using specially designed experiments and found little to no difference between real and hypothetical rewards (Johnson & Bickel, 2002; Madden, Begotka, Raiff, & Kastern, 2003; Madden, et al., 2004; Lagorio & Madden, 2005). While these results are based on relatively small sample sizes (6 to 20 subjects), they conclude that measuring DDR using hypothetical rewards in a single session is a valid procedure.[6]

[6]See Appendix C for a more detailed literature review on the topics covered in this paper.

Figure 1: Present value of 100 units in x days (k=0.1 and k=0.01)



2.2 Decision-Making with Delay Discount Rates

Much of the interest in time preferences surrounds its ability to explain variation in decision-making and behaviour. There is therefore a large literature on risk and time preferences, especially in the realm of expected utility and discounted expected utility. The model presented in this section is a variant of the classical discounted expected utility, where the form of time discounting is explicitly given by the hyperbolic function presented in Equation 1. This differs from traditional economic models because the model has a present bias, whereas exponential discounting assumes symmetry in both present and future behaviour. The model also describes choices rather than optimal decisions and is based on the intuitive explanation that is commonly given for the relationship between the DDR and addictive behaviour: a person weighs the discounted value of future costs versus the immediate rewards.

Suppose that a person perceives that they will receive an immediate reward z_0 in exchange for an initial monetary outlay of m_0 and a cost schedule $\{c_1, ..., c_T\}$ in the future that will occur with probability $\{\pi_1, ..., \pi_T\}$. Suppose also that $\{w_0, ..., w_T\}$ is the expected background consumption of the composite good. Then, similar to Viscusi (1990), the person will engage in the behaviour if, at least at the subconscious level:[7]

$$U(w_0) + \sum_{i=1}^{\infty} \frac{U(w_i)}{1+ki} < U(w_0, z_0, m_0) + \sum_{i=1}^{\infty} \frac{U(w_i, c_i, \pi_i)}{1+ki} \tag{2}$$

where k is the DDR for that particular good and U(·) is a time separable utility function.[8]

Note that $\mathrm{w_i}$, $\mathrm{z_i}$, and π_i are the person's perceptions of future events because the future is inherently uncertain. Subjective perceptions are also more relevant to personal decisions if the person has no prior experience and can only estimate the initial reward and its costs. While standard expected utility models multiply $\mathrm{U(w_i, z_i)}$ by π_i, the above model allows for the possibility of a preference for certainty, as suggested by Andreoni and Sprenger (2012).[9]

It immediately follows that a person will decide to engage in the behaviour if:

$$0 < (U(w_0, z_0, m_0) - U(w_0)) + \left(\sum_{i=1}^{\infty} \frac{U(w_i, c_i, \pi_i) - U(w_i)}{1+ki} \right) \tag{3}$$

Equation 3 defines the choice as a comparison of the initial costs and rewards (the first expression) against the potential future costs (the second expression). If k is very large, then the decision primarily rests upon whether the initial outlay is worth the perceived pleasure. Furthermore, if k is a time-varying primitive, then the changes in k should be taken into account in empirical analysis.

An implication of this model is that it is not clear whether changes in DDR, if it is time-varying, will change a person's decision. Assuming that only the DDR changes, a person who has never engaged in the risky behaviour will suddenly change their decision if before:

[7]Assume that there is a non-binding monetary constraint for ease of exposition, and as there is no data on the subject in this particular study.

[8]This does not assume that there is a unique discount rate for all goods, as suggested by a number of previous studies for both risk and time preferences (e.g. Barseghyan, Prince, and Teitelbaum, 2011; Einav et al., 2012; Chapman, 1996; Weatherly, Terrell, & Derenne, 2010).

[9]In standard expected utility models, Equation 2 is $U(w_0) + \sum_{i=1}^{\infty} \frac{U(w_i)}{1+ki} < U(w_0, z_0, m_0) + \sum_{i=1}^{\infty} \pi_i \frac{U(w_i, c_i)}{1+ki} + \sum_{i=1}^{\infty} (1-\pi_i) \frac{U(w_i)}{1+ki}$ or $U(w_0) < U(w_0, z_0, m_0) + \sum_{i=1}^{\infty} \pi_i \frac{U(w_i, c_i) - U(w_i)}{1+ki}$. However, this requires interchangeability between certain consumption and uncertain consumption, which may not be the case, as noted in Andreoni & Sprenger (2012).

$$U(w_0) + \sum_{i=1}^{\infty} \frac{U(w_i)}{1+k_1 i} > U(w_0, z_0, m_0) + \sum_{i=1}^{\infty} \frac{U(w_i, c_i, \pi_i)}{1+k_1 i} \tag{4}$$

but after the change in DDR:

$$U(w_0) + \sum_{i=1}^{\infty} \frac{U(w_i)}{1+k_2 i} < U(w_0, z_0, m_0) + \sum_{i=1}^{\infty} \frac{U(w_i, c_i, \pi_i)}{1+k_2 i} \tag{5}$$

Put another way, if a person decides not to engage in the risky behaviour in the first period, the person will choose to begin partaking of the risky behaviour in the second period only if:

$$\sum_{i=1}^{\infty} \frac{U(w_i, c_i, \pi_i) - U(w_i)}{1+k_2 i} > U(w_0) - U(w_0, z_0, m_0) > \sum_{i=1}^{\infty} \frac{U(w_i, c_i, \pi_i) - U(w_i)}{1+k_1 i} \tag{6}$$

For people who were initially at the margin, such that the far right expression is close to the middle expression, very small changes in k will results in changes in behaviour. Otherwise, however, changes in k will not necessarily result in changes in behaviour.

3 Data

The Georgetown Adolescent Tobacco Research (GATOR) study was a unique longitudinal study of high school students in northern Virginia. Students who enrolled in one of five randomly selected public high schools in the same county and in normal classroom placements (e.g. did not have a severe learning disability) were eligible for participation.[10] Parental and student consent was also required. To encourage participation, participants received $5 gift certificates to media stores, up to three waves of mailings were sent to houses, and telephone calls were placed to parents. Relative to the 1,040 students who started the study in 1999 with data on the non-genotype covariates examined in Table 14, follow-up in waves 2-5 was 94%, 95%, 94%, and 91% respectively.[11]

The initial cohort was formed in grade 9 spring (wave 1) and subsequent follow ups were

[10]There were 21 high schools in this county during this period. The county had over 950,000 residents with a median household income of $70,000 in 1995 (Ding, et al., 2007).

[11]Some students did not answer the survey in one wave but answered the survey in the next.

conducted in grade 10 fall, grade 10 spring, grade 11 spring, and grade 12 spring (waves 2-5). Data was collected by distributing a survey to participating students during compulsory classes. A member of the research team read aloud a set of instructions, after which the student completed the questionnaire. The research team was available for questions and the survey took approximately 30 minutes to complete. Confidentiality was emphasized to encourage honesty in self-report questions and parents also answered a set of classification questions during the first wave. Genetic data was also collected using DNA extracted from buccal swabs and 20% of the samples were retested for quality control.[12]

After high school, students were given the choice of continuing with the research study by joining the Adolescent Longitudinal Outcomes Health Assessment (ALOHA). The people who agreed to continue to participate in this study were measured annually during the spring of the four years following high school (waves 6-9). Most of the same self-report measures were asked in both GATOR and ALOHA (Table 1 and Table 2). Follow up during waves 6-9, once more in comparison to the 1,040 initial students, was 76%, 65%, 68%, and 64%.[13]

One advantage of GATOR is that it contains panel data on ln(k) over a longer period than other studies.[14] Furthermore, there is substantial information on the evolution of risky behaviours over time, genetic and psychological information, and much larger sample sizes than comparable experimental studies.

[12]The DNA was extracted using standard phenol-chloroform techniques. Buccal cells were used to accommodate subjects who might have a blood or injection phobia (Ding, et al., 2009). Similar to other genetic studies, the genotypes tested in this study are related to the dopamine and serotonin pathways. Dopamine is a neurotransmitter that contributes to a number of biological systems, including reward-motivated behaviour, and serotonin is associated with feelings of well-being and happiness. The DRD2, DAT1, and COMT genes code for different parts of the dopamine system (DRD2 is responsible for the density of dopamin receptors on brain neurons, DAT1 regulates dopamine in brain synapses, and COMT is responsible for the inactivation of dopamine), the TPH gene is associated with the biosynthesis of serotonin, and the CYP gene is associated with breaking down various organic compounds inside the body. See Appendix C for a more detailed discussion of previous studies linking ln(k) to these genes.

[13]Characteristics of those who follow up will be investigated in Section 7.

[14]Most of the other studies that have studied within-subject stability of time preferences have a test-retest period of at most one year (e.g. Ohmura et al., 2006; Kirby, 2009; Meier & Sprenger, 2010). The initial sample size of 1,040 students is also larger than all but 5 of the 64 studies sampled in MacKillop et al. (2011).

Table 1: Classification variable definitions

Variable	Waves measured	Type of data	Definition
Caucasian	1	Binary	1=Student was Caucasian.
Male	1	Binary	1=Student was male.
Biological parent	1	Binary	1=Student lived with biological parent.
Parent's education	1	Binary	1=Responding parent had at least some college education.
Parent regularly smoked	1	Binary	1=Responding parent had regularly smoked.
Biological parent regularly smoked	1	Binary	1=A biological parent was a regular smoker during their lifetime.
AD	1	Binary	1=Student scored at least moderate severity on at least 6 of 9 inactivity items in the CSSF-D. (1)
HD	1	Binary	1=Student scored at least moderate severity on at least 6 of 9 inattention items in the CSSF-D. (1)
Depressed	1, 3-9	Binary	1=Student scored >24 for female adolescents or >22 for male adolescents on the CES-D. (2)
Peers smoke	1-9	Binary	1=Student has at least one male or female friend that smokes.
Smoker in the household	1-9	Binary	1=Someone in the student's household smokes.
GPA	3-5	Continuous	1=Mostly D's and F's to 4=Mostly A's.
A1A1/A1A2/A2A2	1	Binary	1=Presence of those DRD2 genotypes.
AA/AC/CC	1	Binary	1=Presence of those TPH genotypes.
TT/CC/CT	1	Binary	1=Presence of those CYP genotypes.
DAT0/DAT1/DAT2	1	Binary	1=Length of the DAT halotype.
HH/HL/LL	1	Binary	1=Presence of those COMT genotypes.

[1] The Current Symptoms Scale-Self Form (CSSF) is an 18-item self-report measure that indicates the presence of attention deficit/hyperactivity disorder (ADHD). Participants are asked to rate their recent behaviour based on how often they experience inattention and hyperactivity-impulsivity symptoms, from 0 (never of rarely) to 3 (very often). Results from the CSSF were found to have reasonable reliability and validity (Rodriguez, Tercyak, & Audrain-McGovern, 2008).

[2] The Center for Epidemiologic Studies-Depression (CES-D) Scale is a 20-item measure of depression symptoms. The participants rate every item based on how often they experience the symptom per week, from 0 (never or rarely) to 3 (very often). The sum of the responses is the respondent's score, and the cutoffs for depression were provided by Roberts et al. (1991). These results are reliable for adolescents and young adults.

Table 2: Behavior and psychological variables

Variable	Waves measured	Type of data	Definition
ln(k)	3, 6, 7	Continuous	Based on answers from the monetary choice questionnaire. (1)
Good self-control	3	Ordinal	Sum of answers to 17 items on positive self-control derived from an inventory of general control in daily situations. (2)
Bad self-control	3	Ordinal	Sum of answers to 24 items on poor self-control derived from an inventory of general control in daily situations. (2)
Impulsivity (sub-group of bad self-control questions)	3	Ordinal	Subset of 10 poor self-control questions derived from an inventory of general control in daily situations. (2)
Novelty-seeking	3	Ordinal	Sum of answers to a twenty question version of the Temperament and Character Inventory (TCI). (3)
Reward-dependence	3	Ordinal	Sum of answers to a twenty question version of the TCI. (3)
Harm avoidance	3	Ordinal	Sum of answers to a fifteen question version of the TCI. (3)
Overall risk in smoking	4	Binary	1="very high" or "high", 0="very low" or "low"
Regular smoker	1-9	Binary	1=Student smoked a cigarette within the past month and over one hundred cigarettes over their lifetime.
Marijuana user	1, 3-7	Binary	1=Student smoked marijuana within the past month and over one hundred times over their lifetime.
Heavy alcohol drinker	1, 3-9	Binary	1=Student had at least 5 or more drinks in at least one day in the past month.

[1] Calculated using Stata's *mcqscore.ado* function described in Wileyto and Audrain-McGovern (2004).
[2] Individual answers are scored from 0 ("not at all" or "never") to 4 ("very true" or "usually"). The sum was transformed to a scale of 0 to 1 by dividing by the maximum possible score.
[3] The TCI was introduced by Cloninger et al., (1994) as part of Tridimensional Personality Theory that linked neurotransmitters to individual personality traits. Reward dependence , novelty-seeking, and harm avoidance were the three original temperaments. Novelty-seeking in particular has been linked to adolescent smoking and substance abuse (Audrain-McGovern, et al., 2004), though it is possible that reward-dependence and harm avoidance could also play a role in a person's decision to engage in risky behaviour. Answers given as "false" are scored as 0, while "true" was scored was 1. The sum was transformed to a scale of 0 to 1 by dividing by the maximum possible score.

In terms of the variables measured once during the study, almost two thirds of the sample were Caucasian (Table 3). The sample was evenly balanced between boys and girls and a large majority of students lived with their biological parents and thought that overall risk in smoking was high. Most of the responding parents had at least some post-secondary education and had not previously regularly smoked.

With respect to the personality traits, the average novelty-seeking, reward dependence, harm avoidance, and good self-control index scores were between 0.40 and 0.65 (on a scale from 0 to 1).[15] The average manifestation of impulsivity and bad self-control traits was particularly low at approximately 0.25 on the same scale.[16]

In terms of the other variables, the proportion of students who were depressed fluctuated between 10% and 20% between wave 3 and 7 (Table 4). While the percentage of students with a peer who regularly smokes rose very slightly over the same period, there was not a substantial change in the presence of smokers in the household or the students' average GPA. In terms of risky behaviours, the prevalence of drinking, smoking, and marijuana use rose rapidly between waves 3 and 7.

