The impact of risk and time preferences on smoking behaviour in the context of a contingency management programme

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Abstract

While there is an established body of research examining risk preferences, time preferences and smoking behaviour, there is little literature exploring the relationship between risk preferences, time preferences, and smoking cessation contingency management (CM) programmes. This dissertation evaluates a CM study and its effect on smokers' ability to quit and smoking intensity, together with their risk and time preferences. The experiment comprises 87 University of Cape Town students wanting to quit smoking, randomly assigned into treatment and control groups. Risk and time preferences are elicited at the beginning of the programme, using incentive-compatible decision-making tasks. The relationship between the individuals' risk preferences, time preferences, and smoking outcomes is explored using two general approaches: standard statistical models and structural models. In the structural models, maximum likelihood estimation is used to estimate time preference parameters jointly with risk preference parameters. Results are broadly consistent across the two approaches. With respect to abstinence, the statistical model suggests that the likelihood of abstinence increases with discount rates, while the structural models suggest CM reduces the effect that time preferences have on abstinence. Neither approach finds a difference in risk preferences between abstinent and non-abstinent participants. In terms of smoking intensity, both approaches unexpectedly find smoking intensity to increase with risk aversion, and neither approach finds a relationship between smoking intensity and time preferences.

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I'm blessed to have parents so willing to support me through university. To them, I owe a huge debt of gratitude, one that I won't forget as I move through life. Mom and dad, I am done now, I swear.

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1.Introduction

Tobacco smoking[1] is harmful. To the smoker, the habit is associated with an increased prevalence of cardiovascular disease, respiratory disease, cancer, pregnancy complications, fertility issues, teeth and gum issues, cataracts, type-2 diabetes, and rheumatoid arthritis. Smoking also increases inflammation in the body and harms the immune system's ability to function. Furthermore, harmful effects are not restricted to the smoker. Second-hand smoke causes several health problems in infants and children, including more frequent and severe asthma attacks, respiratory infections, and sudden infant death syndrome (SIDS). Non-smokers who are exposed to second-hand smoke at home or at work increase their risk of developing heart disease by 25%-30%, and their risk for stroke and lung cancer by 20-30% (Centers for Disease Control and Prevention, 2018).

Despite its harmful effects being well-known, smoking is widespread in South Africa. Among the country's adults, almost 18% are smokers (Reddy et al., 2015). Annually, approximately 44 000 South Africans die from smoking-related diseases and complications (Western Cape Government, 2018). This toll on South African lives is substantial, but smoking's harm can also be viewed through the lens of the heavy burden it leaves on the tax-payer funded public healthcare system. Treatment for smoking-related diseases is expensive and means that limited resources are diverted away from other patients and other primary health care programmes (The National Department of Health, 2018). Globally, the amount spent on treating smoking-attributable diseases amounts to 5.7% of total health expenditure, with 40% of these costs occurring in developing countries (Goodchild, Nargis and D'Espaignet, 2018).

There is good reason for governments to not only pursue policies that prevent citizens from starting smoking, but also those that help smokers to quit. After 15 years of quitting smoking,

[1] Henceforth, 'smoking' is used to refer to 'tobacco smoking.'

the risk of death among ex-smokers reverts to the same as those who have never smoked. Ten years after having quit smoking, the risk of cancer is reduced by 30-50% (Fagerström, 2002). The excess risk of coronary heart disease halves within one year of stopping smoking and the excess risk of stroke returns to that of non-smokers within 5 to 15 years of smoking cessation (Fagerström, 2002). Among other health benefits, quitting smoking also carries significant improvements in the ex-smoker's gastrointestinal system, and reproductive system (Fagerström, 2002).

Thus, tools that help smokers to quit are invaluable. Since 1994, South African government interventions have included banning advertising tobacco products, classifying nicotine as an addictive drug, adding warning labels to packs, restricting smoking in public places, increasing excise duties (sin taxes) on cigarettes, and including smoking's harms in the school curriculum. These measures have undoubtedly had an impact, with aggregate cigarette consumption falling by 39% between 1991 and 2004 (Reddy et al., 2013). However, after the sharp decline in cigarette consumption over that period, reductions have steadied. Between 2010 and 2015, South Africans consistently consumed slightly less than 30 packs of cigarettes per capita per year with no noticeable decrease over that period (Filby, 2018).

The diminishing reductions in smoking has made it important to expand the toolset used to curb tobacco demand. Pharmacotherapies (such as nicotine replacement therapy), exercise-based interventions, and behavioural therapies are receiving increased focus as measures to increase smoking abstinence. One such behavioural therapy is contingency management (CM), which is characterised by rewarding individuals that achieve a particular positive behavioural change. In the case of smoking, it would mean people addicted to smoking are rewarded for abstaining from cigarettes. CM programmes rely on the principle that a behaviour reinforced through a reward will increase that behaviour's frequency by the individual (Stitzer and Petry, 2006).

CM programmes have been successfully used to treat a range of addictions, including smoking (Cahill, Hartmann-Boyce and Perera, 2015). Furthermore, Hofmeyr, Kincaid and Rusch (HKR, 2020) show that the rewards need not be substantial, nor the treatment intensive, for the programmes to have any effect. Nevertheless, degrees of effectiveness vary between smoking cessation CM programmes and between the individuals within these programmes. Thus, it is important to understand what underlying factors lead people to quit smoking. These factors may include the smokers' external characteristics such as social background, socio-economics and shifting cultural norms, or the smokers' internal characteristics which include their risk and time preferences.

Because smoking significantly increases the likelihood of developing a range of health issues, we would expect that the more risk averse one is, the less likely it is that they smoke. However experimental evidence for this relationship is mixed (Sato and Ohkusa, 2003; Anderson and Mellor, 2008; Goto et al, 2009; Harrison et al., 2018). Similarly, because smoking offers one immediate gratification that, at face-value, is outweighed by its long-term harms, we would expect the more one discounts their future well-being, the likelier it is that they smoke. Evidence largely supports this hypothesis (Barlow et al., 2017).

This paper examines the relationship that smokers' risk and time preferences have on their likelihood of quitting and their smoking intensity[2] within the context of a CM programme. For this analysis, a CM programme is useful because it provides a sample of smokers incentivised to quit smoking. As some will manage to quit while others fail, this offers the opportunity to explore the reasons behind the participants' different outcomes.

The CM programme used in this paper, conducted in 2017, recruited UCT students wanting to quit smoking. The programme was run as a randomised controlled trial (RCT) with 87

[2] Smoking intensity is measured as the average number of cigarettes smoked per day.

participants, and it was efficacious in promoting abstinence, but only while participants received rewards (HKR, 2020).

At the baseline session, participants completed two separate and incentive-compatible decision-making tasks that elicited their risk and time preferences. Risk preferences were elicited using the Random Lottery Pair design developed by Hey and Orme (1994), while time preferences were elicited using a choice-based method similar to Coller and Williams (1999). These data are used to investigate the relationship between risk preferences, time preferences, and smoking behaviour using two main statistical approaches. By including variables for risk and time preferences, the first method builds upon HKR's random-effects probit model for investigating smoking abstinence, as well their random-effects negative binomial model for investigating smoking intensity. The second approach, introduced by Andersen et al. (2008), is to jointly estimate risk and time preference models by maximum likelihood, conditioning the estimates on the participants' likelihood of abstinence and smoking intensity.

Results are broadly consistent across the two approaches. With respect to abstinence, neither approach finds risk preferences to be a predictor of abstinence. However, the random-effects probit model suggests that the likelihood of abstinence nonlinearly increases with discount rates, while the parameter estimates for the jointly estimated discounting models suggest CM reduces time preference's significance as a predictor of abstinence. In terms of smoking intensity, both approaches unexpectedly finds that smoking intensity tends to increase with risk aversion, and neither approach finds a relationship between smoking intensity and time preferences.

Section 2 provides a literature review of economic theories of addiction, CM programmes, risk preferences, time preferences, and how all these relate to smoking behaviour. Section 3 discusses the experiment's design and methods, and Section 4 outlines the statistical methodology. Section 5 presents results and Section 6 concludes.

2. Literature Review

A. Theories of Addiction

This section introduces economic models of addiction. I examine the Rational Addiction Model (RAM) of Becker and Murphy (BM, 1998) and the contribution of Orphanides and Zervos (OZ, 1995). Dual system and dual self models are then discussed, models, which unlike RAM, account for time-inconsistent behaviour and the associated pattern of quit attempts and relapse that is a hallmark of addiction.

BM developed a model of rational addiction that incorporates some salient features of addiction, including tolerance, reinforcement, and withdrawal. The model posits that agents choose to consume an addictive good after calculating the benefits and costs, while accounting for the interdependency between past, present, and future consumption when maximizing utility over their lifespan. BM introduces the idea of consumption capital, which is a depreciating accumulated stock of the addictive good. Welfare declines as consumption capital rises. However, the greater one's consumption capital of an addictive good, the greater the benefit from consuming more of the addictive good now. Thus, past consumption of the addictive good affects current utility through the accumulation of consumption capital. Adjacent complementarity, the pattern of past consumption reinforcing current consumption, is an assumption that explains why agents continue to consume addictive goods despite the decline in their welfare (Hofmeyr, 2015).

RAM is a deterministic, as opposed to stochastic, model, and thus does not include subjective beliefs nor risk preferences in its framework. However, RAM does incorporate time preferences because agents discount exponentially any future costs and benefits. The stronger an agent's rate of preference for the present, the more weight they would attribute to present consumption relative to the costs it has on their future welfare. Thus, an agent with a high discount rate favours the immediate benefit of consuming the addictive good at the expense of long-term welfare (Hofmeyr, 2015).

OZ made significant contributions to RAM. Their theory is based on three fundamentals. First, consumption of the addictive good is not equally harmful to all. Second, individuals have subjective beliefs regarding this harm. Third, beliefs are optimally updated (via Bayesian updating) with information gained through consumption. The model assumes that consumers do not have perfect foresight, but that agents are rational in the sense that they form plans to maximise *expected* utility through time. For example, decidedly casual smokers risk the possibility of addiction because they believe their personal propensity for addiction is below the addiction threshold given their consumption capital. Thus, the benefits of smoking a casual cigarette makes it worthwhile. But because the casual smoker may later find that their past assessment of the potential harm and possibility of addiction is inaccurate, they may come to regret their past decisions to smoke.

OZ's model also provides insight into quitting. Once consumers come to realize their true addictive tendency, potential addicts rapidly change their consumption pattern. If they are above the critical level of consumption capital, they go on a binge. If they are below the critical level, they quit by going 'cold turkey'.

The model also provides important insights into the way these subjective beliefs, which manifests in the model's stochastic nature, interact with risk preferences to influence addiction. The agents' uncertainty concerning harmful consequences and their own addictiveness type leads to more risk averse agents being less inclined to experiment with addictive goods.

Models of rational addiction are widely used by economists to deal with a range of topics such as tobacco (Labeaga, 1999; Baltagi and Griffin, 2001), alcohol (Waters and Sloan, 1995) and even coffee consumption (Olekalns and Bardsley, 1996). However, Ross (2010) points out that in reality people do not, as the models imply, either quit immediately or keep consuming the addictive good until they have exhausted their budgets. Akerlof (1991) criticises the tenuous assumption that addicts knowingly become addicted after a series of choices made to consume the addictive good. Rogeberg (2004) criticizes RAM particularly strongly, along with economic theory generally, for being divorced from reality. He makes the argument that economists anchor their trust in the truthfulness of theories such as RAM through sophisticated but ultimately baseless mathematical models.

While the models are imperfect, they provide some useful insights. The BM model emphasises that the consumption of addictive goods is affected by the extent to which the agents discount future utility. The stochastic nature of the OZ model shows how risk preferences may lead to experimentation with addictive goods, like cigarettes, which eventually lead to a harmful and regretful addiction. This said, time-consistent RAM cannot account for the time-inconsistent behaviour typical of quit attempts and relapse. Additionally, models of rational addiction cannot explain the need for (often costly) commitment devices that many people use to limit consumption of addictive goods (Hofmeyr, 2015). The subsequent dual self and dual system models provide a solution to these shortcomings.

Dual system models are typically synchronic in that there are competing subpersonal agents vying for control of behaviour at each point in time. By contrast, dual self models are framed such that the agent is not a construction of competing subagents at each point in time, but a succession of competing selves over time. Moreover, dual self models typically emphasise the importance of time preferences while dual system models highlight the role that risk preferences play in the aetiology of addiction (Hofmeyr, 2015).

Dual system models, developed by Bernheim and Rangel (2004) and Benhabib and Bisin (2005), incorporate the idea of two subagents competing for control of the agent's behaviour at each point in time. The one subagent makes decisions that are reflective and controlled while the other subagent makes decisions that are automatic and myopic. The model incorporates time-inconsistent choice behaviour through *stochastic temptations*. These temptations potentially steer the agent towards immediate gratification by overwhelming the rational decision-making process.

The agent's initial decisions to use the addictive good are decided by the 'cold' and controlled self but as use increases the agent becomes more suggestive to environmental cues that trigger the impulsive, myopic, 'hot mode' decision-making self. Over time, continued impulsive consumption leads to addiction. Susceptibility to be triggered into 'hot mode' thinking also explains relapse after trying to quit an addiction. When a hot mode is triggered, the agent always consumes the addictive good regardless of their underlying preferences (Hofmeyr, 2015).

Gruber and Koszegi's (2001) dual self model incorporates present-biased decision makers who make choices that are always aligned with their preferences at the time of making the choice but may not align with their long-term interests. Present bias refers to people's tendency to more strongly weight payoffs that are closer to the present time when considering trade-offs between two future moments (O'Donoghue and Rabin, 1999). Thus, for the sake of immediate gratification, the agent may systematically make choices contrary to their true long-run preferences. Like the dual system model, this approach also allows for time-inconsistent choice behaviour but through quasi-hyperbolic discounting. For example, you may decide to eat pudding this week and delay the start of a diet until next week, but once next week comes around, you may decide to eat pudding again. The model also considers repeated quit attempts and relapse. The present self may decide to quit the addictive good only for their efforts to be undone by a future self tempted by the immediate benefit that the addictive good offers.

The model has been criticized by Bernheim and Rangel (2004) for two shortcomings. Firstly, the agent consumes all pleasurable goods excessively, not just addictive goods. Secondly, the present bias is not triggered by any environmental cue. All the agent's choices are affected by present bias.

RAM (with OZ's contributions), along with the dual self and dual system models provide important insights into explaining addictive behaviour. Of particular relevance to this dissertation is the role of risk and time preferences in explaining addiction. The OZ model shows how an individual's risk preferences may lead to experimentation with, and ultimately an addiction to, an addictive good. With the dual system models, risk preferences drive inconsistent choice behaviour through the stochastic realization of environmental cues that trigger the consumption of an addictive good. RAM incorporates time preferences with consumers exponentially discounting future costs and benefits. The dual system and dual self models also incorporate time preferences, but with non-exponential discounting, which allows for the time-inconsistent choice behaviour that characterizes addiction.

B. Contingency Management

Literature involving smoking contingency management (CM) interventions is now discussed. Based upon Petry's (2000) review, I discuss CM best practices, particularly in the context of smoking. The discussion then draws from the extensive review conducted by Cahill, Hartmann-Boyce & Perera (CHP, 2015). In the review, I discuss the respective interventions' settings, the participants, detail the interventions' incentive structure(s), measurement techniques and benchmarks, risk of bias, and, lastly, the overall results.

CM intervention design

A contingency management (CM) intervention is a type of behavioural therapy where treated subjects are rewarded for positive behavioural change. Originating from the token economy approaches of 40 years ago, CM procedures have been used to treat a variety of addictions, including nicotine (Kazdin, 1982). The behavioural principles are centred about three basic tenets. The first is that the CM intervention is set up so that the target behaviours (e.g., smoking abstinence) are easily detected. This would entail the frequent monitoring of breath carbon monoxide (CO) levels or urinalysis testing. Secondly, those enrolled in the programme are provided tangible reinforcers whenever they demonstrate the targeted behaviour. These rewards may include an amount of money for testing negative for tobacco smoking. Thirdly, when subjects fail to exhibit the targeted behaviour, these rewards are withheld (Petry, 2000).

The reinforcers (or incentives) used should depend on how available and practical they are for the specific CM intervention. Halpern et al. (2015) discuss the effectiveness of voucher versus cash rewards. Voucher-based reinforcement therapy (VBRT), popularized by Higgins et al. (1991), allows individuals to choose between desirable goods and services for testing abstinent. Because cash is not provided, vouchers reduce the likelihood of the reward being used to purchase drugs. VBRT is disadvantageous in that it can be difficult to employ and manage. The rewards can become expensive and there is the logistical burden of purchasing and transporting the specific requested items (Petry, 2000; Prendergast et al., 2006).

Cash avoids the logistical issues associated with vouchers. Additionally, because cash is usually preferred to a voucher of equivalent value (Amass et al., 1996), changes in the targeted behaviour may be brought about at lower cost. The concern that cash will be used to buy and use the drugs that the programme is targeting is alleviated when the subjects are tested regularly. Furthermore, there is evidence that cash rewards do not lead to higher rates of drug use, cravings, or high-risk behaviours within CM (Festinger et al., 2014). As with vouchers, programmes that use cash reinforcers face the difficult task of raising enough funds for the rewards (Petry, 2000).

Another incentive system is one where participants deposit some of their own money into an (often) interest-bearing account and only receive the principle (with interest) if they successfully complete the programme. This method has the advantage of not requiring the intervention's implementors to raise funds for rewards but it is more difficult to enrol participants (CHP, 2015).

Once the desired behaviours and rewards have been chosen, the next stage is to design the monitoring and reward schedule. Substance addiction is a preferred target because usage is testable biochemically through breath, urine, or blood tests. When designing CM interventions that reinforce drug abstinence, the goal is to detect whenever subjects use the targeted drug. CM interventions thus usually test subjects 2-3 times a week as this is regular enough for most urine testing systems to detect any instance of use of the targeted drug. CO testing, the method used in this dissertation, needs to be done more regularly for the programme managers to be confident that participants have not been smoking. This is because a smoker's CO levels will be the same as a non-smoker's by 24 to 48 hours after their last cigarette. This allows a still-smoking participant to 'game' the intervention by not smoking two days before the CO test and then smoking again afterwards. But while CO testing as regularly as every day would alleviate this concern, logistical and budgetary constraints may make this standard impractical to uphold (Petry, 2000; Stitzer and Petry, 2006).

The CO threshold used to measure abstinence varies widely. Maximum thresholds range from 4 parts per million (ppm) (Secades-Villa et al., 2014; Dallery, Raiff and Grabinski, 2015), to 6ppm (Alessi and Petry, 2014; Ledgerwood et al., 2014), 7ppm (Drummond et al., 2014), 9ppm

(Glasgow et al., 1993), 10ppm (Crowley, Macdonald and Walter, 1995; Gallagher et al., 2007) and as high as 11ppm (Rand et al., 1989).

An alternative biochemical test to breath CO, and one not used in this study, is to test urine or blood cotinine levels. Cotinine is a chemical compound that is formed in the body after nicotine is consumed. The advantage over the breath CO test is that cotinine has a half-life nine times that of CO, which means that it can detect if a participant smoked a lot further back than CO testing (Schepis et al., 2008). While this advantage is significant, this dissertation only tests breath CO as additionally testing cotinine would have been too expensive and subjects may have been uncomfortable with the somewhat invasive testing method, possibly leading to attrition.

In CM studies, subjects that provide a negative test result receive the reinforcer. To best reinforce desired behaviour, rewards should be provided immediately, a standard that can be difficult to keep if test samples need to be sent to external laboratories or hospitals for screening (Petry, 2000; Prendergast et al., 2006). The magnitude of the reinforcer is another important consideration. The larger the reinforcer, the likelier the CM intervention is to change behaviour. Stitzer and Bigelow (1984) found that smoking abstinence increased as a function of the magnitude of the reinforcer. In addition, Meredith et al. (2014) argue that the magnitude should be adjusted depending on the severity of the addiction and the difficulty in bringing about the target behaviour.

Another common feature of CM programmes is to increase the reward the longer the period of abstinence. For example, the first negative test result earns a voucher equivalent to R100, the second negative result R120, and so on. The reward typically resets to its original level after a subject submits a positive test result (i.e., relapses). Roll, Higgins and Badger (1996) compared the escalating schedule to one that provided a constant rate of reinforcement in a smoking CM intervention, finding that the escalating schedule resulted in longer periods of continuous abstinence than constant rewards (Petry, 2000; Meredith et al., 2014).

In contrast to the escalating schedule is the front-loaded or tapering schedule; the incentive is largest in the beginning of the programme and reduces over time. Feelings of withdrawal are strongest at the beginning of a quit attempt. Thus subjects may need a higher reward as a substitute for the addictive good initially, but the reward can be decreased the longer the subject maintains abstinence (Meredith et al, 2014).

Another aspect of CM programmes is whether to include additional behaviour reinforcement like group therapy, counselling, maintenance therapy (for example nicotine patches) or other kinds of support. Higgins et al. (2019) find that interventions that combine reinforcers and therapy produce better outcomes than CM on its own.

Review of smoking cessation CM interventions

CHP (2015) review 21 smoking cessation CM intervention RCTs. Of the studies, 16 were based in the USA, 3 studies were based in the UK (Paxton, 1980, 1981, 1983), 1 in the Philippines (Giné, Karlan and Zinman, 2010), 1 in Spain (Secades-Villa et al., 2014), and 1 in Thailand (White, Dow and Rungruanghiranya, 2013). Ten of the studies were set in clinics or health centres (Paxton, 1980, 1981, 1983; Crowley, Macdonald and Walter, 1995; Shoptaw et al., 2002; Volpp et al., 2006; Gallagher et al., 2007; Alessi and Petry, 2014; Drummond et al., 2014; Secades-Villa et al., 2014), one in villages served by community health workers (White, Dow and Rungruanghiranya, 2013), two in an academic institution (Tevyaw, Colby, Tidey, Kahler, et al., 2009; Ledgerwood et al., 2014), one in an urban community (Giné, Karlan and Zinman, 2010), and the rest in worksites. Worksites are a common CM intervention setting due to the structure of the American healthcare system which obliges employers to cover the healthcare costs of their employees. In other countries, where the state or private insurance covers healthcare costs, there is less incentive for employers to involve themselves with their employees' health.

The studies cover 8413 individuals, with sample sizes ranging from 45 (Alessi and Petry, 2014) to 2538 (Halpern et al., 2015). Importantly, most of the participants are employees from American companies that are predominantly white with relatively high levels of education and income. This may undermine the generalisability of the studies' results to other populations with different socio-economic, ethnic, and cultural mixes.

A variety of incentives were used in these studies. Three studies used lottery or raffle tickets as the incentive rewarding verified abstinence (Crowley, Macdonald and Walter, 1995; Alessi and Petry, 2014; Ledgerwood et al., 2014). Nine studies used cash payments as the incentive (Windsor and Lowe, 1988; Rand et al., 1989; Jason et al., 1995; Shoptaw et al., 2002; Volpp et al., 2006; Gallagher et al., 2007; Kim et al., 2009; Drummond et al., 2014; Halpern et al., 2015). Two studies (Glasgow et al., 1993; Hennrikus et al., 2002) combined cash payments with a grand-prize lottery draw with quitters eligible for entry. Six studies (Paxton, 1980, 1981, 1983; Giné, Karlan and Zinman, 2010; White, Dow and Rungruanghiranya, 2013; Halpern et al., 2015) used the system where participants deposit their own money at the beginning and are refunded after successful abstinence over the course of the programme.[3] In one VBRT study (Secades-Villa et al., 2014), subjects accumulated points for each successful abstinence test which could later be used as vouchers for goods and services. The magnitude of the rewards across studies ranged from $100 (Volpp et al., 2006) to $800 (Halpern et al., 2015).

The frequency at which subjects received rewards varied significantly. Some studies delivered incentives daily (Crowley, Macdonald and Walter, 1995; Jason et al., 1995; Tevyaw et al., 2009; Alessi and Petry, 2014; Ledgerwood et al., 2014) whereas Giné, Karlan and Zinman

[3]As part of their study, Halpern et al (2015) assessed the outcomes of cash reward versus participants being paid out from their own deposit accounts.

(2010) only provided an incentive at the end of the programme. Two different incentive schedules were used: a constant incentive schedule (Rand et al., 1989; Glasgow et al., 1993; Crowley, Macdonald and Walter, 1995; Jason et al., 1995; Hennrikus et al., 2002, Halpern et al., 2015), and an escalating incentive schedule (Shoptaw et al., 2002; Tevyaw et al., 2009; Drummond et al., 2014; Secades-Villa et al., 2014).

Only one study, Glasgow et al. (1993), did not provide participants any kind of additional support over and above the CM incentives. The other studies used a range of additional forms of encouragement to quit smoking. These included giving the participants brochures containing information on quitting tips and the dangers of smoking (Paxton, 1980, 1981, 1983; Windsor and Lowe, 1988; Rand et al., 1989; Crowley, Macdonald and Walter, 1995; Jason et al., 1995; Giné, Karlan and Zinman, 2010; Halpern et al., 2015), to nicotine replacement therapy (Crowley, Macdonald and Walter, 1995; Shoptaw et al., 2002; Volpp et al., 2006; Gallagher et al., 2007), and individual or group counselling (Hennrikus et al., 2002; Tevyaw et al., 2009; Alessi and Petry, 2014; Secades-Villa et al., 2014). Thirteen of the studies used multi-component support programmes, and some combination, therefore, of the smoking cessation programmes described above.

All the included studies used some form of biochemical verification. All but one, Rand et al. (1989), tested cotinine at baseline to confirm smoking status, and later to validate the subjects' claims of abstinence. Rand et al. (1989) only made use of CO testing while ten of the other trials used CO testing to supplement cotinine testing (Glasgow et al., 1993; Crowley, Macdonald and Walter, 1995; Jason et al., 1995; Shoptaw et al., 2002; Gallagher et al., 2007; Tevyaw et al., 2009; Alessi and Petry, 2014; Drummond et al., 2014; Ledgerwood et al., 2014; Secades-Villa et al., 2014).

All studies followed up with participants for at least six months from the beginning of the intervention. The period over which subjects could be rewarded for abstinence ranged from three weeks (Tevyaw et al., 2009), to one month (Paxton, 1980; Hennrikus et al., 2002; Alessi and Petry, 2014; Ledgerwood et al., 2014), six weeks (Secades-Villa et al., 2014), two months (Paxton, 1981; Crowley, Macdonald and Walter, 1995), seventy-five days (Volpp et al., 2006), three months (Shoptaw et al., 2002; White, Dow and Rungruanghiranya, 2013), four months (Paxton, 1983), six months (Windsor and Lowe, 1988; Rand et al., 1989; Jason et al., 1995; Gallagher et al., 2007; Giné, Karlan and Zinman, 2010; Drummond et al., 2014; Halpern et al., 2015), and one year (Glasgow et al., 1993; Kim et al., 2009).

I now consider to what extent the studies may have been biased. Potential sources of bias are important considerations when assessing the outcomes of interventions. Selection bias describes the bias that results from the treatment and control groups systematically differing in some important way. This bias can be mitigated if participants are randomly assigned to the control and treatment groups (Kendall, 2003). Every study except Paxton (1980, 1981, 1983) at least claim to have used a randomisation procedure. Of the studies using randomisation, seven conducted sequence generation and allocation concealment (Windsor and Lowe, 1988; Volpp et al., 2006; Kim et al., 2009; White, Dow and Rungruanghiranya, 2013; Drummond et al., 2014; Ledgerwood et al., 2014; Halpern et al., 2015), while four were found not to have implemented adequate allocation concealment (Shoptaw et al., 2002; Gallagher et al., 2007; Alessi and Petry, 2014; Secades-Villa et al., 2014). For the rest of the studies, they claimed to have used randomisation but details concerning how they were employed were not provided.

Performance bias occurs when the behaviour of those in the treatment group (or control group) is influenced by virtue of being in the treatment group (or control group). One way in which to alleviate this bias is through blinding, a protocol where participants' do not have their group allocation revealed to them (Kendall, 2003). Blinding participants and assessors is not emphasised among the studies, with only four (Crowley, Macdonald and Walter, 1995; Jason et al., 1995; Volpp et al., 2006; Tevyaw et al., 2009) making any attempt to do so. While blinding would reduce concerns of performance bias, rewards for abstinence typically reveal to participants which group they are in, rendering blinding futile.

