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Risk Preferences, Time Preferences, and Smoking Behavior

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There is a rich theoretical literature in economics which models habit-forming behaviors, of which addiction is the exemplar, but there is a paucity of experimental economic studies eliciting and comparing the preferences that economic theory suggests may differ between addicts and nonaddicts. We evaluate an incentive-compatible risk and time preference experiment conducted on a sample of student smokers and nonsmokers at the University of Cape Town in 2012. We adopt a full information maximum likelihood statistical framework, which is consistent with the data generating processes proposed by structural theories and accounts for subject errors in decision making, to explore the relationship between risk preferences, time preferences, and addiction. Across different theories and econometric specifications, we find no differences in the risk preferences of smokers and nonsmokers but do find that smokers discount significantly more heavily than nonsmokers. We also identify a nonlinear effect of smoking intensity on discounting behavior and find that smoking intensity increases the likelihood of discounting hyperbolically, which means heavier smokers may be more prone to time inconsistency and more recalcitrant to treatment. These results highlight the importance of the theory-experimental design-econometric trinity and have important implications for theories of addiction.

JEL Classification: I1, D81, D91

1. Introduction

Addiction is a puzzle for economic theory: how can rational-agent modelling accommodate the fact that most addicts expend resources to acquire their targets of addiction but simultaneously incur real costs to try to reduce or limit their consumption of these goods? Furthermore, why is the typical course of addiction characterized by repeated unsuccessful attempts to quit prior to final abstention? From the standpoint of standard consumer theory in economics these patterns of behavior are difficult to rationalize.

A number of economists over the years have risen to the challenge. In section 2, we review these efforts, and conclude that making further progress, especially in critically

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bringing economic modelling of addiction to bear on psychological and clinical studies, requires as a first step more rigorous specification and identification of the relationships between structural risk and time preferences, on the one hand, and statistical vulnerability to addiction, on the other. Such progress requires careful experimentation to calibrate parametric relationships among preference structures and choices that generate, sustain, and mitigate addiction. We undertake such experimentation, using regular smokers as the representative addicts.

An incentive-compatible experimental design allows us to explore potential differences in the risk and time preferences of smokers and nonsmokers and jointly estimate utility function curvature and discounting functions. We find no significant differences in the risk preferences of smokers and nonsmokers but do find that *smokers discount the future significantly more heavily than nonsmokers*. These results are robust to different assumptions about the way people evaluate lotteries and the way they discount utility flows. In addition, we identify *a nonlinear effect of smoking intensity on discounting behavior* and find that *smoking intensity increases the likelihood of discounting hyperbolically*, which, under the assumption of an additively separable intertemporal utility function, means smokers, and in particular, heavier smokers, may be more prone to time inconsistency.

This research makes a number of contributions to the literature. Instead of adopting the standard two-step approach to data analysis (see section 3), which is statistically invalid, we estimate risk and time preference parameters as a linear function of observable characteristics (e.g., age, gender, and smoking status) so that the uncertainty of the parameter estimates propagates into the inferences which are drawn from the data.

In addition, when analyzing risk preferences and smoking behavior, we allow risk attitudes to be determined both by utility function curvature and probability weighting. Prior studies in the literature either focus on utility function curvature or probability weighting, but not on both together.

This is only the second study in the smoking-discounting literature to incorporate utility function curvature in the estimation of time preference models, and it is the first which allows rank-dependent utility theory to characterize choice under risk. In addition, this is the first study to identify a nonlinear relationship between smoking intensity and discounting behavior. Smoking more cigarettes is associated with increased discounting but only up to a point, after which each additional cigarette is associated with lower discounting.

The design and analysis are sensitive to the recognition that multiple decision processes characterize the discounting of delayed rewards. It is crucial for researchers to be cognizant of this fact when exploring the addiction-discounting relationship. Smoking intensity increases the likelihood of discounting hyperbolically, which may be an important factor in tobacco addiction and explain recalcitrance to treatment.

Following the review of economic models of addiction in section 2, section 3 reviews previous research on the relationship between risk preferences, time preferences and smoking behavior. Section 4 discusses our experimental design and presents summary statistics for the sample. Section 5 formulates our statistical approach to data analysis. Section 6 presents the results and section 7 concludes.

2. Economic Models of Addiction

Existing work by economists in modelling addictive consumption may be grouped into two broad approaches.[1]

The first approach, often referred to in the literature as *rational addict* modelling, was pioneered by Becker and Murphy (1988). It attributes addiction to unusual properties of certain goods, which causes flows of utility from their consumption to accumulate as capital that incentivizes further consumption and reduces marginal utility from nonaddictive substitutes. On this kind of account, agents fall into addiction without at any point behaving contrary to their consistent preferences, and it is not even necessary to posit uncertainty about outcomes or forecasts of utility.

Rational addiction models have been widely criticized for systematically mis-predicting the patterns of temporary cessation and relapse, followed by eventual success in achieving control, that characterizes the typical life course of an addiction (e.g., Ross 2010). The natural prediction of the basic Becker and Murphy (1988) model is that an addict will simply keep consuming their addictive target unless and until its price rises beyond the point where its consumption is optimal at the moment of choice. The model does, however, offer a prediction, which psychologists have generally considered reasonable, about the characteristics of people who are likely to be most vulnerable to addiction: those who discount future utility most steeply.

Orphanides and Zervos (1995) added an additional dimension to rational addict modelling by incorporating uncertainty on the part of potential consumers about the extent of their vulnerability to addiction when they first sample potentially addictive goods. This model yields the further prediction, which has again been regarded by many addiction scientists and clinicians as intuitive, that risk aversion, both instantaneous[2] and intertemporal, should be a protective factor against addiction.

The second broad approach to economic modelling of addiction responds to criticisms of rational addict models for failing to capture the observed synchronic and diachronic preference ambivalence of most addicts that is reflected in their apparent efforts to resist and modify their own revealed preferences for addictive goods. Economists have attempted to deal with this by complicating the agency of addicts in one or both of two ways: with either diachronic or synchronic dual self-models.

Diachonic dual self models (Winston 1980, Thaler and Shefrin 1981, Schelling 1984, Gruber and Köszegi 2001, Bénabou and Tirole 2004) divide the addicted agent into temporal successions of subagents that implement divergent temporal discounting functions. Both Gruber and Köszegi (2001) and Bénabou and Tirole (2004) incorporate the quasi-hyperbolic intertemporal discounting model of Laibson (1997) to explain why addicts choose to consume addictive targets at a present

[1] Outside of the two general approaches we review, some economists have favoured models in which the dynamics of addictive processes occur outside the logical space of economic agency, even if within the brain and nervous system of the person (e.g., Laibson 2001, Loewenstein, O'Donoghue, and Rabin 2003, Gul and Pesendorfer 2007). In such models, addictive temptations are exogenous sources of costs to maintenance of consistent or welfare-maximising choice that under some circumstances overwhelm the agent's budget of resources for resistance. For further discussion of these models see Ross (2011, 2014a, 2014b).

[2] The prefix "instantaneous" is used to differentiate instantaneous risk preferences from intertemporal risk preferences. Intertemporal risk preferences refer to preferences over intertemporal lotteries, the outcomes of which may be temporally correlated. By contrast, instantaneous risk preferences define atemporal attitudes to risk and uncertainty. We only empirically examine instantaneous risk preferences so all subsequent references to "risk preferences" refer to the instantaneous or atemporal variety.

moment while simultaneously preferring to refrain from such consumption in the future. Such a pattern implies inconsistent choice over time by the succession of subagents considered as a group. Diachronic dual self-models can then capture varying levels of success in resolving such ambivalence by allowing for variation in the extent to which addicts accurately recall or predict their own preference histories and courses. Consequently, these models also often involve choice under uncertainty.

By contrast, *synchronic dual self* models incorporate subagents that compete for control of the agent's choices at a given point in time (Benhabib and Bisin 2004, Bernheim and Rangel 2004). In these models, the competing agents again differ from one another in the intertemporal discounting behavior that they implement when they respectively gain control, and also face varying degrees of uncertainty concerning the implications of addictive consumption for present welfare, future welfare, or both. Fudenberg and Levine (2006, 2011, 2012) develop models that combine diachronic and synchronic complexity of agency. While varying in their details and the specific behavioral phenomena they are designed to capture, the three Fudenberg and Levine models share as their core strategic interaction and partial conflict between short-run sub-agents ("selves") that are relatively less patient than, and relatively more risk averse than, long-run sub-agents ("selves").

As we document in section 3 with specific reference to addictive smoking, psychological studies of addiction have also focused recurrently on steep temporal discounting and relative indifference to risk as factors that may contribute to the formation and persistence of addiction; for a review of psychological literature of this kind going beyond smoking, see Ross et al. (2008) chapters 3 and 4. There is, furthermore, increasing consensus among psychologists that addictions are learned, and modifiable by incentivizing interventions (Redish, Jensen, and Johnson 2008, Heyman 2009). Psychologists might therefore be expected to welcome efforts by economists to contribute improved specification precision and technical rigor with respect to the empirical identification of risk and time preference idiosyncrasies that distinguish addicts.