[15]These personality trait indices are based on the subject's answers to a number of questions. The questions asked during in the TCI include "I often try new things just for fun or thrills?", and "I like to think about things for a long time before I make a decision". The subject's score on each individual question range from 0 ("not at all" or "never") to 4 ("very true" or "usually"). The questions that pertain to each subscale are then added together and transformed to a scale from 0 (lowest expression of trait) to 1 (highest expression of trait). Novelty-seeking measures the degree to which the subject is excited by new experiences, harm avoidance measures the degree to which the subject passively avoids potentially adverse experiences, and reward dependence measures the degree to which the subject responds intensely to receiving rewards (Tercyak & Audrain-McGovern, 2003).

Questions in the self-control portion include whether the person is easily distracted, gets carried away, or thinks before acting. The subject's score on each individual question range from 0 ("false") or 1 ("true"). The questions that pertain to each subscale are then added together and normalized to a scale from 0 (lowest expression of trait) to 1 (highest expression of trait).

[16]The self-control indices are based on two different sets of questions. Therefore, a person who does not make choices associated with good self-control might not necessarily make choices associated with bad self-control. The good and bad self-control indices are nonetheless negatively correlated with each other, as the Pearson correlation coefficient between the good self-control and bad self-control indices is -0.504 with a 95% confidence interal of [-0.547, -0.458].

Table 3: Summary characteristics of variables that are measured once

Genotypes				Other variables			
Variable	Mean	Std Dev	N	Variable	Mean	Std Dev	N
(TPH) AA	0.137	(0.344)	1,113	Caucasian	0.627	(0.484)	1,139
(TPH) AC	0.429	(0.495)	1,113	Male	0.480	(0.500)	1,128
(TPH) CC	0.434	(0.496)	1,113	Biological parent	0.971	(0.167)	1,113
(CYP) TT	0.035	(0.184)	1,061	Parent had some post-secondary education	0.807	(0.395)	1,082
(CYP) CT	0.220	(0.414)	1,061	Parent regularly smoked	0.345	(0.476)	1,096
(CYP) CC	0.746	(0.436)	1,061	Perceived smoking risk	0.938	(0.241)	1,036
(DRD2) A1A1	0.062	(0.242)	1,073	Novelty-seeking	0.540	(0.193)	1,101
(DRD2) A1A2	0.327	(0.469)	1,073	Reward dependence	0.608	(0.194)	1,107
(DRD2) A2A2	0.610	(0.488)	1,073	Harm avoidance	0.419	(0.219)	1,110
(DAT) DAT0	0.091	(0.287)	1,127	Good self-control	0.583	(0.173)	1,083
(DAT) DAT1	0.360	(0.480)	1,127	Bad self-control	0.277	(0.166)	1,074
(DAT) DAT2	0.549	(0.498)	1,127	Impulsivity trait	0.259	(0.195)	1,079
(COMT) HH	0.302	(0.459)	1,065	School 1	0.175	(0.380)	1,138
(COMT) HL	0.470	(0.499)	1,065	School 2	0.246	(0.431)	1,138
(COMT) LL	0.227	(0.419)	1,065	School 3	0.211	(0.408)	1,138
				School 4	0.156	(0.363)	1,138
				School 5	0.212	(0.409)	1,138

Note: Personality traits were normalized to a scale from 0 to 1, with 0 as the lowest possible manifestation of the personality trait and 1 as the highest. Genotypes are presented for the TPH, CYP, DRD2, and COMT genes. DAT genotypes refer to the length of the gene, from shortest (DAT0) to longest (DAT2).

Table 4: Summary characteristics of variables that are measured more than once

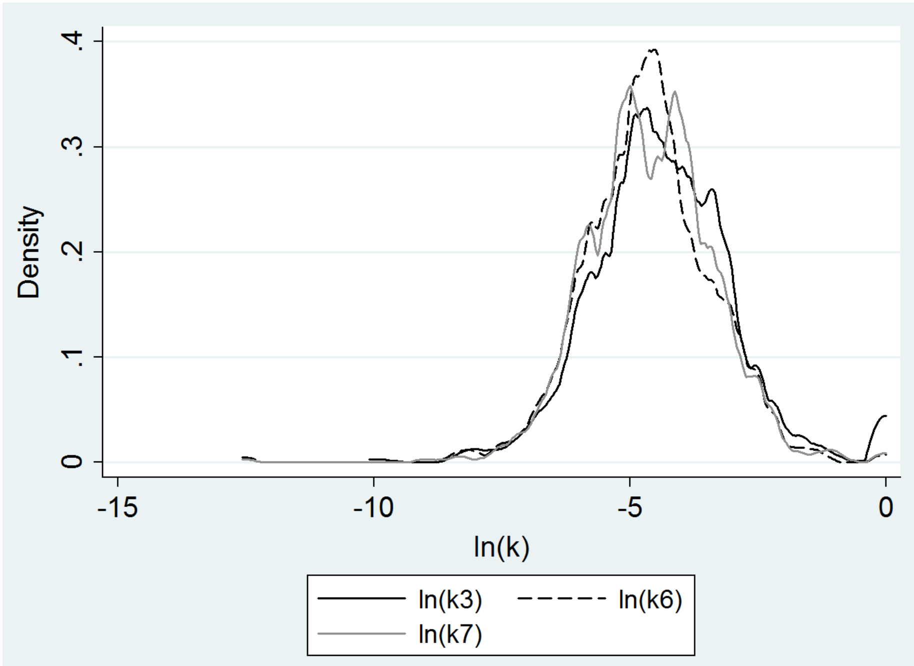
		Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Peers smoke	mean	0.588	0.620	0.615	0.664	0.620
	sd	(0.492)	(0.486)	(0.487)	(0.473)	(0.486)
	N	1,071	1,043	1,003	833	715
Depression symptoms	mean	0.176	0.150	0.114	0.109	0.159
	sd	(0.381)	(0.357)	(0.317)	(0.312)	(0.366)
	N	1,080	1,043	1,004	834	717
Smoker in the household	mean	0.264	0.254	0.244	0.277	0.259
	sd	(0.441)	(0.436)	(0.430)	(0.448)	(0.439)
	N	1,059	1,038	1,004	834	717
GPA	mean	3.150	3.125	3.170		
	sd	(0.578)	(0.607)	(0.568)		
	N	1,032	1,026	988		
Regular smoker	mean	0.124	0.175	0.216	0.301	0.365
	sd	(0.33)	(0.38)	(0.412)	(0.459)	(0.482)
	N	1,085	1,073	1,042	925	844
Heavy drinker	mean	0.169	0.237	0.326	0.412	0.453
	sd	(0.375)	(0.426)	(0.469)	(0.493)	(0.498)
	N	1,071	1083	1,084	868	771
Marijuana smoker	mean	0.032		0.085	0.109	0.148
	sd	(0.176)		(0.279)	(0.311)	(0.356)
	N	1,066		1,014	874	768

While individual ranks may vary between measurements, the aggregate distribution of ln(k) was extremely similar in all three measurements (Figure 2). More specifically, the average value of $\ln(k_3)$ in GATOR/ALOHA was approximately -4.3, with an interquartile range of 1.7 (Table 5). None of these summary statistics changed significantly between measurements.

Table 5: Summary statistics of ln(k)

	N	Mean	Std dev	25^{th} percentile	50^{th} percentile	75^{th} percentile
$\ln(k_3)$	1,030	-4.343	1.410	-5.228	-4.410	-3.529
$\ln(k_6)$	795	-4.642	1.273	-5.491	-4.673	-3.953
$\ln(k_7)$	695	-4.590	1.254	-5.279	-4.650	-3.840

Figure 2: Kernel density plots of ln(k)



4 Stability of Monetary Delay Discount Rates

Empirical analysis of intertemporal decision-making usually assumes that time preferences are stable over a person's lifetime. If not, then some of the measured effect of economic incentives could instead reflect changes in time preferences.

The similar distribution of ln(k) measured during different periods is indicative of absolute stability from adolescence to young adulthood. The overall decrease in average impulsivity between waves 3 and 6 is consistent with between-group comparisons of adolescents and young adults (Green, Fry, & Myerson, 1984; Steinberg, et al., 2009). In contrast, the average ln(k) very slightly increased between waves 6 and 7.

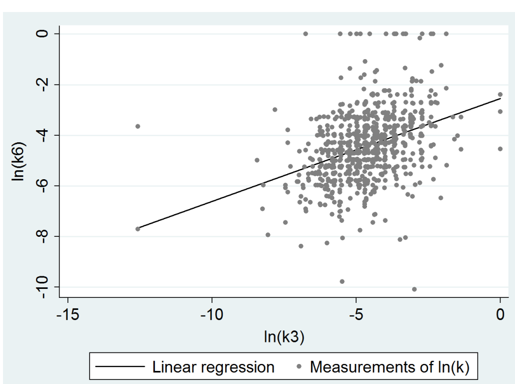
A possible explanation put forth by Kirby (2009) is that changes in ln(k) in college-age young adults may differ from the overall trend. It is also interesting to note that the change in ln(k) in GATOR/ALOHA was much smaller than the 0.2 to 0.3 ln(k) per month trend observed by within-group studies. As the monetary choice questionnaire was used in both GATOR/ALOHA and Kirby (2009), it is not simply a matter of how ln(k) was derived.

While the overall average ln(k) appears to be stable, it may not be the case at the level of the individual. Relative stability is traditionally concerned with the test-retest reliability of ln(k) over a period of time. Ohmura et al. (2006) and Kirby (2009) found that ln(k) was stable over three months and a year respectively, especially among young adults and undergraduate students. This has led some researchers to conclude that the DDR may be treated as a personality trait (Odum, 2011).

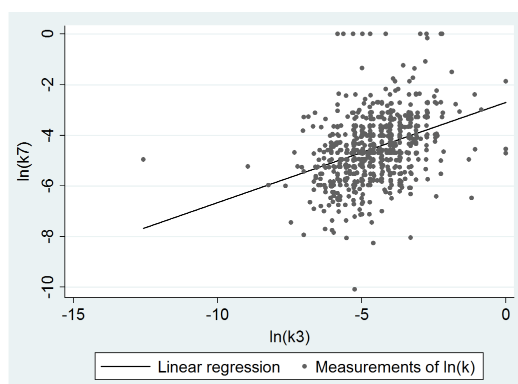
One of the principal assumptions inherent in using OLS and Pearson correlations coefficients is that there is a linear relationship between the two measures of ln(k). This seems to be the case in the GATOR/ALOHA dataset (Figure 3). As expected, there appears to be a much closer relationship between ln(k_7 and ln($k_{6)}$ (top), when compared to ln(k_6) and ln(k_3) (bottom left), or ln(k_7) and ln(k_3) (bottom right).

Figure 3: Scatterplots of the monetary delay discount rates

(a) ln(k_7) and ln(k_6)



(b) ln(k_6) and ln(k_3)



(c) ln(k_7) and ln(k_3)

The relationships between ln(k) measured during different periods will be examined using three different methods. The Spearman rank correlation coefficient offers a non-parametric test of whether there is a monotonic relationship between the variables using the relative ranks of the variables. The Pearson correlation coefficient, on the other hand, assumes that there is a linear relationship between the variables. Finally, moving beyond bivariate comparisons might be of interest as other variables are also correlated with ln(k) (Table 14). OLS assumes a linear relationship between ln(k) and other variables and allows for the inclusion of other variables that might also be correlated with ln(k). The OLS equation takes the following form for student i at time t_{it2}:

$$ln(k_{it2}) = \beta_0 + \beta_1 ln(k_{it1}) + \alpha X_i + \varepsilon_{it2} \tag{7}$$

where $\ln(k_{it2})$ and $\ln(k_{it1})$ are ln(k) measured at time $t_2 > t_1$, X_i are the same variables as those in Table 14, and ε_{it2} includes unobserved factors.[17] Values of β_1 that are close to one are indicative of test-retest reliability, while small values of β_1 suggest that ln(k) is not stable over the time period. Similarly, Spearman or Pearson correlation coefficients that are close to one are indicative of test-retest reliability.

While all three measures of within-subject stability reject the null hypothesis of no relationship between ln(k), they are all also significantly different from one (Table 6). The correlation coefficients are also smaller than those associated with similar re-test intervals of questionnaire-based personality trait measurements (Schuerger, Tait, & Tavernelli, 1982).[18]

As expected, the highest correlation was 0.58 between ln(k) measured with a one-year test-retest interval, though this is still lower than those found in previous studies. Kirby (2009) found that the correlation coefficient associated with ln(k) measured with a one year and 57 week test-retest interval was 0.71 (95% confidence interval of 0.50-0.84) and 0.63 (95% confidence interval of 0.41-0.77) respectively. However, comparing the result obtained here with previous results is problematic due the low sample size in Kirby (2009) that contribute to imprecise results.

[17]These variables are chosen because they plausibly predate determination of ln(k) to minimize the possibility of reverse-causation.

[18]When stratifying by gender, both genders had similar within-subject correlations between $\ln(k_6)$ and $\ln(k_7)$. On the other hamd, three or four year within-subject correlation of ln(k) for females was higher than that for males (approximately 0.45 versus 0.25). While there is some heterogeneity between the genders, there are still large intertemporal differences in ln(k).