Attrition bias is when there is a systematic difference between the treatment and control groups in terms of the number of participants leaving the experiment (Kendall, 2003). In terms of attrition bias, fifteen of the studies (Windsor and Lowe, 1988; Rand et al., 1989; Glasgow et al., 1993; Crowley, Macdonald and Walter, 1995; Jason et al., 1995; Volpp et al., 2006; Gallagher et al., 2007; Kim et al., 2009; Giné, Karlan and Zinman, 2010; White, Dow and Rungruanghiranya, 2013; Alessi and Petry, 2014; Secades-Villa et al., 2014; Drummond et al., 2014; Ledgerwood et al., 2014; Halpern et al., 2015) treated programme drop-outs and losses to follow-up as not abstinent. Of all the studies, only one (Rand et al., 1989) is deemed to be at high risk of attrition bias, with significantly more in the treatment group lost than in the control group.

Halpern et al. (2015) and Volpp et al. (2006) show promising results for the efficacy of CM interventions. At their last post-payment follow-ups,[4] sustained quit rates were significantly higher among the treatment group(s) compared to their control groups. Notably, among all studies, Halpern et al. (2015) offered subjects the highest rewards for testing abstinent as well as the largest sample sizes of over 400 subjects. The study on which this dissertation is based offered participants a far more modest reward. The other studies reviewed by CHP show that CM interventions often have a significant effect during the period when subjects earn rewards for abstinence, but thereafter differences between treatment and control groups are not

[4] Halpern et al. (2015) had their last follow-up session twelve months after the final reward payment. Volpp et al. (2006) had their last follow-up session six months after the final reward payment.

clinically significant.[5] Overall, the studies suggest that CM is an effective long-term cessation strategy only if the programme's rewards are substantial.

The CM studies discussed above show that there is a wide degree of variation in their setting, method, and outcomes. The studies look to see if CM programmes lead to higher long-term quit rates among smokers. The studies do not seek to explain the underlying reasons why within a study some subjects successfully abstain, and others fail. The following sections introduce ways in which to incorporate risk and time preferences, two characteristics unique to individuals that may offer an explanation.

C. Risk preferences

This section explores methods of eliciting individuals' risk preferences and provides a brief review of different estimation procedures. The elicited preferences are used to estimate the curvature of a utility function and sometimes, a probability weighting function. This section draws substantially on Harrison and Rutström (2008).

The first method to elicit risk preferences is the multiple price list (MPL) design. The earliest MPL design in the context of risk attitudes is Miller, Meyer and Lanzetta (1969) though instead of subjects being presented with alternatives on a single list, alternatives were presented individually over 100 trials. Other versions were developed, with that of Holt and Laury (HL, 2002) becoming the standard framework of many subsequent experimental designs.

[5] CHP, in their analysis of all 21 studies, report that cessation rates at the six-month follow-up are significantly greater among the treated, with an adjusted odds ratio (OR) of 1.72 (95% confidence interval 1.43 to 2.08). The cessation rate at each studies' *last* follow-up report is slightly lower, with an adjusted OR of 1.42 (95% CI 1.19 to 1.69).

Table 1: Holt and Laury (2002) MPL

Row	Lottery A	Lottery B	Expected payoff difference (A – B)
1	1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.10	$1.17
2	2/10 of $2.00, 8/10 of $1.60	2/10 of $3.85, 8/10 of $0.10	$0.83
3	3/10 of $2.00, 7/10 of $1.60	3/10 of $3.85, 7/10 of $0.10	$0.50
4	4/10 of $2.00, 6/10 of $1.60	4/10 of $3.85, 6/10 of $0.10	$0.16
5	5/10 of $2.00, 5/10 of $1.60	5/10 of $3.85, 5/10 of $0.10	-$0.18
6	6/10 of $2.00, 4/10 of $1.60	6/10 of $3.85, 4/10 of $0.10	-$0.51
7	7/10 of $2.00, 3/10 of $1.60	7/10 of $3.85, 3/10 of $0.10	-$0.85
8	8/10 of $2.00, 2/10 of $1.60	8/10 of $3.85, 2/10 of $0.10	-$1.18
9	9/10 of $2.00, 1/10 of $1.60	9/10 of $3.85, 1/10 of $0.10	-$1.52
10	10/10 of $2.00, 0/10 of $1.60	10/10 of $3.85, 0/10 of $0.10	-$1.85

HL's MPL table is presented Table 1. Descending the rows, subjects choose lottery A ("safe" lottery) or lottery B ("risky" lottery). The last row can be regarded as a test of whether the subject understood the instructions because lottery B clearly dominates lottery A. The lottery of interest is the one where the subject makes a "switch" from lottery A to lottery B. We would expect a risk neutral subject to switch from lottery A to lottery B where the expected payoff difference becomes negative, which first occurs on row 5 of Table 1. A risk averse subject would make the switch after the payoff difference becomes negative, and a risk seeking subject would make the switch before. Typically, only one row is randomly selected to be played out, lowering the experiment's cost while maintaining the subjects' incentive to maximize their earnings.

By putting some parametric structure on a subjects' utility function, we can use the subjects' pattern of choices to define upper and lower bounds on the risk preference parameter *r* of the power utility function:

$$U(y) = y^r \qquad (1)$$

where *y* is the outcome of the lottery, and the above function displays constant relative risk aversion (CRRA). As an example, assume a subject satisfies expected utility theory (EU) and chooses lottery A until row 6 and lottery B thereafter. The upper bound can be solved for using the following equation:

$$0.6(\$2)^r + 0.4(\$1.6)^r = 0.6(\$3.85)^r + 0.4(\$0.10)^r \approx 0.6$$

To calculate the lower bound:

$$0.7(\$2)^r + 0.3(\$1.6)^r = 0.7(\$3.85)^r + 0.3(\$0.10)^r \approx 0.3$$

This implies that the subject has a risk preference parameter *r* lying in the open interval (0.3, 0.6) if they choose lottery A until row 6 and lottery B thereafter. These elicited bounds may be appropriately analysed using interval regression.[6]

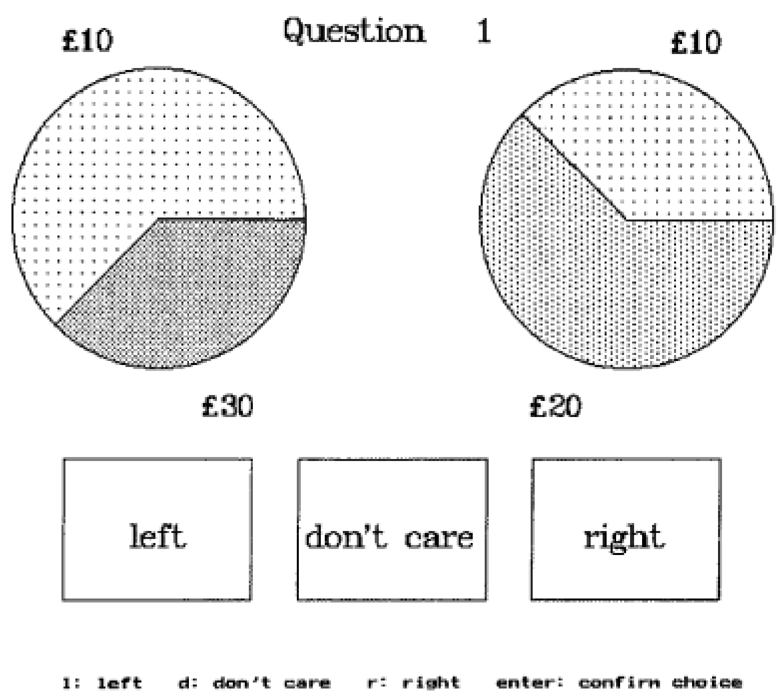
MPLs have the advantage of being simple: subjects usually understand the logic, allowing them to respond in a way that accurately reflects their risk preferences. Another consistent feature is that the respondents see all choices in a single ordered table. Subjects may use the table to compare their current choice against their past choices, possibly leading them to make choices more consistent than they would be in settings without their past choices available for them to see. However, despite subjects being able to refer to their previous choices, subjects still often make inconsistent choices by selecting multiple switch points. Andersen et al. (2006) argue

[6] Hofmeyr (2015) criticises the approach that uses the midpoint of the interval, e.g., 0.45 in this case, arguing that doing so discards useful information regarding the uncertainty of the parameter estimates.

that multiple switch points may indicate indifference between the choices as MPLs typically do not have an option to signify indifference.

The Random Lottery Pair (RLP) design, developed by Hey and Orme (1994), is another method used to elicit preferences which can then be estimated parametrically or non-parametrically. It is the risk preference elicitation method used for this dissertation. An RLP asks subjects to make binary choices over lottery pairs, in which probabilities vary for a set of monetary prizes of, say, R0, R100, R200 or R300 (Harrison and Rutström, 2008). An example of one lottery choice, from Hey and Orme (1994), is presented in Figure 1.

Figure 1: Lottery display used by Hey and Orme (1994)



Subjects may express preference for one lottery over the other or indifference. The lotteries are presented on computer screens, with pie charts representing the prizes and probabilities in the lotteries. Typically, only one of the lottery choices is randomly picked to be played out which promotes incentive compatibility while lowering overall costs. The main advantage of RLP is how easy it is to explain to subjects. However, unlike MPL, it is not possible to directly infer risk attitudes from the pattern of responses, so some form of estimation is required (Hey and Orme, 1994; Harrison and Rutström, 2008).

Titration is another method used for eliciting risk preferences. Richards et al. (RZMW, 1999) popularized the method in their paper that looked at the effect that addictive drugs have on impulsive decision-making.

In titration, participants are given a series of choices between a small certain amount of money, or \$10 with a probability of receipt of 1.0, 0.9, 0.75, 0.5 or 0.25. The certain amount of money is adjusted across successive trials until a certainty equivalent is found, where the subject is indifferent between the smaller but certain amount and the risky \$10. Certainty equivalents are elicited for each of the five probabilities using a random adjusting-amount procedure (Richards et al., 1999). The answer to the previous question is used to narrow the range of values from which the next question is selected. In the first trial for one of the five probabilities, the variable amount is randomly selected to be anywhere between \$0 and \$10 in \$0.50 increments. The variable amount in the next trial adjusts according to the response from the current trial. Suppose a subject was asked to choose between a certain \$4 or \$10 with probability 0.5, and the subject chooses the certain amount. The variable amount in the next trial will be an amount (in \$0.50 increments) between \$0 and \$4.[7] If the subject is presented with a choice of \$3 for sure, or \$10 with a probability of 0.5, and the subject chooses the latter, the certainty equivalent is calculated as \$3.50. That is, the subject is found to be indifferent between a certain \$3.50 and a 50/50 chance of getting \$10 or \$0. The process of choosing between adjusting certain amounts and lotteries repeats across trials until the certainty equivalent is calculated for each probability (Richards et al., 1999).

[7] Had the subject preferred the \$10 lottery instead, the variable amount in the following trial would be some amount between \$4 and \$10.

Titration has at least two issues. The first is that if a subject makes a mistake, it becomes impossible to recover the subject's true indifference point. That mistake will be incorporated into the algorithm that determines the following set of choices (Hofmeyr, 2015). The second is an incentive-compatibility issue. A subject that realizes that their future choices depend on their current choices can 'game' the mechanism so that they are offered higher rewards on subsequent decisions. Let's suppose a subject chooses between $4 for sure, and $10 with probability 0.5. If the subject chooses the gamble, the subsequent decision will involve certain amounts higher than $4. If the next certain amount is $7 and the subject again chooses the gamble, the next certain amount will be an amount greater than $7. A subject with a true indifference point of $3.50 has thus increased their expected reward by misrepresenting their preferences (Hofmeyr, 2015).

There are ways in which these issues can be overcome. The first issue can be overcome by using two top and two bottom limits rather than just one top limit ($10 in the previous example) and one bottom limit ($4 in the previous example). By using multiple top and bottom limits, as RMZW do, the subject's indifference point can be elicited even after a mistake (Richards et al., 1999).

When the experiment is a combination of both risk and time preference elicitation tasks, the adjustment algorithm can be hidden (to a degree) from subjects by mixing risk and time preference decisions. Distractor trials are also often presented: trials with responses that are not recorded and with parameters not determined by previous responses. Like mixing tasks, the distractor trials hopefully prevent subjects from figuring out the algorithm. However the drawback is that it makes the task more complex and increases the cognitive burden required to complete it (Richards et al., 1999).

Risk attitudes can be estimated from observed behaviour using the two main procedures mentioned above. The first approach is to calculate bounds based on the observed choices from a risk preference elicitation method, typically using utility functions which only have a single parameter to be inferred. The second and preferred method is to directly estimate risk attitudes by maximum likelihood.[8] This method, used by Hey and Orme (1994), is useful for non-EU specifications, where several core parameters combine to determine risk attitudes.

D. Time preferences

People tend to prefer receiving an amount of money sooner rather than later. One of the earliest treatments of this behavioural trait is due to Samuelson (1937), where he proposed the discounted utility model. The model was rapidly accepted as both a standard for public policies (e.g., in cost-benefit analysis), and also as an accurate depiction of real-life behaviour (Frederick, Loewenstein and O'Donoghue, 2002). However, despite its appealing mathematical tractability, by the 1950s the model's assertion of time-consistent preferences led to alternative models such as Phelps and Pollak's (1968) quasi-hyperbolic (QH) discounting function and Mazur's (1987) hyperbolic discounting function. Describing each model is important as each proposes a unique conceptualization of the decision-making process. As I use all three functions in my later analysis, I will discuss each, drawing from Andersen, Harrison, Lau and Rutström (2014).

However, before discussing the different discounting functions, I will explain the relationship between the discount factor D and the utility function $U(\cdot)$. D is the scalar, for a particular time horizon τ, which equates the utility of income (y) received at time t with the utility of income received at time $t + \tau$:

$$U(y_t)=DU(y_{t+\tau}) \tag{2}$$

[8] Discussed further in the next section addressing time preferences.

If we assume $U(\cdot)$ is linear in y then D is the discount factor that equalises income received at time t with income received at time $t + \tau$.

Samuelson's (1937) discounted utility model uses the exponential discount factor:

$$D^E(t) = 1/(1+\delta)^t \tag{3}$$

For $t \geq 0$ and where the discount rate d is:

$$d^E(t) = \delta \tag{4}$$

The model has two useful features. First, it is mathematically tractable as the geometric series $\sum_t D^E(t)$ converges in the limit. Second, the discount rate $d^E(t)$ is constant over time, thus implying time-consistent preferences.

The exponential discounting function’s property of time-consistent preferences contrasts with other models, the first of which I discuss is Phelps and Pollak's (1968) QH discounting function:

$$D^{QH}(t) = 1 \qquad if \qquad t = 0 \tag{5}$$

$$D^{QH}(t) = \beta / (1 + \delta)^t \quad if \qquad t > 0 \tag{6}$$

The QH model accounts for present bias in discounting behaviour and time inconsistency.[9] That is, preferences over future options can change depending on the point in time at which these future options are evaluated. The QH model incorporates the tendency for people to prefer, as an example, R100 today to R105 tomorrow but prefer R105 in 31 days to R100 in 30 days. In other words, the rate of discounting decreases as rewards are delayed further in the future. If $\beta = 1$ the QH specification collapses to the exponential model, whereas if $\beta < 1$ discounting is quasi-hyperbolic.

[9] Present bias refers to people’s tendency to more strongly weight payoffs that are closer to the present time when considering trade-offs between two future moments (O’Donoghue and Rabin, 1999).

The discount rate in the QH model is the value of $d^{QH}(t)$ which solves $D^{QH}(t) = 1 / (1 + d^{QH})^t$. Thus,

$$d^{QH}(t) = [\ \beta / (1 + \delta)^t]^{(-1/t)} - 1 \tag{7}$$

For $t > 0$, present bias manifests itself when $\beta < 1$ as there is a sharp drop in the value of a reward if it is not available immediately. The extent of this drop in the reward's value declines over time as the discount rate asymptotes towards δ (Phelps and Pollak, 1968; Hofmeyr, 2015).

Loewenstein (1996) attributes present biased preferences to 'visceral factors' – feelings of hunger, thirst, sexual desire, and addiction-caused cravings. He argues that people underweight and ignore visceral factors that will be experienced in the future, leading to inconsistent choice behaviour (Loewenstein, 1996).

The hyperbolic specification has a discount factor:

$$D^H(t) = 1 / (1 + \delta t) \tag{8}$$

Unlike the previous two discounting specifications, the harmonic series does not converge making the hyperbolic function not as popular in the economics literature. However, because quasi-hyperbolic discounting received wider usage only after Laibson (1997), much of the available literature, particularly in psychology, has made use of the hyperbolic function. The discount rate for this model is:

$$D^H(t) = (1 + \delta t)^{1/t} - 1 \tag{9}$$

The discount rate declines over time and thus allows time-inconsistent preferences under the assumption of an additively-separable intertemporal utility function (Mazur, 1987).

The dominant methods for eliciting time preferences are similar to the elicitation methods for risk preferences. The methods can be divided into two main types: choice-based and titration, of which the latter is an extension of the former.

Choice-based methods present participants with a series of choices between a larger, later (LL) and a smaller, sooner (SS) reward. The presented choices often offer real rewards but can also be hypothetical. Real rewards provide a more reliable revelation of the participant's preferences as hypothetical rewards are not incentive compatible, but some studies have argued that hypothetical rewards are a dependable proxy (Madden et al., 2003). Typically, at the end of the experiment one of the subject's choices is randomly selected for payment.

The choices between SS and LL rewards can be organized from lowest to highest implied discount rates or the order of presentation can be random. The more choices presented to subjects, the more accurate the elicited discount rate can be, in principle. Another important consideration in the development of a time preference task is the inclusion of a front-end delay (FED) to the SS reward. Prior to Coller and Williams (1999), the SS reward was always immediate. However, at least some of the subjects' preference for SS rewards may be due to transaction costs and uncertainty associated with the receipt of the LL reward. When the SS reward is not immediate, i.e., a positive FED, these issues are negated. Thus, an FED holds these costs constant across the two rewards (Hofmeyr, 2015).

The titration procedure builds upon the choice-based method and works in much the same way as the procedure to elicit risk preferences. An algorithm is used so that when a subject makes a choice between SS and LL, that choice then determines the subsequent SS and LL choices the subject faces. Titration narrows down the subject's indifference point for a particular delay period (Hofmeyr, 2015).

As an example, if a subject chooses $10 after 7 days over $5 now, the algorithm assumes that $10 after 7 days will be chosen over all amounts less than $5 available now. Thus, the search interval for the subject's indifference point will be narrowed to between $5 and $10. The difference is often split so that the next choice will be between $10 in 7 days or $7.50 now. If the subject chooses $7.50 now, the next question's SS reward will be narrowed to between $5 and $7.50. If the subject instead chose the $10, the next question will offer an SS reward between $7.50 and $10. This algorithm continues until it converges upon an open interval containing the subject's indifference point (Hofmeyr, 2015).

The indifference points can then be fitted to a discounting function (Hofmeyr, 2015). However, taking the average value between the two SS rewards from the titration procedure arbitrarily discards information regarding the uncertainty of the estimate. All that one can infer from the pattern of choices is that an indifference point lies in the open interval, for example ($7.50, $8). Taking the average of these values, e.g., $7.75, should not be used for making statistical inferences.

Similar to the procedure used to elicit risk preferences, the nature of the algorithm means that titration cannot find a subject's true indifference point if the subject makes a mistake. The other issue mentioned earlier is that the subject can 'game' the system to earn higher rewards (Hofmeyr, 2015).

There are a few statistical methods in which time preference data may be analysed, with maximum likelihood estimation and the area under the curve (AUC) method being the two most prominent in literature relating time preferences to CM interventions. As it is the method used in this dissertation, I will provide a detailed discussion of maximum likelihood estimation in the statistical methodology section.

The AUC method, introduced by Myerson, Green and Warusawitharana (2001), differs to the maximum likelihood method in that it does not assume that discounting follows a particular theoretical framework, such as the exponential discounting function. Consequently, the method is regarded as "theoretically neutral" as it avoids the potential problems created by the lack of consensus regarding the mathematical form of the discounting function. The method also avoids the statistical problems created by skewed distributions.

Figure 2: Calculation of the area under the empirical discounting function (Myerson, Green and Warusawitharana, 2001)

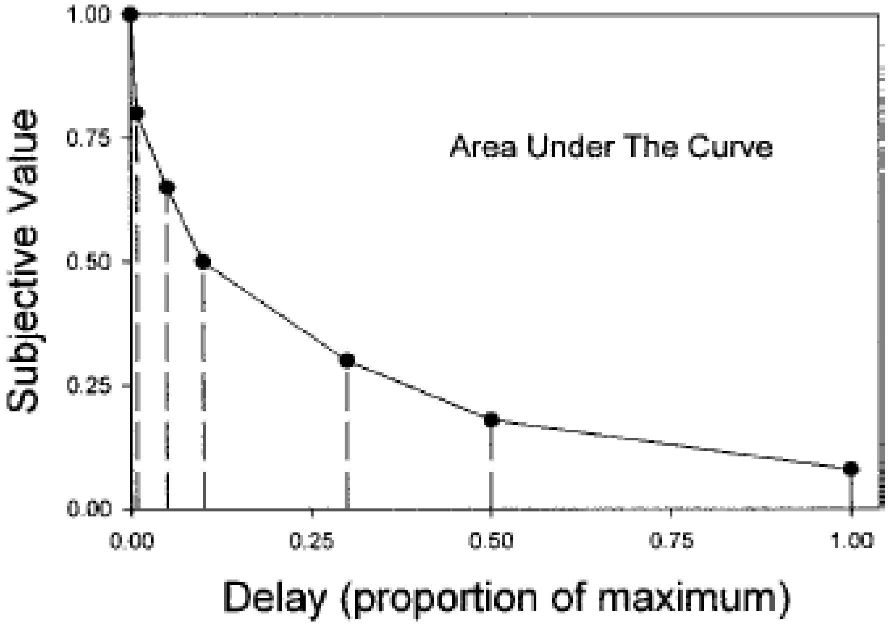


Figure 2 represents the AUC with a plot, where the y-axis represents the 'normalized subjective value' for each data point and the x-axis represents the 'normalized delay.' The plot shows the delay discounting data for a single subject, with the data being point estimates of the indifference values taken from a delay discounting task. The subjective value is normalized by dividing the subjective value by the actual delayed amount. The delay is normalized by expressing the delay as a proportion of the maximum delay. A curve can then be constructed by plotting the subjective values against the respective delays. Vertical lines are drawn from each data point on the x-axis, subdividing the graph into a series of trapezoids. The sum of the areas of these trapezoids gives the area under the empirical discounting function. The steeper the discounting, the smaller will be the area under the curve. Because the x and y values are normalized, the area under the curve can vary between 0.0 (steepest possible discounting) to 1.0 (no discounting) (Myerson, Green and Warusawitharana, 2001).

While AUC does have the advantage of being theoretically neutral, its use of point estimates is a major drawback. We can compare the AUCs of the two groups, but we cannot use valid statistical methods to test hypotheses that the AUCs of the two groups are different (Harrison et al., 2018). Maximum likelihood estimation, which will be discussed in the section addressing statistical methodology, avoids this use of point estimates when drawing inferences.

E. Risk preferences, time preferences, and smoking cessation

Of the 21 smoking CM studies reviewed in CHP, none investigated the effect of subjects' risk and time preferences on the programme's success. In this section I review CM studies that address subjects' risk and time preferences. Of particular importance are Krishnan-Sarin et al. (2007), Dallery, Raiff and Grabinski (2015), González-Roz et al. (2019), and Weidberg et al. (2015), as they look at smoking CM interventions whereas Stanger et al. (2012) and Washio, et al. (2011) look at other substance addictions. The discussed studies were searched for in Google Scholar, EBSCOhost and PubMed using the search terms 'contingency management', 'time preferences', 'risk preferences', 'delay discounting', 'probability discounting', 'smoking', and 'tobacco.' Surprisingly, no papers were found that sought to investigate the link between CM programmes and risk preferences.

Stanger et al. (2012) conducted a CM study among adolescent marijuana abusers or dependent users and tested whether delay discounting is a predictor of treatment outcome. All participants received one of three 14-week treatments. The first was cognitive behaviour therapy (CBT) only, the second was CBT and CM, and the third was CBT, CM and a Family Management Curriculum.[10] The CM programme used an escalating reward schedule with a reset contingency if subjects tested positive for marijuana use. Participants in the CM programme could earn a

[10] The Family Management Curriculum is received during weekly counselling sessions and covers identifying and labelling adolescent behaviour, developing incentives and consequences for change, limit-setting, monitoring, and relationship skills. For further reading see Dishion, Nelson and Kavanagh (2003).

maximum of $590 over the 14-week period. Substance use was validated biochemically twice a week using urine tests. There was no post-treatment follow-up to check the long-term effectiveness of the CM programme (Stanger et al., 2012).

Stanger et al. (2012) used a titration method for their delay discounting task with delay periods of 1 day, 1 week, 1 month, and 6 months. They did not elicit risk preferences. The rewards were hypothetical amounts of money or amounts of marijuana. A hyperbolic discounting function was used to estimate the discount rate. The method in which the elicited data was fitted was not mentioned but presumably they employed nonlinear least squares.

The study found lower delay discounting to predict both a higher number of negative drug tests and a longer period of continuous abstinence. The discount rates elicited from the high money amount ($1000) were a better predictor of marijuana abstinence than the discount rates elicited from the low money amount ($100). Interestingly, the discount rates elicited from delay discounting tasks involving marijuana did not predict marijuana abstinence (Stanger et al, 2012).

Looking at cocaine dependent subjects, Washio et al. (2011) implemented a study examining whether delay discounting is associated with the duration of cocaine abstinence. The participants consisted of 36 adults equally divided into 'low CM reward' and 'high CM reward' groups. Treatment occurred over a period of 24 weeks.

The CM programme used VBRT, but the magnitudes of the rewards in the 'low CM reward' and the 'high CM reward' treatments nor the reward schedule, were mentioned in the paper. In addition to the CM programme, subjects also received additional information regarding the Community Reinforcement Approach.[11] Participants were only rewarded for testing negative

[11] The Community Reinforcement Approach is a comprehensive behavioural treatment package that focuses on the management of substance-related behaviours and other disrupted life areas. The programme's goal is to

for cocaine use. Urine specimens were collected from all study participants according to a thrice-weekly schedule, with specimens screened immediately on-site.

The delay discounting task used a titration method, asking subjects to choose between an immediate SS and a LL ($1000) reward that could be received 1 day, 1 week, 1 month, 6 months, 1 year, 5 years, or 25 years in the future. The amounts were hypothetical and the procedure did not utilize a FED. A non-linear regression was used to fit each participant's indifference points to the hyperbolic model.

Regression analyses showed delay discounting to be statistically significantly related to the duration of continuous cocaine abstinence, with higher discounting predicting a lower likelihood of abstinence. Additionally, participants receiving the higher magnitude vouchers on average achieved an additional 6.3 weeks longer abstinence than those receiving the lower magnitude vouchers. Importantly, participants were not followed up after the treatment period.

As mentioned above, while there is substantial literature concerning smoking CM interventions, there is little delving into its relationship with participants' risk and time preferences. Dallery, Raiff and Grabinski (2015) carried out an internet-based smoking CM study. The primary objective was to evaluate the efficacy of internet-based CM to promote smoking cessation. A secondary objective was to assess predictors of outcomes during treatment based on demographics, smoking characteristics, and individual differences in time preferences.

The participants were 77 smokers between the ages of 18 and 60 who had smoked for at least 2 years and smoked at least 10 cigarettes per day. The participants also had to express a desire to quit smoking. Applicants were excluded if they were addicted to any other substance or

substitute a lifestyle involving the use of addictive goods with activities related to a pleasurable and healthy lifestyle. For further reading see Miller, Meyers and Hiller-Sturmhöfel (2003).

reported a history of psychiatric or medical illness that could interfere with the study. Participants were screened in-person. The study took place over a period of 24 weeks with no follow-ups after treatment.

The CM programme made use of VBRT, with participants earning a maximum of $530.00 in voucher earnings. The rewards escalated with successive negative CO readings. The study used a two-group RCT with the difference between the two groups being whether the vouchers were delivered contingently or noncontingently, based on smoking abstinence. The main treatment phase occurred over 21 days with CO test submissions made twice daily. Those in the noncontingent group were matched with someone in the contingent group and only received a voucher when the person that they were matched with received a voucher. To earn vouchers, noncontingent participants still had to submit CO readings. For participants from both groups, the subjects recorded their own CO readings on video which were then submitted to an online application. From these recordings the participants would earn rewards, with readings less than 4ppm considered negative. After the main treatment phase, test submissions and voucher delivery were decreased to twice a week.