It thus constitutes a significant gap in the literature that economists have not yet directly empirically estimated differences in risk and time preferences, specified with full theoretical precision, between addicts and nonaddicts. An important aspect of such precision is to respect the need for joint estimation of risk and time preferences established by Andersen et al. (2008). Unsurprisingly, none of the many empirical studies by psychologists of temporal discounting differences between addicts and nonaddicts attempt, or indeed recognize the importance of, such joint estimation. In its absence, as Andersen et al. (2008) demonstrate theoretically and empirically, discount rate estimates are significantly biased upward for risk averse agents, which is also likely to result in mis-estimation of whether their structure is exponential, hyperbolic, or quasi-hyperbolic. Nor have structural interactions between risk and time preferences been explicitly specified in existing economic models of addiction. Such specification as it might feature in the distinguishing characterization of addicts cannot be based on a priori theorizing, but depends on empirical data.

Our empirical comparisons of temporally indexed and risky choice behavior in a sample of smokers and a sample of nonsmokers are motivated by this concern with improved economic modelling of addiction in general. We chose to study smokers for three reasons: nicotine is the most readily available addictive drug in general populations; there is widespread agreement among addiction scientists and clinicians that almost all regular, daily smokers meet the criteria for addiction (West 2006); and the relative noninterference of nicotine with basic cognition and judgment makes nicotine addicts a natural starting point population for any new laboratory paradigm.

In our view, improved unification of economic and psychological approaches to addiction is most likely to the extent that research in both disciplines is alert to a self-conscious philosophical orientation. We are guided by the approach that Ainslie (1992, 2001) has dubbed "picoeconomics" (see also Ross et al. 2008). This approach emphasizes, as does Heyman (2009), that addiction is in large part learned behavior, expressed through choices that are 'voluntary' in the nonmetaphysical sense of being responsive to incentives.

The framework of Ainslie (1992, 2001) recognizes that both exogenous and endogenous neurophysiological and neurochemical states and processes give rise to vulnerabilities and barriers to controlling addiction that an economic model will represent as variable costs. The picoeconomic model emphasizes the role of inconsistent intertemporal discounting in generating and maintaining addictive choice patterns, but it does *not* predict, counterfactually, that most human choice over time reflects hyperbolic discounting. Rather, it applies a philosophical thesis that consistent valuation of rewards over time requires explanation and should not simply be assumed as a natural default disposition. Ainslie himself emphasizes the importance of "personal rules," that is, self-enforcing linkages between discrete choices that should be reflected in agents' revealed preferences, but he is also alert to the importance of institutional and other environmental "scaffolding" (Clark 1997) as providing support for intertemporally consistent valuation and choice.

Economists and psychologists, notwithstanding their different practical priorities, can join in seeking explanation of addiction in breakdowns and loopholes in personal rules, in challenges to their implementation resulting from errors in risk perception and estimation, and in strategic complications in the relationships between individuals and their social environments.

3. Review of the Literature on Risk Preferences, Time Preferences, and Smoking Behavior

Smoking is known to be one of the primary behavioral risk factors for the additional utilization of health resources and expenditures on health. For just over 50 years, the U.S. Surgeon General has been collating careful epidemiological evaluations of the causal effect of smoking on a large number of diseases (U.S. Department of Health and Human Services 2014). And major litigation efforts have generated estimates of additional health expenditures running into the hundreds of billions of dollars (Coller, Harrison, and McInnes 2002). Evidently, a better understanding of the determinants of smoking behavior continues to have great significance for health policy.

Smoking involves an intertemporal trade-off that should be apparent: any short-term benefits from smoking are coupled with the potential for large long-term costs. In addition, the decision to smoke involves risks that should be apparent, such as the possibility of negative health consequences, and is made under conditions of uncertainty, without the person knowing his or her susceptibility to these risks.

Table 1 provides a detailed summary of experimental studies investigating the relationship between smoking and time preferences. Online searches of PubMed and Econlit, using the search criteria "smoking" and "discounting" and their variants (e.g., "smoke," "discount," and "time preference"), were used to locate these studies. An initial list of over 50 studies was trimmed

Table 1. Review of Experimental Literature on Smoking and Discounting Behavior

Study	Sample (size)	Elicitation Method	Task-Related Incentives (max LL)	Horizon	Front End Delay (FED)	Correct for Nonlinear Utility	Models (Estimated Rates)	Statistical Method	Hyperbolicky Discounting?	Significant Relationship with Smoking?
Bickel, Odum and Madden (1999)	Adults in Burlington, VT, USA ($N_S = 23$, $N_{NS} = 22$, $N_{ES} = 21$)	Choice (ordered)	No ($1000)	7–9131 days	No	No	H and E ($\delta^H{}_S = 0.054$) ($\delta^H{}_{NS} = 0.007$) ($\delta^H{}_{ES} = 0.007$)	NLLS for discounting, ANOVA and nonparametric tests for analysis	Yes (compared to E) based on R^2 comparisons	Yes, positive for S relative to NS ($p < 0.01$) and ES ($p < 0.01$); No for NS relative to ES.
Mitchell (1999)	Adults in Durham, NH, USA ($N_S = 20$, $N_{NS} = 20$)	Choice (random)	Yes ($10)	0–365 days	No	No	H ($\delta_S = 0.012$) ($\delta_{NS} = 0.006$)	NLLS for discounting, nonparametric tests for analysis	By assumption	Yes ($p < 0.06$), positive.
Baker, Johnson and Bickel (2003)	Adults in Burlington, VT, USA ($N_S = 30$, $N_{NS} = 30$)	Titration (random - Richards et al. (1999))	Yes ($100)	Real: 1–183 days	No	No	H NRD but from Figure 2: ($10: $\delta_S = 0.008$, $\delta_{NS} = 0.001$) ($100: $\delta_S = 0.005$, $\delta_{NS} = 0.001$)	NLLS for discounting, ANOVA for analysis	By assumption	Real: Yes ($p < 0.01$), positive.
			No ($1000)	Hypothetical: 1–9131 days	No	No	H NRD but from Figure 2: ($10: $\delta_S = 0.008$, $\delta_{NS} = 0.003$) ($100: $\delta_S = 0.006$, $\delta_{NS} = 0.0008$) ($1000: $\delta_S = 0.004$, $\delta_{NS} = 0.0005$)			Hypothetical: Yes ($p < 0.01$), positive.
Reynolds, Karraker, Horn and Richards (2003)	Adolescents in Morgantown, WV, USA ($N_S = 19$, $N_{NS} = 19$, $N_T = 17$)	Titration (random - Richards et al. (1999))	1-out-of-2-tasks ($10)	1–365 days	No	No	H ($\delta_S = 0.010$) ($\delta_{NS} = 0.007$) ($\delta_T = 0.016$)	NLLS for discounting, ANOVA for analysis	By assumption	No.
Reynolds (2004)	Adolescents and young adults in Morgantown, WV, USA ($N_{S(adolescent)} = 19$, $N_{S(adult)} = 25$, $N_{NS} = 29$)	Titration (random - Richards et al. (1999))	1-out-of-2-tasks ($10)	1–365 days	No	No	H ($\delta_{S(adolescent)} = 0.016$) ($\delta_{S(adult)} = 0.075$) ($\delta_{NS(adult)} = 0.012$)	NLLS for discounting, ANOVA, correlations and post hoc tests for analysis	By assumption	Yes, positive for $S_{(adult)}$ relative to $S_{(adolescent)}$ ($p < 0.05$) and $NS_{(adult)}$ ($p < 0.05$). No for $S_{(adolescent)}$ relative to $NS_{(adult)}$.