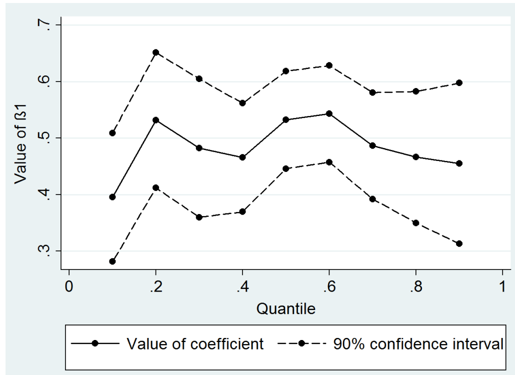
Table 6: Relative stability of monetary delay discount rates

	$\ln(k_7)$ compared $\ln(k_3)$	$\ln(k_6)$ compared $\ln(k_3)$	$\ln(k_7)$ compared to $\ln(k_6)$
Spearman rank correlation coefficient	0.395*** [0.330, 0.458]	0.395*** [0.334, 0.453]	0.582*** [0.528, 0.631]
Pearson correlation coefficient	0.361*** [0.294, 0.425]	0.366*** [0.303, 0.426]	0.583*** [0.530, 0.633]
Linear regression with other variables	0.296*** (0.0368)	0.306*** (0.0395)	0.502*** (0.0451)

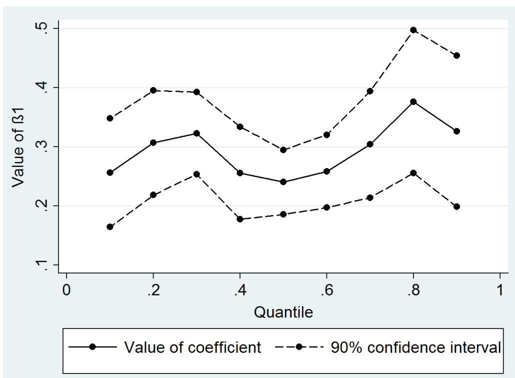
Note: Each regression cell represents β_1 for a different regression. Regressions include school indicator variables. Controls refer to the same characteristics as those presented in Table 14 without genotype indicator variables. Robust standard errors are presented in ( ) parenthesis. 95% confidence intervals for the correlation coefficient using Fischer's transformation are presented in [ ] parenthesis. ***, **, * represent that the statistic is statistically different from one at the 1%, 5%, and 10% significance levels respectively.

Homogeneity of the relative stability of ln(k) can be tested by examining how β_1 changes along different percentiles of $\ln(k_{it1})$. Overall, there is some indication that ln(k) is more stable among people with a higher initial value of ln(k), though still fairly low (Figure 4). This is particularly important because people who have high initial ln(k) are also those who are typically associated with risky behaviours. Empirically analyzing the decision-making process among these people may rely upon repeated measurements of time preferences, which to date has not become standard practice.

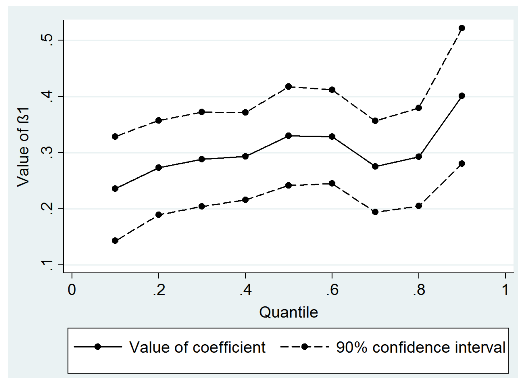
Figure 4: Unconditional quantile regressions for relative stability of monetary delay discount rates



(a) ln(k_7) and ln(k_6)



(b) ln(k_6) and ln(k_3)



(c) ln(k_7) and ln(k_3)

Note: 90% confidence interval based on bootstrapped standard errors.

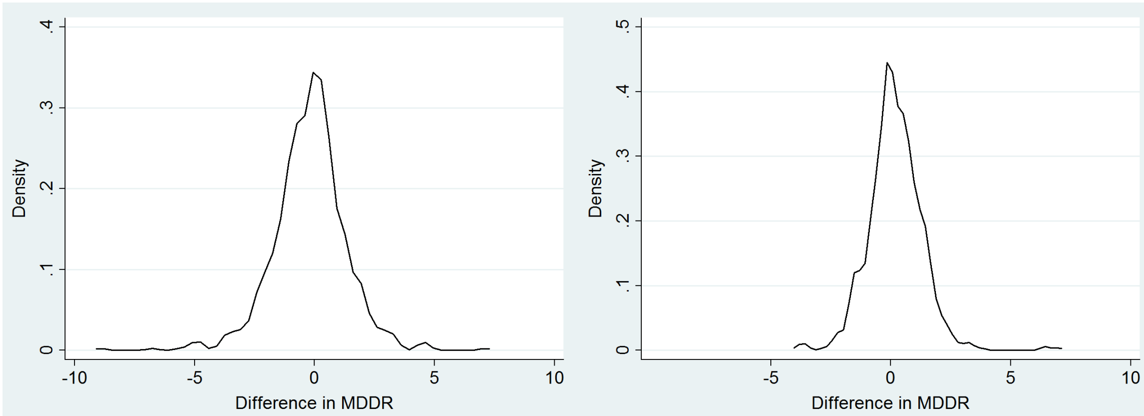
It is also not clear whether changes in ln(k) over shorter periods follows an overall trend. Indeed, for over two thirds of people where ln(k_6)<ln(k_3), it is also the case that ln(k_7)≥ln(k_6) (Table 7). Furthermore, the average change in ln(k_6))-ln(k_3) and ln(k_7)-ln(k_6) is close to zero and they each have similar distributions, though there appears to be slighly more variation in ln(k_6)-ln(k_3) than in ln(k_7)-ln(k_6) (Figure 5).

Table 7: Relative stability of monetary delay discount rates

	ln(k_7) ≥ ln(k_6)	ln(k_7) < ln(k_6)	Total
ln(k_6) ≥ ln(k_3)	119 (0.194)	153 (0.250)	272 (0.444)
ln(k_6) < ln(k_3)	235 (0.383)	106 (0.173)	341 (0.556)
Total	354 (0.577)	259 (0.423)	613

Note: Marginal probabilities are presented in ( ) parenthesis.

Figure 5: Kernel densities of changes in monetary delay discount rates



(a) ln(k_6)-ln(k_3) (b) ln(k_7)-ln(k_6)

The four groups described in Table 7 do not seem to significantly differ in terms of personality traits or evolution of risky behaviours (Table 8). The only variables in which the null hypothesis of equal means between the groups can be rejected are the bad self-control and impulsivity traits. For these traits, the fourth group has a slightly higher mean than the others.[19]

Put together, this has a number of implications. Evidence suggests that within-subject ln(k) is not as stable as previously believed to be the case as the correlations between ln(k) measured at different times are fairly low. Furthermore, ln(k) can have fluctuations over one year that are of similar size as fluctuations over three years. It is unclear whether changes in ln(k) are indicative of a long-term trend or these short-term fluctuations. As a result, it is difficult to make inferences about short term changes in ln(k) on the basis of longer-term trends.[20]

[19]The similar distributions of ln(k), and the worse initial self-control among those who become less patient later during the study, may indicate possible reversion to the mean. If this were the case then for a significant portion of the population, $|ln(k_{3i}) - \mu_3| > |ln(k_{6i}) - \mu_6|$ for student i. However, this was only the case for 418 of 766 (54.6%) students.

[20]It is relevant to contrast the results obtained in this analysis and that of Audrain-McGovern et al. (2009). While the same dataset was used in both studies, this paper found that ln(k) was unstable and Audrain-McGovern et al. (2009) found that it was stable. The conclusion in the latter paper is based on the finding that the trend in ln(k) was not a significant predictor of the timing of smoking uptake. However, this does not directly test within-group stability of ln(k), but rather whether the relationship between ln(k) and risky behaviour is stable from adolescence to young adulthood.

Table 8: Summary characteristics based on changes in ln(k)

	(1) $\ln(k_6) \geq \ln(k_3)$ and $\ln(k_7) \geq \ln(k_6)$	(2) $\ln(k_6) < \ln(k_3)$ and $\ln(k_7) \geq \ln(k_6)$	(3) $\ln(k_6) \geq \ln(k_3)$ and $\ln(k_7) < \ln(k_6)$	(4) $\ln(k_7) < \ln(k_6)$ and $\ln(k_6) < \ln(k_3)$	F-test of equal means
Good self-control	0.604 (0.167)	0.587 (0.170)	0.582 (0.162)	0.568 (0.174)	0.84 [0.471]
Bad self-control	0.274 (0.169)	0.261 (0.153)	0.276 (0.160)	0.321 (0.175)	3.02** [0.0293]
Impulsivity	0.254 (0.199)	0.238 (0.180)	0.258 (0.191)	0.298 (0.210)	2.19* [0.0885]
Novelty-seeking	0.524 (0.210)	0.529 (0.206)	0.527 (0.197)	0.548 (0.223)	0.28 [0.8370]
Reward dependance	0.651 (0.196)	0.621 (0.202)	0.623 (0.191)	0.603 (0.207)	1.15 [0.327]
Harm avoidance	0.400 (0.217)	0.408 (0.228)	0.420 (0.228)	0.438 (0.233)	0.60 [0.612]
Marijuana use in wave 3	0.017 (0.129)	0.021 (0.145)	0.013 (0.114)	0.029 (0.167)	0.28 [0.842]
Marijuana use in wave 7	0.143 (0.351)	0.149 (0.357)	0.170 (0.377)	0.179 (0.385)	0.28 [0.838]
Heavy drinker in wave 3	0.144 (0.353)	0.160 (0.368)	0.163 (0.371)	0.219 (0.416)	0.75 [0.525]
Heavy drinker in wave 7	0.487 (0.502)	0.528 (0.500)	0.477 (0.501)	0.519 (0.502)	0.39 [0.758]
Regular smoker in wave 3	0.085 (0.280)	0.094 (0.292)	0.065 (0.248)	0.067 (0.252)	0.44 [0.724]
Regular smoker in wave 7	0.252 (0.436)	0.238 (0.427)	0.261 (0.441)	0.283 (0.453)	0.27 [0.850]

Note: Standard deviations are presented in ( ) parenthesis. F-tests are for the null hypothesis of equal averages among the four groups and prob > F presented in [ ] parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels respectively.

5 Risky Behaviours and Monetary Delay Discount Rates

5.1 Differences in Monetary Delay Discount Rates

Equation 3 suggests that people with a preference for present rewards place a lower weight of future costs compared to the immediate rewards. Therefore, all else equal, they would be expected to have a higher probability of substance abuse.

This implication was tested in a number of studies in both behavioural economics and psychology. Previous studies in the former domain indicate that those with more impatience also tend to have worse health outcomes (e.g. Sutter et al., 2013). In the latter domain, MacKillop et al. (2011) performed a meta-analysis of studies published in peer-reviewed journals on relationship between MDDR and addictive behavior. The qualitative study results are replicated in Table 9. Three quarters of the studies surveyed by MacKillop et al. (2011) found that the null hypothesis of equal MDDR could be rejected in favour of the alternate hypothesis that MDDR was higher among those who engage in risky behaviour.

Table 9: Relationship between addictive behaviours and monetary delay discount rates

Behavior	Total number of studies	Number of studies where $k_{\text{behaviour}} > k_{\text{control}}$	Number of studies where $k_{\text{behaviour}} = k_{\text{control}}$
Alcohol	17	11	6
Tobacco	19	15	4
Stimulant	6	6	0
Marijuana	1	0	1
Opiate	3	3	0
Pathological gambling	7	4	3
Mixed	11	9	2

Source: Table 1 in MacKillop et al. (2011)

Of the three MDDR collected in GATOR/ALOHA, $\ln(k_3)$ is most closely associated with behaviours (Table 10). Regularly smoking, heavy drinking, and marijuana use is associated with higher $\ln(k)$ in at least half of the waves. This pattern is what would have been expected ex ante if $\ln(k)$ proxies for the true DDR used in the decision-making process.

Table 10: Differences in monetary delay discount rates for risky behaviours

			Time period				
			Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Regular smoker	$\ln(k_3)$	mean for behaviour	-3.853 (1.34)	-4.062 (1.379)	-4.045 (1.478)	-4.029 (1.524)	-4.08 (1.52)
		mean for others	-4.407 (1.408)	-4.407 (1.407)	-4.449 (1.384)	-4.556 (1.321)	-4.624 (1.3)
		difference	0.554*** [0.138]	0.345*** [0.119]	0.403*** [0.111]	0.527*** [0.103]	0.544*** [0.102]
	$\ln(k_6)$	mean for behaviour	-4.529 (1.47)	-4.471 (1.397)	-4.461 (1.35)	-4.445 (1.261)	-4.437 (1.286)
		mean for others	-4.653 (1.257)	-4.671 (1.253)	-4.681 (1.257)	-4.702 (1.271)	-4.802 (1.279)
		difference	0.123 [0.162]	0.200 [0.133]	0.220* [0.120]	0.257** [0.107]	0.365*** [0.106]
	$\ln(k_7)$	mean for behaviour	-4.328 (1.175)	-4.521 (1.182)	-4.386 (1.219)	-4.386 (1.166)	-4.452 (1.382)
		mean for others	-4.609 (1.259)	-4.602 (1.265)	-4.632 (1.26)	-4.618 (1.244)	-4.637 (1.204)
		difference	0.281* [0.171]	0.082 [0.141]	0.245* [0.129]	0.232** [0.114]	0.185* [0.109]
Heavy drinker	$\ln(k_3)$	mean for behaviour	-4.158 (1.306)	-4.26 (1.497)	-4.316 (1.384)	-4.346 (1.363)	-4.398 (1.387)
		mean for others	-4.387 (1.425)	-4.37 (1.382)	-4.355 (1.424)	-4.52 (1.408)	-4.567 (1.372)
		difference	0.229** [0.117]	0.110 [0.103]	0.038 [0.094]	0.174* [0.098]	0.169* [0.102]
	$\ln(k_6)$	mean for behaviour	-4.538 (1.092)	-4.581 (1.299)	-4.614 (1.234)	-4.559 (1.201)	-4.701 (1.205)
		mean for others	-4.674 (1.302)	-4.664 (1.267)	-4.66 (1.295)	-4.711 (1.324)	-4.725 (1.314)
		difference	0.136 [0.122]	0.083 [0.106]	0.045 [0.095]	0.152* [0.091]	0.024 [0.098]
	$\ln(k_7)$	mean for behaviour	-4.49 (1.159)	-4.452 (1.196)	-4.517 (1.172)	-4.529 (1.197)	-4.574 (1.277)
		mean for others	-4.618 (1.261)	-4.635 (1.27)	-4.634 (1.296)	-4.634 (1.299)	-4.603 (1.233)
		difference	0.129 [0.126]	0.183 [0.111]	0.118 [0.099]	0.105 [0.097]	0.03 [0.095]
Marijuana use	$\ln(k_3)$	mean for behaviour	-3.832 (1.357)		-4.179 (1.297)	-4.143 (1.437)	-4.298 (1.348)
		mean for others	-4.368 (1.404)		-4.389 (1.428)	-4.456 (1.392)	-4.494 (1.396)
		difference	0.536** [0.256]		0.210 [0.165]	0.313** [0.156]	0.195 [0.145]
	$\ln(k_6)$	mean for behaviour	-4.52 (1.14)		-4.556 (1.58)	-4.544 (1.362)	-4.646 (1.306)
		mean for others	-4.649 (1.281)		-4.651 (1.253)	-4.655 (1.261)	-4.74 (1.295)
		difference	0.129 [0.323]		0.095 [0.183]	0.111 [0.140]	0.093 [0.140]
	$\ln(k_7)$	mean for behaviour	-4.659 (1.222)		-4.462 (1.140)	-4.538 (1.04)	-4.475 (1.106)
		mean for others	-4.597 (1.251)		-4.608 (1.264)	-4.572 (1.252)	-4.612 (1.28)
		difference	-0.062 [0.307]		0.146 [0.183]	0.033 [0.151]	0.137 [0.129]

Note: Standard deviations are presented in ( ) parenthesis. Standard errors are presented in [ ] parenthesis. ***, **, and * represent statistical significance of differences in the delay discount rate at the 1%, 5%, and 10% levels respectively.