The delay discounting task used a titration method and hypothetical money amounts with an adjusting SS amount and $100 LL amount that could be 'received' after 1 week, 2 weeks, 1 month, 4 months, 8 months, 1 year, 5 years, and 10 years, presented in random order. To measure the extent of delay discounting Dallery, Raiff and Grabinski (2015) adopted the AUC approach. It is not apparent whether a FED was used.

The study's results suggest that internet-based CM can promote abstinence. The median percentages of negative samples in the control and treatment groups were 25% and 67% respectively.[12] Interestingly, over the course of the programme the noncontingent group saw its

[12] A two-sided Mann-Whitney test yielded a statistically significant difference ($p = 0.048$).

average CO levels decline despite not being rewarded for abstinence. The study found higher discount rates to be marginally associated with a lower likelihood of abstinence, suggesting attempts to tailor CM programmes to the subjects' discount rates may not work. However given the paper's lack of emphasis on delay discounting's relationship to quitting smoking, reasons for this weak relationship were not explored (Dallery, Raiff and Grabinski, 2015).

Krishnan-Sarin et al. (2007) examined the relationship between impulsivity and smoking cessation treatment response among adolescents. The study involved 30 subjects between 14-18 years old, smoking at least 10 cigarettes a day, and wanting to quit smoking. Participants with diagnosed major depressive disorder were excluded from the study. The intervention was conducted in a school.

The CM programme took place over 4 weeks. Participants were divided into two groups: the treatment group received CBT and CM while the control group received CBT alone. Participants were randomly assigned to either group. CO levels were measured twice a day in the first two weeks, once a day in the third week, and once every other day in the fourth week. Participants in the treatment group were subject to an escalating reinforcement schedule with a reset contingency, with $1 for the first CO level that was below 8ppm and increments of 25 cents for each successive negative test result. Moreover, subjects received a non-escalating $5 for providing a negative result on a urine cotinine test, presumably to incentivize participants to take the more invasive but more reliable test. Participants in the treatment group could earn up to $313.75 over the 1-month programme (Krishnan-Sarin et al., 2006; Krishnan-Sarin et al., 2007).

Time preferences were measured before the participants' quit date. Measurements were made using the Barratt Impulsiveness Scale-11 (Patton, Stanford and Barratt, 1995), a choice-based delay discounting task using hypothetical amounts of money, and an "experiential discounting task" that used small amounts of real money and short time delays (Reynolds and Schiffbauer, 2005). The Conners' Continuous Performance Test-II was also used to measure the subjects' level of impulsivity (Conners, 2000). For the choice-based delay discounting task and experiential discounting task, the data were analysed by calculating the AUC directly from the indifference point values.

In terms of the experiential discounting task, non-abstinent participants discounted more heavily than abstinent subjects, on average. No significant differences were observed on other discounting/impulsivity measures (Krishnan-Sarin et al., 2007).

González-Roz et al. (2019) looked to identify clusters of treatment-seeking smokers, and to see if these clusters responded differently to CM treatment. Two clusters were identified, the first being characterized by participants with excessive tobacco demand and the second with steep delay discounting. The study used the combined data from two previous smoking cessation trials, one an 8-week programme and the other a 6-week programme (Secades-Villa et al., 2014; González-Roz el al., 2019). Accordingly, the number of participants was relatively high, comprising 305 treatment-seeking smokers. For inclusion, participants had to be aged 18 or over, smoke at least 10 cigarettes per day, and meet the diagnosis of nicotine dependence. Individuals who reported mental health issues and/or abuse of a substance other than nicotine were excluded.

Both CM programmes had a control group that received CBT and a treatment group that received CBT and CM. The CM reward schedule was escalating, with participants potentially earning up to \$307 or \$342 depending on the cessation trial. Along with self-reports, abstinence was confirmed biochemically with CO readings ≤ 4ppm and cotinine levels ≤ 80ng/mL. At both the post-treatment and 6-month follow-up, neither study found statistically significant evidence that would suggest CBT and CM is a more effective strategy at bringing about smoking cessation than CBT alone.

Time preferences were elicited 1 week before treatment began.[13] Participants were tasked to make a series of choices between hypothetical SS amounts of money (but subject to a FED), and hypothetical LL amounts of money available 1 day, 1 week, 1 month, 6 months, 5 years, or 25 years after the SS reward is available. The choices that were presented to participants were determined by a titration procedure. The discount rates were measured by an AUC method and separate binary regression analyses were performed for assessing the treatment response (i.e. abstinent vs. smoker) at the posttreatment and 6-month follow-up, broken down by treatment condition.

González-Roz et al. (2019) found there to be similar short-term and long-term cessation rates between the control and treatment groups, regardless of cluster membership. However, smokers in the "steep discounting" cluster were likelier to quit smoking than smokers in the "excessive tobacco valuation" cluster

Weidberg et al. (2015) took a different approach to assessing the relationship between CM and time preferences, instead looking at whether over time CM influences subjects' level of delay discounting. Their study comprised 123 adults, smoking at least 10 cigarettes a day, and looking for treatment to quit smoking. The participants were randomly assigned into a CBT only control group and a CBT + CM treatment group. The intervention period was 6 weeks, with a follow-up 6 months after the intervention period. Participants were tested for cotinine once weekly. Participants that tested abstinent were rewarded according to an escalating VBRT

[13] The participants' levels of cigarette demand were elicited using a cigarette purchase task. For details, see González-Roz et al. (2019).

schedule with a reset contingency. The maximum amount that participants could earn was €300.

The delay discounting task was presented to participants at intake, end-of-treatment, and at the 6-month follow-up. A titration procedure was used with delays of 1 day, 1 week, 1 month, 6 months, 1 year, 5 years, and 25 years. The fixed amount was €1000 with the rewards being hypothetical. The elicited data was analysed using both AUC and by using a non-linear regression model to estimate a hyperbolic discounting equation.

Weidberg et al. (2015) found there to be no significant differences between the treatment and control groups' change in delay discounting over the six-week and six-month periods. They also found that treatment led to higher rates of abstinence than those in the control group. The study did not explore whether an individual's discount rate affects the likelihood of CM being a successful smoking cessation strategy.

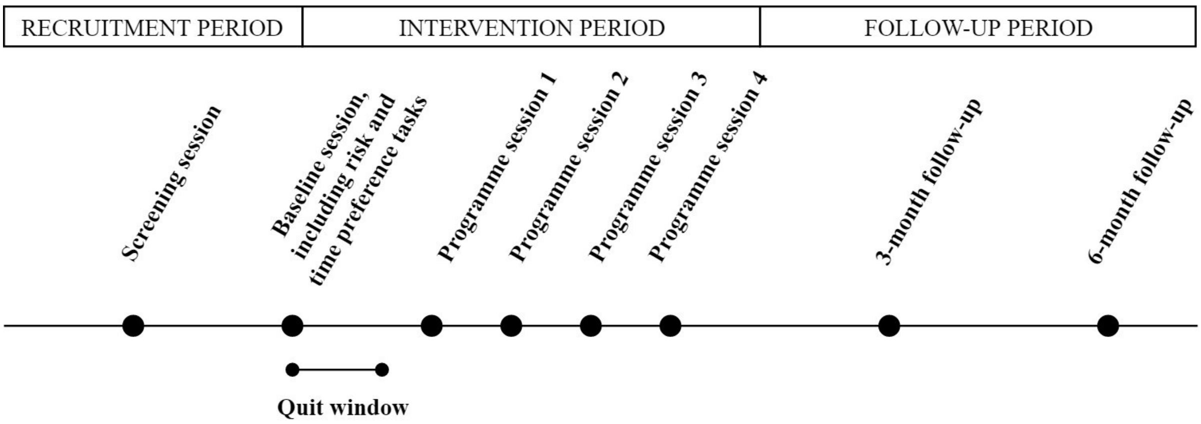
These studies generally suggest that there is a relationship between participants' time preferences and CM intervention success. This dissertation's approach will differ in a few significant respects. First, I will incorporate risk preferences in the estimation of time preferences by using the joint estimation technique of Andersen et al. (2008). Second, the sample size is larger than most of the aforementioned studies (87 subjects). Third, the rewards offered in the risk and time preference tasks were real rather than hypothetical, adding to the robustness of this dissertation's findings. Interestingly, none of the literature discussed in this section used real rewards. This may be because, as discussed earlier, in the context of risk and time preference tasks, hypothetical rewards have been argued to be reliable proxies for real rewards. However, hypothetical rewards cannot be incentive compatible. Fourth, the participants are followed up over a longer period (6 months), which provides a better indicator of the programme's long-term success. Fifth, this study's delay discounting task made use of a

FED. Sixth, this study examines the effect of risk and time preferences on smoking intensity too, an aspect the other studies have neglected.

3. Design and Methods

In this section, I discuss the CM smoking cessation programme, and the risk and time preference elicitation tasks that were conducted during the CM programme's baseline session. Figure 3 provides an overview of the study.

Figure 3: Study overview



A. Recruitment and Screening

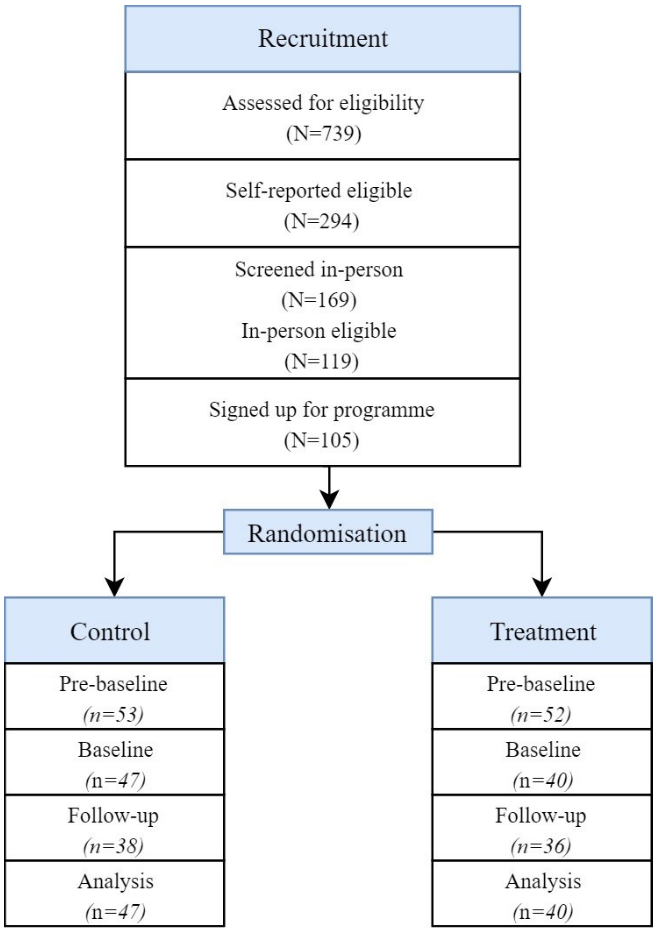
Recruitment commenced once ethics approval[14] was granted to conduct the study and permission to access students had been secured. Participants were recruited via an email sent to UCT's central email list. The email provided an outline of the intended research and provided information to prospective subjects about the expected time burden and potential earnings from taking part. Prospective subjects were screened with a questionnaire that collected their

[14] Ethics approval reference: REC/2017/05/002

demographic information, smoking patterns, and whether they were interested in quitting smoking.[15]

Of the 700 students that responded to the questionnaire, 294 were deemed eligible for the next stage of screening based on their self-reported information. Inclusion criteria were: participants had to express an interest in quitting smoking; had to be at least 18 years old and a UCT student; smoked at least 100 cigarettes in their lifetime; smoked in the 10 hours prior to recruitment; smoked at least five cigarettes a day; and had a CO reading of at least 8 ppm. Figure 4 shows the participant induction and attrition over each stage of the experiment.

Figure 4: Flow chart showing the number of participants through each stage of the study



[15] The initial screening measure was done to reduce the time and cost burden of the subsequent in-person screening sessions

These eligible students were invited to sign up for an in-person screening session via an announcement sent through the university's virtual learning environment (VLE). The announcement also explained that the screening session would take about 15-minutes,[16] and students would earn a R50 show-up fee. Of the 294 students that were contacted, 169 signed up for and attended a screening session. Students were reminded of their session via an email and two SMS-reminders.

In the screening session, after the prospective participants gave written informed consent, one of two research assistants (RAs)[17] verbally went through and recorded the participants' responses to the same questionnaire completed prior to the in-person screening session. A CO reading was also taken to determine the students' smoking status. Of the 169 students who attended the screening sessions, 119 were eligible for the baseline session. These students were invited to sign up for the baseline session via the VLE. Of the 119 eligible students, 105 signed up for the baseline session.

B. Randomisation

Randomisation into the treatment (n = 52) or control group (n=53) was done using stratified random assignment (Glennerster and Takavarasha, 2013: 153–158). The stratification variables were gender, race, and CO reading.

C. Baseline

The baseline sessions consisted of two components: the collection of baseline data on the subjects' smoking characteristics, and the elicitation of the subjects' risk and time preferences. The seven sessions were run between 14-18 August 2017 in a computer lab at UCT. To ensure

[16] Screening sessions were scheduled between 09:00-12:00 and 13:00-17:00 so that students could attend without lecture clashes. The same approach was adopted for the programme and follow-up sessions.
[17] The number of RAs was limited to two so as to better ensure consistency across sessions.

consistency, a single researcher with the help of three research assistants (RAs) conducted the sessions.

The baseline sessions lasted two hours on average, making it the longest of all the sessions. Subjects were reminded of the session with an email and two SMSs. The component collecting the subjects' baseline smoking characteristics was first done in groups and then individually. The component eliciting risk and time preferences was done in groups. The average group size was 13 subjects.

Upon arrival to the lab, subjects were randomly allocated to computer terminals separated by partitions. Subjects were instructed to not communicate with each other, and they provided written informed consent. Thereafter the researcher delivered a detailed explanation of what the study would entail with subjects then signing up for the programme sessions through the university's VLE.

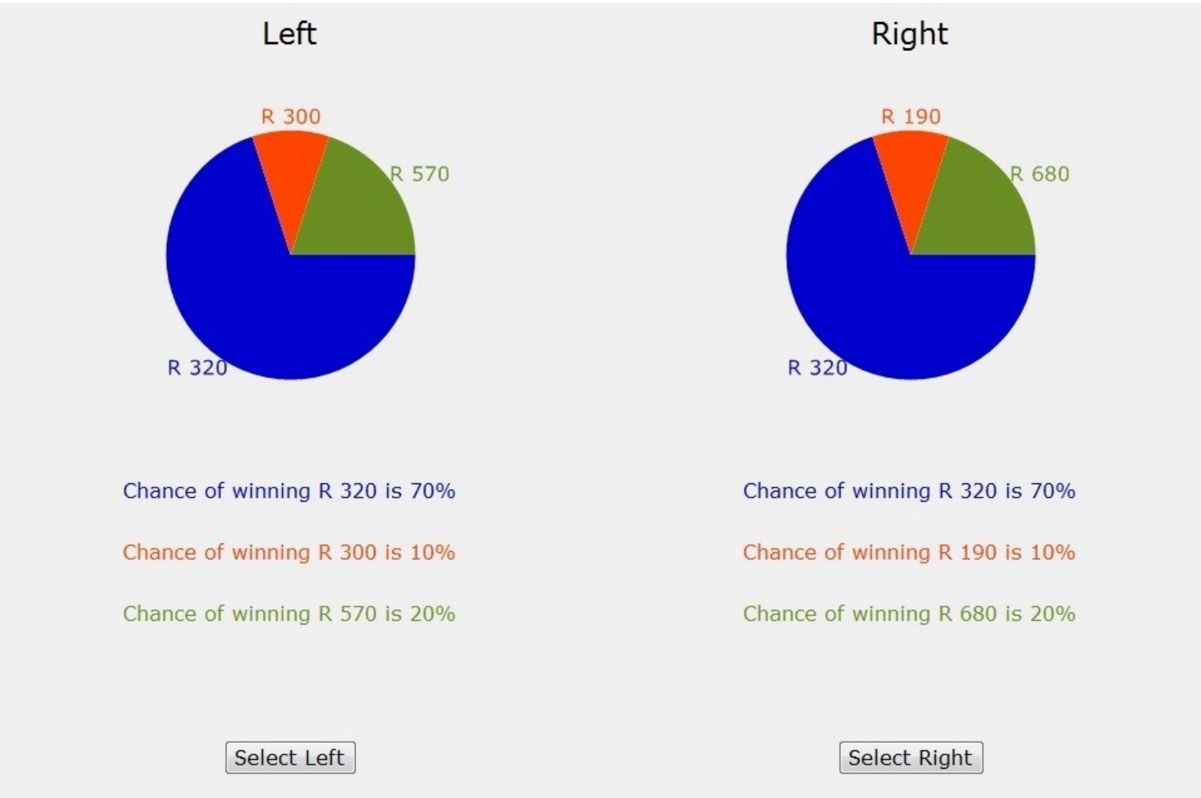
Following sign-up, participants completed the risk and time preferences tasks. Subjects were given both written and audio-visual instructions for the tasks. Once a subject had finished these instructions and familiarised themselves with the screen-based decision-making environment, the subject raised their hand to receive permission to complete the task. Subjects were permitted to ask questions at any time. The order of the tasks alternated between sessions such that subjects either performed the risk or time preference task first. Subjects finished the first task at their own pace, and once completed, went through the written and audio-visual instructions before completing the second task. They then completed the second task before responding to a questionnaire collecting information on their demographic characteristics and smoking behaviour.

After completing the risk preference task, a subject rolled two 10-sided dice to randomly select one of the choices that were made, and then rolled the two 10-sided dice again to resolve the selected lottery. After completing the time preference task, a subject rolled a 4-sided die and a 10-sided die to randomly select one of the choices that was made. The show-up fee and the earnings from the risk preference task were paid immediately in cash, and earnings from the time preference task were paid out on the date corresponding to the subject's choices on the randomly selected question. The risk preference task, on average, took subjects 20 minutes to complete and yielded R226 in earnings. Correspondingly, the time preference task, on average, took subjects 10 minutes to complete and yielded R331 in earnings.

Risk preference task

The risk preference task followed Hey and Orme (1994), with an example of the interface displayed in Figure 5:

Figure 5: Risk preference task interface



Subjects were presented with a choice between two lotteries displayed on a computer screen. The lottery pairs were drawn from the designs of Wakker, Erev and Weber (1994), Loomes and Sugden (1998), Cox and Sadiraj (2008), and Harrison, Martínez-Correa and Swarthout (2015). For each lottery pair, the corresponding amounts and probabilities were shown. Subjects made 90 lottery pair choices and then a dice was used to randomly select one choice for payment.

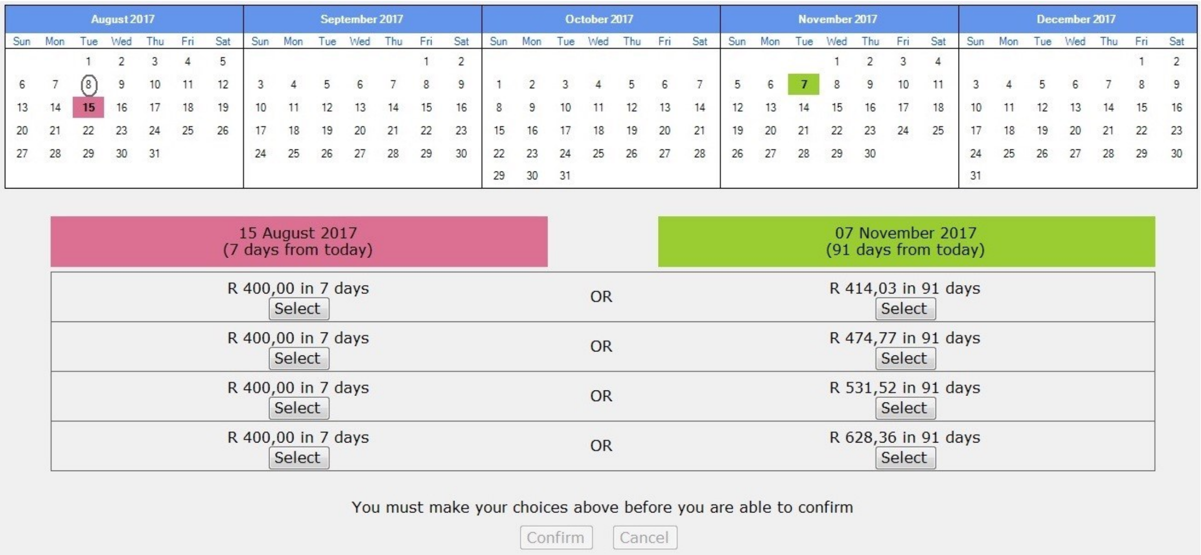
The lottery pairs captured the full range of risk preferences (i.e., risk averse, risk neutral, and risk loving), provided good coverage of the probability space[18], and facilitated the estimation of non-EU models of choice under risk. The lotteries subjects faced were drawn randomly, without replacement, from the battery of lottery pairs, and presented to subjects sequentially. The prizes varied in magnitude between R0 - R700, with the probabilities varying between 0 and 1 in increments of 0.05.

Time preference task

Time preferences were elicited by asking subjects to choose between a series of SS and LL rewards. As shown in Figure 6, 4 choices were presented on a screen at a time. Once the subject had made their choices on a screen, another set of 4 choices were presented on the next screen. The SS reward was fixed on each screen but varied across screens. A calendar was also displayed as a visual aid for subjects, showing when they would be receiving the amount they chose.

[18] See Appendix A

Figure 6: Time preference task interface



Subjects faced two FEDs to the SS rewards: a zero-day FED and a 7-day FED. The 7-day FED allows us to control for subjective transaction costs across the SS and LL rewards. This transaction cost arises because experimenters cannot give subjects the same level of certainty they will receive their payment at a later date as they can on the day of the experiment. Moreover, the FED facilitates the estimation of the parameters of a QH function because the zero-day FED captures present bias (β) in decision making, whereas the 7-day FED allows for the identification of the long-term discounting parameter (δ).

Each subject made 60 choices in the task that were randomly drawn, without replacement, from a battery of 224 possible choice pairs. The possible choice pairs were constructed using a combination of two SS rewards (R250 and R400), four time horizons (7, 14, 42, and 84 days), nominal annual interest rates between 5% and 250%, and the two FEDs. At the end of the task, the subject rolled dice to randomly select one of these choices for payment.

Questionnaire on smokers' baseline characteristics and smoking habits

After completion of the time preference and risk preference tasks, subjects completed a baseline questionnaire that collected information on their socioeconomics, demographics, psychological well-being,[19] and measures of gambling behaviour and alcohol use.[20] Addressing tobacco use, the questionnaire included the Fagerström Test for Cigarette Dependence (FTCD, Fagerström et al., 2012), the Smoking Abstinence Self-Efficacy Questionnaire (SASEQ, Spek et al., 2013), the Minnesota Tobacco Withdrawal Scale-Revised (MTWS-R, Etter and Hughes, 2006), and the Reasons for Quitting Questionnaire (Curry, Wagner and Grothaus, 1990). Additional smoking-related questions included questions focused on past quit attempts (Ontario Tobacco Research Unit, 2015), motivation to quit (National Centre for Smoking Cessation and Training, 2017), attitudes towards UCT's new smoking policy, and environmental factors that may affect a quit attempt (Ontario Tobacco Research Unit, 2015).

After completion of the questionnaire, subjects then entered the baseline session's individual component. Subjects were taken to a private room in the computer lab where, along with a printed handout, RAs presented subjects with a summary of the cessation programme. RAs also gave subjects an aid-to-quit document[21] and took their CO reading. Subjects in the treatment group were then informed that they had been randomly assigned to receive abstinent-contingent rewards.[22] Following the baseline session, subjects had one week to quit smoking.

Subjects were only informed of their group status at the end of the baseline session so as to avoid selection bias. There is still the potential for performance bias as the explicit nature of the reward mechanism makes blinding subjects to treatment allocation impossible. To mitigate this issue, only subjects allocated to the treatment group were informed of their group status,

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[19]The Barratt Impulsiveness Scale (Patton, Stanford and Barratt, 1995), The Beck Anxiety Inventory (Beck et al., 1988), and The Beck Depression Inventory-II (Beck, Steer and Brown, 1996) were administered

[20] The Alcohol Use Disorders Identification Test (Babor et al., 2001), and the Problem Gambling Severity Index (Ferris and Wynne, 2001) were used

[21] The aid-to-quit document was HelpGuide.org's (2017) online guide for quitting smoking.

[22] As per Meredith et al. (2014), this is a necessity for an effective CM programme.

not those in the control group. This design reduces the possibility of a John Henry effect[23], and a resentment and demoralisation effect.

D. Programme Sessions

The programme sessions ran from 28 August 2017 to 22 September 2017 at UCT. In these sessions the subjects' quit attempts were monitored, and treatment subjects were given abstinence-contingent incentives. The sessions started 1 week after the quit date set in the baseline session with subjects attending 4 sessions, once each week. Subjects were reminded of their sessions by an email and two SMSs. The sessions were conducted by RAs and took about 15 minutes to complete. All subjects earned a R50 show-up fee while those in the treatment group received an additional R150 contingent on smoking abstinence over the previous week.

Abstinence was determined through two methods: timeline follow-back (TLFB) questionnaires and CO readings. The SASEQ, the MTWS-R, and the FTCD were also used at each session to collect data on smoking behaviour.[24] An RA administered a TLFB questionnaire with subjects to capture their self-reported cigarette use over the 7 days prior to each programme session. Participants were given a printed calendar (Figure 7) which was used to track the amount they had smoked, beginning with the day before the session. For each day, a RA asked the subject if they were abstinent, and if not, how much they had smoked on that day. Subjects were instructed to give their best estimates of the amounts they had smoked on each day.

[23] The John Henry effect refers to an experimental bias that is introduced when members of the control group are made aware of their group status. Members in the control group may compare their performance to those in the treatment group and put in additional effort (in this case to quit smoking) to overcome their perceived disadvantage of being in the control group (Saretsky, 1972).

[24] The final session's questionnaire included several additional questions. The questionnaire asked the subjects to list the names of other participants that they knew in the study, provide reasons for why their quit attempt succeeded or failed, and asked treatment subjects whether they felt the R150 had helped them quit.

Figure 7: Timeline Follow-back Calendar

	MON	TUES	WED	THURS	FRI	SAT	SUN
		1 VAC	2 VAC	3 VAC	4 VAC	5 VAC	6 VAC
AUG	7 VAC	8 VAC	9 VAC	10 VAC	11 VAC	12 VAC	13 VAC
	14 **SESSION 1**	15	16	17	18	19	20
	21 **QUIT DATE**	22	23	24	25	26	27
	28	29	30	31	1	2	3
SEP	4	5	6	7	8	9	10
	11	12	13	14	15	16	17
	18	19	20	21	22	23 VAC	24 VAC
	25 VAC	26 VAC	27 VAC	28 VAC	29 VAC	30 VAC	1 VAC
OCT	2	3	4	5	6	7	8
	9	10	11	12	13	14	15
	16	17	18	19	20	21	22
	23	24	25	26	27	28	29
	30	31	1	2	3	4	5
NOV	6	7	8	9	10	11 CONSOLIDATION	12 CONSOLIDATION
	13 CONSOLIDATION	14 CONSOLIDATION	15 EXAMS	16 EXAMS	17 EXAMS	18 EXAMS	19 EXAMS
	20 EXAMS	21 EXAMS	22 EXAMS	23 EXAMS	24 EXAMS	25 EXAMS	26 EXAMS
	27 EXAMS	28 EXAMS	29 EXAMS	30 EXAMS	1 VAC	2 VAC	3 VAC
DEC	4 VAC	5 VAC	6 VAC	7 VAC	8 VAC	9 VAC	10 VAC
	11 VAC	12 VAC	13 VAC	14 VAC	15 VAC	16 VAC	17 VAC
	18 VAC	19 VAC	20 VAC	21 VAC	22 VAC	23 VAC	24 VAC
	25 VAC	26 VAC	27 VAC	28 VAC	29 VAC	30 VAC	31 VAC

Subjects were recorded as abstinent, and thus eligible for the R150 positive reinforcement reward, if they reported being abstinent on the 7-day TLFB questionnaire *and* if they had a CO reading of 6 ppm or less. As discussed in the literature review, CO tests only reliably detect smoking within the previous 24 hours. Thus, rather than being used to detect whether subjects had smoked between sessions, CO tests were used to deter deception in the TLFB questionnaire as well as to tell whether the subject had smoked in the previous 24 hours. To minimise attrition, all subjects were paid a R200 show-up fee at the final programme session if they had attended all four programme sessions.[25]

[25] To ensure that the attendance reward remained salient, participants were reminded of this reward at each programme session.