Table 1. (*Continued*)

Study	Sample (size)	Elicitation Method	Task-Related Incentives (max LL)	Horizon	Front End Delay (FED)	Correct for Nonlinear Utility	Models (Estimated Rates)	Statistical Method	Hyperbolicky Discounting?	Significant Relationship with Smoking?
Reynolds, Richards, Horn and Karraker (2004)	Mostly students in Morgantown, WV, USA ($N_S = 25$, $N_{NS} = 29$)	Titration (random - Richards et al. (1999))	1-out-of-2-tasks ($10)	1–365 days	No	No	H ($\delta_S = 0.066$) ($\delta_{NS} = 0.015$)	NLLS for discounting, ANOVA for analysis	By assumption	Yes ($p < 0.05$), positive.
Ohmura, Takahashi and Kitamura (2005)	Students in Sapporo, Japan ($N_S = 27$, $N_{NS} = 23$)	Titration (random - Richards et al. (1999))	No (¥100,000 = $1000)	7–1826 days)	No	No	H, E and AUC. ($AUC_S = 0.54$) ($AUC_{NS} = 0.58$)	AUC and NLLS for discounting, correlations and t tests for analysis	Yes (compared to E) based on R^2 comparisons	No.
Heyman and Gibb (2006)	Students in Cambridge, MA, USA ($N_S = 19$, $N_{NS} = 31$, $N_{LS} = 21$)	Choice (ordered)	Yes ($29)	Real: 1–30 days	No	No	H Real: ($\delta_S = 0.074$) ($\delta_{NS} = 0.036$) ($\delta_{LS} = 0.045$)	Algebra and averaging for discounting, *F*-test and posthoc tests for analysis	By assumption	Real: Yes, positive for S relative to NS ($p < 0.01$) and LS ($p < 0.05$); No for LS relative to NS. Hypothetical: No.
			No ($1000)	Hypothetical: 7–3650 days	No	No	H Hypothetical: ($\delta_S = 0.007$) ($\delta_{NS} = 0.009$) ($\delta_{LS} = 0.004$)			
Reynolds (2006)	Adults in Buffalo, NY, USA ($N_S = 15$, $N_{NS} = 15$)	Titration (random – Richards et al. (1999))	No ($10)	1–365 days	No	No	H ($\delta_S = 0.088$) ($\delta_{NS} = 0.020$)	NLLS for discounting, nonparametric tests for analysis	By assumption	Yes ($p < 0.01$), positive.
Johnson, Bickel and Baker (2007)	Adults in Burlington, VT, USA ($N_S = 30$, $N_{NS} = 30$, $N_{LS} = 30$)	Titration (random – Richards et al. (1999))	Yes ($100)	Real: 1–183 days	No	No	H Real: ($10: $\delta_S = 0.006$, $\delta_{LS} = 0.003$, $\delta_{NS} = 0.0009$) ($100: $\delta_S = 0.003$, $\delta_{LS} = 0.001$, $\delta_{NS} = 0.0008$)	NLLS for discounting, ANOVA for analysis	By assumption	Real: Yes, positive for S ($p < 0.05$) and LS ($p < 0.05$) relative to NS; No for S relative to LS.
			No ($1000)	Hypothetical: 1–9131 days	No	No	H Hypothetical: ($10: $\delta_S = 0.006$, $\delta_{LS} = 0.007$, $\delta_{NS} = 0.002$) ($100: $\delta_S = 0.004$, $\delta_{LS} = 0.002$, $\delta_{NS} = 0.0005$) ($1000: $\delta_S = 0.002$, $\delta_{LS} = 0.0008$, $\delta_{NS} = 0.0003$)			Hypothetical: Yes, positive for S (p<0.01) and LS (p<0.05) relative to NS; No for S relative to LS.

Table 1. (*Continued*)

Study	Sample (size)	Elicitation Method	Task-Related Incentives (max LL)	Horizon	Front End Delay (FED)	Correct for Nonlinear Utility	Models (Estimated Rates)	Statistical Method	Hyperbolicky Discounting?	Significant Relationship with Smoking?
Reynolds et al. (2007)	Adolescents in Columbus, OH, USA ($N_S = 25$, $N_{NS} = 26$)	Titration (random – Richards et al. (1999))	Yes ($10)	1–365 days	No	No	AUC NRD but from Figure 1: ($AUC_S = 0.129$) $AUC_{NS} = 0.234$)	AUC for discounting, ANOVA and ANCOVA for analysis	AUC, but dropped subjects that had poor H fit	Yes ($p < 0.05$), positive.
Bickel, Yi, Kowal and Gatchalian (2008)	Adults in Little Rock, AR, USA ($N_S = 30$, $N_{NS} = 29$)	Titration (random - Richards et al. (1999))	No ($1000)	1–9131 days	No	No	H and E ($\delta^H{}_S = 0.007$) ($\delta^H{}_{NS} = 0.001$)	NLLS for discounting, ANCOVA for analysis	Yes (compared to E) based on R^2 comparisons	Yes ($p < 0.05$), positive.
Chabris et al. (2008)	1. Adults in Boston, MA, USA ($N = 126$)	Choice (random – Kirby et al. (1999))	1-in-6-chance ($85)	7–186 days	No	No	H ($\delta = 0.015$, SD = 0.02)	ML for discounting, OLS, Tobit, Probit for analysis	By assumption	Yes ($p < 0.05$), positive.
	2. Adults in the USA (recruited online) ($N = 326$)		1-in-6-chance ($85)	7–186 days	No	No	H ($\delta = 0.008$, SD = 0.009)	ML for discounting, OLS, Tobit, Probit for analysis	By assumption	No
Sweitzer et al. (2008)	Adults in Allegheny County, PA, USA ($N_S = 101$, $N_{NS} = 145$, $N_T = 279$, $N_{ES} = 185$)	Choice (random)	No ($100)	7–1825 days	No	No	H ($\delta_S = 0.120$) ($\delta_{NS} = 0.079$) ($\delta_T = 0.090$) ($\delta_{ES} = 0.086$)	NLLS for discounting, ANCOVA for analysis	By assumption	Yes, positive for S relative to NS ($p < 0.01$), ES ($p < 0.01$) and T ($p < 0.01$); No for all other comparisons.
Adams and Nettle (2009)	Adults in 15 major urban areas in the USA (recruited online) ($N_S = 70$, $N_{NS} = 346$)	Choice (ordered)	No ($1000)	30–3652 days	No	No	H ($\delta = 1.3$)[a]	NLLS for discounting, logistic regression for analysis	By assumption	No.
Audrain-McGovern et al. (2009)	High school students in northern Virginia, USA ($N_{NS} = 556$, $N_{FS} = 112$, $N_{SS} = 241$)	Choice (random - Kirby et al. (1999))	Not reported ($85)	7–186 days	No	No	H Assuming ln transformation: ($\delta_{FS} = 0.023$) ($\delta_{SS} = 0.016$) ($\delta_{NS} = 0.010$)	Algebra and averaging for discounting, latent growth curve modeling (LGCM) and growth mixture modeling (GMM) for analysis	By assumption	LCGM: Yes ($p < 0.05$), positive. GMM: Yes, positive for FS ($p < 0.05$) and SS ($p < 0.05$) relative to NS; No for FS relative to SS.
Jones, Landes, Yi and Bickel (2009)	Adults in Little Rock, AR, USA ($N_S = 86$, $N_{NS} = 141$)	Titration (ordered or random)	No ($1000)	1–9131 days	No	No	H NRD but from Figure 3: ($100: $\delta_{S(men)} = 0.012$, $\delta_{NS(men)} = 0.001$,	NLLS for discounting, ANCOVA for analysis	By assumption	Yes, positive for $S_{(men)}$ ($p < 0.01$) relative $NS_{(men)}$ at $100 and $1000 magnitudes; No for

Table 1. (*Continued*)

Study	Sample (size)	Elicitation Method	Task-Related Incentives (max LL)	Horizon	Front End Delay (FED)	Correct for Nonlinear Utility	Models (Estimated Rates)	Statistical Method	Hyperbolicky Discounting?	Significant Relationship with Smoking?
							$\delta_{S(women)} = 0.0015$, $\delta_{NS(women)} = 0.002$) ($1000: $\delta_{S(men)} = 0.0075$, $\delta_{NS(men)} = 0.0005$, $\delta_{S(women)} = 0.001$, $\delta_{NS(women)} = 0.001$)			$S_{(women)}$ relative to $NS_{(women)}$ at both magnitudes.
Melanko et al. (2009)	Adolescents in central Ohio, USA ($N_S = 50$, $N_{NS} = 25$). Smokers were split into high and low pyschopathology groups.	Titration (random - Richards et al. (1999))	Yes ($10)	1–365 days	No	No	AUC NRD but from Figure 1: ($AUC_{S(low)} = 0.126$) ($AUC_{S(high)} = 0.214$) ($AUC_{NS} = 0.275$)	AUC for discounting, ANOVA for analysis	AUC, no assumption about form of discounting	Yes, positive for $S_{(low)}$ relative to NS ($p = 0.01$); No for all other comparisons.
Businelle, McVay, Kendzor and Copeland (2010)	Adults in southern USA ($N_S = 20$, $N_{NS} = 34$)	Choice (ordered)	No ($1000)	0.25–9131 days	No	No	H and AUC ($\delta_S = 0.077$) ($\delta_{NS} = 0.039$)	NLLS and AUC for discounting, ANCOVA for analysis	By assumption (but also used AUC)	Yes ($p = 0.01$), positive.
Harrison, Lau, and Rutström (2010)	Adults in Denmark ($N_S = 71$, $N_{NS} = 181$)	Choice (ordered)	1-in-10-chance ($1175)	30–730 days	Yes	Yes	H and E Linear utility: ($\delta^H_{S(men)} = 0.341$)[a] ($\delta^H_{NS(men)} = 0.240$)[a] ($\delta^H_{S(women)} = 0.329$)[a] ($\delta^H_{NS(women)} = 0.250$)[a] H and E Concave utility: ($\delta^H_{S(men)} = 0.127$)[a] ($\delta^H_{NS(men)} = 0.093$)[a] ($\delta^H_{S(women)} = 0.109$)[a] $\delta^H_{NS(women)} = 0.095$)[a]	ML for discounting and analysis	25–40% of choices by smokers and non-smokers best characterised by H	Linear utility: Men: Yes ($p < 0.05$), positive; Women: Yes ($p < 0.10$), positive. Concave utility: Men: Yes ($p < 0.05$), positive; Women: No.