There are a number of factors that may influence these results. For example, the legal drinking age in Virginia is 21 years of age and marijuana use was not legal at the time of the study. It might also be more difficult to obtain alcohol and marijuana. In contrast, cigarettes can be legally purchased at 18 years of age (wave 5).

Perhaps more importantly, ln(k) in the GATOR/ALOHA study is derived from a person's intertemporal monetary choices. On the other hand, the model presented in Section 2 explicitly discounts the utility loss caused by future costs. The present value of the utility loss depends on whether the person treats the cost as a health outcome or in monetary terms. A person's intertemporal choices and the implied DDR depend on which is given more weight.[21] It is possible that the DDR associated with these decisions may be similar to ln(k) during adolescence but not change significantly during the transition to adulthood, especially as the magnitude of the differences in $\ln(k_3)$ were larger than those of $\ln(k_6)$ and $\ln(k_7)$. It is possible, for example, that people make these types of decisions intuitively, while decisions concerning money are more calculated, especially at an older age.

5.2 Testing with GATOR/ALOHA

Let $y_{it}(Z_{1it}, Z_{2it}, \pi_{it}, ln(k_{it}))$ represent the individiual i's decision in at time t, where Z_{1it} is a vector of variables that influences how much the person thinks that they will gain (i.e. represents variables that influence the first expression in Equation 3), Z_{2it} is a vector of variables that influences how much the person thinks that the behaviour will cost them in the future (i.e. represents variables that influence the second expression in Equation 3), and π_{it} is a perceived generalized index of probability of risk associated with the risky behaviour. Then it can be parametrized by an additively separable model and student i will decide to engage in the risky behaviour at time t if:

$$\beta_0 + \beta_1 Z_{1it} - \beta_2 Z_{2it} - \alpha_1 \pi_{it} - \alpha_2 ln(k_{it}) + \varepsilon_{it} > 0 \tag{8}$$

[21] Chapman (1996) found that while the average DDR for the health and money domains were similar, within-subject cross-domain DDR had a Spearman rank correlation of only 0.11. The extremely low Spearman rank correlation coefficient implies that when comparing two people with different ln(k), it does not necessarily follow that the person with the higher ln(k) will also have the higher health outcome DDR. The findings were replicated in Weatherly (2010), who found that within-subject cigarette DDR, health DDR, and MDDR were not correlated with each other.

where ε_{it} is an error term. In this case, the random shocks might not be serially correlated. A negative random shock in the form of rain could increase negative emotions and contribute to the decision to take up smoking, but not directly affect the smoking decision in future years.

Equation 8 can be estimated empirically using a probit regression because the observed behaviour inferred from the above decision process is a dichotomous latent variable. However, there are a number of considerations that should be recognized when attempting to test the model using the GATOR/ALOHA dataset.

First, the above model represents the overall decision to engage in the behaviour. This can be divided into three distinct types of decisions depending on the person's past history:

1. People who have no previous experience
2. People who have previous experience but are currently not engaged in the behaviour
3. People who have previous experience and are currently engaged in the behaviour

Previous experiences will likely influence the person's decision. Therefore, lagged consumption should enter into the vector Z_1 or Z_2 for the second and third decision types, as is typically the case in rational addiction models. Unfortunately, data limitations prevent us from properly taking lagged consumption into account. The decision of whether to engage in the behaviour, given that they had no previous experience, is a model that can be reasonably tested using this dataset.

Second, only ln(k) or MDDR are provided in this study and are the only available proxy for the DDR that governs the decision process. As most research to date has focussed on MDDR, it may also be of interest to link this benchmark DDR to behaviour patterns. It is also important to note that the monetary choice questionnaire elicits information about time preferences using certain present and future rewards, while the future in real life is inherently risky. However, no data is available on risk preferences.

Third, several variables of interest were only measured in one period and must therefore be assumed to remain constant. For example, personality traits were measured in wave

3, while risk perception ("Overall, how risky is it to smoke?"[22]) was measured in wave 4. Research has shown that personality trait test-retest correlations over three years can vary from 0.41 to 0.55 (Schuerger, Tait, & Tavernelli, 1982). The possibility of changes in personality traits may be especially pertinent during the transition period from adolescence to young adulthood.

Given these limitations and the abundance of variables that specifically pertain to the person's smoking history and environment, the above empirical model will be tested for the smoking decision among those who have never smoked before, using a contemporaneous model. The main assumptions inherent in this approach are that:

1. Only contemporaneous variables have an effects on the dependent variable, or the value of the variables do not change over time

2. Contemporaneous variables are not related to unobserved factors that persist over time

The first assumption naturally holds for time invariant characteristics. In terms of the time varying variables, current circumstances are likely to be more relevant than past circumstances. For example, depression two years ago is unlikely to be a significant factor when compared to whether the person is currently depressed.

The second assumption is more controversial, though most factors that persist over time are directly taken into account. For example, home environment is likely related to the parent's education or whether there is a smoker in the household, while outside influences are at least partially measured by whether the person had friends who smoked. Psychological variables in particular may offer a proxy for a wide variety of relevant variables that are typically not directly measured.

Given the instability of within-subject measurements of ln(k), observations from waves 6 and 7 will be used to test if changes in ln(k) impact the smoking decision of people who had never smoked before.[23] These particular observations were chosen to focus on people who

[22] It is reasonable to assume that the answer to this question reflects perceived risk. Note that this does not indicate the person's risk preferences, which depends on the functional form of U(π).

[23] All regressions in this section use pooled estimators with wave and school indicator variables to maximize efficiency. While this does not take advantage of the panel structure of the data, both fixed and within

were capable of legally purchasing cigarettes in Northern Virginia and for whom current-period ln(k) was measured.[24] The other variables in this baseline specification include all of the correlates examined in Table 14, as well as perceived smoking risk and time varying covariates that could influence the decision of people who had never smoked before, such as depression, smoking by peers, and household smokers.[25]

The coefficient of $\ln(k_3)$ was positive and statistically significant in both regressions where it was included, while current-period ln(k) was not found to be a significant predictor when included by itself or with $\ln(k_3)$ (Table 11). Therefore, there is some evidence that $\ln(k_3)$ is a more appropriate indicator of the DDR used in the decision process of new smokers. Other variables that were found to be associated with a higher probability of becoming a new smoker in all three regressions include lower perceived smoking risk, parents with some post-secondary education, lower GPA in grade 5, living with a smoker in the household, and having peers that smoke.

Observations from waves 6 and 7 were also used to examine whether the statistical significance of the coefficient for $\ln(k_3)$ can be explained by the personality trait indices measured during early adolescence. The coefficient of $\ln(k_3)$was found to be statistically significant in that case as well and while none of the personality traits were by themselves significant predictors, an F-test of their joint significance was statistically significant. Genotype variables were also added to the baseline specification in Table 12. Here too, the coefficient for $\ln(k_3)$ was found to be statistically significant. While the (COMT) HH genotype indicator variable was statistically significant, an F-test for the inclusion of genotype indicator variables was insignificant.[26]

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estimators may accentuate measurement error issues that lie at the heart of calculating ln(k) through the monetary choice questionnaire. The monetary choice questionnaire is designed to determine the person's indifference point by inferring when the person begins to prefer the present reward instead of the future reward. Therefore, while ln(k) can be identified to be between two possible values, it is not clear where it truly lies in that range. Furthermore, people may respond with inconsistent answers. While the use of logistic regression alleviates some of these concerns, there is non-ignorable and fairly substantial measurement error when calculating ln(k) through this method. Panel data methods will also not allow us to use several variables of interest, such as psychological variables, that were only measured in one period.

[24] Earlier analysis revealed that there was substantial short-term variation in ln(k), such that imputation of ln(k) based on longer-term trends (e.g. linear interpolation) was not advisable.

[25] The covariates used in this analysis that are measured more than once are depression symptoms, smoker in the household, and peers smoking. It is unlikely, given that the person had never smoked before, that these factors would change over the short term based on the smoking decision. Therefore, it is reasonable to assume reverse-causation is not a significant issue in the following analysis.

[26] The joint insignificance of the genotype indicator variables suggests that unobserved individual hetero-

Overall, $\ln(k_3)$ was positively correlated to the decision to begin smoking, as would be expected from the model presented in Section 2. This was also found when perceived smoking risk, personality trait, and genetic variables were included in the specification, suggesting that it has a role outside of those particular variables.

It is important to note that the overall effect of increasing $\ln(k_3)$ by one was to increase the probability of smoking at around 1.3 percentage points in all regressions.[27] This was much smaller than several other potential influences, such as having a high perceived risk in smoking (decreases the probability of becoming a smoker by around 6.5 percentage points), having a smoker in the household (increases the probability of becoming a smoker by around 5 percentage points), having peers that smoke (increases the probability of becoming a smoker by around 10 percentage points). Somewhat surprisingly, having a parent with some post-secondary education also increased the probability of deciding to smoke by around 8 percentage points. While ln(k) is positively correlated with the decision to become a smoker, there are several other variables that are also correlated with a person's decision to smoke.

geneity is not a significant concern in this analysis.

[27]Though ln(k) can range from -10 to 0, increasing ln(k) by only two units would increase the amount of time required to halve the present value of a reward to 13.5% of its original value, which would be fairly extreme.

Table 11: Probit regression of the new smoking decision with different proxies for the delay discount rate

	Baseline monetary delay discount rate	Current period monetary delay discount rate	Both monetary delay discount rates
$\ln(k_3)$	0.013**		0.013**
	(0.006)		(0.006)
ln(k) measured during the current period		0.005	-0.00021
		(0.006)	(0.006)
Perceived smoking risk	-0.063**	-0.063**	-0.063**
	(0.031)	(0.031)	(0.031)
Caucasian	-0.008	-0.007	-0.008
	(0.018)	(0.018)	(0.018)
Male	0.007	0.011	0.007
	(0.015)	(0.015)	(0.015)
Parent had some post-secondary education	0.071**	0.066**	0.071**
	(0.028)	(0.029)	(0.028)
Parent smoked regularly	-0.004	-0.004	-0.003
	(0.017)	(0.017)	(0.017)
Lives with biological parent	-0.08	-0.073	-0.08
	(0.05)	(0.051)	(0.05)
Grade 12 GPA	-0.027*	-0.03*	-0.027*
	(0.016)	(0.016)	(0.016)
Smoker in household	0.054***	0.054***	0.054***
	(0.017)	(0.017)	(0.017)
Peers smoke	0.103***	0.106***	0.103***
	(0.021)	(0.021)	(0.021)
Depression symptoms	0.017	0.017	0.017
	(0.022)	(0.022)	(0.022)
N	1046	1046	1046
Adjusted r-squared	0.1465	0.1372	0.1465

Note: Coefficients presented are marginal effects from the probit regression. Regressions include school and wave indicators. Observations are those from waves 6 and 7 and only include those who had never reported smoking during the study. Heteroskedastic-consistent standard errors are in ( ) parenthesis. ***, **, * denote statistical significance at 1%, 5%, and 10% respectively.

Table 12: Probit regression of the new smoking decision with personality trait and genotype variables

	Personality traits	Genotype indicator variables
ln(k_3)	0.013** (0.006)	0.017*** (0.006)
Perceived smoking risk	-0.069** (0.029)	-0.061** (0.031)
Caucasian	0.003 (0.018)	-0.004 (0.019)
Male	0.018 (0.017)	0.004 (0.015)
Parent had post-secondary education	0.081*** (0.03)	0.086*** (0.03)
Parent smoked regularly	-0.014 (0.016)	-0.005 (0.016)
Lives with biological parent	-0.029 (0.048)	-0.052 (0.05)
Grade 12 GPA	-0.026 (0.017)	-0.025* (0.015)
Smoker in household	0.052*** (0.017)	0.055*** (0.017)
Peers smoke	0.096*** (0.021)	0.092*** (0.021)
Depression symptoms	0.017 (0.022)	-0.029 (0.024)
Novelty-seeking	0.049 (0.042)	
Reward dependence	0.036 (0.041)	
Harm avoidance	0.003 (0.039)	
Good self-control	0.06 (0.057)	
Bad self-control	-0.011 (0.054)	
(DRD2) A1A1		0.006 (0.038)
(DRD2) A1A2		0.014 (0.016)
(TPH) AA		0.014 (0.023)
(TPH) AC		0.009 (0.016)
(CYP) TT		-0.035 (0.045)
(CYP) CC		0.025 (0.021)
(DAT) DAT0		0.026 (0.026)
(DAT) DAT1		0.006 (0.016)
(COMT) HH		-0.05** (0.024)
(COMT) HL		0.009 (0.018)
N	893	893
Adjusted r-squared	0.1686	0.1937
F-test for inclusion of additional variables	70.34*** [0.000]	1.66 [0.7972]

Note: Coefficients presented are marginal effects from the probit regression. Regressions include school and wave indicators. Observations are those from waves 6 and 7 and only include those who had never reported smoking during the study. Heteroskedastic-consistent standard errors are in ( ) parenthesis. ***, **, * denote statistical significance at 1%, 5%, and 10% respectively.