E. Follow-up sessions

After the programme sessions, 3-month and 6-month follow-up sessions were conducted. The purpose was to determine abstinence rates after a 3-month and 6-month period. Subjects in the treatment and control groups were invited to the sessions via the VLE. The announcement asked subjects to sign-up for a 15-minute one-on-one session with an RA and reminded the subjects of the R200 show-up fee.[26] Subjects were reminded of their sessions by an email and two SMSs.

In the session, the RA ran through a questionnaire with the subject, took the subject's CO reading, and lastly paid the subject's show-up fee.[27] The questionnaire employed TLFB to determine smoking behaviour in the 7-days prior to the session, as well as the SASEQ, the MTWS-R, and FTCD were also administered. At the 3-month and 6-month follow-up, subjects were also asked if they had smoked since the last programme session, and if they had, the average number of cigarettes they smoked per day.

F. Payment and earnings

To ensure that the programme was administered correctly, a script was developed for the RAs to read when giving subjects their earnings in each of the programme sessions. The script was designed to encourage subjects to quit smoking and attend programme sessions.[28] The scripts that were read to subjects varied depending on whether the subject was abstinent in the current programme session, whether they had attended previous programme sessions, and whether they had been abstinent in previous programme sessions.

[26] The show-up fee was larger than in previous sessions to minimise the risk of attrition after a prolonged period of not participating in the programme.
[27] At the 3-month follow-up, the RA also reminded the subject of the 6-month follow-up and its R200 show-up fee. Subjects were also made aware that the show-up fee would be paid irrespective of smoking status.
[28] The script was developed using the principles outlined in the Contingency Management Competence Scale for Reinforcing Abstinence (Petry et al., 2010) and the Contingency Management Competence Scale for Reinforcing Attendance (Petry et al., 2010).

In terms of earnings, subjects received a R50 show-up fee in the screening, baseline, and four programme sessions. Subjects earned a R200 show-up fee in each of the two follow-up sessions. The combined earnings for the risk and time preference tasks was R557, on average. In the programme sessions, treatment subjects who were abstinent earned an additional R150 over and above the R50 show-up fee.

4. Statistical Methodology

A. Overview

The aim of this dissertation is to link smoking cessation and smoking intensity, under a CM programme, to participant's risk and time preferences. To this end, the dissertation's statistical methodology adopts two approaches. The first is an extension of the probit models used in HKR (2020), where they implemented a random-effects probit model to see if the CM programme increases smoking cessation rates, as well as a random-effects negative binomial regression to investigate the CM programme's effect on smoking intensity. This paper expands upon HKR (2020) by adding explanatory variables that capture risk and time preferences to the two regression models.

The second approach is to estimate risk and time preference models by maximum likelihood, conditioning the parameter estimates on the participants' treatment status and smoking intensity. With this method, I adopt the approach of first estimating the risk preference parameters and then using this estimate to provide the shape of the utility function when estimating the time preference parameters.

B. Random-effects probit model

A random-effects probit (REP) model is used to test whether a smoker's probability of quitting is influenced by the CM programme and the subject's risk and time preferences. As with HKR

(2020), along with a treatment dummy variable, this REP model includes regressors controlling for demographics and smoking characteristics. However, this dissertation extends the previous REP model by including regressors capturing risk and time preferences.

A REP model is appropriate because it accounts for the panel structure of the dataset and therefore the correlation in standard errors over time. A random-effects model is preferable to a fixed-effects model because the subjects' risk and time preferences are time-invariant, implying that they would drop out of a FE model. A REP model is also appropriate because the dependent variable, $Abstinent_{it}$, is a binary response variable. The model's specification is:

$$\Pr(Abstinent_{it} = 1 \mid \mathbf{x}_{it}) = \Phi(\beta_1 Treatment_i + \boldsymbol{\beta}_2\mathbf{x}_{2i} + \boldsymbol{\beta}_3\mathbf{x}_{3i}) + \varepsilon \tag{10}$$

where Pr, Φ, and ε, denote probability, the standard cumulative normal distribution function, and the error term, respectively. $Treatment_i$, and the vectors $\mathbf{x}_2$ and $\mathbf{x}_3$, are explanatory variables that explain the dependent variable's variation. Their coefficients, β_1, β_2 and β_3 are used when calculating the marginal effect each explanatory variable has on the probability of abstinence. $Treatment_i$ is a binary response variable equal to 1 if subject *i* is in the treatment group and 0 if she is in the control group.

Vector $\mathbf{x}_2$ contains independent variables capturing the subjects' demographic characteristics: Age_i and Age_i^2 are continuous variables;[29] $Male_i$ is a binary variable equal to one if the subject is male; $Race_i$ is a categorical variable that includes African (the base category), Coloured, Indian, and White; $Income(ln)_i$ is a continuous variable that is the natural logarithm of the subject's total income in the previous month.

Vector $\mathbf{x}_3$ contains variables related to risk and time preferences. *Number of risky choices*$_i$ is a discrete variable that is a count of the number of times the subject chose the riskier option from

[29] A quadratic term for age is included as we expect age to have a declining marginal effect on abstinence.

each lottery pair in the risk preference task. Similarly, *Number of LL choices*$_i$ is a discrete variable that is a count of the number of times the subject chose the LL reward in the time preference task. Also included are the quadratic terms *Number of risky choices squared*$_i$ and *Number of LL choices squared*$_i$ as the number of risky choices and LL choices made in the tasks have a nonlinear relationship with subjects' risk and time preferences, respectively.

C. Random-effects negative binomial model

A random-effects negative binomial (RENB) model is used to examine smoking intensity among the participants who failed to remain abstinent. The model is ideal for this analysis as the model accounts for the data's panel structure, and the dependent variable, *Smoking intensity*$_{it}$, is a count variable. The RENB model used is specified as:

$$\Pr(Y_{it} = y_{it} \mid \mathbf{X}_{it}, \delta_i) = [\Gamma(\lambda_{it} + y_{it}) / \Gamma(\lambda_{it})\, \Gamma(\lambda_{it} + \delta_i)] \cdot [1 / (1 + \delta_i)]^{\lambda_{it}} \cdot [\delta_i / (1 + \delta_i)]^{y_{it}}, \qquad (11)$$

where Γ is the gamma distribution that loosens the Poisson regression's assumption that the variance is equal to the estimated mean. Variable y_{it} is the count dependent variable *Smoking intensity*$_{it}$, which indicates the average weekly number of cigarettes smoked by subject i at session t.[30] Parameter λ_{it} is the gamma noise variable which gives the model its Poisson-gamma mixture (negative binomial) distribution and is equal to $\exp(\mathbf{x}_{it}\beta)$. Parameter δ_i is the dispersion parameter that varies randomly across subjects. Except for the addition of the categorical variable *Session*$_i$, vector $\mathbf{X}_{it}$ contains the same independent variables used in the REP model.[31] This is a categorical variable that includes the baseline session (the base category), the intervention period, and the two follow-up sessions.

This RENB model is the second stage of a hurdle model, with the first stage being the earlier discussed REP model. Equation (10) determines whether participant i smoked cigarettes or not

[30] *Smoking intensity*$_{it}$ differs from *Smoking intensity*$_i$ in that it is time variant. The latter variable was a measure taken at the baseline session, whereas the former was measured at each programme and follow-up session.
[31] *Session*$_i$ is not included in the REP model as doing so introduced numerical instability during estimation.

(y = 0 versus y > 0) over the past 7 days, while equation (11) determines the number of cigarettes smoked over that period conditional on the participant having failed to remain abstinent. A hurdle model is appropriate because it accounts for the participants' initial decision to smoke or abstain (equation (10)), and then the decision of how much to smoke (equation (11)). Importantly, a hurdle model also accounts for the possibility that the first decision and second decision are affected by the regressors in different ways. For example, we may expect low-income participants to be less likely to remain abstinent than higher income participants, but also expect low-income non-abstinent participants to smoke less cigarettes than their higher-income counterparts.

D. Maximum likelihood estimation

I will draw from Harrison et al. (2018) in this discussion of maximum likelihood estimation. In describing the strategy's logic, I will focus on the EU and exponential discounting models, though it can be extended to the other models mentioned earlier quite easily. This approach has the benefit of using all the collected data to estimate the risk and time preference parameters, as well as the uncertainty of these estimates.

Risk preferences

We first look at estimating, r, the parameter that determines the shape of the utility function. We assume that the utility of income is defined by a power utility function which displays constant relative risk aversion (CRRA):

$$U(y) = y^r, \tag{12}$$

where y is the lottery prize awarded in the risk preference task. Under EU, if $r > 1$, the representative agent is risk-seeking with a convex utility function. Similarly, if $r = 1$, the agent is risk neutral with a linear utility function, and if $r < 1$, the agent is risk averse with a concave utility function.

Under EU, the expected utility of a lottery is the probability-weighted utility of each outcome in each lottery. As per our risk preference experiment, we assume the representative agent faces a lottery i with three possible outcomes, each of which have their own probability of occurrence:

$$\mathrm{EU}_i = \sum_{j=1,2,3}[p(y_j) \times U(y_j)] \tag{13}$$

To calculate r, the EU of each lottery in a lottery pair is calculated using a candidate value of r (for instance, $r = 1$), and we create a latent index that is the difference in EU between the left (L) and right (R) lottery:

$$\nabla\mathrm{EU} = [(\mathrm{EU}_\mathrm{R} - \mathrm{EU}_\mathrm{L}) / \lambda] / \mu \tag{14}$$

where λ is a normalising term and μ is the Fechner error term. This latent index (14) incorporates Wilcox's (2011) "contextual utility" behavioural error specification, permitting the possibility of subjects making simple mistakes such as selecting lottery L when wanting to select lottery R. The latent index is linked to the participants' elicited choices using the cumulative normal distribution function $\Phi(\nabla\mathrm{EU})$. This function takes any value between $\pm\infty$ and smoothly transforms it to a number between 0 and 1, yielding the "probit" link function[32]:

$$\Pr(\text{Choose lottery R}) = \Phi(\nabla\mathrm{EU}) \tag{15}$$

This expression tells us that lottery R is chosen when $\Phi(\nabla\mathrm{EU}) > ½$, thus linking the participants' observed choices to the latent index (14). If $\Phi(\nabla\mathrm{EU}) > ½$, this means that the EU of lottery R is greater than the EU of lottery L, and so the probability of selecting the R lottery is greater than 0.5. Simply put, there is a greater probability of selecting lottery R than lottery L if the EU of lottery R is greater than lottery L.

[32] Alternatively, a cumulative logistic function $\Lambda(\nabla \mathrm{EU})$ may be used, which also takes any argument of ∇ EU between $\pm\infty$ and transforms it into a number between 0 and 1. This gives the " logit" link function.

The likelihood of the observed responses, assuming the power utility and EU model are true, depends on the estimates of r given the probit link function and the choices subjects made in the risk preference task. These requirements are expressed in the conditional log-likelihood function:

$$\ln L_i^{RP}(r; z, X) = \sum_i[(\ln \Phi(\nabla EU)\times I(z_i=1)) + (\ln(1 - \Phi(\nabla EU)))\times I(z_i=0))] \qquad (16)$$

where $I(\cdot)$ is the indicator function, and $z_i = 1(0)$ means that the participant chose lottery R (L) in choice pair i. X is a vector that captures the participants' individual characteristics and behaviour that include gender, age, smoking abstinence etc.

Extending the above to Quiggin's (1982) rank-dependent expected utility (RDU) model is straightforward. The model incorporates the possibility that individuals overweight and/or underweight the probabilities assigned to outcomes. Thus, unlike EU, it allows for nonlinear weighting of probabilities. When estimating a RDU model, risk preference is determined by two sources: the curvature of the utility function (as under EU), and the shape of the embedded probability weighting function (PWF). Thus, RDU's PWF is an additional source of the risk premium not captured by EU.

When using RDU, this paper incorporates the Prelec (1998) PWF for its considerable flexibility. Its functional form is:

$$\pi(p)=\exp[-\eta(-\ln p)^{\varphi}] \qquad (17)$$

which is defined for $1 > p > 0$, and $\varphi > 0$, $\eta > 0$. Parameter φ controls the convexity/concavity of the Prelec function, while parameter η controls the location of the inflexion point relative to the 45º line.[33]

[33] See Appendix B for more on the Prelec (1998) PWF

Joint estimation of time preferences with risk preferences

We also want to estimate δ, the discounting parameter which equalises the utility of income received at time t with the utility of income received at time t + τ. Assume exponential discounting with some utility function $U(\cdot)$ and a FED on the SS reward :

$$[1 / (1 + \delta)^{t}]U(y_{t}) = [1 / (1 + \delta)^{t+\tau}]U(y_{t+\tau}) \tag{18}$$

where (18) is an indifference condition that equalizes the utility of SS and LL rewards. By assuming EU and a power utility function as in (12), (18) can be expressed as:

$$[1 / (1 + \delta)^{t}](y_{t})^{r} = [1 / (1 + \delta)^{t+\tau}](y_{t+\tau})^{r} \tag{19}$$

The left hand side and the right hand side can be regarded as the present value (PV) of the utility of the SS reward and LL reward, respectively. To determine the value of δ, the PVs of each reward are calculated for an initial estimate of δ and the latent index below is formed:

$$\nabla PV = (PV_{SS} - PV_{LL}) / v \tag{20}$$

which is conditional on the assumptions that EU, power utility, and exponential discounting hold. Similar to μ in (14), v is the Fechner error term. The latent index (20) gives us the difference in present values of the *utility* of the SS and LL rewards. This index is linked to the subjects' observed choices using the cumulative normal distribution function Φ(∇PV), taking any argument ∇PV between ±∞ and transforming it into a number between 0 and 1.[34] This gives the probit link function:

$$\Pr(\textit{Choose SS reward}) = \Phi(\nabla \mathrm{PV}) \tag{21}$$

This latent index is linked to the subjects' elicited choices by specifying that the SS reward is chosen whenever $\Phi(\nabla PV) > ½$. If $\Phi(\nabla PV) > ½$, this means that the PV of the SS reward is

[34] Again, the logit link function can be used instead.

greater than the PV of the LL reward, and so the probability of selecting the SS reward is greater than 0.5.

Thus, the likelihood of the elicited responses, conditional on EU, the power utility function, and an exponential model fitting the subjects' responses, depends on the estimates of r and δ. The conditional log-likelihood of the "jointly" estimated model is:

$$\ln \mathrm{L}_i(r,\ \delta;\ z,\ X) = \textstyle\sum_i[(\ln \Phi(\nabla\mathrm{PV}) \times \mathrm{I}(z_i = 1)) + (\ln (1 - \Phi(\nabla\mathrm{PV})) \times \mathrm{I}(z_i = 0))] \qquad (22)$$

where $I(\cdot)$ is the indicator function, $z_i = 1(0)$ denotes the choice of the SS (LL) reward in the discounting task choice pair *i,* and X is a vector of individual characteristics which may capture age, gender, socioeconomic status, smoking abstinence, and other relevant variables. The conditional likelihood function (22) can be decomposed into its risk and time preference parts as:

$$\ln \mathrm{L}_i(r,\ \delta,\ z,\ X) = \ln \mathrm{L}_i^{\mathrm{RP}} + \ln \mathrm{L}_i^{\mathrm{TP}} \qquad (23)$$

Why joint estimation matters

Andersen et al. (2008) were the first to incorporate utility function curvature in the estimation of discounting models, while Harrison, Lau and Rutström (HLR, 2010) were the first to use this joint estimation technique in the context of smoking. The idea is to use data from a task that elicits risks preferences to estimate the parameters that determine the curvature of the utility function. Elicited time preference data is then used to calculate the parameters of a discounting model subject to the shape of the estimated utility function.

We can show the importance of joint estimation using the following expression:

$$U(y_t) = (1 / (1 + \delta)^{\tau})\ U(y_{t+\tau}) \qquad (24)$$

While joint estimation can be done using various combinations of utility and discounting models, for this discussion I still assume that EU holds for risk preference choices, and that discounting is exponential. A subject is indifferent between income options y_t and $y_{t+\tau}$ if and only if the above expression holds. $U(y_t)$ is the utility of monetary outcome y_t for delivery at time t, δ is the discount rate, and τ is the horizon for delivery of the later monetary outcome. The indifference condition shows that the discount rate equalizes the present value of the utility of the two monetary outcomes of y_t and $y_{t+\tau}$ (Harrison and Rutström, 2008).

What is clear from (24) is that we cannot say anything about the discount rates without knowing or assuming something about the curvature of the utility function. If we were to assume the subjects had linear utility functions and instead use the formula:

$$y_t = (1 / (1 + \delta)^{\tau})\, y_{t+\tau} \tag{25}$$

when subjects actually have concave utility functions, the estimated discount rates would be biased upwards. Thus, separate tasks to elicit the curvature of the utility function should be implemented to estimate discount rates. Andersen et al. (2008) show that joint estimation of discount rates and risk preferences led to significantly lower discount rates than if they did the same as the previous literature and assumed linear utility functions.

While HLR differs by examining the relationship between the likelihood of someone *being* a smoker and their risk and time preferences, their methodology is broadly like that used in this dissertation. HLR found that discount rates have a significant and positive relationship with smoking for both genders when a linear utility function is used, whereas when a concave utility function is used the relationship is only significant and positive among males.[35] The latter finding that there is no statistically significant difference in the discount rates between smoking and non-smoking females when using joint estimation is important. The result means that the female smokers were significantly more risk averse (yielding more curved utility functions) than the female non-smokers. If the utility function was assumed linear, this would result in

[35] 'Positive' relationship means that smokers discount more heavily than non-smokers.

wrongly concluding a difference in discounting behaviour (Harrison, Lau and Rutström, 2010; Hofmeyr, 2015).

5. Baseline Summary Statistics

Table 2 displays the summary statistics, categorised by the sample's demographics, smoking characteristics, and risk and time preferences. The table also shows the sample's split by treatment and control group.

With respect to the entire sample's demographics, the average age is approximately 22 years old, about 23% classify themselves as White, about 29% classify themselves as African or Coloured, and 19.5% as Indian. Males comprise 78% of the sample, and the average monthly income is R2970. The sample's ratio of males to females is similar to the population of smokers in the country, with South African men four times likelier to smoke than South African women (Reddy et al., 2015).

Looking at the smoking-related indicators, the sample's average number of years smoked is about 3.5 years, a figure that makes sense given that the sample is primarily composed of students. Smoking intensity, which is the average number of cigarettes smoked per day in the 7 days prior to the baseline session, was about 10. This variable's standard deviation suggests that the sample is made up of smokers with varying smoking intensity. The FTCD score of about 3.5 (out of a possible 10) and MTWS score of about 17 (out of a possible 60), suggest that the sample's smokers have low to moderate cigarette dependence, on average.

Table 2: Summary statistics

Variable	Combined	Treatment	Control	Significantly different?[36]
Size	87	40	47	
Demographics				
Age	21.632 (2.985)	21.100 (1.594)	22.085 (3.741)	0.269
Population group[37]				
White	22.990	20.000	25.530	0.945
Black/African	28.740	30.000	27.660	
Coloured	28.740	30.000	27.660	
Indian	19.540	20.000	19.150	
Male[2]	0.780	0.800	0.761	0.663
Monthly income	2970 (2216.077)	2500.769 (1547.895)	3376.667 (2603.071)	0.252
Smoking behaviour				
Smoking duration	3.376	2.769	3.891	0.077
Smoking intensity	9.857 (5.895)	9.821 (6.696)	9.821 (6.696)	0.756
FTCD score	3.459 (1.842)	3.513 (1.906)	3.413 (1.784)	0.816
MTWS score	17.233 (9.969)	17.256 (8.691)	17.213 (10.937)	0.699
CO reading (ppm)[2]	11.149 (9.449)	11.800 (12.662)	10.596 (5.508)	0.952
Quitting smoking				
Quit attempt in past 5 years	0.659	0.564	0.739	0.090
Importance of current quit attempt	2.929 (0.897)	2.846 (0.875)	3.000 (0.919)	0.724
Determination for current quit attempt	3.047 (0.770)	2.923 (0.739)	3.152 (0.788)	0.285
SASEQ score	11.442 (5.489)	11.436 (5.406)	11.447 (5.559)	0.945
RFQ intrinsic score	4.555 (1.749)	4.205 (1.939)	4.852 (1.500)	0.097
RFQ extrinsic score	2.444 (1.261)	2.31 (1.255)	2.557 (1.254)	0.279
Risk and time preferences				
Time preference task completed first	0.517	0.475	0.553	0.467

[36] The Mann-Whitney test was used for continuous variables and a Pearson's chi-squared test was used for binary and categorical variables.
[37] Stratification variable

Table 2: continued

Variable	Combined	Treatment	Control	Significantly different?[38]
% of time preference choices with FED	0.506	0.512	0.501	0.430
% of time preference choices with high amount	0.505	0.498	0.511	0.376
Number of risky choices[39]	37.653 (13.706)	40.25 (12.891)	35.426 (14.120)	0.111
Number of LL choices[40]	11.724 (12.191)	12.400 (12.800)	11.149 (11.757)	0.736

Note: FTCD = Fagerstrom Test for Cigarette Dependence; MTWS = Minnesota Tobacco Withdrawal Scale; SASEQ =Smoking Abstinent Self-efficacy Questionnaire Score; FED = front end delay

The average SASEQ score[41], Intrinsic RFQ score, and Extrinsic RFQ score[42] of about 11, 5, and 2, respectively, suggest that at baseline participants were not confident in their ability to quit smoking. The average scores for Determination for current quit attempt and Importance of current quit attempt suggest that on average, participants were "Very determined" to quit and regarded their current quit attempt as "Very important."

Participants were equally likely to first complete the time preference task as they were to first complete the risk preference task. Half of the time preference choices incorporated a FED, and half of the time preference choices had the high SS amount (R400). The riskier lottery was chosen about 42% of the time and the LL reward 20% of the time, choice behaviour that is consistent with risk aversion and relatively high discounting.

Mann-Whitney and chi-squared tests were used to test whether the baseline characteristics are balanced across the treatment and control groups. The p-values shown in the last column show

[38] The Mann-Whitney test was used for continuous variables and a Pearson's chi-squared test was used for binary and categorical variables.
[39] Out of a maximum possible score of 90.
[40] Out of a maximum possible score of 60
[41] Out of a maximum possible score of 24
[42] Both RFQ scores have a maximum possible score of 40

that with the exception at the 10% confidence level for Smoking duration, Quit attempt in past 5 years, and RFQ intrinsic score, the experimental groups are well-balanced.

6. Results

A. Statistical Models

Smoking abstinence

Table 3 presents the estimated coefficients (as opposed to marginal effects) of the REP model that investigates the effect that the CM programme, along with the subjects' demographics, smoking characteristics, and risk and time preferences, have on smoking cessation.

Regression 1a shows that the CM programme has a statistically significant treatment effect, with a marginal effect implying that the likelihood of a subject in the treatment group being abstinent is 12.2 percentage points higher than a subject in the control group (p=0.014). A statistically significant treatment effect is also found in Regression 1b and Regression 1c, with the significance and magnitude of the treatment effect increasing as more independent variables are included.

Regression 1b includes independent variables related to the subjects' demographic characteristics. Of these variables, only the population group White is statistically significant at the 5% level, with the marginal effects showing that White participants are on average 13.5 percentage points more likely to be abstinent than African subjects (p=0.066), the omitted base category. This relationship strengthens in Regression 1c, where regressors related to the risk and time preference tasks are included.

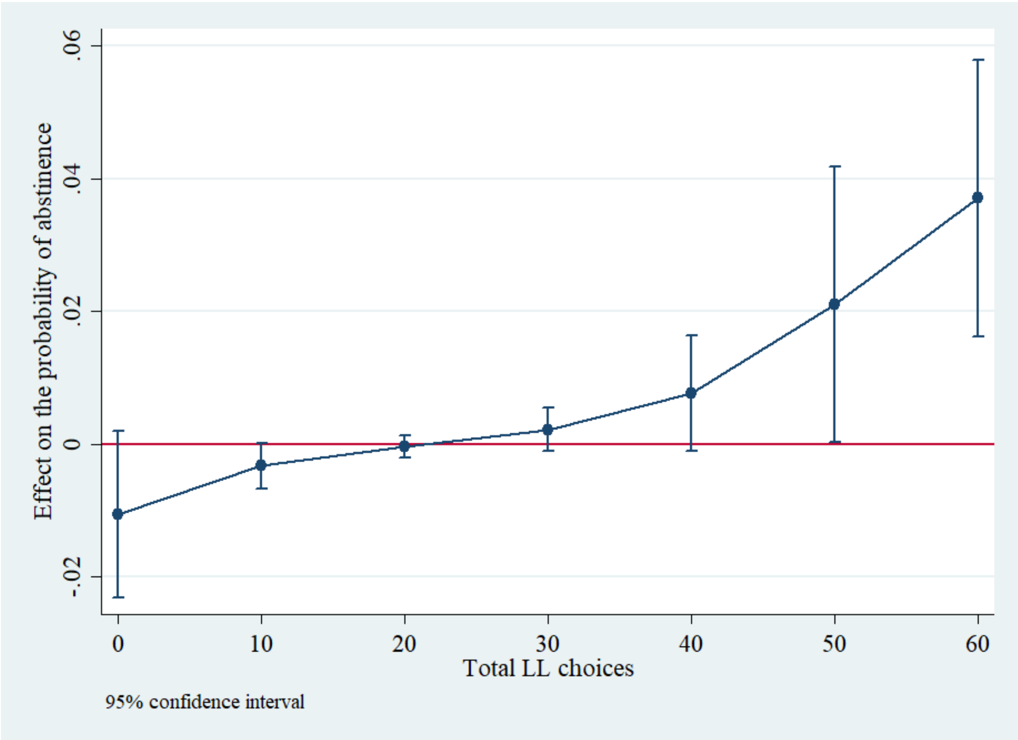
Table 3: REP models testing abstinence

	Regression 1a	Regression 1b	Regression 1c
Treatment	1.285***	1.366***	1.398***
	(0.314)	(0.324)	(0.304)
Age		0.283	0.209
		(0.267)	(0.277)
Age squared		-0.003	-0.002
		(0.004)	(0.004)
Male		0.305	0.180
		(0.464)	(0.442)
Coloured		0.716*	0.697
		(0.428)	(0.478)
Indian		0.180	0.318
		(0.533)	(0.551)
White		1.099**	1.075***
		(0.443)	(0.397)
Income (ln)		-0.223	-0.115
		(0.307)	(0.309)
Number of risky choices			-0.029
			(0.043)
Number of risky choices squared			0.000
			(0.001)
Number of LL choices			-0.065**
			(0.028)
Number of LL choices squared			0.002***
			(0.000)
Constant	-2.410***	-6.144	-5.015
	(0.297)	(3.804)	(4.034)
N	609	574	574
log-likelihood	-191.192	-175.135	-171.729

Coefficient estimates reported
Standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The regressors "Number of risky choices" and "Number of risky choices squared" do not suggest that there is a relationship between risk preferences and smoking abstinence within the context of a CM programme. On the other hand, "Number of LL choices" and "Number of LL choices squared” does suggest a relationship, as shown in Figure 8 below, with the marginal effects evaluated at successive 10 LL choice intervals to the maximum of 60 LL choices.

Figure 8: Average marginal effects of LL choices



The direction of the reported marginal effects is as expected, with marginal effects becoming positive and increasing with cumulative LL choices. Thus, Figure 8 shows a nonlinear relationship between the total number of LL choices and its marginal effect on the probability of abstinence. When evaluated at 50 LL choices and 60 LL choices, there is a statistically significant relationship between the number of LL choices and abstinence (p=0.046 and p<0.001, respectively). Making 50 LL choices and 60 LL choices means, on average and respectively, a 2.3 and 3.9 percentage point increase in the likelihood of abstinence. When evaluated at 0 LL choices, 10 LL choices and 40 LL choices, there is a statistically significant relationship but only at the 10% significance level.