Table 1. (*Continued*)

Study	Sample (size)	Elicitation Method	Task-Related Incentives (max LL)	Horizon	Front End Delay (FED)	Correct for Nonlinear Utility	Models (Estimated Rates)	Statistical Method	Hyperbolicky Discounting?	Significant Relationship with Smoking?
Bickel et al. (2012)	Adults in the USA (recruited online) ($N_S = 182$, $N_{NS} = 614$)	Choice (random)	No ($85)	10–75 days	No	No	H (Not reported)	Algebra and averaging for discounting, ANCOVA for analysis	By assumption	Yes ($p < 0.01$), positive.
Mitchell and Wilson (2012)	1. Adults in Portland, OR, USA ($N_S = 20$, $N_{NS} = 20$)	Choice (random)	Yes ($50)	14–154 days	Yes	No	H and QH (0 FED: $\delta^H{}_S = 0.230$, $\delta^H{}_{NS} = 0.020$) (+ FED: $\delta^H{}_S = 0.070$, $\delta^H{}_{NS} = 0.010$)	NLLS and ML for discounting, ANOVA for analysis	By assumption (but also estimated QH)	Yes ($p < 0.01$), positive.
	2. Adults in Portland, OR, USA ($N_S = 16$, $N_{NS} = 16$)		No ($50)	14–154 days	Yes	No	H and QH (0 FED: $\delta^H{}_S = 0.120$, $\delta^H{}_{NS} = 0.020$) (+ FED: $\delta^H{}_S = 0.050$, $\delta^H{}_{NS} = 0.010$)			Yes ($p < 0.01$), positive.
Reynolds and Fields (2012)	Adolescents in Columbus, OH, USA ($N_S = 50$, $N_{NS} = 50$, $N_T = 41$)	Titration (random - Richards et al. (1999))	Yes ($10)	1–365 days	No	No	AUC NRD but from Figure 1: ($AUC_S = 0.166$) ($AUC_T = 0.224$) ($AUC_{NS} = 0.347$)	AUC for discounting, ANOVA and ANCOVA for analysis	AUC, no assumption about form of discounting	Yes, positive for S ($p < 0.01$) and T ($p < 0.05$) relative to NS; No for S relative to T.
Stillwell and Tunney (2012)	International online study ($N_S = 1592$, $N_{LS} = 669$, $N_{NS} = 6777$)	Choice (ordered or random)	No ($1000)	7–1826 days	No	No	H NRD but from Figure 3: ($\delta_S = 0.437$) ($\delta_{LS} = 0.397$) ($\delta_{NS} = 0.369$)	NLLS for discounting, ANOVA for analysis	Yes (compared to E) based RSS comparisons	Yes, positive for S relative to LS ($p < 0.01$) and NS ($p < 0.01$) and positive for LS relative to NS ($p < 0.01$).
Wing et al. (2012)	Adults in the greater Toronto area, Canada ($N_S = 23$, $N_{NS} = 37$)	Choice (random - Kirby et al. (1999))	No ($85)	7–186 days	No	No	H NRD but from Figure 1: ($\delta_S = 0.017$) ($\delta_{NS} = 0.011$)	Algebra and averaging for discounting, ANCOVA for analysis	By assumption	No.
Balevich, Wein and Flory (2013)	Students in Flushing, NY, USA ($N_S = 50$, $N_{NS} = 102$, $N_T = 91$)	Choice (random) or titration (random)	No ($100)	1–1825 days	No	No	H ($\delta_S = 0.126$) ($\delta_{NS} = 0.135$) ($\delta_T = 0.138$)	NLLS for discounting, ANOVA for analysis	By assumption	No.

Table 1. (*Continued*)

Study	Sample (size)	Elicitation Method	Task-Related Incentives (max LL)	Horizon	Front End Delay (FED)	Correct for Nonlinear Utility	Models (Estimated Rates)	Statistical Method	Hyperbolicky Discounting?	Significant Relationship with Smoking?
Poltavski and Weatherly (2013)	Students in Grand Forks, ND, USA ($N_S = 16$, $N_{LS} = 74$, $N_{NS} = 92$)	Choice (random)	No ($100,000)	183–3652 days	No	No	H and AUC ($1000: $\delta_S = 0.010$, $\delta_{LS} = 0.010$, $\delta_{NS} = 0.007$) ($100,000: $\delta_S = 0.008$, $\delta_{LS} = 0.008$, $\delta_{NS} = 0.007$)	NLLS and AUC for discounting, ANOVA for analysis	By assumption (but also used AUC)	No.
Sheffer et al. (2013)	Adults in Little Rock, AR, USA ($N_S = 47$, $N_{NS} = 19$)	Titration (random - Richards et al. (1999))	No ($1000)	1–9131 days	No	No	H NRD but from Figure 1: ($\delta_S = 0.020$) ($\delta_{NS} = 0.004$	NLLS for discounting, ANCOVA for analysis	By assumption	Yes ($p < 0.05$), positive.
Kang and Ikeda (2014)	Adults in Japan ($N_S \approx 862$, $N_{NS} \approx 2588$)	Choice (ordered)	No (¥1000,000 = $10000)	7–365 days	Yes	No	E and proxies for H (See Table 2, the mean of δ^E ranges from 0.022 to 1.904)[a]	ML for discounting, hurdle model for analysis	Assumes E but constructs H proxies	Yes ($p < 0.01$), positive.
Kobiella et al. (2014)	Adults in Mannheim, Germany ($N_S = 27$, $N_{NS} = 31$)	Choice (random)	Yes (€41.32)	14–28 days	Yes	No	H ($\delta_S = 0.055$)[b] ($\delta_{NS} = 0.038$)[b]	NLLS for discounting, *t*-tests for analysis	By assumption	Yes ($p < 0.05$), positive.
Hofmeyr et al. (2017)	Adults in Los Angeles, CA, USA ($N_S = 163$, $N_{NS} = 834$, $N_{ES} = 208$)	Choice (random - Kirby et al. (1999))	UCLA: No ($85) USC: 1-out-of-2-tasks ($85)	7–186 days	No	No	H, E and QH ($\delta^H{}_S = 0.021$) ($\delta^H{}_{NS} = 0.012$) ($\delta^H{}_{ES} = 0.013$)	ML for discounting and analysis	41–52% of choices best characterised by H	Yes, positive for S relative to NS ($p < 0.01$) and ES ($p < 0.01$); No for ES relative to NS.

Source: Authors' construction. See Supporting Information Appendix A for more details on these studies.

S = smoker; NS = nonsmoker/never-smoker; ES = ex-smoker; LS = light smoker; T = trier; FS = fast smoking adopter; SS = slow smoking progressor; H = hyperbolic; E = exponential; QH = quasi-hyperbolic; AUC = area under the curve; NRD = not reported directly; NLLS = nonlinear least squares; ML = maximum likelihood; ANOVA = analysis of variance; ANCOVA = analysis of covariance.

[a]Annual rate.

[b]Weekly rate.

according to the following criteria: the study had to include a clear smoker, nonsmoker comparison[3]; study participants had to make choices between amounts of real money, rather than cigarettes or quality-adjusted life years, available at different points in time[4]; and the instrument used to assess discounting had to include at least 20 questions.[5] The 31 studies satisfying our inclusion criteria are listed in Table 1; a detailed discussion of this table is provided in Supporting Information Appendix A.

The last column of Table 1 reports whether a significant statistical relationship was found between smoking and discounting behavior. A "positive" relationship between smoking and discounting means that smokers discount more heavily than nonsmokers, consistent with expectations before the reported observations. Some of the entries in Table 1 report findings from several studies or from different treatments in the same study. For example, Baker, Johnson, and Bickel (2003) report results from real and hypothetical experimental treatments whereas Chabris et al. (2008) report findings from multiple studies. In some cases (e.g., Baker, Johnson, and Bickel 2003) results were the same across studies and treatments, while in others (e.g., Chabris et al. 2008, Heyman and Gibb 2006) they differed. The last column of Table 1 therefore summarizes the set of 37 reported findings from the 31 studies.

Of the 37 reported findings in Table 1, 29 were positive and significant while the remaining 8 were null results.[6] Thus, the bulk of findings in this literature point to a positive relationship between smoking and greater discounting behavior, irrespective of whether real or hypothetical rewards, long or short temporal horizons, choice or titration elicitation mechanisms, small or large samples, or simple or complex statistical procedures were used.