6 Correlates of the Monetary Delay Discount Rate

6.1 Genes

Given the correlation between ln(k) and risk-taking behaviour, it is of interest to examine factors that can explain heterogeneity of ln(k). Decomposing the variation in ln(k) into between- and within-subject variation reveals that the former is slightly larger than the latter (1.181 versus 0.753). Individual differences may therefore explain a significant portion of the heterogeneity in ln(k).

Human genes code for specific functions in the body and are constructed of two alleles, one of which is inherited from each parent at conception. Individuals that inherit two of the same alleles for a gene are homozygous for the gene, while those that inherit different alleles for a gene are heterozygous for the gene. The specific combination of alleles that form a gene is known as the genotype, while the functional influence of the genotype is known as the phenotype. Therefore, different alleles, or variants of a gene, may combine to produce different outcomes.[28] The path from genotype to phenotype may not be straightforward and may also be influenced by environmental factors.

Advancements in the understanding of genetics have allowed researchers to examine which genotypes are correlated with certain behaviours. As the genes are inherited at conception, it is possible that they could represent exogenous primitives. In this context, impulsivity can be considered as an intermediate phenotype, or a behavioral characteristic that is genetically influenced and associated with risk for a disorder (MacKillop, et al., 2011).

The genetic basis of impulsivity has been previously studied in animals but only recently in humans. Wilhelm and Mitchell (2009) examined different inbred rat strains and found that there are significant DDR differences between certain strains. These findings are consistent with those of Anderson and Woolverton (2003) and Perry et al. (2007). Anokhin et al. (2011) studied DDR associated among twins and found significant heritability of DDR

[28]To illustrate using a simplified example, there is a gene that codes for human blood type. Each parent passes on an A, B, or O allele from the blood type gene that they possess. These alleles combine to form one of six genotypes (AA, AB, AO, BB, BO, and OO) that then manifest as either Type A (AA or AO genotype), Type B (BB or BO genotype), Type AB (AB genotype), or Type O (OO genotype) blood types, which are the possible phenotypes.

at ages 12 and 14. The results suggest the existence of an environmental and/or genetic effect on the DDR. However, while some studies have been able to find specific genotypes associated with higher DDR, other studies were not able to replicate these findings (e.g. White, Morris, Lawford, & Young, 2008; Eisenberg, et al., 2007).

Table 13 provides the average ln(k) for different genes, as well as tests for equality among the different halotypes or genotypes for the individual genes. Ex ante, it would be expected that if a gene was associated with significant differences in average ln(k), the differences in average ln(k) would manifest itself in all three measurements of ln(k). This is not the case for any of the genes. The gene that is the closest is the CYP gene, where the null hypothesis of equal average ln(k) for all three genotypes was rejected at the 10% significance level in $\ln(k_3)$ and $\ln(k_7)$, but not in $\ln(k_6)$.

Table 13: Differences in monetary delay discount rate for different genotypes

Gene	Genotype	$\ln(k_3)$	$\ln(k_6)$	$\ln(k_7)$
TPH	AA	-4.392 (1.450)	-4.493 (1.244)	-4.585 (1.334)
	AC	-4.405 (1.329)	-4.601 (1.379)	-4.584 (1.300)
	CC	-4.267 (1.486)	-4.741 (1.152)	-4.601 (1.188)
	F-test of equal means	1.131 [0.323]	1.914 [0.148]	0.016 [0.984]
CYP	TT	-3.794 (1.601)	-4.530 (1.359)	-4.175 (1.267)
	CT	-4.358 (1.431)	-4.575 (1.18)	-4.434 (1.358)
	CC	-4.364 (1.405)	-4.633 (1.311)	-4.639 (1.219)
	F-test of equal means	2.417 [0.090]*	0.181 [0.834]	2.434 [0.089]*
DRD2	A1A1	-4.091 (1.665)	-4.415 (1.407)	-4.355 (0.996)
	A1A2	-4.361 (1.421)	-4.486 (1.277)	-4.573 (1.444)
	A2A2	-4.369 (1.388)	-4.723 (1.248)	-4.616 (1.141)
	F-test of equal means	1.049 [0.351]	3.415 [0.033]**	0.741 [0.477]
DAT	DAT0	-4.300 (1.328)	-4.729 (1.108)	-4.527 (1.181)
	DAT1	-4.253 (1.460)	-4.663 (1.191)	-4.592 (1.307)
	DAT2	-4.417 (1.393)	-4.616 (1.355)	-4.603 (1.231)
	F-test of equal means	1.559 [0.219]	0.295 [0.745]	0.095 [0.909]
COMT	HH	-4.218 (1.401)	-4.605 (1.393)	-4.534 (1.183)
	HL	-4.388 (1.395)	-4.650 (1.196)	-4.670 (1.304)
	LL	-4.406 (1.516)	-4.702 (1.286)	-4.535 (1.297)
	F-test of equal means	1.546 [0.214]	0.292 [0.747]	0.931 [0.395]

Note: Standard deviations are presented in ( ) parenthesis. F-tests are for the null hypothesis of equal average ln(k) among the three genotypes and prob > F presented in [ ] parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels respectively.

A potential reason for the sporadic statistical significance could be that genotypes respond to environmental stimuli at different points within a person's life cycle. Another, more likely explanation, is that repeatedly testing for equality of means with five different genes produces false positives. Indeed, after accounting for the number of different comparisons using the Bonferroni procedure, the null hypothesis of equal average ln(k) could not be rejected for any of the genotypes.[29]

The significance of individual genotypes after accounting for other variables can be tested using the following linear regression for student i at time t:

$$ln(k_{it}) = \beta_0 + \beta_1 X_i + \beta_2 G_i + \varepsilon_{it} \tag{9}$$

where $\ln(k_{it})$ is ln(k) measured at time t, X_i includes parental and personal variables, G_i includes genotype indicator variables, and ε_{it} includes unobserved factors.[30]

Genotype indicator variables are not found to be significant correlates of ln(k) when they are all added into the specification at the same time (Table 14).[31] Once more, while some genes are correlated with ln(k), none of them are correlated with ln(k) for more than one period. Furthermore, F-tests of the inclusion of all genotype indicator variables are also not statistically significant at conventional levels. Overall, there does not appear to be a strong link between the genotypes considered in this analysis and ln(k).

In terms of the other variables, characteristics of those with higher ln(k) on average are similar in all regressions. More specifically, being Caucasian, male, and having a parent without any post-secondary education is positively correlated with ln(k). It is interesting to note that $\ln(k_3)$ is not statistically significantly correlated with being Caucasian, while $\ln(k_7)$ is not statistically significantly correlated with being male.[32] The small number of

[29] As the number of tested hypotheses increases, so too does the probability of making a type 1 error. The Bonferroni correction is a conservative method of accounting for simultaneous inference by adjusting the required p-value of m number of tests to α/m, where α is the normal significance level of an individual test. For example, in this case with five different tests for equality of means, the p-value of equality of means would need to be 0.10/5=0.02 to be considered statistically significant at the 10% level. Other methods of accounting for simultaneous inference that are less conservative, such as the Holm-Bonferroni method, were also explored. Here too, the null hypothesis of equal ln(k) is not rejected for any of the genes.

[30] Controlling for different parental and personal variables is a variant on population stratification in the geneitcs literature. This may be important as there are differences by race in certain markers.

[31] The same results are found if the genotypes are added into the specification one at a time.

[32] It is difficult to explain these differences. One possible reason is that the influence of race on time preferences increases, while the influence of gender on time preferences decreases. However, it is unlikely

students who did not live with a biological parent contributed to large standard errors and imprecision associated with that coefficient. These results are similar in regressions with and without genotype indicator variables.

Table 14: Linear regression of ln(k) on covariates

	With genotypes			Without genotypes		
	$\ln(k_3)$	$\ln(k_6)$	$\ln(k_7)$	$\ln(k_3)$	$\ln(k_6)$	$\ln(k_7)$
Caucasian	-0.121 (0.107)	-0.330*** (0.124)	-0.256** (0.114)	-0.115 (0.109)	-0.320** (0.128)	-0.273** (0.118)
Male	0.343*** (0.0967)	0.252** (0.0996)	0.155 (0.105)	0.329*** (0.0969)	0.241** (0.102)	0.156 (0.106)
Parent had some post-secondary education	-0.544*** (0.141)	-0.347** (0.148)	-0.416** (0.175)	-0.558*** (0.140)	-0.330** (0.149)	-0.413** (0.174)
Parent regularly smoked	0.160 (0.102)	0.159 (0.104)	0.140 (0.112)	0.135 (0.102)	0.164 (0.107)	0.123 (0.113)
Lives with biological parent	0.161 (0.316)	-0.246 (0.311)	-0.0278 (0.407)	0.120 (0.324)	-0.274 (0.303)	-0.165 (0.416)
(DRD2) A1A1	0.0244 (0.228)	0.0716 (0.237)	0.197 (0.188)			
(DRD2) A1A2	-0.0243 (0.104)	0.214** (0.106)	0.0356 (0.122)			
(TPH) AA	-0.0822 (0.153)	0.273* (0.140)	-0.0254 (0.162)			
(TPH) AC	-0.108 (0.103)	0.212** (0.106)	0.0205 (0.110)			
(CYP) TT	0.675** (0.298)	0.00920 (0.299)	0.190 (0.282)			
(CYP) CC	0.00976 (0.116)	-0.0543 (0.112)	-0.177 (0.136)			
(DAT) DAT0	0.220 (0.176)	-0.0191 (0.162)	0.286 (0.196)			
(DAT) DAT1	0.206** (0.104)	-0.0294 (0.103)	0.0702 (0.109)			
(COMT) HH	0.117 (0.137)	-0.0210 (0.142)	-0.118 (0.144)			
(COMT) HL	0.0223 (0.128)	0.0532 (0.120)	-0.179 (0.130)			
N	855	665	581	855	665	581
Adj. r-squared	0.049	0.045	0.037	0.053	0.044	0.032
F-test of genes	1.35 [0.1994]	1.23 [0.2649]	1.01 [0.4303]			

Note: Regressions include school indicator variables. Robust standard errors are presented in ( ) parenthesis. Prob > F are presented in [ ] parenthesis. ***, **, * represent statistical significance at the 1%, 5%, and 10% significance levels respectively.

that these differences would appear after only one year, as is the case with the gender coefficient. Attrition is investigated later in this analysis but was not found to significantly change these results (Section 8).

6.2 Personality Traits

As a measure of present bias, it is natural to consider ln(k) as a measure of impulsivity or impatience. However, there are a couple of differences between ln(k) and the impulsivity index. First, ln(k) is based on a person's hypothetical intertemporal monetary choices, while the answers to questions are influenced by subjective judgement. Two people could make the same intertemporal choices, but these choices could be considered to be indicative of 'average' impulsivity by one person and 'above average' impulsivity by another. Second, impulsivity as a personality trait may encompass other aspects than simply intertemporal choice, such as whether the person consciously evaluates a situation. The ln(k) approach assumes that the person is making rational decisions based on personal preferences, even if that decision takes place at a subconscious level.

Research in behavioural economics and psychology has evolved largely separately, despite their common interest in examining heterogeneity in behaviours. Analyzing the relationship between ln(k) and personality traits can help integrate these two sets of literature. Furthermore, analysis also provides further insight on what ln(k) represents.

Personality traits are commonly considered to be "the relatively enduring patterns of thoughts, feelings, and behaviors that reflect the tendency to respond in certain ways under certain circumstances" (Roberts, 2009, p.140). Therefore, personality traits may not be a primitive of behaviour and could be the result of preferences, constraints, and available information (Almlund et al., 2011). Nonetheless, as past behaviours can help predict future behaviours, measures of personality traits can also provide valuable clues on individual preferences in empirical economic research.

The correlation between personality traits and delay discount rates has been previously examined in Bobova et al. (2009). They found that delay discount rates were positively correlated with higher levels of impulsivity traits, lower working memory capacity, and lower intelligence. On the other hand, harm avoidance was not found to be correlated with delay discount rates.

As in Section 4, the relationships between ln(k) and personality traits are examined through Spearman and Pearson correlation coefficients, as well as linear regressions. The

OLS equation takes the following form for student i at time t:

$$ln(k_{it}) = \beta_0 + \beta_1 pers_{i3} + \alpha X_i + \varepsilon_{it} \tag{10}$$

where $\mathrm{pers_{i3}}$ is the personality trait index measured in wave 3 normalized to a scale from 0 to 1, $\ln(\mathrm{k_{it}})$ is ln(k) measured at time t, $\mathrm{X_i}$ are the same variables as those in Table 14, and $\varepsilon_{\mathrm{it}}$ includes unobserved factors.

In this study, good self-control and reward dependence are both negatively correlated with $\ln(\mathrm{k_3})$, while bad self-control, novelty-seeking, and impulsivity are positively correlated with $\ln(\mathrm{k_3})$ (Table 15 and Table 16). This matches the ex ante interpretation of ln(k) as a measure of present bias. For example, an intuitive explanation is that people with a strong present bias are likely to exhibit bad self-control because they value the current reward over the potential consequences in the future. On the other hand, the correlations are also fairly small, even when they are statistically significant.