Smoking intensity

Table 4 presents the estimated coefficients (as opposed to marginal effects) of the RENB model, showing the relationship between a range of independent variables and smoking intensity when subjects are not abstinent.[43]

Table 4 shows that there is no evidence that the CM programme influences smoking intensity in Regressions 2b-2c. In Regression 2b, variables related to demographic characteristics and programme sessions are added to the model. This regression's marginal effects show that Coloured and White participants on average smoke about 1.5 cigarettes a day more than their African counterparts, the omitted base category (p=0.022 and p=0.089, respectively). The regression also suggests a "programme effect," with participants on average smoking about 6.5 cigarettes less when in the programme sessions than in the baseline session (p<0.001), the omitted base category. Participants also reported smoking on average about 4 cigarettes less during the follow-up sessions than in the baseline session (p<0.001 for Regressions 2b-2c).

Regression 2c includes variables for risk and time preferences, and apart from the race variables, shares results in line with Regression 2b. In comparison to Regression 2b, only White participants now have a statistically significantly higher smoking intensity than African participants, with the estimated average marginal effect showing White participants smoking on average nearly 2 cigarettes more per day than African participants (p= 0.046).

[43] This data is gathered at each session with the TLFB questionnaire.

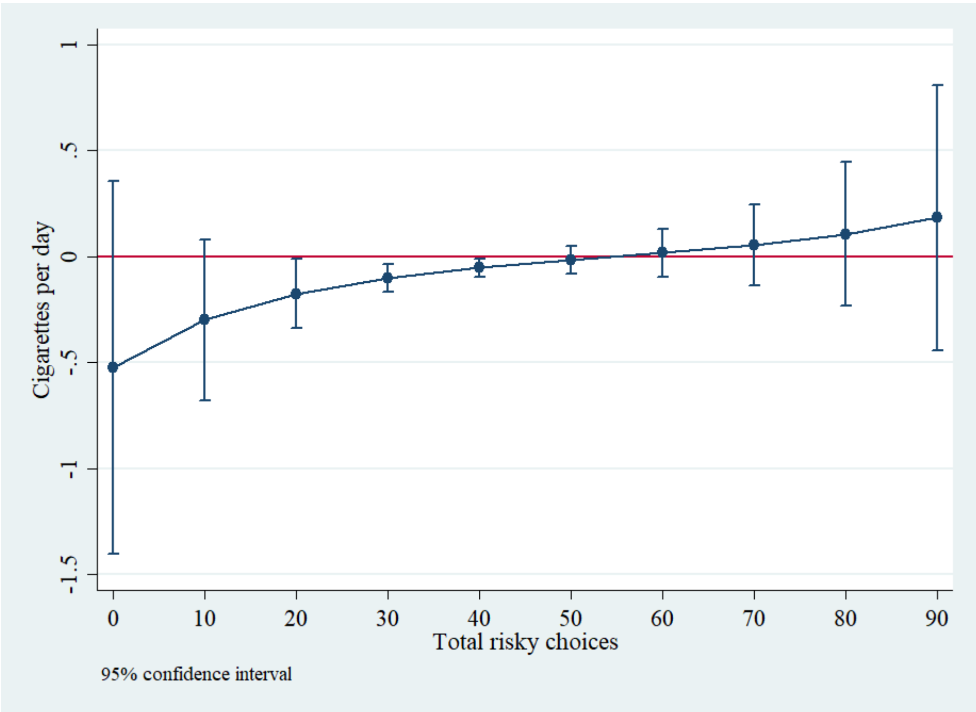
Table 4: RENB models testing smoking intensity

	Regression 2a	Regression 2b	Regression 2c
Treatment	0.186*	0.074	0.167
	(0.103)	(0.114)	(0.110)
Age		-0.026	-0.046
		(0.121)	(0.114)
Age squared		0.001	0.001
		(0.002)	(0.002)
Male		0.003	0.006
		(0.135)	(0.127)
Coloured		0.336**	0.112
		(0.144)	(0.151)
Indian		0.242	0.147
		(0.169)	(0.161)
White		0.279*	0.325**
		(0.166)	(0.155)
Income (ln)		0.033	0.030
		(0.094)	(0.091)
Programme sessions		-1.060***	-1.012***
		(0.062)	(0.059)
3-month follow-up session		-0.512***	-0.493***
		(0.074)	(0.072)
6-month follow-up session		-0.505***	-0.506***
		(0.075)	(0.072)
Number of risky choices			-0.040**
			(0.020)
Number of risky choices squared			0.000
			(0.000)
Number of LL choices			-0.004
			(0.011)
Number of LL choices squared			0.000
			(0.000)
Constant	1.242***	2.858*	4.379***
	(0.138)	(1.580)	(1.635)
N	455	437	437
log-likelihood	-1193.846	-1040.857	-1036.132

Coefficient estimates reported
Standard errors in parentheses
* *p*<0.10, ** *p*<0.05, *** *p*<0.01

The reported coefficients for the time preference variables are not statistically significant. "Number of risky choices" has a statistically significant coefficient, and a test of the joint significance of "Number of risky choices" and "Number of risky choices squared" is also statistically significant (p=0.008). Figure 9, below, shows that when evaluated at 20, 30, and 40 risky choices, the number of risky choices has a statistically significant marginal effect on smoking intensity (p=0.035, p=0.003, and p=0.02 respectively). As we could reasonably assume that the more 'risky choices' one makes, the less risk averse they are, this figure counterintuitively suggests that on average, the more risk averse a smoker is, the greater their smoking intensity.

Figure 9: Average marginal effects of risky choices



To assess the robustness of the REP and RENB models, a pooled probit regression and a pooled negative binomial regression are shown in Appendix C, and the results are qualitatively identical.

B. Structural Models

Sample's risk preferences

Table 5 presents the estimates for EU and RDU models, using a power utility function and the CU error specification. Homogenous preferences are assumed, with the parameter estimates a reflection of the risk preference of the entire sample. As each subject makes 60 choices in the risk preference task, clustering is accounted for at the individual level.

Table 5: EU and RDU ML estimates - homogenous preferences

	EU	RDU
Power function parameter (r)	0.506***	0.655***
	(0.040)	(0.045)
PWF parameter (φ)		0.592***
		(0.037)
PWF parameter (η)		0.983***
		(0.039)
Risk error (μ)	0.267***	0.216***
	(0.016)	(0.011)
N	7830	7830
Log-likelihood	-5112.026	-4957.875

Results account for clustering at the individual level
Standard errors in parentheses
$^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.001$

For the EU model, a Wald test rejects the null hypothesis that $r=1$ ($p<0.001$), implying that, on average, the sample is risk averse. The model's error term μ is also statistically significant, implying subjects made behavioural errors in the risk preference task ($p<0.001$).

A null hypothesis that $r=1$ is also rejected for the RDU model. The Prelec PWF parameter φ is significantly less than 1 ($p<0.001$), implying an inverse S-shaped PWF where the subjects, on average, overweight low probabilities and underweight high probabilities. The null hypothesis that $\eta=1$ cannot be rejected ($p=0.669$), thus we cannot say that participants, on average, overweighted low-probability outcomes relatively more or less than they underweighted high-probability outcomes.[44] In terms of overall risk preferences, the RDU model's power function parameter *r* and the PWF parameters both suggest a pool of participants who are, on average, risk averse. Further, because the PWF parameter estimates imply probability weighting, RDU better characterises the data than EUT. As with the EU model, the CU error parameter μ indicates that subjects made behavioural errors in the risk preference task (p<0.001).

Table 6 presents the EU and RDU model estimates where parameters vary as a function of the subjects' treatment status, a host of covariates related to demographic characteristics, and a binary variable for whether the risk preference task was completed before the time preference task. First looking at the EU model, participants in the treatment group are on average statistically significantly less risk averse than participants in the control group (p=0.01). In terms of the demographic covariates, the model suggests that Coloured participants are more risk averse than African and White participants (p=0.071 and p=0.002 respectively), and Indian participants are more risk averse than White participants (p=0.078). Lastly, the covariate for whether the risk preference task was done first suggests that participants that did the risk preference task first were less risk averse than participants that did it second (p=0.080).

For the RDU model, risk preferences are inferred from the power function parameter *r* and the PWF parameters φ and η. Looking at treatment, *r* suggests participants in the treatment group have a less concave utility function than those in the control group (p=0.011), while φ and η do not suggest there to be differences in the way participants in the treatment and control groups weight probabilities (p=0.579 and p=0.479, respectively). In conjunction, these parameters suggest that treatment group participants are less risk averse than control group participants. For age, the power function parameter suggests participants' utility function becomes less concave with age (p=0.057), and the parameter η suggests that the range of high probabilities

[44] See Figure 19 in Appendix B, which illustrates the effects that variations in the PWF parameters has on probability weighting.

that are underweighted increases with age while the range of low probabilities that are underweighted decreases with age (*p*=0.035). Together, this implies that risk aversion decreases with age. Parameter η for the gender covariate suggests males overweight low probabilities across a wider range and underweight high probabilities across a narrower range than do females (*p*=0.052).

For Coloured participants, φ suggests they overweight low probabilities and underweight high probabilities more than African participants (*p*=0.048). While the power function parameter *r* does not suggest differences between the two racial groups' utility function shape (*p*=0.353), relatively less probability optimism implies Coloured participants are more risk averse relative to their African counterparts. Using similar reasoning, we find that Coloured participants are also more risk averse relative to White participants, and Indian participants are more risk averse than White participants. Thus, in terms of race, the RDU model is consistent with the EU model but risk preferences stem from different sources.

For income, the parameter φ counterintuitively suggests underweighting high probabilities and overweighting low probabilities increases with income (*p*=0.060).[45] Lastly, the value of parameter *r* on the covariate 'Risk task first', suggests participants that did the risk preference task first have less concave utility functions.

[45] This result is counterintuitive as we may expect risk aversion to decline as income rises.

Table 6: EU and RDU ML estimates - heterogenous preferences with treatment variable

	EU	RDU
Power function parameter (r)		
Treatment	0.195**	0.261**
	(0.076)	(0.102)
Age	-0.005	0.027*
	(0.010)	(0.014)
Male	0.027	-0.073
	(0.085)	(0.118)
Coloured	-0.175*	0.089
	(0.097)	(0.096)
Indian	-0.028	0.148
	(0.102)	(0.114)
White	0.206	0.221
	(0.134)	(0.163)
Income (ln)	0.047	0.033
	(0.059)	(0.073)
Risk task first	0.143*	0.161*
	(0.080)	(0.096)
Constant	0.083	-0.438
	(0.412)	(0.526)
PWF parameter (φ)		
Treatment		-0.038
		(0.068)
Age		-0.013
		(0.011)
Male		-0.039
		(0.078)
Coloured		-0.148**
		(0.075)
Indian		-0.144
		(0.093)
White		0.065
		(0.096)
Income (ln)		-0.106*
		(0.057)
Risk task first		0.012
		(0.062)
Constant		1.836***
		(0.410)
PWF parameter (η)		
Treatment		0.056
		(0.078)
Age		0.040**
		(0.019)
Male		-0.204*
		(0.105)
Coloured		0.357***
		(0.132)

Table 6: continued

	EU	RDU
Indian		0.188**
		(0.086)
White		0.088
		(0.108)
Income (ln)		-0.087
		(0.057)
Risk task first		-0.009
		(0.071)
Constant		0.795*
		(0.046)
Risk error (μ)	0.241***	0.200***
	(0.014)	(0.010)
N	7380	7380
Log-likelihood	-4717.750	-4512.987

Results account for clustering at the individual level
Standard errors in parentheses
**p*<0.1, ***p*<0.05, ****p*<0.001

In terms of the CM programme's overall effectiveness, treatment group participants on average being less risk averse than control group subjects is an important result that deserves further attention. *A priori*, we expect individuals who are more risk averse to find smoking less appealing than individuals who are less risk averse. As discussed earlier, smoking increases the probability of developing a range of debilitating and even lethal health issues by a substantial degree. Framing the smoker's decision in terms of a lottery, they have the choice to avoid the increased likelihood of negative health outcomes like cancer with certainty but forgo the enjoyment to be had from smoking, or to increase their likelihood of developing smoking-related illnesses but get the enjoyment to be had from smoking.

Thus, we would expect the more risk averse an individual is, the less tolerant they would be of smoking's impact on their chances of developing health issues. In terms of the earlier REP model, this means that the statistically significant treatment effect is possibly attenuated by the treatment group's lower level of risk aversion. This would imply that the treatment effect could have been greater than what was estimated if there were no statistically significant differences in risk aversion by treatment status.

Sample's time preferences

Table 7 presents the ML results for the exponential, hyperbolic, and quasi-hyperbolic (QH) discounting models, assuming a linear utility function. Thus, any curvature in the shape of the subjects' utility functions is ignored. A CU error specification is again assumed, and individual heterogeneity is ignored.

Table 7: Discounting function ML estimates - linear utility and homogenous preferences

	Exponential	Hyperbolic	QH
Discounting parameter (δ)	3.371***	39.638***	2.435***
	(0.351)	(3.512)	(0.258)
Discounting parameter (β)			0.926***
			(0.006)
Time error (ν)	40.100***	253.061***	39.781***
	(4.166)	(27.218)	(3.907)
N	5220	5220	5220
Log-likelihood	-2790.649	-2890.490	-2632.237

Results account for clustering at the individual level
Standard errors in parentheses
**p*<0.1, ***p*<0.05, ****p*<0.001

Immediately noticeable is the magnitude of parameter δ's values. The exponential model's δ estimate of 3.371 translates to an annual discount rate of almost 340%. The error parameter ν is statistically significant, indicating that subjects made behavioural errors in the time preference task (p<0.001 for all three models).

As there is evidence of probability weighting, Table 8 presents parameter estimates for the exponential, hyperbolic, and QH discounting models under the assumption of RDU. Compared to Table 7, these estimates of δ, employing joint estimation, are more modest and consistent across the models. Not accounting for probability weighting and instead jointly estimating with an EU model would lead to biased discounting parameter estimates because the estimates for the power function parameter *r* would capture risk aversion generated by probability weighting.

Table 8: Discounting function ML estimates - RDU and Homogenous Preferences

	Exponential	Hyperbolic	QH
Power function parameter (r)	0.642***	0.688***	0.623***
	(0.042)	(0.048)	(0.040)
PWF parameter (φ)	0.595***	0.584***	0.599***
	(0.037)	(0.037)	(0.037)
PWF parameter (η)	0.974***	1.006***	0.960***
	(0.038)	(0.040)	(0.038)
Discounting parameter (δ)	1.558***	1.145***	1.129***
	(0.198)	(0.117)	(0.139)
Discounting parameter (β)			0.950***
			(0.005)
Risk error (μ)	0.216***	0.217***	0.216***
	(0.011)	(0.011)	(0.011)
Time error (ν)	3.288***	4.519***	2.867***
	(1.055)	(1.578)	(0.877)
N	13050	13050	13050
Log-likelihood	-7737.862	-7691.891	-7567.082

Results account for clustering at the individual level
Standard errors in parentheses
**p*<0.1, ***p*<0.05, ****p*<0.001

The exponential model's δ parameter implies annual discount rates of about 155. The discounting parameter β, which captures present bias in the QH model, is statistically significantly less than 1 (p<0.001), providing evidence of discount rates that decline at longer delays.

Table 9 presents the results from the three discounting models where the parameters can vary as a function of treatment assignment, demographic characteristics, and task parameters.[46] First looking at the exponential model, we find that Coloured and Indian participants discount more than their African counterparts (p=0.042 and p=0.027, respectively).

[46] The estimates for the risk preference parameters are not displayed.

The results for the hyperbolic discounting model are similar. Indian participants discount more than African participants (p=0.03). Moreover, and counter to expectations, the hyperbolic model shows that when a decision involves a one-week FED, discount rates are higher than when there is not a FED (p=0.062).

In the QH discounting model, looking at parameter δ, we again find that Indian participants discount more heavily than African participants (p=0.013). We also again find that when a decision involves a one-week FED, participants exhibit higher discount rates than when there is no FED (p<0.001). Parameter β, however, shows that a FED attenuates the effect of present bias (p=0.009), and that treatment group participants have a lower degree of present bias than control group participants (p=0.059). The latter result is interesting because it may mean that the statistical models' results showing the effectiveness of the CM programme are attenuated.

A priori, we believe that smokers who manage to abstain from smoking have less present bias than smokers who do not: Referring back to Gruber and Koszegi's (2001) dual-self model, present bias can lead one to systematically make choices that counter their long-run preferences. In this case, this would mean that a smoker may have decided to quit, but the greater their present bias, the more they would struggle to resist the temptation of a cigarette when faced with the decision to continue abstaining, or to smoke. In terms of this CM programme, treatment group participants having a lower degree of present bias may thus mean the intervention is *less* effective than what was suggested by the statistical models.

Table 9: Discounting function ML estimates assuming RDU - heterogenous preferences

	Exponential	Hyperbolic	QH
Discounting parameter (δ)			
Treatment	-0.084	-0.029	0.043
	(0.281)	(0.158)	(0.190)
Age	0.085	0.048	0.008
	(0.114)	(0.073)	(0.062)
Male	-0.235	-0.111	-0.232
	(0.354)	(0.186)	(0.245)
Coloured	0.862**	0.445	0.434
	(0.423)	(0.292)	(0.272)
Indian	1.018**	0.502**	0.806**
	(0.461)	(0.229)	(0.323)
White	0.419	0.226	0.318
	(0.487)	(0.301)	(0.306)
Income (ln)	0.200	0.080	0.170
	(0.241)	(0.144)	(0.160)
Risk task first	0.262	0.107	0.155
	(0.331)	(0.211)	(0.209)
FED	0.084	0.069*	1.003***
	(0.068)	(0.037)	(0.160)
Constant	-2.250	-0.770	-1.322
	(2.646)	(1.720)	(1.413)
Discounting parameter (β)			
Treatment			0.021*
			(0.011)
Age			-0.003
			(0.007)
Male			-0.022
			(0.015)
Coloured			-0.009
			(0.019)
Indian			0.025
			(0.018)
White			0.019
			(0.017)
Income (ln)			0.003
			(0.011)
Risk task first			0.009
			(0.013)
FED			0.428***
			(0.165)
Constant			0.953***
			(0.150)
Risk error (μ)	0.119***	0.120***	0.119***
	(0.007)	(0.007)	(0.007)
Time error (ν)	1.383***	1.840***	1.415***
	(0.469)	(0.699)	(0.395)
N	12300	12300	12300
Log-likelihood	-6978.346	-6933.805	-6702.067

Results account for clustering at the individual level
Standard errors in parentheses
**p*<0.1, ***p*<0.05, ****p*<0.001

Abstinence and risk preferences

Table 10 presents the abbreviated[47] EU and RDU model ML results where, along with the covariates already included in Table 6, the parameters now vary as a function of the subjects' abstinence status at each session. As shown earlier in the REP model, treatment assignment has a statistically significant effect on the subjects' likelihood of abstinence, thus interaction terms between treatment and abstinence at each of the programme sessions are also included.

I first discuss the results of the EU model and because of the interaction terms' inclusion, I do so by comparing the predictive margins.[48] For example, the predictive margins on the covariate 'treatment' would tell us the predicted probability of a subject being abstinent when they are in the treatment group versus when they are in the control group, with all other covariates held at their mean.

There is a statistically significant difference in the power function parameter *r* between abstinent and non-abstinent participants at programme session 3 and at the 6-month follow-up session (p=0.016 and p=0.016, respectively). Expectedly, at programme session 3 abstinent participants are more risk averse than those non-abstinent at the same session. Counter to expectations, however, at the 6-month follow-up session abstinent subjects are *less* risk averse than those non-abstinent at the same session. However, the proportion of abstinent subjects at the 6-month follow-up is (very) low so this result should be treated with caution.[49]

[47] Only the results of the covariates of interest are included so as to make the table easier to read.
[48] See Table 17 in Appendix D, which presents the predictive margins of the EU and RDU models.
[49] Only 7 out of the 87 subjects are abstinent at the 6-month follow-up session.

Table 10: EU and RDU ML estimates - heterogenous preferences with smoking abstinence and interaction term

	EU	RDU		
	r	r	φ	η
Treatment	0.195**	0.315**	-0.117	0.037
	(0.080)	(0.155)	(0.074)	(0.101)
Abstinent at programme session 1	0.244	-0.049	-0.310**	-0.704***
	(0.157)	(0.179)	(0.146)	(0.157)
Abstinent at programme session 2	0.076	0.134	0.117	0.126
	(0.225)	(0.302)	(0.371)	(0.355)
Abstinent at programme session 3	-0.485***	-0.191	0.383***	1.135***
	(0.147)	(0.180)	(0.134)	(0.106)
Abstinent at programme session 4	-0.174	-0.195	-0.075	-0.355***
	(0.229)	(0.287)	(0.317)	(0.128)
Abstinent at 3-month follow-up	-0.103	0.214	-0.364	0.202
	(0.306)	(0.315)	(0.375)	(0.315)
Abstinent at 6-month follow-up	0.387**	0.053	0.128	-0.380***
	(0.155)	(0.173)	(0.200)	(0.136)
Abstinent at programme session 1×Treatment	0.050	-0.568	0.847***	0.402
	(0.325)	(0.440)	(0.234)	(0.252)
Abstinent at programme session 2×Treatment	0.022	0.666	-0.501	-0.097
	(0.280)	(0.810)	(0.454)	(0.452)
Abstinent at programme session 3×Treatment	0.489**	0.356	-0.457*	-1.024***
	(0.232)	(0.337)	(0.259)	(0.196)
Abstinent at programme session 4×Treatment	-0.079	-0.048	0.218	0.536***
	(0.254)	(0.332)	(0.342)	(0.195)
Abstinent at 3-month follow-up×Treatment	0.222	-0.453	0.592	-0.462
	(0.368)	(0.397)	(0.424)	(0.355)
Abstinent at 6-month follow-up×Treatment	-0.416**	0.027	-0.261	0.554**
	(0.198)	(0.283)	(0.241)	(0.226)
Constant	0.457	-0.365	1.768***	0.103
	(0.384)	(0.685)	(0.440)	(0.475)
Risk error (μ)	0.234***		0.193***	
	(0.013)		(0.009)	
N	7380		7380	
Log-likelihood	-4671.649		-4416.766	

Table 10: continued

Output for demographic-related variables and task order variable omitted Results account for clustering at the individual level Standard errors in parentheses **p*<0.1, ***p*<0.05, ****p*<0.001

Examining by treatment status, at programme session 3 and at the 6-month follow-up session, the statistically significant difference in *r* between abstinent and non-abstinent participants is only seen in the control group.[50] That is, at programme session 3, abstinent control group participants are more risk averse than non-abstinent control group subjects ($p<0.001$), but abstinent treatment group participants are not statistically more or less risk averse than non-abstinent treatment group participants ($p=0.988$).[51] Similarly, at the 6-month follow-up session, abstinent control group participants are statistically less risk averse than non-abstinent control group participants, with the same result not found among their treatment group counterparts.[52]

However, despite the above findings, a relationship between risk preferences and abstinence, and their link to treatment assignment is not clear. At programme session 4, abstinent *treatment* group participants are more risk averse than non-abstinent treatment group participants ($p=0.032$), while abstinent control group participants are not statistically more or less risk averse than non-abstinent control group participants. Further, at each of the other sessions and evaluating by treatment group assignment, there is no statistical difference in risk preferences between abstinent and non-abstinent participants.

The EU model broadly supports the findings of the RDU model. That said, the RDU model finds risk preferences to differ not in terms of the power function parameter but rather the PWF

[50] See Table 17 in Appendix D, which presents the predictive margins of the EU and RDU models. The ensuing discussion refers this table.
[51] In this discussion, statistically significant differences in marginal effect estimates are identified using a Wald test.
[52] Again, the estimate for 'Abstinent at 6-month follow-up' should be treated with caution due to the very low number of abstinent participants at the 6-month follow-up.

parameters. As with the results of the ML estimates for the demographic variables, this suggests that any differences in risk preferences between abstinent and non-abstinent participants are due to differences in the way they perceive probabilities rather than, as suggested by the EU model, in the shape of their utility functions.

With respect to PWF parameter φ, we do not find a statistically significant difference between abstinent and non-abstinent participants at any of the sessions. Analysing by treatment status, we find that at programme session 3, however, abstinent control group subjects weight extreme probabilities more heavily than their non-abstinent control group counterparts (p=0.004). This implies that at programme session 3, abstinent control group subjects are more risk averse than non-abstinent control group subjects. At programme session 2, abstinent control group subjects weight extreme probabilities *less* heavily than the non-abstinent control group subjects (p=0.033), but the abstinent treatment group subjects weight extreme probabilities *more* heavily than the non-abstinent treatment group subjects (p=0.004). This suggests that at this session, abstinent control group subjects are less risk averse than their non-abstinent counterparts, whereas the treatment group subjects are more risk averse than their non-abstinent counterparts.

With respect to parameter η, we find that at programme session 1 abstinent subjects overweight low probabilities and underweight high probabilities relatively more than non-abstinent participants do (p<0.001). The converse holds at programme session 3 (p<0.001). In terms of risk preferences, these results imply that at programme session 1, because they overweight a wider range of low probability outcomes than they underweight high probability outcomes, abstinent subjects are more risk averse than their non-abstinent counterparts. Similarly, but conversely, at programme session 3 abstinent subjects are less risk averse than their non-abstinent counterparts. This finding conflicts with the conclusion drawn from programme session 3's parameter φ estimate for control group subjects.

In summary, while at a few programme sessions there is evidence of differing risk preferences between abstinent and non-abstinent participants, both structural models paint a similar overall picture to that given earlier by the REP model: there is *not* strong evidence that the more risk averse a smoker is, the likelier it is that they will quit when enrolled in a CM programme.

Abstinence and time preferences

Table 11 and Table 12 present the three discounting models' parameter estimates for the control group and treatment group, respectively. For the discounting parameters, the covariates included in the model are abstinence status at the programme sessions and the two follow-up sessions, the demographic covariates age, gender, race, and income, as well as a covariate for whether subjects did the risk preference task first. Of these covariates, only those pertaining to abstinence are presented in the tables.

Within the control group, the pairwise correlation between the variables 'Abstinent at programme session 2' and 'Abstinent at programme session 3' is 0.856, implying high collinearity.[53] This amount of collinearity prevents the models from converging and so to overcome this, I combine these variables to form 'Abstinent at programme sessions 2 and 3.' Thus, the discounting function parameters are evaluated by treatment group assignment, with the treatment group's model specification identical to that of the control group except for the inclusion of the covariates 'Abstinent at programme session 2' and 'Abstinent at programme session 3' rather than 'Abstinent at programme sessions 2 and 3.'

[53] For comparison, the next highest correlation coefficient within the control group is between variables 'Abstinent at programme session 2' and 'Abstinent at programme session 4' with a value of 0.644.

Table 11: Discounting function ML estimates assuming RDU - Heterogenous preferences with smoking abstinence and interaction term for the control group

	Exponential	Hyperbolic	QH
Power function parameter (r)	0.554***	0.593***	0.534***
	(0.056)	(0.058)	(0.051)
PWF parameter (φ)	0.609***	0.600***	0.613***
	(0.049)	(0.049)	(0.049)
PWF parameter (η)	0.984***	1.014***	0.968***
	(0.062)	(0.060)	(0.060)
Discounting parameter (δ)			
Abstinent at programme session 1	0.983**	0.582*	-0.013
	(0.470)	(0.323)	(0.016)
Abstinent at programme sessions 2 and 3	-2.104**	-1.327***	0.066***
	(0.855)	(0.410)	(0.019)
Abstinent at programme session 4	-0.999***	-0.682***	0.019
	(0.332)	(0.234)	(0.017)
Abstinent at 3-month follow-up	-2.963	-0.491	-0.111***
	(2.456)	(0.967)	(0.028)
Abstinent at 6-month follow-up	5.100***	1.911***	0.024
	(1.975)	(0.585)	(0.015)
Constant	2.572	1.618	0.963***
	(2.167)	(1.141)	(0.052)
Discounting parameter (β)			
Abstinent at programme session 1			0.754**
			(0.351)
Abstinent at programme sessions 2 and 3			-1.470**
			(0.691)
Abstinent at programme session 4			-0.798***
			(0.259)
Abstinent at 3-month follow-up			-3.076
			(2.177)
Abstinent at 6-month follow-up			4.547**
			(1.787)
Constant			1.901
			(1.695)
Risk error (μ)	0.216***	0.216***	0.217***
	(0.014)	(0.014)	(0.014)
Time error (ν)	1.419**	1.893**	1.235***
	(0.578)	(0.786)	(0.464)
N	6600	6600	6600
Log-likelihood	-3740.623	-3718.628	-3626.475

Output for demographic-related variables and the task order variable omitted
Results account for clustering at the individual level
Standard errors in parentheses
*p<0.1, **p<0.05, ***p<0.001

Looking at the control group's estimates for the exponential discounting model in Table 11, the results do not suggest a consistent relationship between time preferences and smoking abstinence. At programme session 1 and at the 6-month follow-up session, abstinent subjects have annual discount rates 98.3% and 510% higher than non-abstinent subjects, respectively (p=0.036 and p=0.01, respectively), unexpectedly suggesting that abstinent subjects discount their future welfare more than their non-abstinent counterparts. However, the estimate for the 6-month follow-up session should be treated with caution as at that session only 3 out of the 47 control group subjects are abstinent. Conversely, and according to our *a priori* expectations, at the combined programme sessions 2 and 3 and at programme session 4, abstinent subjects have annual discount rates 210% and 100% lower than non-abstinent participants at those sessions, respectively (p=0.014 and p=0.003, respectively).