From a statistical perspective, the most striking feature of Table 1 is the near-universal two-step approach to data analysis. This approach entails using nonlinear least squares (NLLS), or some similar technique, to estimate discounting parameters at the level of the individual, and then using the, typically log-transformed, point estimates as data in subsequent statistical models. Harrison, Lau, and Rutström (2010) (HLR) and Hofmeyr et al. (2017) are the only studies in Table 1 which do not use this method. The problem with the two-step approach, aside from typically relying on tiny samples to estimate discounting parameters at the level of the individual, is that estimated discounting parameters are estimates, not data. Such estimates comprise both a point estimate (of the mean) and a standard error, and to use only the point estimate is to throw away information on the sampling variability of that estimate.

Moreover, using an estimated discounting parameter as data violates one of the statistical assumptions of the second-stage models: that the covariates are measured without error. Thus,

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[3] A number of studies (e.g., Field et al. 2006, Dallery and Raiff 2007, Epstein et al. 2003) focus purely on discounting among smokers and were excluded due to the lack of non-smokers in the sample.

[4] Odum, Madden, and Bickel (2002) and van der Pol and Ruggeri (2008) focus on the discounting of health outcomes and Field et al. (2006) and Odum and Baumann (2007) focus on the discounting of hypothetical cigarette rewards.

[5] Some panel studies, such as the Health and Retirement Study (HRS), include a module to assess discounting behavior but the limited number of questions (e.g., three questions in the HRS, see Bradford 2010) makes precise estimation and inference difficult. Hence these studies were excluded.

[6] Some studies classified smokers using more than one category (e.g., heavy and light smokers in Stillwell and Tunney 2012), others classified non-smokers using more than one category (e.g., never-smokers and ex-smokers in Bickel, Odum and Madden 1999), and still others separated male and female smokers and nonsmokers (e.g., Jones et al. 2009 and Harrison, Lau and Rutström 2010). In a few of these cases, comparisons between some of the groups were significant while others were not, which makes coding the study problematic. Studies were therefore coded as having found a significant result if at least one smoker, nonsmoker comparison was statistically significant. This procedure is preferable to coding a study as having found no statistically significant results just because one comparison (between, say, light smokers and nonsmokers) was not significant even though another comparison (between, say, heavy smokers and nonsmokers) was significant.

statistical inferences drawn from this approach are simply invalid. HLR and Hofmeyr et al. (2017) estimate discounting parameters as a linear function of observable characteristics (e.g., age, gender, and smoking status) so that the uncertainty of the discounting parameter estimates propagates into the inferences which are drawn from the data.[7] This valid statistical approach will be used here.

Table 2 provides a detailed summary of studies investigating the relationship between smoking and risk preferences. Unlike the literature on time preferences and smoking behavior, there is a dearth of studies analyzing the risk preferences of smokers and nonsmokers. Online searches of PubMed and Econlit, using the search criteria "smoking" and "risk preferences" and their variants (e.g., "smoke," "risk," and "probability discounting"), were used to locate these papers. An initial list of studies was trimmed according to the following rules: the study had to include a clear smoker, nonsmoker comparison[8]; and study participants had to have made choices between lotteries[9] involving amounts of money, rather than cigarettes or quality-adjusted life years.[10] The 11 studies satisfying our inclusion criteria are listed in Table 2; a detailed discussion of this table is deferred to Supporting Information Appendix B.

Table 2 shows that a majority of the studies (8 out of 11) adopted the probability discounting (PD) approach to risk preferences, which defines risk aversion solely in terms of the shape of the probability weighting function (PWF).[11] The PD model is just Yaari's (1987) dual theory of choice under risk limited to a circumscribed class of lotteries and with a specific PWF: $\pi(p) = p/[p + \gamma(1 - p)]$. If $\gamma > 1$ this specification represents probability pessimism and risk aversion. As subjective probability distortions drive risk preferences in the PD framework, it is surprising that 6 out of these 8 studies only used 5 probabilities in the elicitation task; the remaining two studies (Mitchell 1999; Yi, Chase, and Bickel 2007) only used 6 and 7 probabilities, respectively.

The final column of Table 2 shows whether the studies found a significant statistical relationship between risk preferences and smoking behavior: the results are equivocal and, other than HLR, the statistical analyses are not valid. A positive relationship between smoking and risk preferences means that smokers are more risk averse than nonsmokers, whereas a negative relationship means that smokers are less risk averse than nonsmokers. Null results were reported in three studies, positive results were reported in five studies, and negative results were reported in three studies.[12] These conflicting results cut across different elicitation mechanisms, real and hypothetical

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[7] To explain the importance of this approach, suppose that the point estimates of a discounting parameter are higher, on average, for smokers than nonsmokers. But assume that the estimates of this discounting parameter have high noise (viz., standard errors). Comparing only the signals (viz., point estimates) may lead one to erroneously conclude that smokers discount at a significantly higher rate than nonsmokers when an analysis that incorporates both the signals and the noise would find no significant difference between the groups. The method we adopt incorporates both the signals and the noise so that valid inferences can be drawn.

[8] Lawyer et al. (2011) investigate whether the risk preferences of smokers and nonsmokers differ when they make choices over hypothetical or real rewards. However, they do not compare the risk preferences of smokers and nonsmokers.

[9] A number of studies (e.g., Bradford 2010, Jusot and Khlat 2013) use survey questions which try to elicit general attitudes toward risk and were excluded for this reason.

[10] van der Pol and Ruggeri (2008) investigate risk preferences over hypothetical health outcomes.

[11] Of these studies, 3 also employed the area under the curve (AUC) method of Myerson, Green, and Warusawitharana (2001). When using the AUC method, one calculates the area under a subject's derived certainty equivalents and normalizes this to lie in the closed unit interval. Larger AUCs imply less risk aversion and, thus, the AUCs of smokers and nonsmokers can be compared to determine whether the groups differ in their risk preferences.

[12] Some studies classified smokers using more than one category (e.g., heavy smokers and light smokers in Poltavski and Weatherly 2013, and smokers and "triers" in Reynolds et al. 2003), and HLR separated male and female smokers and nonsmokers. We again adopt the classification scheme that codes a study as having found a statistically significant result if at least one smoker, nonsmoker comparison was significant, even if all comparisons were not.

Table 2. Review of Experimental Literature on Smoking and Risk Preferences

Study	Sample (Size)	Elicitation Method	Incentives (Max Prize)	Probabilities	Models (Estimated Rates)	Statistical Method (valid?)	Significant Relationship with Smoking?
Mitchell (1999)	Adults in Durham, NH, USA ($N_S = 20$, $N_{NS} = 20$)	Choice (random)	Yes ($10)	0.1, 0.25, 0.5, 0.75, 0.9, 1	PD ($\gamma_S = 1.328$) ($\gamma_{NS} = 1.371$)	NLLS for risk aversion, non-parametric tests for analysis. (not valid)	No.
Reynolds et al. (2003)	Adolescents in Morgantown, WV, USA ($N_S = 19$, $N_{NS} = 19$, $N_T = 17$)	Titration (random - Richards et al. (1999))	1-out-of-2-tasks ($10)	0.25, 0.5, 0.75, 0.9, 1	PD NRD but from Figure 2: ($\gamma_S = 1.610$) ($\gamma_{NS} = 1.110$) ($\gamma_T = 3.820$)	NLLS for risk aversion, ANOVA for analysis. (not valid)	Yes, positive for T relative S ($p < 0.05$) and NS ($p < 0.05$); No for S relative to NS.
Reynolds et al. (2004)	Mostly students in Morgantown, WV, USA ($N_S = 25$, $N_{NS} = 29$)	Titration (random - Richards et al. (1999))	1-out-of-2-tasks ($10)	0.25, 0.5, 0.75, 0.9, 1	PD ($\gamma_S = 1.910$) ($\gamma_{NS} = 1.470$)	NLLS for risk aversion, ANOVA for analysis. (not valid)	Yes ($p < 0.05$), positive (smokers are more risk averse)
Ohmura, Takahashi, and Kitamura (2005)	Students in Sapporo, Japan ($N_S = 27$, $N_{NS} = 23$)	Titration (random - Richards et al. (1999))	No (¥100,000 = $1000)	0.1, 0.3, 0.5, 0.7, 0.9	PD and AUC $AUC_S = 0.230$ $AUC_{NS} = 0.180$	AUC and NLLS for risk aversion, correlations and *t*-tests for analysis. (not valid)	Yes ($p = 0.08$), negative (smokers are less risk averse)
Reynolds (2006)	Adults in Buffalo, NY, USA ($N_S = 15$, $N_{NS} = 15$)	Titration (random - Richards et al. (1999))	No ($10)	0.25, 0.5, 0.75, 0.9, 1	PD ($\gamma_S = 3.908$) ($\gamma_{NS} = 1.574$)	NLLS for risk aversion, nonparametric tests for analysis. (not valid)	Yes ($p < 0.05$), positive (smokers are more risk averse)
Reynolds et al. (2007)	Adolescents in Columbus, OH, USA ($N_S = 25$, $N_{NS} = 26$)	Titration (random - Richards et al. (1999))	Yes ($10)	0.25, 0.5, 0.75, 0.9, 1	AUC and PD (Not reported)	AUC for risk aversion, ANOVA for analysis. (not valid)	No.
Yi, Chase, and Bickel (2007)	Adults in Little Rock, AR, USA ($N_S = 30$, $N_{NS} = 29$)	Titration (ordered)	No ($1000)	0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 0.95	PD and AUC (Not reported)	NLLS and AUC for risk aversion, ANOVA	No when analysing all the data; Yes ($p < 0.05$),