As the results are extremely similar using both the Spearman and Pearson correlation coefficients, the assumption of a linear relationship likely does not significantly influence the result. The inclusion of other variables using a linear regression without genotype indicator variables does not change the qualitative results, though the statistical significance of the coefficients are smaller than when only taking the correlation.[33]

The size of the coefficients is also large in almost all cases when the coefficient is statistically significant, though it is important to note that they represent how much ln(k) would change if the personality trait index increased by one, or if the person went from no expression of the trait to full expression of the trait.[34]

As the personality traits were only measured in wave 3, it is not surprising that the psychological variables are more correlated with $\ln(\mathrm{k_3})$ than $\ln(\mathrm{k_6})$ or $\ln(\mathrm{k_7})$. This implies that the personality traits, ln(k), and/or the relationship between the personality traits and

[33]Including genotype indicator variables in the regressions does not substantially influence the links between personality traits and genes. The biggest differences are, somewhat surprisingly, in the relationship between $\ln(\mathrm{k_3})$ and the bad self-control index, and $\ln(\mathrm{k_3})$ and the impulsivity index. However, the differences in the size of the coefficients are economically insignificant.

[34]Another way of examining the coefficients is to note that the standard deviation of these personality traits was approximately 0.2 for all of the traits. Therefore, for example, the effect on $\ln(\mathrm{k_3})$ of increasing good self-control by one standard deviation would be -1.106*0.2=-0.221. This is fairly small and reflects the results using the correlation analysis: while statistically different from zero, the correlations are fairly small.

ln(k) might change over time frame. Nonetheless, there is significant evidence that ln(k) is closely tied to various personality traits when they are measured during the same period.

Table 15: Monetary delay discount rate and self-control personality traits

		Self-control indices		
		Good self-control	Bad self-control	Impulsive index
Spearman rank correlation coefficient	$\ln(k_3)$	-0.152***	0.094***	0.093***
		[-0.212, -0.092]	[0.033, 0.155]	[0.032, 0.154]
	$\ln(k_6)$	-0.100**	0.104***	0.099**
		[-0.174, -0.024]	[0.028, 0.179]	[0.023, 0.174]
	$\ln(k_7)$	-0.049	-0.008	0.008
		[-0.129, 0.033]	[-0.090, 0.073]	[-0.074, 0.089]
Pearson correlation coefficient	$\ln(k_3)$	-0.150***	0.082***	0.089***
		[-0.210, -0.089]	[0.021, 0.143]	[0.027, 0.150]
	$\ln(k_6)$	-0.086**	0.038	0.055
		[-0.155, -0.016]	[-0.032, 0.108]	[-0.015, 0.125]
	$\ln(k_7)$	-0.014	-0.020	-0.006
		[-0.089, 0.061]	[-0.095, 0.055]	[-0.081, 0.069]
Linear regression without genotype variables	$\ln(k_3)$	-1.106***	0.606**	0.474*
		(0.272)	(0.275)	(0.244)
	$\ln(k_6)$	-0.627**	0.284	0.269
		(0.288)	(0.295)	(0.251)
	$\ln(k_7)$	-0.140	-0.112	-0.0672
		(0.296)	(0.268)	(0.230)
Linear regression with genotype variables	$\ln(k_3)$	-1.083***	0.445	0.357
		(0.293)	(0.307)	(0.269)
	$\ln(k_6)$	-0.630**	0.184	0.231
		(0.308)	(0.324)	(0.274)
	$\ln(k_7)$	-0.166	-0.277	-0.169
		(0.327)	(0.291)	(0.249)

Note: Each regression cell represents β_1 for a different regression with the psychological variable as the independent variable and the monetary delay discount rate as an dependent variable. All regressions include school indicator variables. Controls refer to the same characteristics as those presented in Table 14. Robust standard errors are presented in ( ) parenthesis. 95% confidence intervals for the correlation coefficient using Fisher's transformation are presented in [ ] parenthesis. Psychological variables were normalized to a scale from 0 to 1, with 0 being the lowest possible manifestation of the psychological variable and 1 being the highest. ***, **, * represent statistically significantly different from zero at the 1%, 5%, and 10% significance levels respectively.

Table 16: Monetary delay discount rate and the TCI

		Temeperament and Character Inventory		
		Novelty-seeking	Reward dependence	Harm avoidance
Spearman rank correlation coefficient	$\ln(k_3)$	0.163***	-0.171***	0.035
		[0.102, 0.223]	[-0.230, -0.110]	[-0.097, 0.027]
	$\ln(k_6)$	0.105***	-0.108***	-0.0002
		[0.029, 0.179]	[-0.182, -0.032]	[-0.076, 0.076]
	$\ln(k_7)$	0.052	-0.084**	-0.034
		[-0.030, 0.133]	[-0.164, -0.003]	[-0.115, 0.048]
Pearson correlation coefficient	$\ln(k_3)$	0.137***	-0.155***	-0.044
		[0.076, 0.198]	[-0.215, -0.094]	[-0.106, 0.017]
	$\ln(k_6)$	0.080**	-0.107***	-0.011
		[0.009, 0.149]	[-0.176, -0.037]	[-0.082, 0.059]
	$\ln(k_7)$	0.069*	-0.049	-0.036
		[-0.007, 0.143]	[-0.124, 0.026]	[-0.11, 0.04]
Linear regression without genotype variables	$\ln(k_3)$	0.920**	-0.815***	-0.0759
		(0.219)	(0.253)	(0.203)
	$\ln(k_6)$	0.460*	-0.481*	0.0866
		(0.236)	(0.269)	(0.220)
	$\ln(k_7)$	0.427**	-0.0870	-0.0725
		(0.217)	(0.267)	(0.206)
Linear regression with genotype variables	$\ln(k_3)$	0.904***	-0.863***	-0.139
		(0.239)	(0.278)	(0.220)
	$\ln(k_6)$	0.504*	-0.473	-0.0757
		(0.259)	(0.297)	(0.246)
	$\ln(k_7)$	0.533**	-0.00552	-0.214
		(0.238)	(0.288)	(0.231)

Note: Each regression cell represents β_1 for a different regression with the psychological variable as the independent variable and the monetary delay discount rate as an dependent variable. All regressions include school indicator variables. Controls refer to the same characteristics as those presented in Table 14. Robust standard errors are presented in ( ) parenthesis. 95% confidence intervals for the correlation coefficient using Fisher's transformation are presented in [ ] parenthesis. Psychological variables were normalized to a scale from 0 to 1, with 0 being the lowest possible manifestation of the psychological variable and 1 being the highest. ***, **, * represent statistically significantly different from zero at the 1%, 5%, and 10% significance levels respectively.

7 Threats to External Validity

The large sample size differences in Table 14 suggests that attrition might be an issue in this analysis. Furthermore, follow-up in ALOHA was particularly low when compared to GATOR (Section 3). Results could therefore be driven by changes in the sample characteristics

Broadly speaking, there are two main types of attrition: selection on observables, and selection on unobservables. Selection on observables can be tested by examining if there are systematic differences between nonrespondents and respondents. These differences could lead to biases in the results, as well as introduce inefficiency problems due to the exclusion of some observations. As the analysis is mainly concerned with ln(k), which was measured during waves 3, 6, and 7, attrition will be tested by observing if the people who remained in wave 7 differed from those who left the sample. Define an attrition variable as follows for student i:

Define an attrition variable as follows:

$$A_{it3} = \begin{cases} 1, & \text{if the student answered the questionnaire in waves 3 but not in} \\ & \text{wave t} \\ 0, & \text{if the student answered the questionnaire in waves 3 and t} \end{cases} \tag{11}$$

The presence of selection on observables can be tested by observing whether $Pr(A_{i73} = 0|X_{i3}) = Pr(A_{i73} = 0)$ using the probit regression of:

$$Pr(A_{i73} = 0|X_{i3}) = 1\left\{\alpha_0 + \alpha_1 X_{i3} + \varepsilon_{i3} \geq 0\right\} \tag{12}$$

In this case, X_{i3} are the variables used in Table 12 with personality traits.[35] These variables were chosen because students can drop out of the sample for a number of reasons, including moving to another school, dropping out of school, or by choice. Household and parental variables may have predictive power as to whether the student will change schools, low GPA may provide some indication of whether the person will drop out of school, and personality

[35]Variables measured at different periods, such as depression symptoms, were measured at wave 3.

traits may predict whether the person will choose to avoid answering the questionnaire later on. This was found to be the case, as several variables were found to be significant predictors of the attrition decision (Table 17).

Following the example of Ding and Lehrer (2010), selective attrition on observables can be accounted for using inverse probability weighting.[36] A general strategy for reweighting is to first observe the following probit for student i:

$$Pr(A_{it3} = 0|X_{i3}) = 1\left\{\alpha_0 + \alpha_1 X_{i3} + \varepsilon_{i3} \geq 0\right\} \tag{13}$$

where t is the period being considered, X_{ij3} are the variables used in Table 12 with personality traits and ε_{i3} are random errors. The predicted probability of staying in the sample $\widehat{p}_{it}$ can then be constructed:

$$\widehat{p_{it}} = \Phi\left(\widehat{\alpha_0} + \widehat{\alpha_1} X_{i3}\right) \tag{14}$$

where $\widehat{\alpha}$ are the estimated probit coefficients and Φ is the normal cumulative distribution function. This procedure was used to estimate the probability of students being in waves 5 through 7.

The weights used in this analysis are the inverse of $\widehat{p_{it}}$. That is to say, if someone has an estimated 25% chance of remaining in the sample, then their weight in the analysis would be twice that of someone who had an estimated 50% chance of remaining in the sample.

The main results are replicated in Appendix D using these inverse probability weights. None of the main conclusions reached by this paper are significantly changed after accounting for selective attrition on observables using inverse probability weights. The largest difference is in Table 20, where the size of the coefficient for the regression with genotype variables between bad self-control and $\ln(k_6)$, and between the impulsive index and $\ln(k_6)$, was much larger after taking selective attrition into account. However, this further substantiates the notion of ln(k) as a measure of present-bias and impulsivity.

[36] While it is possible that there is selection on unobservables, accounting for it would require making assumptions on the functional form of the unobservables. Without an ex ante reason to think that there is substantial selection on unobservables that are not covered by observed variables, selection on unobservables will not be accounted for in this analysis.

Table 17: Testing for selective attrition between waves 3 and 7

	Attrition between waves 3 and 7
ln(k_3)	0.031***
	(0.011)
Perceived smoking risk	-0.054
	(0.059)
Novelty-seeking	0.265***
	(0.088)
Reward dependence	-0.001
	(0.088)
Harm avoidance	0.227***
	(0.075)
Good self-control	0.31***
	(0.115)
Bad self-control	-0.098
	(0.117)
Caucasian	-0.047
	(0.036)
Male	0.074**
	(0.035)
Parent has some post-secondary education	-0.094**
	(0.044)
Parent smoked regularly	-0.015
	(0.034)
Lives with biological parent	0.031
	(0.094)
Grade 10 GPA	-0.136***
	(0.03)
Smoker in the household in grade 10	0.029
	(0.038)
Peers smoke in grade 10	-0.003
	(0.034)
Depression symptoms in grade 10	-0.057
	(0.044)
Regular smoker in grade 10	0.038
	(0.054)
N	838
Adj. r-squared	0.0826

Note: Coefficients represent marginal effects of a probit regression with the attrition variable as the dependent variable. Regressions include school indicator variables. Robust standard errors are presented in ( ) parenthesis. Prob¿F are in [ ] parenthesis. ***, **, * represent statistical significance at the 1%, 5%, and 10% significance levels respectively.

8 Discussion

This paper examines whether recent findings on the economics of time preferences hold using MDDR in GATOR/ALOHA as a proxy for these variables. More specifically, the paper examines what the MDDR represents, if it can be captured by other variables and treated as invariant, and its relationship to risk-taking behaviour. Contrary to previous studies in the psychology literature that examined related questions directly with MDDR, within-subject relative stability of ln(k) was fairly low, and there was also not a strong statistical link between specific genotypes and ln(k). However, there is evidence that people who engage in risky behaviour have higher $\ln(k_3)$ in a manner that cannot be explained by personality traits or perceived smoking risk, and there is also evidence in favour of the interpretation of ln(k) as a measure of present bias.

The intuitive interpretation of the MDDR as a measure of impulsivity was tested in this study by examining the correlation between ln(k), a potential behavioural primitive, and a number of psychological variables. The sign and statistical significance of the results are consistent with the interpretation of ln(k) as a measure of present bias, particularly if ln(k) measured during the same period as the personality trait. On the other hand, ln(k) measured during the later periods, especially wave 7, have a much weaker relationship with personality traits measured earlier. Further data on the personality traits measured during that period would be required to test whether there is still a link between personality traits and ln(k) in young adults.

A couple of other observations can be made using these results. While the commonly held interpretation is that ln(k) is a measure of impulsivity, it also has close ties to the novelty-seeking and reward dependence temperaments measured in the TCI. Furthermore, while statistically significant, the correlations were not very large. A reason for these observations may lie in the use of the monetary choice questionnaire, which frames the choices in terms of monetary rewards. The person's response includes at least some element of their expectations on their future financial situation. Similarly, the focus on rewards in the monetary choice questionnaire may emphasize the reward dependence and novelty-seeking personality traits, but not the harm avoidance personality trait. The lack of a statistically significance correlation between harm avoidance and ln(k) lends credence to this hypothesis. The way that the options are framed may therefore have a substantial effect on what the derived time preference parameter truly measures, which should be taken into account when conducting future experiments.

The connection between ln(k) and environmental factors and potentially time-varying personality traits suggests that ln(k) may not be stable over time. Indeed, between-subject variation in ln(k) is only slightly larger than the within-subject variation in ln(k). Within-subject correlations of ln(k) over four years indicate that while earlier ln(k) are correlated with later ln(k), they are not very stable during the transition from adolescence to young adulthood. These results are more precise than previous studies due to the much larger sample sizes available in GATOR/ALOHA. It is not clear, however, whether the changes in ln(k) are representative of a longer-term trend. Evidence suggests otherwise because changes in ln(k) over one year were similar in size to changes in ln(k) over three years. It is also puzzling that average ln(k) did not change substantially but the within-subject correlation was very low. A possible explanation is that ln(k) may be significantly influenced by short-term, transient events.