The estimates for the hyperbolic discounting model are qualitatively similar to those of the exponential model.[54] However, in terms of magnitude, the differences in discount rates between abstinent and non-abstinent participants are more modest in the hyperbolic model than in the exponential model. Further, for the hyperbolic model's covariate 'Abstinent at programme session 1', the estimate is statistically significant at only the 10% level.

Like the exponential and hyperbolic model estimates, the QH model's discounting parameter estimates are also inconsistent in terms of their relationship between discounting and abstinence, but do not match the exponential and hyperbolic model's estimates in terms of direction. With respect to parameter δ, abstinent participants have higher discount rates than non-abstinent participants at the combined programme sessions 2 and 3 (p<0.001), whereas at the 3-month follow-up session, abstinent participants have lower discount rates than non-

[54] The δ estimates of the covariates 'Abstinent at programme session 1', 'Abstinent at programme session 2 and 3', 'Abstinent at programme session 4', and 'Abstinent at the 6-month follow-up session' have p-values of p=0.072, p<0.001, p=0.004, and p<0.001, respectively.

abstinent participants ($p<0.001$). Moreover, the magnitude of the difference in the δ estimates between abstinent and non-abstinent subjects is substantially less than that of the exponential and hyperbolic discounting models, with the largest difference in the long term discount rate δ being 11.1%.

Parameter β is statistically significantly greater among abstinent participants at programme session 1 and at the 6-month follow-up session compared to their non-abstinent participants (p=0.031 and p=0.011, respectively), implying that at these sessions, abstinent participants have a lower degree of present bias than their non-abstinent counterparts.[55] However, at the combined programme sessions 2 and 3 and at programme session 4, parameter β is statistically significantly lower among abstinent participants than non-abstinent participants (p=0.033 and p=0.002, respectively). Together, these results do not suggest there is a consistent relationship between smoking abstinence and present bias among control group participants.

Overall, the results presented in Table 11 suggest control group participants' time preferences have an inconsistent relationship with smoking abstinence across the sessions, as well as between the QH discounting model and the other two discounting models.[56]

Now looking at the results for the treatment group participants presented in Table 12, the exponential and hyperbolic discounting function parameter δ estimates do not suggest there to be a statistically significant difference in time preferences between abstinent and non-abstinent participants at any of the sessions. The estimates for the QH model, like those for the control group participants, are conflicting. At programme session 2, abstinent subjects have a *higher* discount rate than non-abstinent subjects (p=0.086), while at programme session 4 and at the 6-month follow-up, abstinent subjects have a *lower* discount rate than non-abstinent subjects

[55] The estimate for 'Abstinent at 6-month follow-up' should be treated with caution.
[56] See Table 18, in Appendix D, which displays the QH function discount rates by solving for equation (7). Overall, the estimates presented suggest that lower discount rates lead to a greater likelihood of abstinence.

(p=0.012 and p=0.081, respectively). The estimates for the parameter β do not suggest differences in present bias between abstinent and non-abstinent participants at any of the sessions.

Table 12: Discounting function ML estimates assuming RDU - Heterogenous preferences with smoking abstinence and interaction term for the treatment group

	Exponential	Hyperbolic	QH
Power function parameter (r)	0.816***	0.788***	0.794***
	(0.138)	(0.080)	(0.141)
PWF parameter (φ)	0.583***	0.590***	0.589***
	(0.063)	(0.054)	(0.063)
PWF parameter (η)	1.052***	1.035***	1.038***
	(0.078)	(0.056)	(0.080)
Discounting parameter (δ)			
Abstinent at programme session 1	-0.724	-0.296	-0.015
	(0.759)	(0.364)	(0.018)
Abstinent at programme session 2	-0.785	-0.234	0.037*
	(0.810)	(0.334)	(0.021)
Abstinent at programme session 3	-0.335	-0.018	0.007
	(0.644)	(0.344)	(0.017)
Abstinent at programme session 4	0.603	0.245	-0.044**
	(0.650)	(0.270)	(0.018)
Abstinent at 3-month follow-up	-0.893	-0.313	-0.003
	(0.701)	(0.264)	(0.014)
Abstinent at 6-month follow-up	2.193	0.717	-0.019*
	(2.005)	(0.466)	(0.011)
Constant	-7.875	-2.652*	1.198***
	(5.617)	(1.557)	(0.093)
Discounting parameter (β)			
Abstinent at programme session 1			-0.684
			(0.604)
Abstinent at programme session 2			-0.388
			(0.553)
Abstinent at programme session 3			-0.265
			(0.496)
Abstinent at programme session 4			0.201
			(0.472)
Abstinent at 3-month follow-up			-0.708
			(0.524)
Abstinent at 6-month follow-up			1.711
			(1.609)
Constant			-5.025
			(4.080)
Risk error (μ)	0.205***	0.204***	0.204***
	(0.018)	(0.016)	(0.018)
Time error (ν)	7.782	6.411	6.785
	(7.957)	(3.978)	(7.121)
N	5700	5700	5700
Log-likelihood	-3216.658	-3209.781	-3136.885

Table 12: continued

Output for demographic-related variables and the task order variable omitted Results account for clustering at the individual level Standard errors in parentheses **p*<0.1, ***p*<0.05, ****p*<0.001

The earlier REP model suggested that the more LL choices a subject made, and thus the lower their discount rate, the likelier it was that they would be abstinent. The discounting model parameters estimated by ML do not definitively support this finding. Among the control group participants, each of the models' statistically significant parameter estimates vary in direction: some of, but not all of the estimates conform with our *a priori* expectation that subjects that discount future welfare more highly are less likely to quit smoking. Among the treatment group participants, the exponential and hyperbolic models do not suggest any relationship between time preferences and smoking abstinence. The QH model again exhibits time preference parameter estimates that both follow and contradict our expectations but to less of a degree than that of the control group's estimates.[57]

The discounting parameter results for the treatment group notably differ from those of the control group. For the treatment group's exponential and hyperbolic discounting models, at none of the sessions is the discounting parameter δ statistically significantly different between abstinent and non-abstinent participants. Furthermore, for the QH model, at none of the sessions is the discounting parameter β statistically significantly different between abstinent and non-abstinent participants. These findings may be interpreted as discount rates losing their importance as a predictor for abstinence because the discounted reward outweighs the immediate gratification from smoking. Furthermore, CM possibly moderates discount rates, meaning that individuals with relatively high (low) discount rates find that their discount rates

[57] See Table 19 in Appendix D. Here, the QH model discount rates also do not suggest any relationship between time preferences and smoking preferences.

move lower (higher) over the course of the CM programme. The way in which CM influences the effect time preferences have on abstinence is discussed in more detail in the Discussion and Conclusion section.

Smoking intensity and risk preferences

Table 13 presents the abbreviated EU and RDU model ML results where, along with the covariates already included in Table 6, the parameters now vary as a function of the non-abstinent subjects' smoking intensity at each session.[58] As with Table 10, treatment assignment interaction terms are included although the RENB model did earlier suggest that there is no statistically significant relationship between treatment assignment and smoking intensity.

Again, I first look at the EU model and evaluate the predictive margins. Because smoking intensity is a continuous variable, I evaluate the predictive margins using plots. For each session, these tell us the predicted values of r at 1, 5, 10, and 15 cigarettes smoked per day, holding all other covariates at their means.

The results shown in Figure 10, below, are notable. The confidence intervals between 1 cigarette per day and 15 cigarettes per day only overlap at the baseline session and at the 6-month follow-up session. Thus, there is a general trend showing parameter r to be inversely related to the number of cigarettes smoked per day. This trend, however, is not at all apparent at the baseline session. These results suggest two effects. First, as shown by the baseline session graph, when smokers are not presently trying to quit, smoking intensity is not related to risk preferences. Second, the more risk averse a smoker is who is making a quit attempt, the *more* cigarettes they smoke when not abstinent. This finding is what was suggested by the RENB

[58] Each session is estimated separately in order to account for the different number of non-abstinent subjects at each session and to produce ML estimates that converge

model and is counterintuitive because, as explained earlier, smoking increases the likelihood of developing debilitating and even lethal health issues.

Figure 10: EU model predictive margins: Smoking intensity and power function parameter (r)

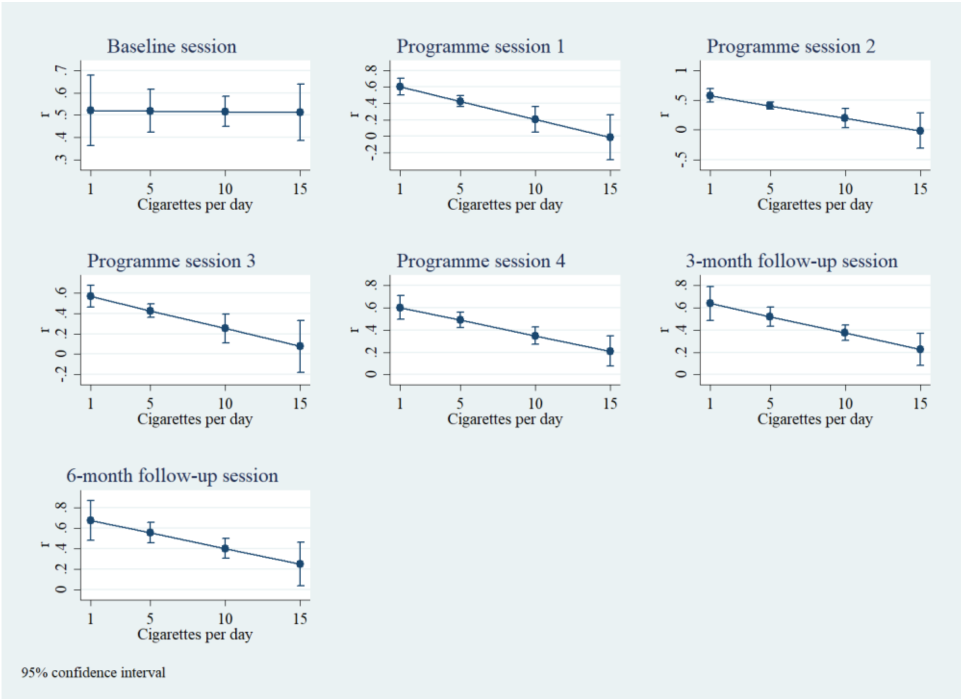


Table 13: EU and RDU ML Estimates - Heterogenous preferences with smoking intensity and interaction term

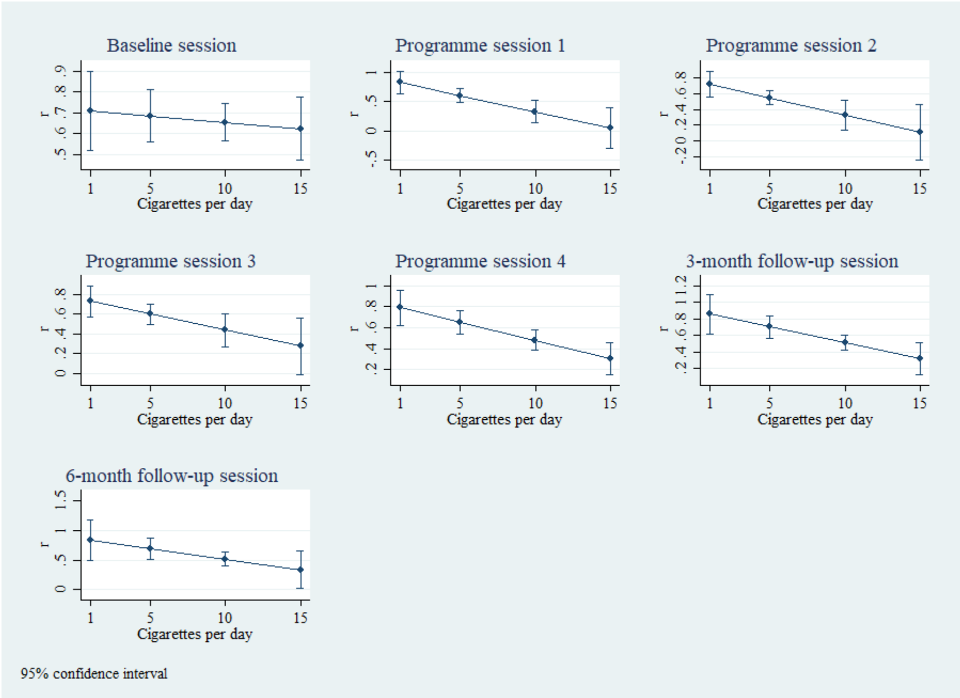
	EU							RDU						
	Baseline Session	Programme Session 1	Programme Session 2	Programme Session 3	Programme Session 4	3-month follow-up	6-month follow-up	Baseline Session	Programme Session 1	Programme Session 2	Programme Session 3	Programme Session 4	3-month follow-up	6-month follow-up
Power function parameter (r)														
Treatment	0.088	0.097	0.067	0.188	0.346***	0.292	0.188	0.165	0.348	0.218	0.426*	0.546**	0.609***	0.600*
	(0.159)	(0.139)	(0.129)	(0.133)	(0.131)	(0.183)	(0.227)	(0.199)	(0.278)	(0.189)	(0.219)	(0.222)	(0.205)	(0.339)
Smoking intensity	-0.006	-0.058***	-0.051**	-0.037**	-0.025***	-0.022**	-0.034***	-0.012	-0.063***	-0.045*	-0.024	-0.024**	-0.013	-0.016
	(0.013)	(0.019)	(0.021)	(0.017)	(0.009)	(0.010)	(0.011)	(0.015)	(0.023)	(0.026)	(0.019)	(0.010)	(0.016)	(0.019)
Smoking intensity×Treatment	0.012	0.035	0.023	0.006	-0.009	-0.016	0.008	0.013	0.017	0.001	-0.023	-0.028	-0.056***	-0.045
	(0.018)	(0.026)	(0.022)	(0.019)	(0.013)	(0.020)	(0.029)	(0.021)	(0.040)	(0.030)	(0.027)	(0.018)	(0.020)	(0.038)
Constant	-0.011	-0.064	0.588	0.254	0.190	-0.011	0.356	-0.568	-0.168	0.255	-0.006	0.014	0.068	0.342
	(0.395)	(0.384)	(0.394)	(0.417)	(0.391)	(0.397)	(0.395)	(0.488)	(0.580)	(0.670)	(0.627)	(0.527)	(0.700)	(0.550)
PWF parameter (φ)														
Treatment								-0.062	-0.135	0.073	-0.013	-0.032	-0.157	0.056
								(0.148)	(0.116)	(0.113)	(0.128)	(0.121)	(0.134)	(0.152)
Smoking intensity								-0.000	-0.006	0.017	0.008	-0.003	0.005	0.010
								(0.010)	(0.017)	(0.019)	(0.015)	(0.007)	(0.010)	(0.009)
Smoking intensity×Treatment								0.001	-0.004	-0.050**	-0.030	-0.012	0.014	-0.022
								(0.013)	(0.022)	(0.024)	(0.020)	(0.012)	(0.018)	(0.017)
Constant								1.838***	1.710***	1.873***	1.891***	1.797***	1.784***	2.037***
								(0.394)	(0.414)	(0.410)	(0.380)	(0.380)	(0.444)	(0.435)
PWF parameter (η)														
Treatment								0.134	0.328*	0.269*	0.366**	0.284*	0.351*	0.578***
								(0.151)	(0.184)	(0.140)	(0.177)	(0.169)	(0.180)	(0.183)
Smoking intensity								-0.002	0.014	0.040	0.049**	0.020	0.027**	0.052*
								(0.010)	(0.022)	(0.026)	(0.024)	(0.015)	(0.013)	(0.028)

Table 13: continued

	EU							RDU						
	Baseline Session	Programme Session 1	Programme Session 2	Programme Session 3	Programme Session 4	3-month follow-up	6-month follow-up	Baseline Session	Programme Session 1	Programme Session 2	Programme Session 3	Programme Session 4	3-month follow-up	6-month follow-up
Smoking intensity×Treatment								-0.006	-0.051	-0.071**	-0.073**	-0.046**	-0.050**	-0.097***
								(0.013)	(0.032)	(0.030)	(0.029)	(0.019)	(0.021)	(0.030)
Constant								0.737	1.267**	1.009*	0.960	1.074*	1.579***	1.642***
								(0.464)	(0.601)	(0.573)	(0.632)	(0.637)	(0.435)	(0.574)
Risk error (μ)	0.234***	0.232***	0.229***	0.231***	0.229***	0.233***	0.232***	0.196***	0.190***	0.189***	0.188***	0.187***	0.193***	0.195***
	(0.013)	(0.016)	(0.015)	(0.015)	(0.014)	(0.013)	(0.014)	(0.010)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)
N	7110	5400	5130	4860	4950	6030	5850	7110	5400	5130	4860	4950	6030	5850
Log-likelihood	-4523.920	-3418.435	-3236.312	-3075.480	-3125.983	-3819.572	-3687.072	-4315.639	-3212.861	-3051.902	-2896.323	-2963.258	-3619.925	-3497.898

Demographic-related variables and task order variable omitted
Results account for clustering at the individual level
Standard errors in parentheses
**p*<0.1, ***p*<0.05, ****p*<0.001

Figure 11: RDU model predictive margins: Smoking intensity and power function parameter (r)



When the margins are evaluated by treatment group assignment, we find the same as Figure 10: that as risk aversion increases among non-abstinent smokers, smoking intensity increases.[59] The RDU model's results generally support those of the EU model. First looking at the predictive margins of parameter *r*, Figure 11 also shows an inverse relationship between smoking intensity and risk aversion, although the statistical significance is not as strong as that seen in Figure 10.

Figure 12 shows the predictive margins for PWF parameter φ. The figure does not suggest that there is a relationship between smoking intensity and the extent to which smokers underweight high probabilities and overweight low probabilities. Similarly, Figure 13 does not suggest that there is a relationship between smoking intensity and the extent to which smokers overweight low probabilities relatively more than they underweight high probabilities (and vice versa).

[59] See Figure 20 and Figure 21 in Appendix D

Together, the results for these PWF parameters do not suggest a relationship between probability weighting and smoking intensity.

The RENB model found a positive relationship between the "number of risky choices" made in the risk preferences elicitation task and the number of cigarettes smoked in the previous 7 days. This implies that, on average, the more risk averse one is, the greater their smoking intensity. Overall, the structural models support this unexpected finding, with both the EU and RDU models suggesting that, on average, as risk aversion increases, smoking intensity increases. This result is discussed further in the Discussion and Conclusion section.

Figure 12: RDU model predictive margins: Smoking intensity and PWF parameter φ

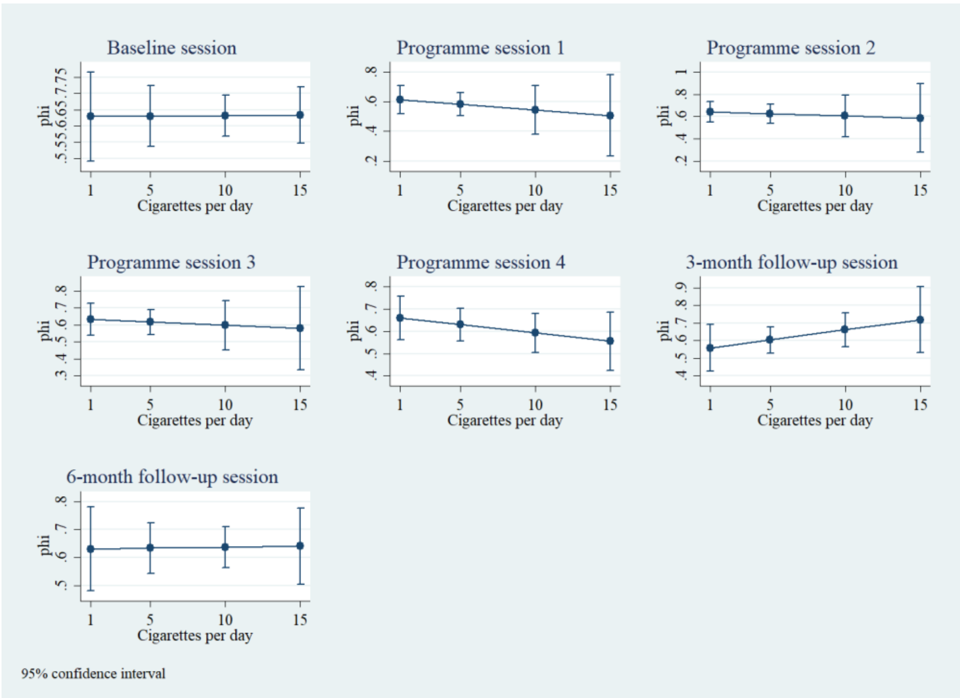
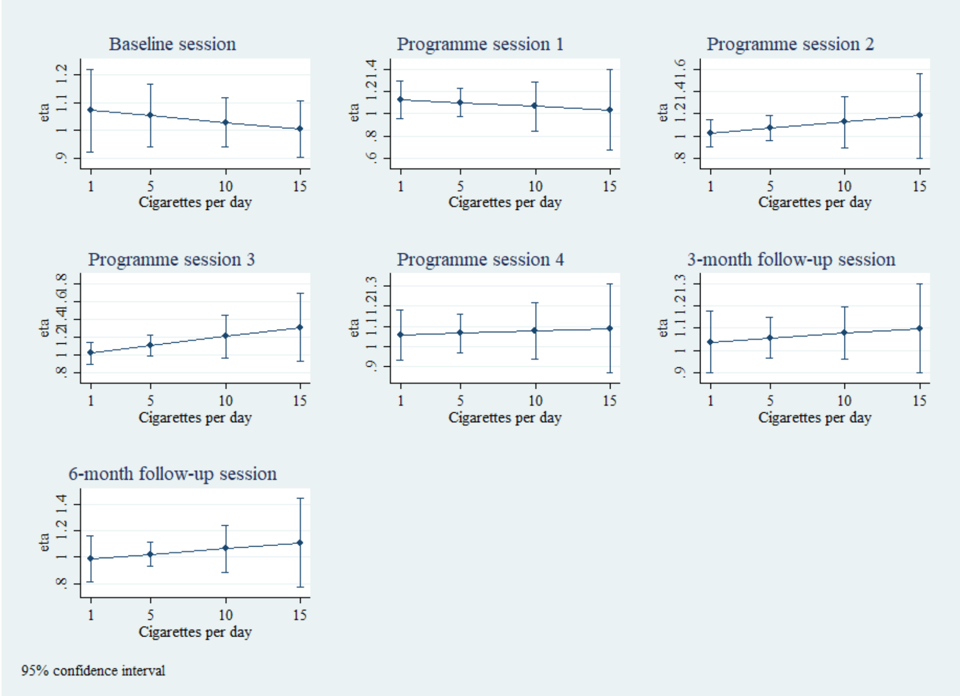


Figure 13: RDU model predictive margins: Smoking intensity and PWF parameter η



Smoking intensity and time preferences

Table 14 extends the RDU estimates presented in Table 13, displaying the exponential and hyperbolic discounting models' estimates for the discounting parameter δ, while omitting the estimates for the risk preference parameters, the covariates associated with the subjects' demographics, and the covariate indicating whether the risk or time preference task was done first. I again analyse these estimates by evaluating the predictive margins, visualized using plots, at 1, 5, 10, and 15 cigarettes smoked per day.

Table 14: Exponential and hyperbolic discounting function ML estimates assuming RDU - heterogenous preferences with smoking intensity and interaction term

	Exponential							Hyperbolic						
	Baseline Session	Programme Session 1	Programme Session 2	Programme Session 3	Programme Session 4	3-month follow-up	6-month follow-up	Baseline Session	Programme Session 1	Programme Session 2	Programme Session 3	Programme Session 4	3-month follow-up	6-month follow-up
Discounting parameter (δ)														
Treatment	0.497	0.081	-1.245	-0.244	0.113	-0.348	-2.778*	-0.058	0.020	-0.712	-0.105	0.061	-0.517	-0.445
	(0.946)	(0.543)	(1.648)	(0.441)	(0.385)	(0.736)	(1.476)	(0.404)	(0.337)	(0.683)	(0.272)	(0.235)	(0.344)	(0.360)
Smoking intensity	0.241	0.320	0.069	0.060	0.133	0.242	0.006	0.033	0.154	0.042	0.045	0.079	-0.023	0.073
	(0.167)	(0.340)	(0.180)	(0.148)	(0.121)	(0.185)	(0.085)	(0.028)	(0.159)	(0.108)	(0.086)	(0.065)	(0.047)	(0.076)
Smoking intensity×Treatment	-0.084	-0.156	0.315	-0.036	-0.136	-0.071	0.302	0.014	-0.079	0.150	-0.035	-0.080	0.083	0.005
	(0.146)	(0.281)	(0.571)	(0.152)	(0.118)	(0.188)	(0.191)	(0.047)	(0.136)	(0.250)	(0.091)	(0.066)	(0.055)	(0.067)
Constant	-7.508**	5.086	-4.972*	-2.185	0.066	-1.907	-8.893*	0.299	2.806	-2.907	-0.683	0.430	-0.124	-0.787
	(3.199)	(4.232)	(3.020)	(5.445)	(3.164)	(2.184)	(4.839)	(2.589)	(2.307)	(1.799)	(3.744)	(1.689)	(2.434)	(1.548)
Risk error (μ)	0.207***	0.189***	0.195***	0.192***	0.191***	0.200***	0.206***	0.205***	0.190***	0.197***	0.194***	0.191***	0.200***	0.210***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.010)	(0.012)	(0.014)	(0.015)	(0.012)	(0.014)	(0.016)	(0.010)	(0.012)	(0.016)
Time error (ν)	5.237**	3.584**	3.494	2.397**	2.323**	3.750**	4.717**	3.382**	4.695*	4.966*	3.125*	3.121**	2.811***	5.366
	(2.299)	(1.760)	(2.385)	(1.050)	(0.903)	(1.676)	(2.301)	(1.340)	(2.643)	(2.929)	(1.725)	(1.280)	(0.968)	(3.912)
N	11850	9000	8550	8100	8250	10050	9750	11850	9000	8550	8100	8250	10050	9750
Log-likelihood	-6678.507	-5013.490	-4698.067	-4511.649	-4612.682	-5629.603	-5405.608	-6649.733	-4976.628	-4666.475	-4482.392	-4579.294	-5623.375	-5395.629

Demographic-related variables and task order variable omitted
Results account for clustering at the individual level
Standard errors in parentheses
**p*<0.1, ***p*<0.05, ****p*<0.001

Figure 14: Exponential discounting model predictive margins: Smoking intensity and discounting parameter (δ)

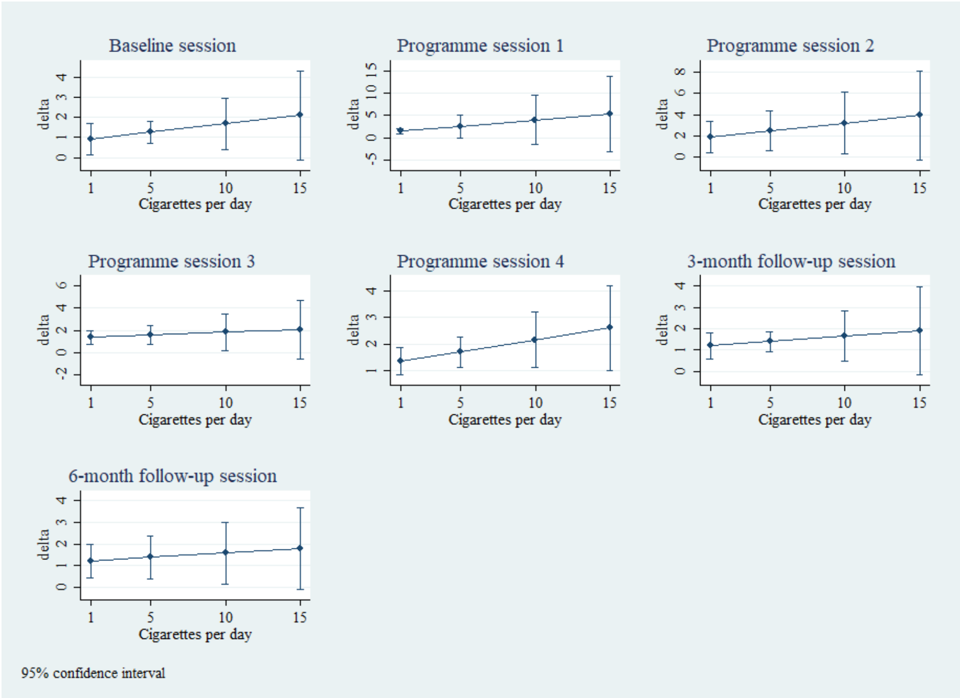
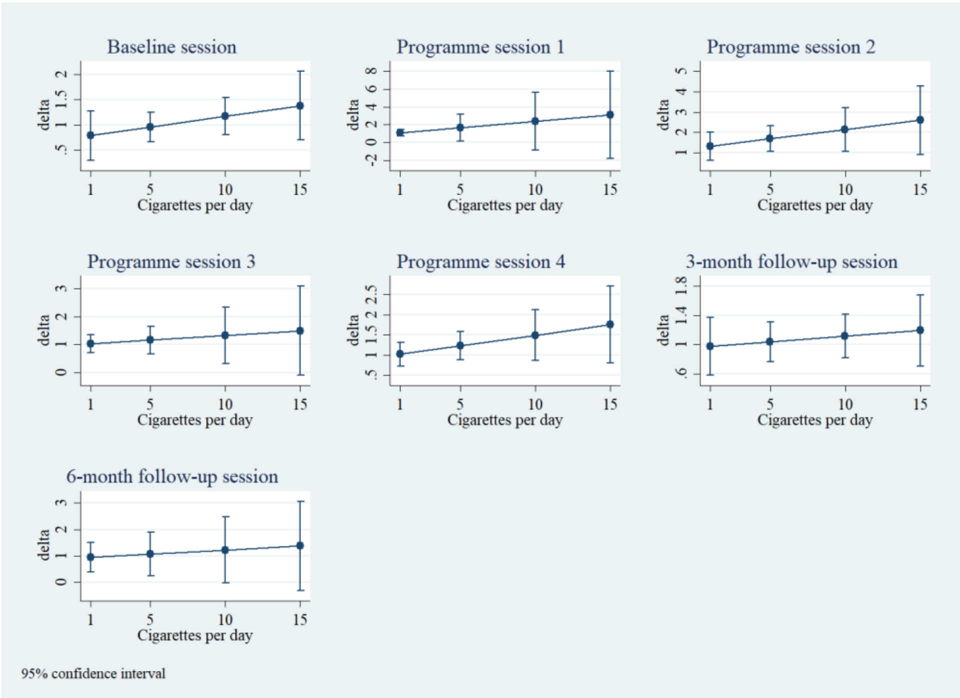


Figure 15: Hyperbolic discounting model predictive margins: Smoking intensity and discounting parameter (δ)



As shown in Figure 14 and Figure 15, neither discounting model suggests a relationship between the discounting parameter δ and smoking intensity at any of the sessions. Thus, neither model supports the hypothesis that smoking intensity increases the more a smoker discounts their future well-being.