Table 2. (*Continued*)

Study	Sample (Size)	Elicitation Method	Incentives (Max Prize)	Probabilities	Models (Estimated Rates)	Statistical Method (valid?)	Significant Relationship with Smoking?
						for analysis. (not valid)	positive, when using only probabilities ≥ 0.5.
Anderson and Mellor (2008)	Adults subjects in Williamsburg, VA, USA ($N_S \approx 79$, $N_{NS} \approx 898$)	Choice (ordered - MPL)	Yes ($11.55)	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1	CRRA (1–r) ($r = 0.257$)	Algebra and averaging for risk aversion, probit model for analysis. (not valid)	Yes ($p < 0.1$), negative (smokers are less risk averse).
Harrison, Lau, and Rutström (2010)	Adults in Denmark ($N_S = 71$, $N_{NS} = 181$)	Choice (ordered - MPL)	1-in-10-chance ($687)	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1	CRRA (1–r) ($r_{S(men)} = 0.729$) ($r_{NS(men)} = 0.746$) ($r_{S(women)} = 0.811$) ($r_{NS(women)} = 0.755$)	ML for risk aversion and analysis. (valid)	Men: No; Women: Yes ($p < 0.06$), positive (smokers are more risk averse)
Szrek et al. (2012)	Adults in Witbank, South Africa ($N_S \approx 59$, $N_{NS} \approx 292$)	Choice (ordered - MPL)	Yes (R48 ≈ $7)	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1	CRRA (1–r) ($r = 0.35$, SD = 0.62)	Algebra and averaging for risk aversion, logit model for analysis. (not valid)	No.
Poltavski and Weatherly (2013)	Students in Grand Forks, ND, USA ($N_S = 16$, $N_{LS} = 74$, $N_{NS} = 92$)	Choice (random)	No ($100,000)	0.01, 0.1, 0.5, 0.9, 0.99	PD and AUC ($1000: $\gamma_S = 0.118$, $\gamma_{LS} = 0.134$, $\gamma_{NS} = 0.307$) ($100,000: $\gamma_S = 0.031$, $\gamma_{LS} = 0.167$, $\gamma_{NS} = 0.181$)	NLLS and AUC for risk aversion, ANOVA for analysis. (not valid)	Yes, negative for S relative to NS ($p < 0.05$); No for all other comparisons.

Source: Authors' construction. See Supporting Information Appendix B for more details on these studies.
S = smoker; NS = nonsmoker/never-smoker; LS = light smoker; T = trier; PD = probability discounting; AUC = area under the curve; NRD = not reported directly; MPL = multiple price list; NLLS = nonlinear least squares; ML = maximum likelihood; ANOVA = analysis of variance.

rewards, different frameworks for choice under risk, and different methods of analysis. Thus Table 2 shows that the relationship between risk preferences and smoking behavior, or lack thereof, differs markedly across studies.

Table 2 also shows that every study except HLR again adopted a two-step approach to statistical analysis: NLLS is used to estimate risk preference parameters at the level of the individual and then these point estimates are used as data in subsequent statistical models. For the reasons outlined above, this approach is statistically invalid.

We add to the extant literature by simultaneously investigating the relationship between risk preferences, time preferences and smoking behavior using an incentive-compatible experimental design, a relatively large sample of South African university students, and a statistical framework which allows one to draw robust inferences about smokers and nonsmokers.

4. Experimental Design and Summary Statistics

We recruited 175 subjects from undergraduate classes at the University of Cape Town (UCT). Given the focus on smoking behavior, sign-up sheets included a simple screening question: "Do you smoke cigarettes (Yes/No)." A pool of over 900 people applied to take part in the study and individuals from the smoking and nonsmoking groups were randomly selected for inclusion in the project. Those who were selected were added to a website which allowed them to sign up for an experimental session that did not conflict with their academic timetable.

The experiment took place in a computer lab at UCT which had been set up to run the risk and time preference software developed by us. Subjects were separated by partitions and were not allowed to talk to each other during the session. The experiment was conducted in August 2012 across 10 sessions. The median group size was 17 participants and one of us assumed the role of experimenter for every session; two research assistants (RAs) were also employed to help administer subject payments and answer questions.

On arrival at the lab, subjects were randomly allocated to computer terminals and given an overview of the tasks that they would complete. Subjects then signed informed consent before being taken through a detailed presentation of the risk or time preference task.[13] The order of these tasks was counter-balanced across sessions so subjects either performed the risk or time preference task first. Participants were given the opportunity to ask questions at any stage of the presentations or during the tasks. After questions had been addressed, subjects completed the first task.

Once all participants had completed the first task, the experimenter went through a detailed presentation of the other task. Subjects then completed this task before filling out a questionnaire which collected standard demographic characteristics and information on smoking behavior. The experimenter or an RA then determined their earnings for the tasks. All subjects received a show-up fee of R20. Earnings for the risk preference task were paid out immediately in cash and earnings for the time preference task were paid out on the date corresponding to the subject's choice on the randomly selected discounting question. Delayed payments were effected via

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[13] The introductory presentation, the risk preference task presentation, and the time preference task presentation are included in Supporting Information Appendix C. The presentations were designed to make the tasks transparent and easy to understand. The payment system was also discussed in detail so that subjects understood how their final earnings were determined. This attention to detail, coupled with salient rewards, promotes incentive compatibility and the truthful revelation of preferences.

Figure 1. Risk Preference Task Interface. [Color figure can be viewed at wileyonlinelibrary.com]

electronic transfer and subjects received a payment notification on their cell phones as soon as the transfer took place. Such transfers are a common means of payment in South Africa and were used to reduce the transaction costs which subjects would have had to incur by coming to collect their delayed payments from us. Experimental sessions lasted approximately an hour and subjects earned R370 (roughly \$66 at purchasing power parity (PPP) at the time) on average.

Risk Preference Task

The risk preference interface was based on Hey and Orme (1994). It presented subjects with a choice between two lotteries on a screen, displayed as pie charts with accompanying text that listed the probabilities and monetary amounts of the prizes. Figure 1 shows a screenshot of the risk preference task. The display seen by subjects used colors, allowing for greater discrimination than might be apparent from a monochrome presentation (e.g., for the Right lottery).

The task used prize magnitudes between R0 and R280 (roughly \$0 to \$50 at PPP at the time) and probabilities which varied in increments of 0.05 between 0 and 1. Thus, other than HLR, this study used larger lottery prizes than any of the studies in Table 2 which have incentive-compatible experimental designs. In addition, this study had more variation in the probability domain than every other study in Table 2. This variation provides for enhanced sensitivity to any probability weighting that might be present.

The lottery pairs in the task were based on the set developed by Loomes and Sugden (1998) (LS) to test different stochastic specifications of choice under risk. LS designed the lottery pairs to accommodate a wide range of risk preferences, to provide good coverage of the probability space,