As a result, the connection between ln(k) and the decision to engage in risky behaviours is unclear. If a person truly weighs the discounted value of future costs in return for immediate rewards, then it raises several important questions for future research. For example, it is not clear whether ln(k) and the true DDR that governs the decision process are the same. The way that the questionnaire is framed has important implications on the calculated DDR (Chapman, 1996; Weatherly, Terrell, & Derenne, 2010).

It is possible that these DDR are similar at a young age but diverge as the person gets older, though more data is required to confirm this hypothesis. This may explain why, when the model was tested, the coefficient for $\ln(k_3)$ was statistically significant but the current-period ln(k) was not statistically significant. It also offers a potential explanation for the diverging conclusions obtained by certain studies with regards to whether ln(k) substantially differs among substance abusers: these studies focus on older-age people, whose measured ln(k) might differ from that which governs the decision process. Whether the future costs are considered to be a health outcome or in terms of the monetary equivalent required to compensate them for the loss is important to determine which DDR to use in this framework. Further data on health discount rates and behaviour data is required to test this hypothesis.

Another consideration that arises from the within-subject instability of ln(k) is the importance of when the decision is taken. The DDR measured during studies are not measured when decisions are taken and so, there will always be some disconnect between behaviours and the DDR measured through these measures. Analysis of the DDR implicitly assumes that the measured ln(k) is representative of ln(k) displayed in real-life behaviour. If ln(k) is unstable in real life for people with high initial ln(k), as was found to be the case in this analysis, then this will not always be the case.

9 Conclusion

Many of the most important decisions have a large impact on our future selves. Therefore, individual time preferences play an important role in explaining heterogeneity in decision-making. However, there are many experimental challenges inherent when trying to collect measurements of time preferences. As a result, there are a number of areas that have not been thoroughly examined by either behavioural economics or psychology, such as the long term stability of time preferences. This paper extends the literature using the MDDR, a related concept in psychology.

The findings in this paper suggest that adolescent MDDR is correlated with future risk-taking behaviour, especially the decision to smoke for those who had never smoked before, in a manner that is robust to the inclusion of many different variables. Furthermore, within-subject MDDR seems to be unstable over a period of three to four years, or from adolescence to young adulthood. Therefore, it is not surprising that there is a small connection between the genes reviewed in this paper and MDDR.

This has a number of implications for future research. The lack of stability suggests that there is a need to either model the evolution of time preferences over a lifetime or relax the traditional assumption that time preferences are fixed. As the MDDR at an early age is a better predictor of risk-taking than MDDR at a later age, the extent to which MDDR is predetermined may be important. There are also a number of correlations between

MDDR and personality traits that suggests that time preference measures are sensitive to the manner in which the choices are framed. Future research should therefore take care when framing the intertemporal choice experiment or questionnaire to ensure that they truly reflect intertemporal trade-offs in real life.

These results are based on adolescents and young adults that participated in the GATOR /ALOHA research study in Northern Virginia. One limitation of this study is that it is not clear whether the results have external validity, either in terms of other age groups or geographic regions. Furthermore, these results rely upon the assumed hyperbolic functional form of the discount rate, which while accepted by many psychologists, is a subject of much debate among economists.

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A Interpretation of Differences in ln(k)

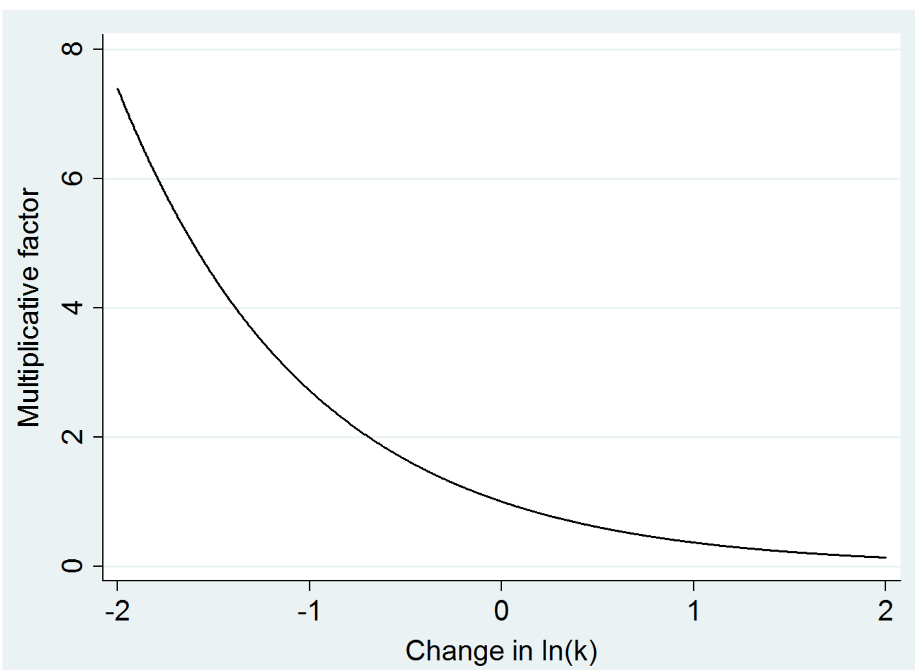
An immediate consequence of the hyperbolic function used to model impulsivity is that the present value is discounted by $\frac{1}{1+k_1T_1}$, or the time T_1 required to reduce the reward to z percent of the amount offered immediately is $T_1 = \left(\frac{1}{z} - 1\right) * \frac{1}{k_1}$.

Let $ln(k_2) = ln(k_1) + x$ where x is the amount by which $\ln(k_1)$ increases. Then the T_2 associated with the amount of time required to reduce the reward to z percent of the amount offered immediately is:

$$T_2 = \left(\frac{1}{z} - 1\right)\frac{1}{k_2} = \left(\frac{1}{z} - 1\right)\frac{1}{e^{ln(k_2)}} = \left(\frac{1}{z} - 1\right)\frac{1}{e^{ln(k_1)+x}} = T_1(e^{-x}) \tag{15}$$

Therefore, the present value curve will be stretched horizontally by a factor of e^{-x} (Figure 6). For example, an increase in ln(k) of one will reduce the time required to halve the value of an immediate reward to approximately a third of the original time required. This factor is independent of the value of the original delay discount rate k.[37]

Figure 6: Illustration of multiplicative factor for changes in ln(k)



[37] This represents an inherent advantage in using ln(k) instead of k. A similar analysis of k reveals that interpretation of changes in the level of k is much more complicated.

B Monetary Choice Questionnaire

For each of the next 27 choices, please indicate which reward you would prefer: the smaller reward today, or the larger reward in the specified number of day.

1. Would you prefer $54 today, or $55 in 117 days?
2. Would you prefer $55 today, or $75 in 61 days?
3. Would you prefer $19 today, or $25 in 53 days?
4. Would you prefer $31 today, or $85 in 7 days?
5. Would you prefer $14 today, or $25 in 19 days?
6. Would you prefer $47 today, or $50 in 160 days?
7. Would you prefer $15 today, or $35 in 13 days?
8. Would you prefer $25 today, or $60 in 14 days?
9. Would you prefer $78 today, or $80 in 162 days?
10. Would you prefer $40 today, or $55 in 62 days?
11. Would you prefer $11 today, or $30 in 7 days?
12. Would you prefer $67 today, or $75 in 119 days?
13. Would you prefer $34 today, or $35 in 186 days?
14. Would you prefer $27 today, or $50 in 21 days?
15. Would you prefer $69 today, or $85 in 91 days?
16. Would you prefer $49 today, or $60 in 89 days?
17. Would you prefer $80 today, or $85 in 157 days?
18. Would you prefer $24 today, or $35 in 29 days?
19. Would you prefer $33 today, or $80 in 14 days?
20. Would you prefer $28 today, or $30 in 179 days?
21. Would you prefer $34 today, or $50 in 30 days?
22. Would you prefer $25 today, or $30 in 80 days?
23. Would you prefer $41 today, or $75 in 20 days?
24. Would you prefer $54 today, or $60 in 111 days?
25. Would you prefer $54 today, or $80 in 30 days?
26. Would you prefer $22 today, or $25 in 136 days?
27. Would you prefer $20 today, or $55 in 7 days?

C Detailed Literature Review of the Delay Discount Rate

Delay Discount Rates Over a Lifetime

One of the main discussions surrounding DDR concerns whether it has the characteristics of a trait. A requirement is temporal stability, or high test-retest reliability after a period of time has passed (MacKillop, et al., 2011).

Previous studies of DDR have found that there are significant differences in comparisons of k between groups of different ages. Green, Fry, and Myerson (1994) found that adolescents discounted more steeply than young adults, who in turn discounted more steeply than older adults. This tendency was also found in Steinberg et al. (2009), where young adolescents were more willing to accept a smaller reward in exchange for the delayed reward than those 16 years or older.

On the other hand, the within-subject stability of k over relatively short periods of time has been found to be relatively stable across short time periods. For example, Ohmura et al. (2006) examined the individual differences across a 3 month period among undergraduate students and found that DDR are stable enough to predict future behaviour. Kirby (2009) re-tested young adults five weeks and one year after the initial delay-discounting task, and suggest the DDR is fairly stable at correlations that are fairly similar to personality traits. In both cases, the mean within-subjects change in k was approximately 0.2 to 0.3 ln(k) per month.

This evidence has led some researchers to suggest that delay discounting may be considered a personality trait and used to predict future behaviour (Odum, 2011). However, considering that reasonable bounds of ln(k) are 0 and -10, a consistent trend of 0.2 ln(k) per month is not trivial. It is also interesting that these studies found that within-group ln(k) increased over time, which is inconsistent with the findings from between-group comparisons of ln(k). An explanation given by Kirby (2009) is that between-group studies have used undergraduate students, and college years may constitute an exception to the longer-term trend.

One reason for the differences in the between-group and within-group study results could be that between-group studies are able to compare subjects over a much larger variation in ages. Changes in individual DDR are likely more apparent over a longer time period, though it is not clear whether this is due to the natural evolution of delay discounting over a lifetime or other variables. For example, DDR has been found to be correlated with potentially time-varying characteristics, such as income or level of schooling (Kirby, et al., 2002).

The average value of k for young adults is not consistent between studies. For example, Simpson and Vuchinich (2000) found a geometric mean of 0.058 (initial) to 0.061 (re-test), while Kirby (2009) found that the geometric mean of k among those who completed all three sessions was between 0.003 to 0.01. This discrepancy is magnified by the use of a $1,000 hypothetical reward in Simpson and Vuchinich (2000), which is theorized to decrease the DDR when compared to the $25-85 hypothetical rewards offered by Kirby (2009). However, the extent to which they contradict each other is difficult to properly assess because they are typically based on fairly non-representative small sample sizes. That is, the samples were taken from different populations with different characteristics that could influence the delay discount rate.

Genes and Delay Discount Rates

Identifying the exact genetic influences on DDR is difficult because impulsivity is a complex behaviour trait that is likely affected by several genes. The link between genes, their effect on the biological processes in the human body, and how these processes influence behaviour are not understood very well. Research in this area has thus far largely concentrated on genes associated with the dopamine and serotonin pathways. Dopamine is a neurotransmitter that contributes to a number of biological systems, including reward-motivated behaviour, and serotonin is associated with feelings of well-being and happiness.

In the dopamine system, DRD2 is thought to code for the density of dopamine receptors on neurons in the brain (Eisenberg, et al., 2007). There are two possible alleles for this gene, the DRD2-A1 allele and the DRD2-A2 allele. Eisenberg et al. (2007) found that the DRD2-ANKK1 A1 allele is associated with a reduced density of dopamine receptors and increased impulsivity, but this was not found by White et al. (2008). Other dopamine receptor genes were found to be significantly related to the level of delay discounting. For example, heterozygotes in the DRD3 gene were also found to have higher impulsivity, though this was measured through a different procedure than delay discounting (Retz, et al., 2003). Longer DRD4 genes in the presence of a DRD2-A1 allele was associated with higher delay discount rates (Eisenberg, et al., 2007). The latter study highlights that interactions between genes may have a crucial role on how genes affect delay discounting.

Two other genes that are part of the dopamine system are the DAT1 and COMT genes. The former regulates the amount of dopamine in the brain's synapses, with shorter variants associated with diminished dopamine reuptake and smaller benefits from dopamine transmission (Ding, et al., 2009). The latter is associated with the inactivation of dopamine, with COMT-H alleles breaking down dopamine much quicker than COMT-L alleles. Boettiger et al. (2007) found that people with COMT-HH genotypes were more impulsive. On the other hand, Paloyelis et al. (2010) found that longer DAT1 halotypes and COMT-LL genotypes were correlated with steeper delay discount rates in the control group.

Another gene that might be of interest is the TPH gene, which is linked to the biosynthesis of serotonin. While it has not been directly linked with delay discounting, numerous studies have shown a connection between TPH and other measures of impulsivity, such as suicidal behavior (e.g. Nielsen, Proudnikov, & Kreek, 2011; Bellivier, Chaste, & Malafoss, 2004; Li & He, 2006).

Risky Behaviour and Delay Discount Rates

There is extensive literature on the relationship between substance abuse and MDDR. Theoretically, the decision to indulge lies in the comparison between the immediate pleasure and the present value of the future consequences. Higher DDR are associated with a lower present value of future events. Therefore, substance abuse could be associated with higher DDR (Kirby, Petry, & Bickel, 1999).

MacKillop et al. (2011) performed a meta-analysis of studies published in peer-reviewed journals on relationship between MDDR and addictive behavior. The sample was limited to those involving human subjects and only delayed-discount studies. The authors note that studies use a wide variety of methods (e.g. laboratory task, questionnaire), population types (e.g. smokers, people suffering from ADHD), sample sizes, and reward sizes. The most common approach was to perform a choice task (69%), followed by the monetary choice questionnaire (16%) and then one to three item measures (9%). Despite these differences, the authors conclude that there is substantial evidence in support of higher MDDR among substance abusers and that there was only modest evidence of small-sample bias (Table 9).