Similarly to Table 14, Table 15 presents the ML estimates for the QH discounting model's parameters δ and β, and Figure 16 and Figure 17 present the predictive margins for the discounting parameters δ and β, respectively. Again, there is no evidence suggesting that smoking intensity is related to the degree in which a smoker discounts their future utility, and moreover, the estimates for parameter β do not suggest there is a relationship between smoking intensity and the smoker's level of present bias.

It does not appear that a statistically significant relationship between time preferences and smoking intensity depends on treatment assignment either.[60] This finding is consistent with the results of the earlier discussed RENB statistical model. Moreover, the lack of a relationship between time preferences and smoking intensity among the structural models is also consistent with the RENB model's results.

[60] See Figure 22 to Figure 29 in Appendix D.

Table 15: QH discounting function ML estimates assuming RDU - heterogenous preferences with smoking intensity and interaction term

	QH						
	Baseline Session	Programme Session 1	Programme Session 2	Programme Session 3	Programme Session 4	3-month follow-up	6-month follow-up
Discounting parameter (δ)							
Treatment	0.388	-0.047	-0.597	-0.150	0.089	-0.385	-0.454
	(0.672)	(0.497)	(0.867)	(0.330)	(0.268)	(0.585)	(0.311)
Smoking intensity	0.154*	0.192	0.041	0.028	0.063	0.162	0.092
	(0.089)	(0.248)	(0.122)	(0.115)	(0.085)	(0.142)	(0.083)
Smoking intensity×Treatment	-0.046	-0.026	0.155	-0.001	-0.063	-0.011	0.001
	(0.092)	(0.235)	(0.306)	(0.119)	(0.084)	(0.150)	(0.074)
Constant	-5.416***	3.973	-2.971	-1.255	-0.033	-1.332	-0.669
	(1.966)	(2.630)	(1.815)	(4.047)	(2.129)	(1.614)	(1.158)
Discounting parameter (β)							
Treatment	-0.005*	-0.009	-0.002	-0.002	-0.006*	-0.010**	-0.004
	(0.003)	(0.007)	(0.006)	(0.004)	(0.004)	(0.005)	(0.002)
Smoking intensity	0.003	0.007	-0.010	0.003	0.007	0.010*	0.003
	(0.003)	(0.006)	(0.008)	(0.007)	(0.005)	(0.005)	(0.003)
Smoking intensity×Treatment	-0.005*	-0.009	-0.002	-0.002	-0.006*	-0.010**	-0.004
	(0.003)	(0.007)	(0.006)	(0.004)	(0.004)	(0.005)	(0.002)
Constant	1.147***	0.832***	1.151***	1.038***	0.962***	1.071***	1.065***
	(0.101)	(0.100)	(0.059)	(0.186)	(0.099)	(0.111)	(0.081)
Risk error (μ)	0.208***	0.189***	0.194***	0.193***	0.191***	0.200***	0.206***
	(0.016)	(0.012)	(0.012)	(0.013)	(0.010)	(0.012)	(0.013)
Time error (ν)	4.379**	3.228**	2.869**	2.125**	2.079***	3.525**	3.111*
	(1.722)	(1.411)	(1.278)	(0.887)	(0.759)	(1.504)	(1.615)
N	11850	9000	8550	8100	8250	10050	9750
Log-likelihood	-6500.526	-4874.353	-4572.991	-4392.090	-4496.670	-5498.076	-5280.976

Demographic-related variables and task order variable omitted
Results account for clustering at the individual level
Standard errors in parentheses
**p*<0.1, ***p*<0.05, ****p*<0.001

Figure 16: QH discounting model predictive margins: Smoking intensity and discounting parameter (δ)

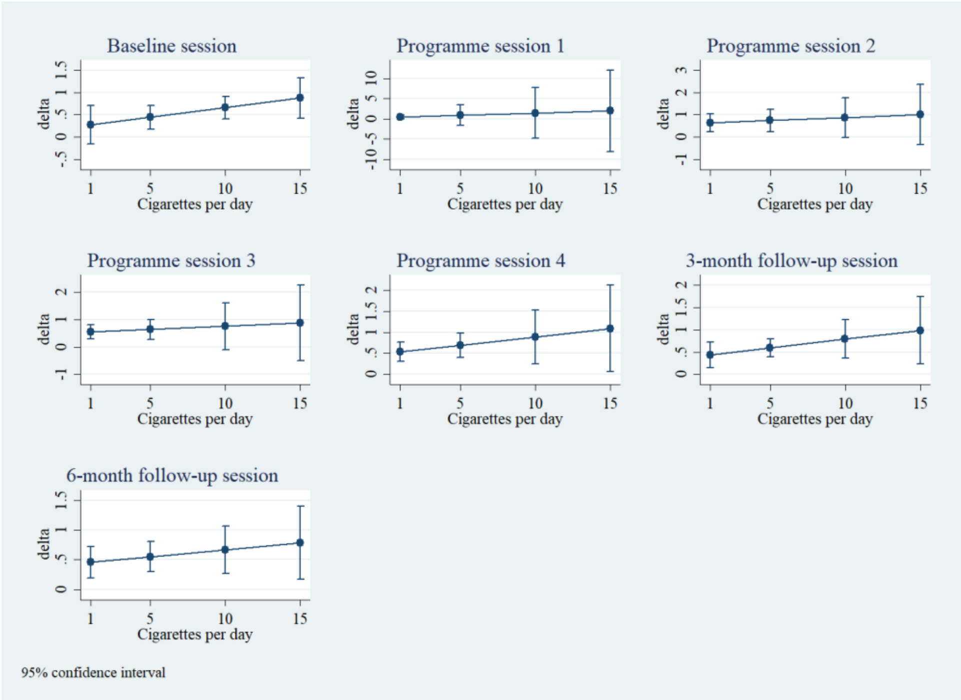
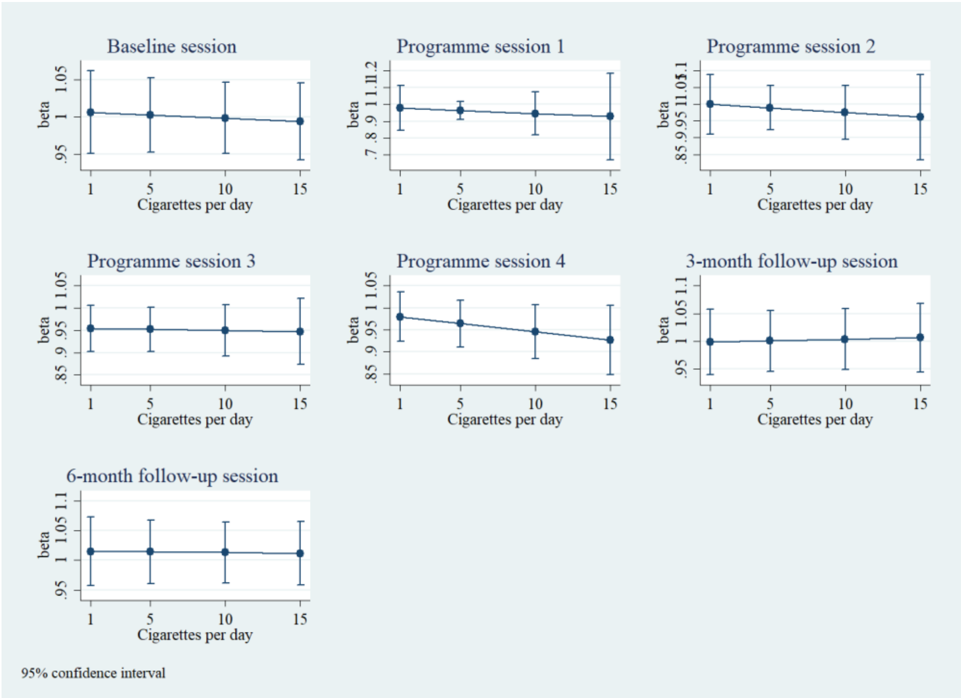


Figure 17: QH discounting model predictive margins: Smoking intensity and discounting parameter (β)



7. Discussion and Conclusion

The aim of this dissertation was to explore the impact CM programme-enrolled smokers' risk and time preferences have on their likelihood of quitting smoking, as well as on their smoking intensity. To this end, I adopted two approaches. The first used statistical models to estimate the relationship between the subjects' abstinence status and smoking intensity levels, with their responses to the risk and time preference tasks. As a second approach, I used structural models to estimate risk and time preference parameters which were compared between abstinent and non-abstinent participants, as well as across different levels of smoking intensity.

Both approaches agreed that within the confines of this CM programme, there is not an apparent relationship between risk preferences and abstinence. This adds to the literature's broadly mixed support for the hypothesis that risk aversion and smoking activity are linked.

On the other hand, the REP model supported the hypothesis that abstinence is likelier among smokers who discount their future well-being less, with the statistical model finding the number of LL rewards chosen in the time preference task to be a predictor of abstinence. The structural models also presented evidence linking abstinence to time preferences, however not necessarily in the way suggested by the REP model. As mentioned earlier, by finding that time preferences are only correlated with abstinence among control group participants, we may infer that CM mitigates the impact time preferences have on the likelihood of quitting smoking.

CM may do this by providing smokers with a choice between a sufficiently valuable monetary reward and smoking a cigarette. This addresses Gruber and Koszegi's (2001) earlier described dual self model of addiction, where individuals' present bias leads them to weight payoffs by how soon they are received. At a point during the treatment period, a decision-maker must choose between the instant utility from smoking, and the discounted utility from the monetary reward. If the reward is large enough, despite it being discounted, the discounted utility from not smoking is greater than the utility from smoking. Without the reward, the utility gained from being healthy relative to a smoker (and likely only experienced decades in the future among a sample of students), is discounted to the point where it is less than the utility gained from smoking.

Furthermore, CM possibly moderates individual's discount rates from relative extremes. This interpretation is loosely supported by Landes, Christensen and Blokel (2012), who found that within a CM programme targeting opiate addiction, participants' measured discount rates on average decreased between treatment onset and the end of the 12-week programme. However, they did not find there to be a correlation between time preferences and abstinence, so a proposed aetiology where the CM programme lowers discount rates, and thereby causes abstinence, is not supported by their findings.

That said, the structural models I presented for treatment group participants do not suggest a relationship between lower discount rates and higher rates of abstinence either. Landes, Christensen and Blokel (2012) did not have a control group, thus preventing analysis that would show that the discount rates for control-group recovering addicts are a predictor of abstinence, while among treatment smokers it is not. As all their participants received treatment, their finding that discount rates are not a predictor of abstinence is consistent with my findings.

However, the discussion above does not adequately explain why at certain sessions, higher discount rates meant an increased likelihood of abstinence. One possibility is that CM moves discount rates from either discounting extreme: low discounting and high discounting. A follow-up study that tracks the change in participant's discount rates over the course of the programme would help answer that question.

With respect to smoking intensity, both the statistical and structural models show, counter to our *a priori* expectations and prior evidence,[61] that smoking intensity has a positive relationship with risk aversion. The more cigarettes one smokes, the likelier one is to develop potentially deadly diseases. Thus, the more risk averse a smoker is, the fewer cigarettes we would expect them to smoke. However, the data show the opposite.

A potential explanation for this result is the subjects' level of stress. With risk aversion increasing with stress levels (Cahlíková and Cingl, 2017), and smoking intensity also increasing with stress levels (Mckee et al., 2011), it is possible the smokers' stress levels rather than their risk preference determine their smoking intensity. However, this explanation does not neatly explain why at the baseline session, when subjects are not making a quit attempt, risk preferences are not a predictor for smoking intensity. Further research exploring this relationship would improve our understanding of why this is the case.

In contrast to the findings of Harrison et al. (2018), neither the statistical nor structural models suggest a relationship between smoking intensity and time preferences. The difference between our findings is possibly because their study's sample was not limited to smokers wanting to quit and enrolled in a CM programme.

Focusing on the implication of these results on the CM programme's outcomes, I found that risk and time preferences are not balanced equally between the control and treatment groups. Because treatment group participants on average have less present bias than the control group participants, the CM programme is possibly less effective at promoting abstinence than what HKR (2020) reported. On the other hand, because treatment group participants are less risk averse than their control group counterparts, the CM programme's reported influence on smoking intensity may have been understated. Nevertheless, when the statistical models

[61] For example, Harrison et al. (2018) did not find any statistically significant relationship between risk preferences and smoking intensity.

include the variables associated with the number of risky choices and number of LL choices made in the decision-making tasks, the magnitude of the treatment effect on abstinence actually increases, while the treatment effect on smoking intensity remains statistically insignificant.

This dissertation contributes to the limited existing literature examining the impact risk and time preferences have on smoking behaviour within the context of a CM programme. First, unlike any of the existing literature, it explores the relationship between risk preferences and smoking behaviour among CM programme enrolled smokers. Second, this dissertation adds to the consensus that individuals' time preferences are a predictor of their likelihood of abstinence. This said, the relationship does not directly support other papers' research which suggests that lower discount rates are correlated with higher rates of abstinence. Third, in terms of methodology, I jointly estimated the time preference parameters with the risk preference parameters, yielding discount rates that are more accurate than when estimated assuming a linear utility function. Finally, the study's design has the advantages of a relatively large sample size, a relatively long study period, the use of real rather than hypothetical rewards, and the use of FEDs in the time preference elicitation task.

Naturally, this study has limitations. First, looking at those particular to the CM programme, despite the sample size being relatively large, having more participants would have increased the power of the models' findings. Second, a CO test only detects if someone has smoked within the previous 2 days, thereby allowing participants to 'game' the programme as each testing session is seven days apart. Finally, due to the nature of the intervention, neither the treatment subjects nor RAs were blind to treatment allocation, thus allowing the possibility of performance bias.

In the risk and time preference tasks, we are assuming there is a correlation between individual's risk and time preferences for monetary rewards, and their risk and time preferences in terms of their health. It may very possibly be that for a significant portion of the sample, this correlation is weak. Overcoming this potential issue is difficult, but an alternative approach could be to use rewards more closely tied to health. As an example, instead of cash rewards, vouchers of varying amounts that can only be spent at places like gyms or health shops could be used.

In terms of limitations of the statistical methodology, the structural models did not converge when covariates were highly correlated. Thus, when examining the relationship between abstinence and time preferences, I had to estimate the discounting models' parameters by treatment assignment, with the control group's session 2 abstinence and session 3 abstinence indicators combined. Given the inconsistency of the those discounting models' results, it would have been useful seeing separate estimates for 'abstinent at session 2' and 'abstinent at session 3'. Lastly, mixture models allow for the possibility that the exponential model explains certain choices better than the hyperbolic model, but the hyperbolic model explains other choices better. Future research incorporating mixture models, as well as a greater variety of discounting models (e.g., a Weibull discounting function), would give us a better understanding of how risk and time preferences affect smoking behaviour in the context of a CM programme.

Despite the above issues, the analysis presented in this dissertation offers important new insights for treating tobacco addiction. Notably, in this CM programme, time preferences, not risk preferences, impact the likelihood of abstinence, but risk preferences, not time preferences, affect smoking intensity. While the directional impact time preferences have on abstinence is unclear, the results do suggest that CM's success at treating addiction is at least partly due to it weakening the influence time preferences have on the individual's choice to break abstinence. In terms of smoking intensity, the results do not suggest time preferences to affect smoking intensity, but do find, unexpectedly and potentially due to an omitted variable, e.g., stress, that smoking intensity increases with risk aversion.

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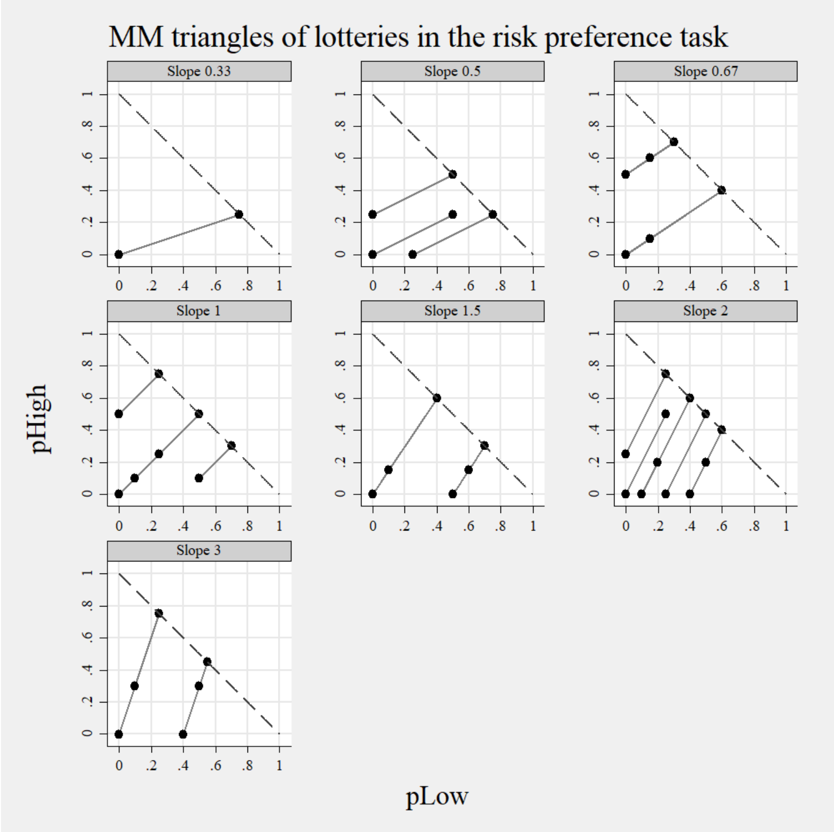
Appendix A

Figure 18 shows the set of Marschak-Machina (MM) triangles representing the lottery pairs in the risk preference task. Each triangles' heading provides the gradient of the lines connecting the lottery pairs. The vertical and horizontal axes show the probability assigned to receiving the lottery's highest and lowest prizes, respectively. Each dot represents a lottery while the lines connecting dots shows a lottery pair used in the risk preference task. These lines are indifference curves, where participants are expected to be indifferent between the lottery pairs shown in each triangle. The probability of the intermediate prize is calculated as the sum of the high and low prizes' probabilities subtracted from 1. Only the lotteries that had no more than three possible outcomes are represented in the MM triangles.

Figure 18: MM triangles of the risk preference task lotteries



Moving north-easterly along the lines means that less probability is assigned to the intermediate reward and more weight to the lowest and highest rewards. This means that the riskiest lotteries are those lying on the hypotenuse while the least risky are situated at the triangle's origin.

Figure 18 shows that the risk preference task provided good coverage of the probability space and covered a full range of risk preferences. Risk seeking behaviour is covered by the lottery pairs with a slope less than 1, risk neutral behaviour by the lottery pairs with a slope of 1, and risk aversion by the lottery pairs with a slope greater than 1.

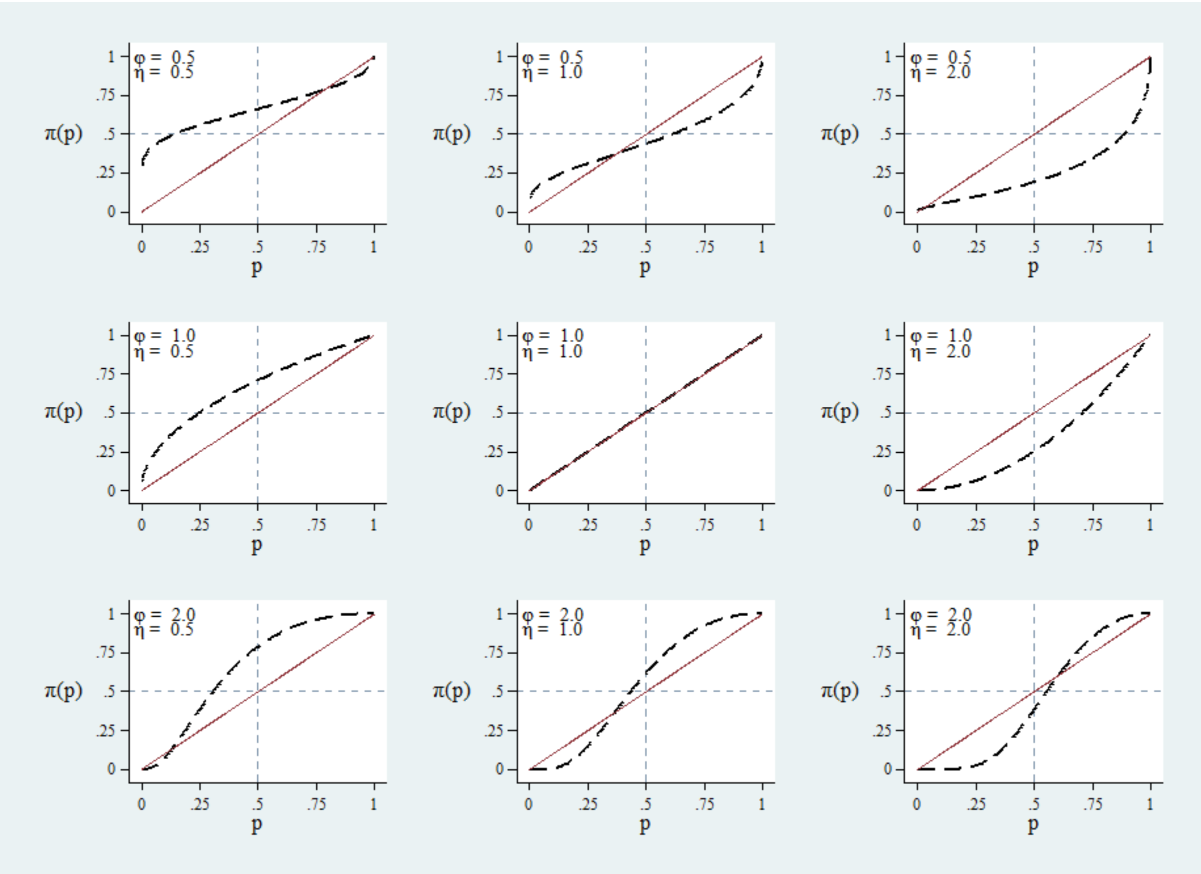
Appendix B

This section provides a description of the Prelec (1998) PWF and serves as a reference when describing the results for the RDU estimates in Table 10 and Table 13. PWFs are an essential component of RDU as they provide the nonlinearity of its probability weighting. As described in the Statistical Methodology section, the Prelec (1998) PWF takes the functional form:

$$\pi(p)=\exp[-\eta(-\ln p)^{\varphi}] \tag{26}$$

which is defined for $1 > p > 0$, and $\varphi > 0$. Figure 19 below provides a series of PWFs taking on a range of values for parameters φ and η:

Figure 19: Representative graphs of the Prelec PWF



They y-axis represents the individual's subjective probability weights associated with the objective probabilities displayed on the x-axis. The second row of figures shows that where φ=1, the Prelec PWF takes the form:

$$\pi(p)=p^{\eta} \tag{27}$$

which is a power function. Thus, the graph at the centre represents no probability weighting. The first row, where φ=0.5, shows graphs resembling an inverse-S shape where a representative individual overweights low-probability events and underweights high-probability events. The converse holds, i.e., an S-shaped curve, for the third row where φ=2.

Where parameter η<1, the curve's inflection point lies above the 45º line, whereas when η>1, the point of inflection lies below the 45º line. A point of inflection above the 45º line means the individual overweights low probabilities relatively more than they underweight high probabilities. The converse holds for points of inflection below the 45º line. When η=1, the individual overweights low probabilities and underweights high probabilities to the same degree.

Appendix C

To assess the methodology's robustness, a pooled probit regression and a pooled negative binomial regression are run. The coefficients estimates are shown in Table 16.

The results of the pooled probit regression and the pooled negative binomial regression are broadly in line with what was reported for Regression 1c and Regression 2c respectively.

The statistically significant intraclass correlation coefficient in Regression 1c (ρ = 0.470) suggests a REP model is preferable to a pooled probit regression.[62] Formally, this coefficient is the ratio of the between-cluster (individual subject) variance to the total variance. As the intraclass correlation is statistically significant, it is important that the serial dependence of the error term is incorporated in the models' statistical specification. Similarly, a RENB model is preferable to a pooled negative binomial regression, as shown by the results of the likelihood ratio test (p<0.001).

[62] Regressions 1a and 1b respectively yield ρ=0.551 and ρ= 0.521, both of which are statistically significant.