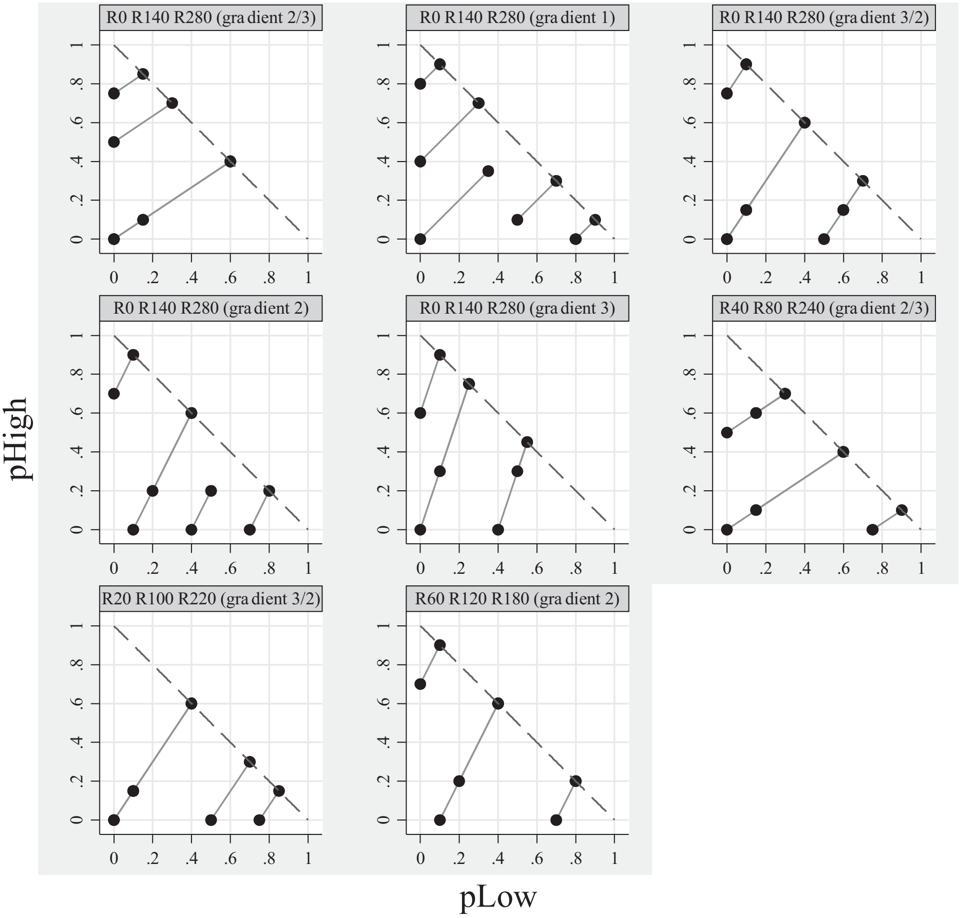

Figure 2. Marschak-Machina Triangles of Lotteries in the Risk Preference Task.

and to generate common-ratio tests of expected utility (EU) theory. However, all the lotteries over which each subject made choices had the same context (i.e., the same set of prizes).[14] By contrast, we used four prize contexts in the experiment: (R0, R140, R280), (R40, R80, R240), (R20, R100, R220), and (R60, R120, R180). Incorporating a number of different prizes and probabilities is helpful for the separate identification of the utility function and the PWF in models which admit both sources of risk preferences (e.g., rank-dependent utility theory).

Figure 2 shows the set of Marschak-Machina (MM) triangles representing the lotteries, and lottery pairs, which were used in the risk preference task. The top of each diagram lists the context of the lotteries (e.g., [R0, R140, R280]) and the gradient of the lines connecting lottery pairs. Each point in the MM triangle represents a lottery and the line connecting two, or more, points represents a lottery pair, or set of lottery pairs, on offer in the choice task. Figure 2 shows that the risk preference task provided thorough coverage of the MM triangle, in the sense of including a combination of interior and boundary choices, and that it captures the

[14] LS used two experimental treatments: one where subjects made choices over lotteries defined on the context ($0, $10, $20) and one where subjects made choices over lotteries defined on the context ($0, $10, $30). The probability distributions over these contexts were identical across the two groups except for 8 out of the 45 lotteries in the task.

full range of risk preferences, under the null hypothesis of EU theory: risk-loving (gradients less than 1), risk neutral (gradients equal to 1), and risk averse (gradients greater than 1). Subjects made 40 choices in the risk preference task and one choice was selected at random at the end of the experimental session for payment.[15]

Time Preference Task

The time preference task presented subjects with choices between smaller, sooner (SS) and larger, later (LL) monetary rewards. Figure 3 shows a screenshot of the time preference task. On each screen subjects had to make four choices before proceeding to the next screen. The principal (i.e., SS reward) and time horizon were fixed on each screen but varied across screens. A calendar was displayed on every screen to show the subjects when they would receive the amounts of money they chose.

Following Coller and Williams (1999), three front end delays (FEDs) to the SS rewards were used: zero days, 7 days, and 14 days. This design allows one to hold subjective transaction costs constant for the SS and LL rewards at positive FEDs. It also facilitates estimation of the parameters of a quasi-hyperbolic or β–δ discounting function because the zero day FED allows one to pin down the estimate of β, which captures a "passion for the present" or "present-bias" in decision making, whereas the positive FEDs allow one to estimate the long-term discounting parameter δ. Subjects in an experimental session were only exposed to one of these FED treatments.

Two principals (R150 and R250: roughly $27 and $45 at PPP at the time), 14-time horizons between the SS and LL rewards (7 to 98 days, in 7-day increments), and nominal annual interest rates between 5 and 250% were used in the time preference task. These parameters define a battery of 224 possible choice pairs. Each subject made 60 choices in the task which were drawn randomly, without replacement, from this battery. At the end of the experimental session, one of these choices was randomly selected for payment.

Summary Statistics

Table 3 presents summary statistics for the sample of 175 students. The average age in the sample is approximately 20 years old, 42% of the sample is White[16], two-thirds are enrolled in the Commerce faculty at UCT, and approximately one-third receives financial aid. Smokers were defined as those people who answered "yes" to the question: "Do you currently smoke

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[15] We decided to use the Random Lottery Incentive Mechanism (RLIM), where one of the 40 choices was chosen at random to be played out for payment. We did so to ensure that we collected enough choices over a wide enough array of lotteries to be able to identify EU and rank-dependent utility models. If we had opted for giving one choice to each subject, to avoid using RLIM, this would have been infeasible. Harrison and Swarthout (2014) find that using RLIM does make a difference behaviorally when estimating non-EU models, but not, as one would expect, when estimating EU models. A logical response to this problem is simply to assume two independence axioms: one axiom that applies to the evaluation of a given prospect, and that is assumed to be violated by non-EU models, and another axiom that applies to the evaluation of the experimental payment protocol. One can then allow for failure of the former axiom, when estimating non-EU models, but assume the validity of the latter axiom. Cox, Sadiraj and Schmidt (2015) also consider the implications of assuming RLIM, and discuss in detail the strengths and weaknesses of alternative payment protocols.

[16] Designation of population groups or 'races' follows the traditional categorisation in South Africa that is still employed in affirmative action and related policies, notwithstanding recognition that it involves cultural and historical discriminations that are without biological significance. Approximately 24% of the sample is Black; 14% is Coloured, a culturally salient population group in South Africa composed of individuals of mainly Indonesian descent who speak Afrikaans as a first language; 17% is Indian; and the remaining 3% preferred not to classify their race.

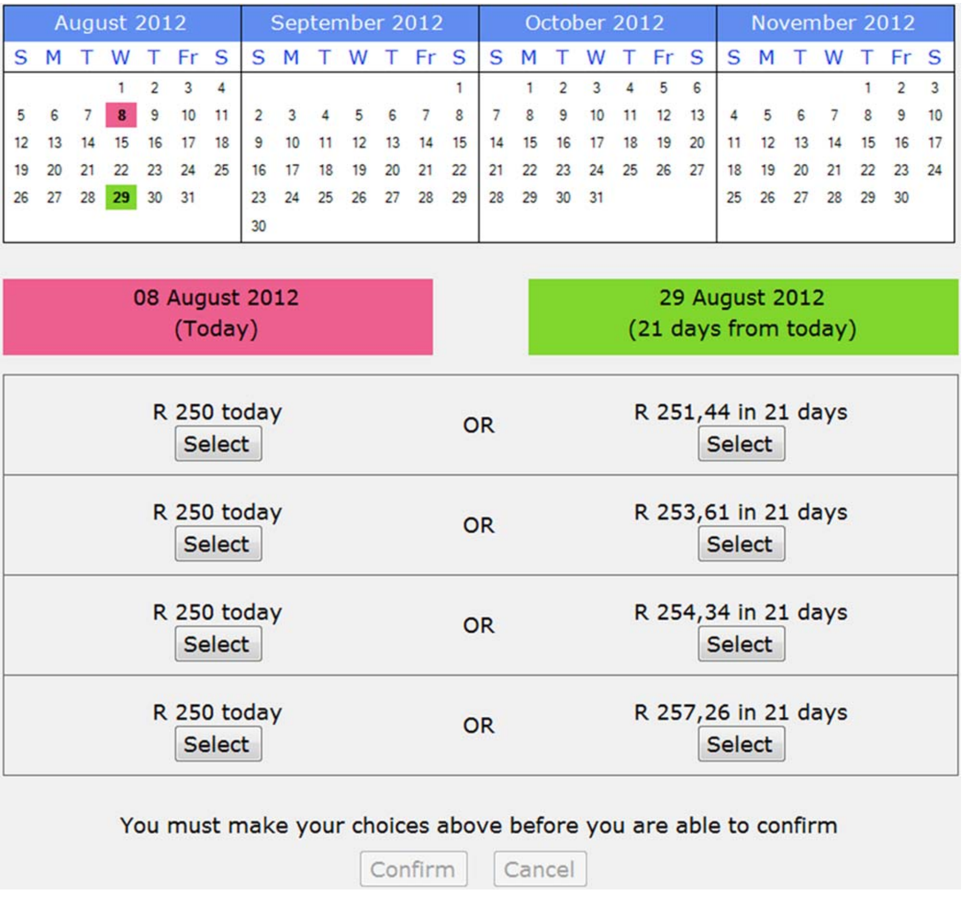

Figure 3. Time Preference Task Interface. [Color figure can be viewed at wileyonlinelibrary.com]

cigarettes?"[17] Current smokers make up 62% of the sample[18] and this is the largest number of smokers (i.e., 108 smokers) ever recruited for a study exploring risk preferences and smoking behavior. Smokers were deliberately oversampled to investigate whether intensity of smoking is