Several studies reported no significant difference in MDDR between the control group and the behaviour group, even if the majority find a significant difference. Furthermore, in many studies, selection bias could be present as participants volunteer to enter the study, which may itself self-select based on impulsivity. Finally, while most studies examine correlation, they frequently do not control for other factors in their analysis that might influence MDDR and have a bearing on their results, such as race or gender. This may not have a significant bearing on the results if the participants all have similar characteristics, though this limits whether the results have external validity.

Studies have also found that people have separate DDR for different categories of substances. Chapman (1996) and Weatherly (2010) both found that MDDR are a poor predictor of DDR for health outcomes. Madden et al. (1997) asked opioid-dependent and control participants to perform a monetary delay discount task and an equivalent heroin delay discount task. They found the correlation between monetary and heroin delay DDR was 0.48.

D Selected Tables and Figures With Inverse Probability Weights

Table 18: Differences in monetary delay discount rate for different genotypes with inverse probability weights

Gene	Genotype	$\ln(k_3)$	$\ln(k_6)$	$\ln(k_7)$
TPH	AA	-4.392 (1.450)	-4.559 (1.207)	-4.507 (1.291)
	AC	-4.405 (1.329)	-4.588 (1.249)	-4.520 (1.130)
	CC	-4.267 (1.486)	-4.647 (1.153)	-4.467 (1.179)
	F-test of equal means	1.131 [0.323]	0.257 [0.773]	0.131 [0.877]
CYP	TT	-3.794 (1.601)	-4.325 (1.104)	-4.213 (0.961)
	CT	-4.358 (1.431)	-4.549 (1.115)	-4.311 (1.323)
	CC	-4.364 (1.405)	-4.617 (1.234)	-4.558 (1.122)
	F-test of equal means	2.417 [0.090]*	0.644 [0.526]	2.471* [0.0855]
DRD2	A1A1	-4.091 (1.665)	-4.412 (1.424)	-4.268 (1.001)
	A1A2	-4.361 (1.421)	-4.484 (1.195)	-4.471 (1.254)
	A2A2	-4.369 (1.388)	-4.67 (1.177)	-4.519 (1.128)
	F-test of equal means	1.049 [0.351]	2.079 [0.126]	0.678 [0.508]
DAT	DAT0	-4.300 (1.328)	-4.637 (1.043)	-4.461 (1.27)
	DAT1	-4.253 (1.460)	-4.582 (1.146)	-4.381 (1.225)
	DAT2	-4.417 (1.393)	-4.633 (1.255)	-4.595 (1.102)
	F-test of equal means	1.559 [0.219]	0.146 [0.865]	2.221 [0.109]
COMT	HH	-4.218 (1.401)	-4.636 (1.300)	-4.412 (1.108)
	HL	-4.388 (1.395)	-4.573 (1.163)	-4.594 (1.148)
	LL	-4.406 (1.516)	-4.67 (1.138)	-4.435 (1.303)
	F-test of equal means	1.546 [0.214]	0.371 [0.390]	1.449 [0.236]

Note: Observations in waves 6 and 7 are weighted using inverse probability weights to account for selective attrition. Standard deviation are presented in ( ) parenthesis. F-tests are for the null hypothesis of equal average ln(k) among the three genotypes and prob > F presented in [ ] parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels respectively.

Table 19: Monetary delay discount rate and self-control personality traits with inverse probability weights

		Self-control indices		
		Good self-control	Bad self-control	Impulsive index
Spearman rank correlation coefficient	ln(k_3)	-0.152***	0.094***	0.093***
		[-0.212, -0.092]	[0.033, 0.155]	[0.032, 0.154]
	ln(k_6)	-0.100**	0.104***	0.099**
		[-0.174, -0.024]	[0.028, 0.179]	[0.023, 0.174]
	ln(k_7)	-0.049	-0.008	0.008
		[-0.129, 0.033]	[-0.090, 0.073]	[-0.074, 0.089]
Pearson correlation coefficient	ln(k_3)	-0.150***	0.082***	0.089***
		[-0.210, -0.089]	[0.021, 0.143]	[0.027, 0.150]
	ln(k_6)	-0.085**	0.082**	0.097**
		[-0.160, -0.009]	[0.006, 0.157]	[0.021, 0.172]
	ln(k_7)	0.003	-0.016	0.014
		[-0.078, 0.085]	[-0.098, 0.065]	[-0.067, 0.096]
Linear regression without genotype variables	ln(k_3)	-1.106***	0.606**	0.474*
		(0.272)	(0.275)	(0.244)
	ln(k_6)	-0.617**	0.575**	0.505**
		(0.276)	(0.264)	(0.228)
	ln(k_7)	-0.106	-0.00827	0.0985
		(0.304)	(0.272)	(0.253)
Linear regression with genotype variables	ln(k_3)	-1.083***	0.445	0.357
		(0.293)	(0.307)	(0.269)
	ln(k_6)	-0.605**	0.550*	0.505**
		(0.296)	(0.291)	(0.252)
	ln(k_7)	-0.145	-0.0834	0.0492
		(0.316)	(0.305)	(0.274)

Note:Each regression cell represents β_1 for a different regression with the psychological variable as the independent variable and the monetary delay discount rate as an dependent variable. All regressions include school indicator variables. Controls refer to the same characteristics as those presented in Table 14. Observations in waves 6 and 7 are weighted using inverse probability weights to account for selective attrition. It is not appropriate to use inverse probability weights with Spearman rank correlation coeffcients, so the values here are the same as in Table 15. Robust standard errors are presented in ( ) parenthesis. 95% confidence intervals for the correlation coefficient using Fisher's transformation are presented in [ ] parenthesis. Psychological variables were normalized to a scale from 0 to 1, with 0 being the lowest possible manifestation of the psychological variable and 1 being the highest. ***, **, * represent statistically significantly different from zero at the 1%, 5%, and 10% significance levels respectively.

Table 20: Monetary delay discount rate and the TCI with inverse probability weights

		Temeperament and Character Inventory		
		Novelty-seeking	Reward dependence	Harm avoidance
Spearman rank correlation coefficient	$\ln(k_3)$	0.163***	-0.171***	-0.352
		[0.102, 0.223]	[-0.230, -0.110]	[-0.097, 0.027]
	$\ln(k_6)$	0.105***	-0.108***	-0.0002
		[0.029, 0.179]	[-0.182, -0.032]	[-0.076, 0.076]
	$\ln(k_7)$	0.052	-0.084**	-0.034
		[-0.030, 0.133]	[-0.164, -0.003]	[-0.115, 0.048]
Pearson correlation coefficient	$\ln(k_3)$	0.137***	-0.155***	-0.045
		[0.076, 0.198]	[-0.215, -0.094]	[-0.106, 0.017]
	$\ln(k_6)$	0.083**	-0.146***	0.002
		[0.007, 0.159]	[-0.219, -0.070]	[-0.074, 0.078]
	$\ln(k_7)$	0.058	-0.123***	-0.073*
		[-0.023, 0.139]	[-0.201, -0.040]	[-0.153, 0.009]
Linear regression without genotype variables	$\ln(k_3)$	0.920***	-0.815***	-0.0759
		(0.219)	(0.253)	(0.203)
	$\ln(k_6)$	0.435*	-0.685**	0.172
		(0.241)	(0.285)	(0.212)
	$\ln(k_7)$	0.294	-0.434	-0.151
		(0.227)	(0.277)	(0.225)
Linear regression with genotype variables	$\ln(k_3)$	0.904***	-0.863***	-0.139
		(0.239)	(0.278)	(0.220)
	$\ln(k_6)$	0.492*	-0.672**	0.0335
		(0.264)	(0.313)	(0.231)
	$\ln(k_7)$	0.386	-0.333	-0.277
		(0.246)	(0.294)	(0.242)

Note:Each regression cell represents β_1 for a different regression with the psychological variable as the independent variable and the monetary delay discount rate as an dependent variable. All regressions include school indicator variables. Controls refer to the same characteristics as those presented in Table 14. Observations in waves 6 and 7 are weighted using inverse probability weights to account for selective attrition. It is not appropriate to use inverse probability weights with Spearman rank correlation coeffcients, so the values here are the same as in Table 16. Robust standard errors are presented in ( ) parenthesis. 95% confidence intervals for the correlation coefficient using Fisher's transformation are presented in [ ] parenthesis. Psychological variables were normalized to a scale from 0 to 1, with 0 being the lowest possible manifestation of the psychological variable and 1 being the highest. ***, **, * represent statistically significantly different from zero at the 1%, 5%, and 10% significance levels respectively.

Table 21: Relative stability of monetary delay discount rates with inverse probability weights

	$\ln(k_7)$ compared $\ln(k_3)$	$\ln(k_6)$ compared $\ln(k_3)$	$\ln(k_7)$ compared to $\ln(k_6)$
Spearman rank correlation coefficient	0.395***	0.395***	0.582***
	[0.330, 0.458]	[0.334, 0.453]	[0.528, 0.631]
Pearson correlation coefficient	0.398***	0.402***	0.580***
	[0.327, 0.464]	[0.336, 0.464]	[0.521, 0.633]
Linear regression with other variables	0.290***	0.314***	0.531***
	(0.0389)	(0.0389)	(0.0430)

Note: Each regression cell represents β_1 for a different regression. Regressions include school indicator variables. Controls refer to the same characteristics as those presented in Table 14 without genotype indicator variables. Observations in waves 6 and 7 are weighted using inverse probability weights to account for selective attrition. It is not appropriate to use inverse probability weights with Spearman rank correlation coeffcients, so the values here are the same as in Table 6. Robust standard errors are presented in ( ) parenthesis. 95% confidence intervals for the correlation coefficient using Fischer's transformation are presented in [ ] parenthesis. ***, **, * represent that the statistic is statistically different from one at the 1%, 5%, and 10% significance levels respectively.

Table 22: Differences in monetary delay discount rates for risky behaviours with inverse probability weights

			Time period				
			Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Regular smoker	ln(k_3)	mean for behaviour	-3.853 (1.34)	-4.062 (1.379)	-4.168 (1.57)	-4.07 (1.628)	-4.072 (1.552)
		mean for others	-4.407 (1.408)	-4.407 (1.407)	-4.512 (1.351)	-4.55 (1.314)	-4.54 (1.298)
		difference	0.554*** [0.138]	0.345*** [0.119]	0.344** [0.137]	0.48*** [0.127]	0.468*** [0.128]
	ln(k_6)	mean for behaviour	-4.529 (1.47)	-4.471 (1.397)	-4.443 (1.203)	-4.363 (1.143)	-4.419 (1.138)
		mean for others	-4.653 (1.257)	-4.671 (1.253)	-4.695 (1.203)	-4.692 (1.2)	-4.736 (1.188)
		difference	0.123 [0.162]	0.2 [0.133]	0.252* [0.137]	0.329*** [0.108]	0.317*** [0.113]
	ln(k_7)	mean for behaviour	-4.328 (1.175)	-4.521 (1.182)	-4.379 (1.187)	-4.319 (1.143)	-4.211 (1.232)
		mean for others	-4.609 (1.259)	-4.602 (1.265)	-4.63 (1.145)	-4.578 (1.138)	-4.606 (1.125)
		difference	0.281* [0.171]	0.082 [0.141]	0.25* [0.144]	0.259** [0.118]	0.395*** [0.108]
Heavy drinker	ln(k_3)	mean for behaviour	-4.158 (1.306)	-4.26 (1.497)	-4.352 (1.423)	-4.288 (1.382)	-4.293 (1.4)
		mean for others	-4.387 (1.425)	-4.37 (1.382)	-4.509 (1.377)	-4.55 (1.422)	-4.531 (1.365)
		difference	0.229** [0.117]	0.11 [0.103]	0.158 [0.107]	0.261** [0.11]	0.237** [0.115]
	ln(k_6)	mean for behaviour	-4.538 (1.092)	-4.581 (1.299)	-4.594 (1.151)	-4.51 (1.111)	-4.584 (1.114)
		mean for others	-4.674 (1.302)	-4.664 (1.267)	-4.691 (1.233)	-4.693 (1.25)	-4.715 (1.247)
		difference	0.136 [0.122]	0.083 [0.106]	0.098 [0.102]	0.183* [0.093]	0.131 [0.102]
	ln(k_7)	mean for behaviour	-4.49 (1.159)	-4.452 (1.196)	-4.538 (1.137)	-4.452 (1.122)	-4.472 (1.178)
		mean for others	-4.618 (1.261)	-4.635 (1.27)	-4.626 (1.161)	-4.575 (1.159)	-4.072 (1.552)
		difference	0.129 [0.126]	0.183 [0.111]	0.088 [0.104]	0.123 [0.099]	-4.54 (1.298)
Marijuana use	ln(k_3)	mean for behaviour	-3.832 (1.357)		-4.209 (1.404)	-4.201 (1.437)	-4.313 (1.418)
		mean for others	-4.368 (1.404)		-4.484 (1.393)	-4.56 (1.36)	-4.622 (1.304)
		difference	0.536** [0.256]		0.275 [0.183]	0.359** [0.168]	0.309** [0.152]
	ln(k_6)	mean for behaviour	-4.52 (1.14)		-4.445 (1.095)	-4.53 (1.089)	-4.586 (1.087)
		mean for others	-4.649 (1.281)		-4.678 (1.203)	-4.677 (1.207)	-4.755 (1.207)
		difference	0.129 [0.323]		0.233 [0.191]	0.148 [0.146]	0.169 [0.141]
	ln(k_7)	mean for behaviour	-4.659 (1.222)		-4.587 (0.983)	-4.622 (0.99)	-4.568 (1.006)
		mean for others	-4.597 (1.251)		-4.612 (1.154)	-4.568 (1.148)	-4.608 (1.165)
		difference	-0.062 [0.307]		0.146 [0.183]	0.033 [0.151]	0.137 [0.129]

Note: Observations in waves 6 and 7 are weighted using inverse probability weights to account for selective attrition. Standard deviations are presented in ( ) parenthesis. Standard errors are presented in [ ] parenthesis. ***, **, and * represent statistical significance of differences in the delay discount rate at the 1%, 5%, and 10% levels respectively.