Table 16: Pooled Probit and Pooled Negative Binomial Regressions

	Pooled Probit	Pooled Negative Binomial
Treatment	1.021***	0.243*
	(0.241)	(0.129)
Age	0.262	-0.048
	(0.200)	(0.114)
Age squared	-0.003	0.001
	(0.003)	(0.002)
Male	0.176	0.067
	(0.316)	(0.128)
Coloured	0.453	0.072
	(0.347)	(0.132)
Indian	0.283	0.162
	(0.380)	(0.160)
White	0.799***	0.270*
	(0.294)	(0.149)
Income (ln)	-0.131	0.071
	(0.226)	(0.083)
Number of risky choices	-0.032	-0.041*
	(0.031)	(0.023)
Number of risky choices squared	0.001	0.001
	(0.001)	(0.001)
Number of LL choices	-0.045**	-0.011
	(0.019)	(0.012)
Number of LL choices squared	0.001***	0.001
	(0.001)	(0.001)
Risk task completed first	0.142	-0.004
	(0.225)	(0.125)
Programme sessions		-0.970***
		(0.085)
3-month follow-up session		-0.495***
		(0.083)
6-month follow-up session		-0.488***
		(0.077)
Constant	-4.596	2.992*
	(2.936)	(1.753)
N	553	425
log-likelihood	-165.403	-996.748

Appendix D

Table 17: Marginal effects of EU and RDU models, abstinence

	EU	RDU		
	r	r	φ	η
Treatment assignment				
Control	0.380***	0.499***	0.671***	1.063***
	(0.050)	(0.049)	(0.054)	(0.061)
Treatment	0.653***	0.871***	0.580***	1.080***
	(0.063)	(0.154)	(0.052)	(0.083)
Abstinence at programme session 1				
Non-abstinent at programme session 1	0.485***	0.779***	0.579***	1.135***
	(0.039)	(0.134)	(0.046)	(0.075)
Abstinent at programme session 1	0.753***	0.467***	0.662***	0.618***
	(0.151)	(0.105)	(0.093)	(0.073)
Control × Non-abstinent at programme session 1	0.336***	0.508***	0.727***	1.191***
	(0.064)	(0.063)	(0.068)	(0.084)
Control × Abstinent at programme session 1	0.580***	0.459***	0.417***	0.487***
	(0.124)	(0.147)	(0.113)	(0.094)
Treatment × Non-abstinent at programme session 1	0.599***	0.983***	0.481***	1.136***
	(0.052)	(0.221)	(0.070)	(0.109)
Treatment × Abstinent at programme session 1	0.894***	0.367*	1.018***	0.834***
	(0.289)	(0.188)	(0.149)	(0.132)
Abstinence at programme session 2				
Non-abstinent at programme session 2	0.520***	0.589***	0.673***	1.047***
	(0.054)	(0.043)	(0.038)	(0.042)
Abstinent at programme session 2	0.606***	1.031***	0.558***	1.128***
	(0.133)	(0.344)	(0.213)	(0.241)
Control × Non-abstinent at programme session 2	0.367***	0.476***	0.651***	1.041***
	(0.063)	(0.086)	(0.078)	(0.051)
Control × Abstinent at programme session 2	0.444**	0.610***	0.768**	1.167***
	(0.193)	(0.232)	(0.319)	(0.337)
Treatment × Non-abstinent at programme session 2	0.636***	0.734***	0.645***	1.075***
	(0.084)	(0.074)	(0.054)	(0.066)
Treatment × Abstinent at programme session 2	0.735***	1.534**	0.261	1.105***
	(0.150)	(0.741)	(0.236)	(0.302)
Abstinence at programme session 3				

Table 17: continued

	EU	RDU		
	r	r	φ	η
Non-abstinent at programme session 3	0.559***	0.682***	0.620***	0.981***
	(0.046)	(0.126)	(0.056)	(0.070)
Abstinent at programme session 3	0.301***	0.656***	0.791***	1.642***
	(0.088)	(0.126)	(0.085)	(0.089)
Control × Non-abstinent at programme session 3	0.487***	0.541***	0.586***	0.813***
	(0.060)	(0.060)	(0.057)	(0.058)
Control × Abstinent at programme session 3	0.002	0.350**	0.970***	1.949***
	(0.125)	(0.154)	(0.126)	(0.118)
Treatment × Non-abstinent at programme session 3	0.652***	0.834***	0.596***	1.056***
	(0.075)	(0.194)	(0.081)	(0.101)
Treatment × Abstinent at programme session 3	0.657***	1.000***	0.522***	1.167***
	(0.143)	(0.225)	(0.153)	(0.135)
Abstinence at programme session 4				
Non-abstinent at programme session 4	0.592***	0.756***	0.601***	1.033***
	(0.048)	(0.098)	(0.037)	(0.062)
Abstinent at programme session 4	0.381***	0.538***	0.627***	0.927***
	(0.122)	(0.174)	(0.170)	(0.078)
Control × Non-abstinent at programme session 4	0.421***	0.544***	0.688***	1.145***
	(0.047)	(0.054)	(0.064)	(0.074)
Control × Abstinent at programme session 4	0.247	0.349	0.613**	0.790***
	(0.209)	(0.253)	(0.276)	(0.103)
Treatment × Non-abstinent at programme session 4	0.712***	0.927***	0.546***	1.038***
	(0.075)	(0.167)	(0.055)	(0.092)
Treatment × Abstinent at programme session 4	0.459***	0.684***	0.690***	1.219***
	(0.096)	(0.187)	(0.127)	(0.120)
Abstinence at 3-month follow-up				
Non-abstinent at 3-month follow-up	0.533***	0.707***	0.622***	1.063***
	(0.039)	(0.094)	(0.035)	(0.057)
Abstinent at 3-month follow-up	0.533***	0.711***	0.533***	1.051***
	(0.159)	(0.210)	(0.206)	(0.189)
Control × Non-abstinent at 3-month follow-up	0.385***	0.489***	0.688***	1.053***
	(0.058)	(0.051)	(0.067)	(0.070)

Table 17: continued

	EU	RDU		
	r	r	φ	η
Control × Abstinent at 3-month follow-up	0.283	0.702**	0.325	1.255***
	(0.273)	(0.306)	(0.324)	(0.276)
Treatment × Non-abstinent at 3-month follow-up	0.647***	0.882***	0.569***	1.093***
	(0.067)	(0.160)	(0.054)	(0.085)
Treatment × Abstinent at 3-month follow-up	0.766***	0.644***	0.797***	0.834***
	(0.116)	(0.207)	(0.182)	(0.184)
Abstinence at 6-month follow-up				
Non-abstinent at 6-month follow-up	0.523***	0.695***	0.628***	1.061***
	(0.037)	(0.092)	(0.035)	(0.058)
Abstinent at 6-month follow-up	0.717***	0.761***	0.635***	0.938***
	(0.084)	(0.138)	(0.112)	(0.088)
Control × Non-abstinent at 6-month follow-up	0.347***	0.494***	0.660***	1.095***
	(0.052)	(0.057)	(0.055)	(0.068)
Control × Abstinent at 6-month follow-up	0.735***	0.547***	0.788***	0.715***
	(0.149)	(0.146)	(0.198)	(0.105)
Treatment × Non-abstinent at 6-month follow-up	0.655***	0.864***	0.591***	1.066***
	(0.063)	(0.155)	(0.055)	(0.083)
Treatment × Abstinent at 3-month follow-up	0.627***	0.944***	0.459***	1.239***
	(0.106)	(0.259)	(0.113)	(0.182)
N	7380	7380	7380	7380

Standard errors in parentheses
**p*<0.1, ***p*<0.05, ****p*<0.001

Table 18: QH discount rate estimates, control group

	$d^{QH}(1)$
Abstinent at programme session 1	-0.0112
	(0.016)
Abstinent at programme sessions 2 and 3	-1.725***
	(0.342)
Abstinent at programme session 4	-2.278***
	(0.411)
Abstinent at 3-month follow-up	-1.289***
	(0.207)
Abstinent at 6-month follow-up	-0.7748***
	(0.0873)

Standard errors in parentheses
*p<0.1, **p<0.05, ***p<0.001
Assuming t=1

Table 19: QH discount rate estimates, treatment group

	$d^{QH}(1)$
Abstinent at programme session 1	-2.440*
	(1.265)
Abstinent at programme sessions 2	-3.673
	(3.777)
Abstinent at programme session 3	-4.805
	(7.097)
Abstinent at programme session 4	3.760
	(11.224)
Abstinent at 3-month follow-up	-2.408**
	(0.207)
Abstinent at 6-month follow-up	-0.427
	(0. 541)

Standard errors in parentheses
*p<0.1, **p<0.05, ***p<0.001
Assuming t=1

Figure 20: EU model predictive margins: Smoking intensity and power function parameter (r) for the control group

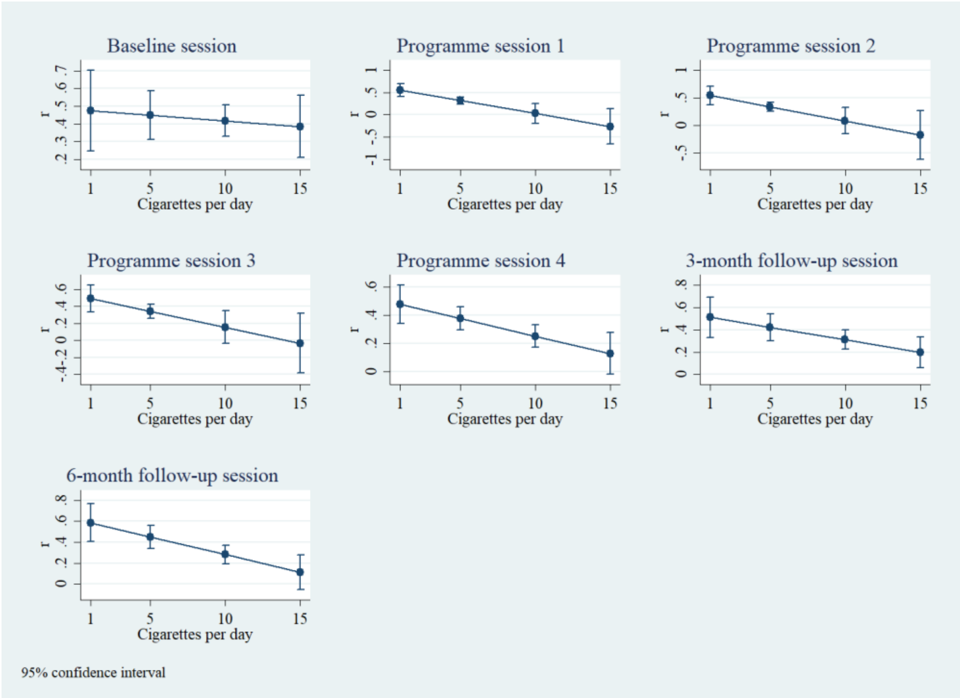


Figure 21: EU model predictive margins: Smoking intensity and power function parameter (r) for the treatment group

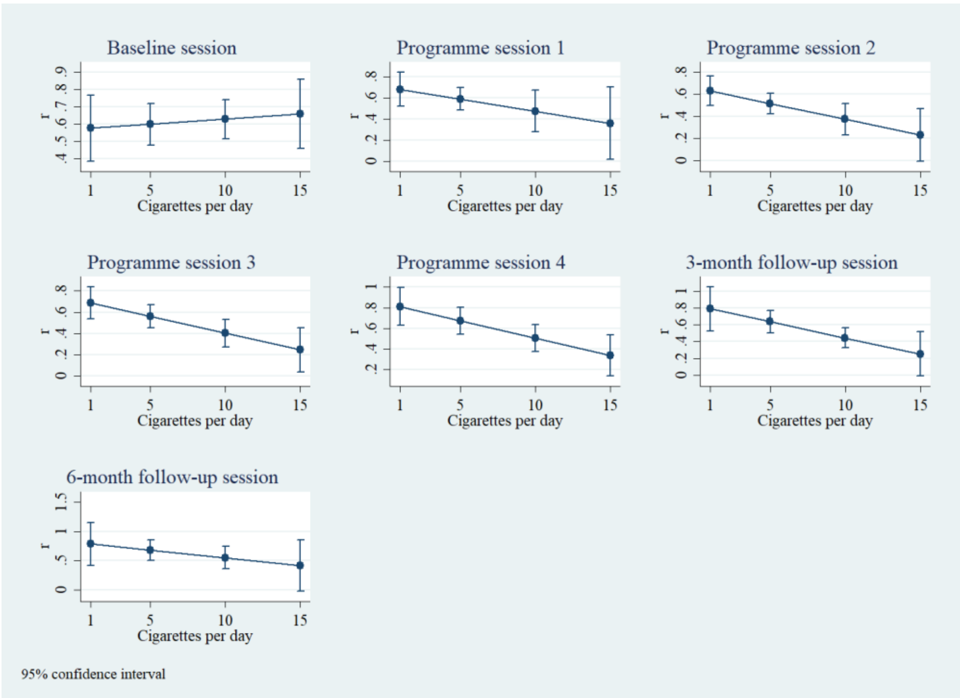


Figure 22: Predictive margins: Smoking intensity and exponential discounting model's parameter (δ) for the control group

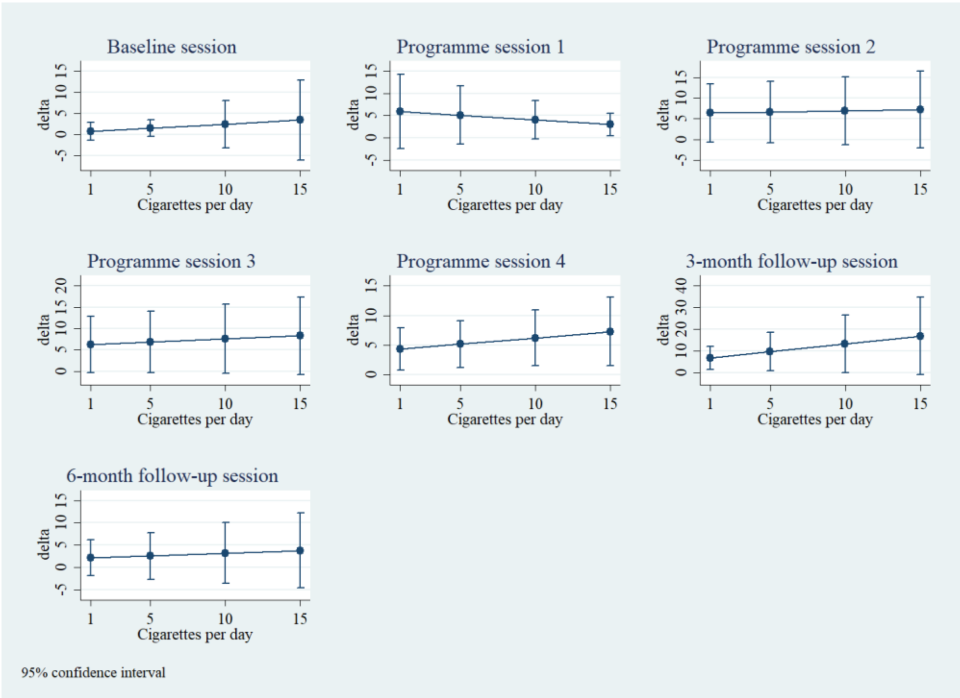


Figure 23: Predictive margins: Smoking intensity and hyperbolic discounting model's parameter (δ) for the control group

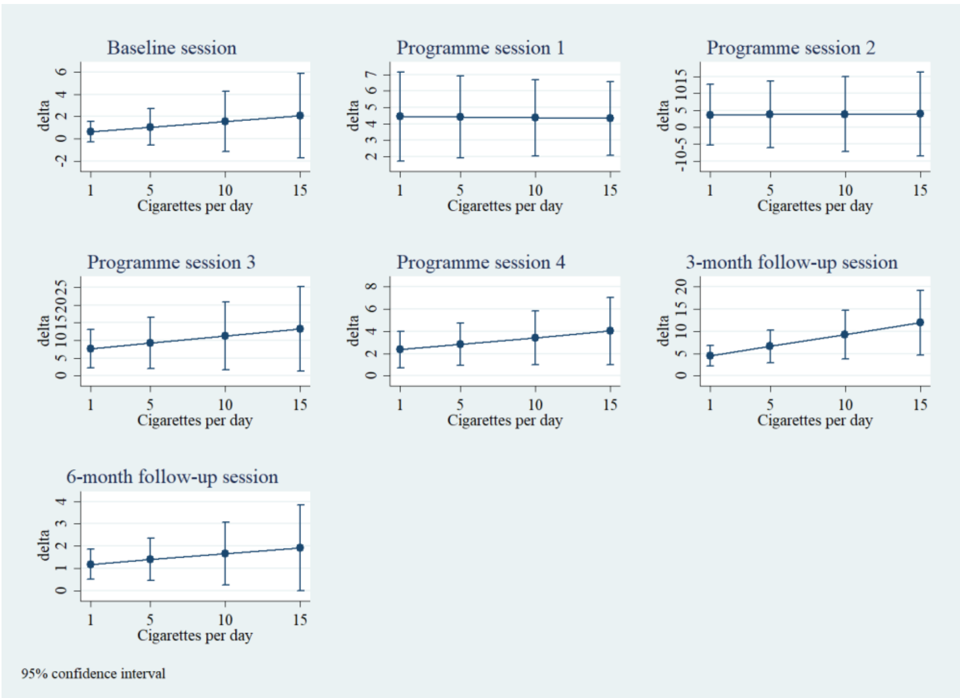


Figure 24: Predictive margins: Smoking intensity and QH discounting model's parameter (δ) for the control group

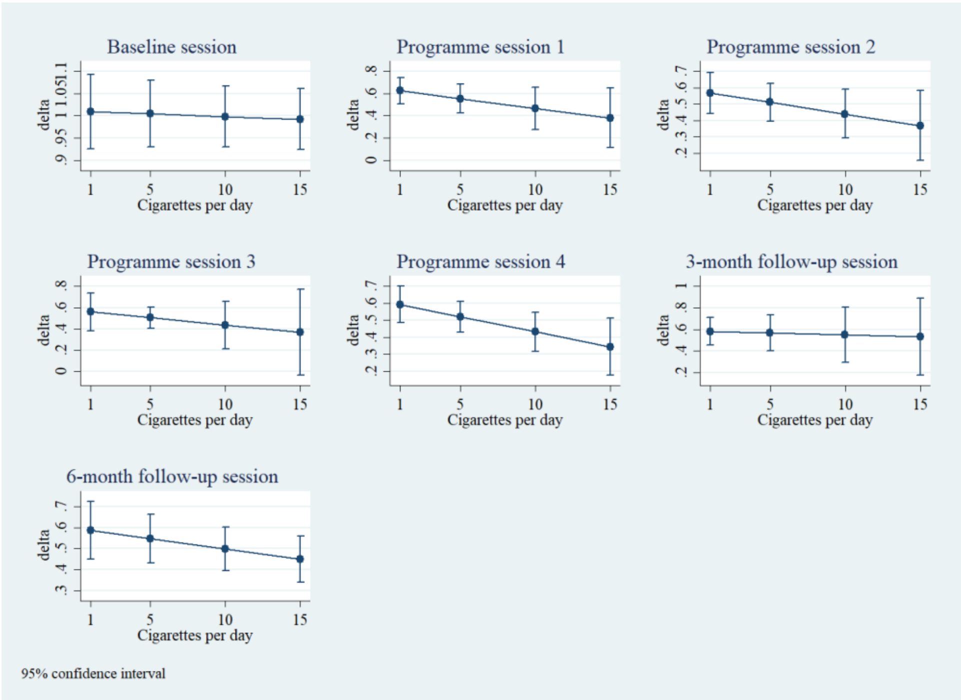


Figure 25: Predictive margins: Smoking intensity and QH discounting model's parameter (β) for the control group

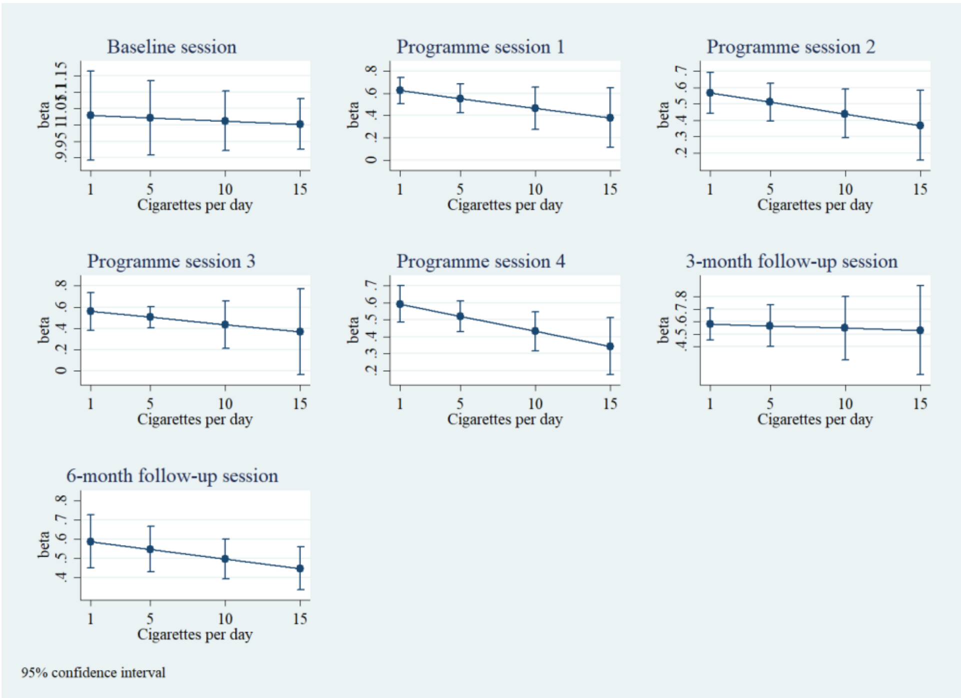


Figure 26: Predictive margins: Smoking intensity and exponential discounting model's parameter (δ) for the treatment group

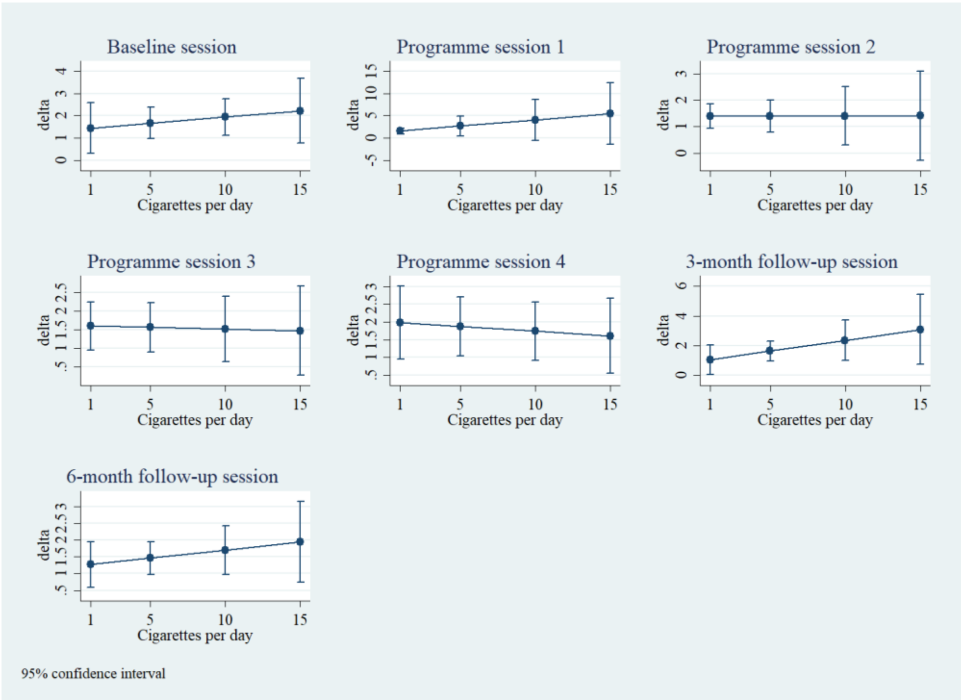


Figure 27: Predictive margins: Smoking intensity and hyperbolic discounting model's parameter (δ) for the treatment group

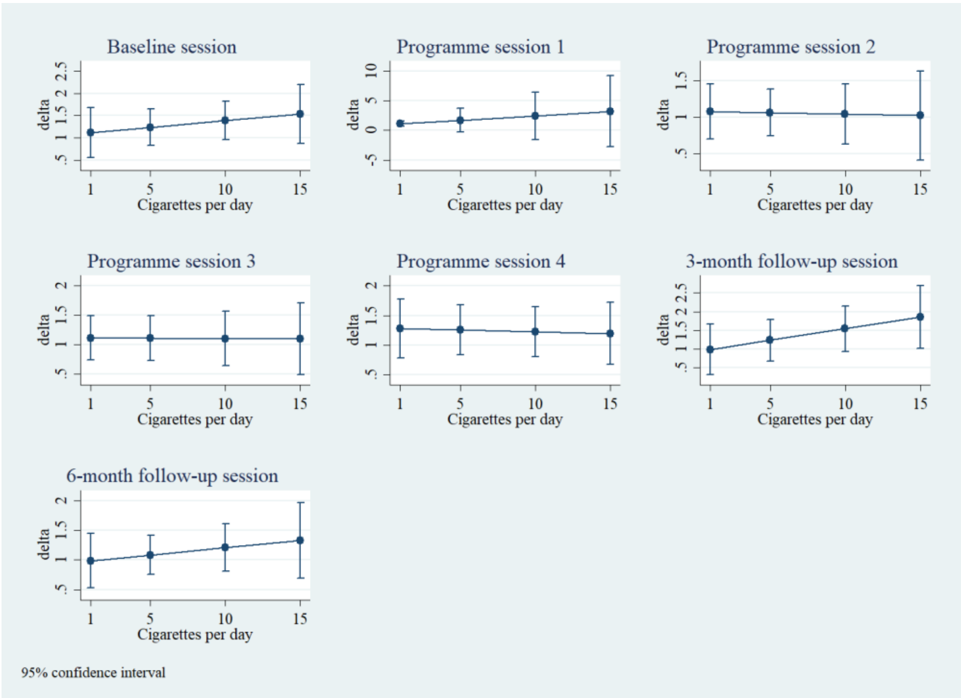


Figure 28: Predictive margins: Smoking intensity and QH discounting model's parameter (δ) for the treatment group

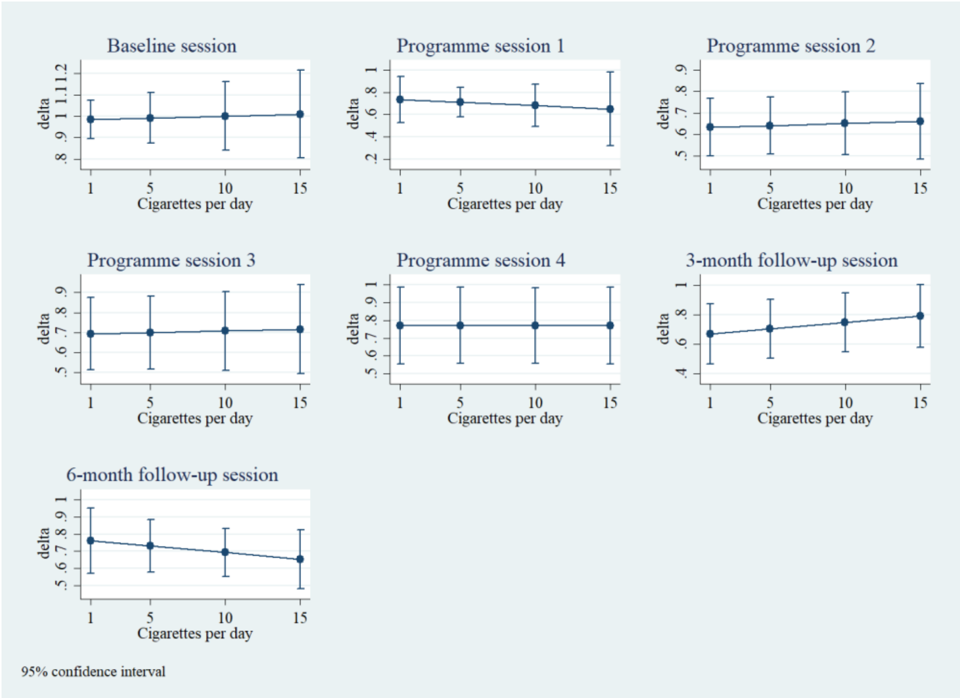


Figure 29: Predictive margins: Smoking intensity and QH discounting model's parameter (β) for the treatment group