[17] There is a vast literature comparing self-reports of smoking with objective measures, e.g., cotinine measures, that are known to be correlated with exposure to smoke (see Gorber et al. 2009 for a survey). Two recent examples come from the Canadian Health Measures Survey (CHMS) and the National Health and Nutrition Examination Survey (NHANES). In the 2007–2009 wave of the CHMS, "ever smokers" were asked detailed questions about their current and recent smoking behavior, and urine cotinine measurements were taken between one day and 6 weeks after the initial survey response. Using these data, Wong et al. (2012) show high levels of consistency between self-reports and objective measures and conclude that, "Representative data for the Canadian population showed no significant difference between national estimates of smoking prevalence based on self-report versus urinary cotinine concentration." Choi and Cawley (2018) reach a similar conclusion using NHANES data from 1999–2012 and find, in addition, that accuracy of self-reported smoking tends to increase with level of education. To the extent that this finding is robust, our university sample of smokers are likely to have given accurate self-reports of smoking.

[18] The remaining 38% of the sample comprises both former-smokers and never-smokers who will be referred to collectively as nonsmokers.

Table 3. Descriptive Statistics

Variable	Mean	Std Deviation
Demographics		
Age	19.789	1.815
White	0.417	0.495
Male	0.549	0.499
Commerce faculty	0.674	0.470
Financial aid	0.314	0.466
Smoke	0.617	0.487
Treatments		
Risk task first	0.514	0.501
FED: 0 days	0.343	0.475
FED: 1 week	0.326	0.469
FED: 2 weeks	0.331	0.471
High Principal	0.498	0.500

related to risk and time preferences. The mean number of cigarettes smoked per day is 8.67 with a standard deviation of 5.81 and a range of 1 to 25.[19,20]

Smokers also completed the Fagerström Test for Nicotine Dependence (FTND) due to Heatherton et al. (1991). The FTND is a measure of smoking severity that scores people on a scale of 0 to 10, where higher numbers indicate greater severity. The average FTND score among smokers is 2.22 with a standard deviation of 2.08. Thus, on average, the smokers in this sample are relatively light smokers. In addition, given the young age of the sample, the smokers' lifetime exposure to cigarettes is relatively low. In the literature on risk preferences, time preferences and smoking behavior, researchers often try to maximize the difference between smokers and nonsmokers by selecting heavy smokers to take part in the study. We recruited smokers across the entire spectrum of severity to determine whether being a smoker, irrespective of intensity, is associated with risk, and time preferences. This also allows us to explore the relationship between risk preferences, time preferences, and smoking intensity.

Table 3 shows that randomization across experimental treatments ensured that approximately 50% of the sample completed the risk preference task prior to the time preference task. FED treatments were split evenly across the sample and 50% of choices in the time preference task involved the high principal of R250.

5. Statistical Specification

The statistical method we use is direct estimation by maximum likelihood of structural models of latent choice processes. The latent choice processes in question are captured by models of

[19] Estimates from the South African National Health and Nutrition Examination Survey of the mean number of cigarettes smoked per day for people aged 15–24 is 5.9 (Shisana et al. 2013, p. 111). For the population as a whole, the mean number of cigarettes smoked per day is 8.5. Thus, our sample, at least in terms of the mean number of cigarettes smoked per day, is very similar to the general population.

[20] According to The Tobacco Atlas (see www.tobaccoatlas.org and Eriksen et al. 2015), 22.2% of men and 9% of women smoke tobacco daily in South Africa. The prevalence rate for men is lower than in other middle-income countries but the prevalence rate for women is higher than in other middle-income countries. Prevalence rates for selected high-income countries are: US – men: 17.2%, women: 14.2%; UK – men: 23.2%, women: 20.3%; Australia – men: 15.1%, women: 11.6% ; Germany – men: 28%, women: 22.2%.

risk and time preferences. These models provide the structure necessary to estimate risk and time preferences using the observed choice data. One of the benefits of the maximum likelihood approach is that it uses all of the available information to estimate discounting and risk preference parameters and the precision of these estimates. This estimation strategy closely follows Andersen et al. (2008) and HLR so we provide a brief explanation of the method below, focusing on the canonical cases of EU theory and exponential (E) discounting. Further details are provided in Supporting Information Appendix D. We also discuss the extension to other risk and time preference models.

Assume that utility of income is defined by a power utility function which displays constant relative risk aversion (CRRA):

$$U(y) = y^r,$$

where y is a lottery prize in the risk preference task and r is a parameter to be estimated.

To estimate the parameter r, we formed a latent index, based on latent preferences that captured the difference in the expected utility of the Right and Left lotteries presented to subjects. The value of this index, for each observation, was determined by the lottery prizes, their associated probabilities, and an initial estimate of r. This latent index was linked to the subjects' binary choices (i.e., the Left or Right lottery) using the cumulative normal distribution function. This "probit" link function determined the likelihood of selecting the Left lottery, and hence the likelihood of selecting the Right lottery, for each observation in the dataset given the value of the latent index. Maximum likelihood estimation was then used to determine the value of r that maximized the likelihood of observing all of the data from the experiment.

It is a straightforward extension to make the parameter r a linear function of individual characteristics to draw robust inferences about potential differences in the risk preferences of participants. In addition, every estimate of r includes a standard error which reflects our uncertainty as to the "true" value of r. This stands in sharp contrast to the bulk of studies in Table 2 which use risk preference point estimates as data in subsequent statistical models. We also extended the model by adopting the "contextual utility" (CU) behavioral error specification of Wilcox (2011) to allow mistakes on the part of subjects from the perspective of the deterministic EU model and to draw robust inferences about the primitive "stochastically more risk averse than" relation.[21]

It is a simple matter to incorporate other theories of choice under risk in this statistical framework. Quiggin (1982) developed the rank-dependent utility (RDU) model, which assumes that a decision maker transforms objective probabilities into subjective decision weights which are then used to evaluate lotteries. In this context, we estimate the parameters of a utility function and PWF which maximize the likelihood of observing the data from the experiment on the basis of a latent index which captures the difference in the rank-dependent utility of the lotteries.

We estimate EU and RDU models to compare the risk preferences of smokers and non-smokers. In addition, we estimate the parameters of a variety of PWFs to ensure that the results are robust across different specifications.

Shifting to time preferences, under the E model, δ is the discounting parameter which equalizes the *utility* of income received at time t (i.e., the utility of the SS reward) with the *utility* of income received at time $t + \tau$ (i.e., the utility of the LL reward):

[21] The "stochastically more risk averse than" relation is the stochastic choice counterpart to the "more risk averse than" relation (see Pratt 1964) which is defined for the deterministic EU model.

$$\left[1 / (1+\delta)^{t}\right] U(y_t) = \left[1 / (1+\delta)^{t+\tau}\right] U(y_{t+\tau}), \tag{2}$$

for some utility function $U(\cdot)$.

Under the assumptions that EU characterizes choices over risky prospects and that subjects use the power utility function, we can add more structure to this indifference condition. Specifically, Equation 2 becomes:

$$\left[1 / (1+\delta)^{t}\right] (y_t)^{r} = \left[1 / (1+\delta)^{t+\tau}\right] (y_{t+\tau})^{r}, \tag{3}$$

where the general form of the utility function $U(\cdot)$ in Equation 2 has been replaced with the specific power utility function $U(y) = y^r$ in Equation 3.

To estimate the parameters of our time preference model, conditional on EU theory, power utility, and the E model, we form a latent index that captures the difference in the present value of the utility of the SS and LL rewards, and we incorporate the behavioral error term originally due to Fechner (1966/1860).

This "joint estimation" approach, developed by Andersen et al. (2008), uses subjects' choices in the risk preference task to pin down the parameters of the utility function, and subjects' choices in the time preference task to pin down the parameters of the E discounting model, conditional on the shape of the utility function. This approach ensures that we estimate time preferences defined over utility flows, and not flows of money.

It is straightforward to incorporate other discounting models in this statistical framework. In the case of Weibull discounting, for instance, Equation 3 becomes:

$$\left[\exp\left(-\delta t^{(1/\beta)}\right)\right] (y_t)^{r} = \left[\exp\left(-\delta (t+\tau)^{(1/\beta)}\right)\right] (y_{t+\tau})^{r} \tag{4}$$

We then form the latent index that captures the difference in the present value of the utility of the SS and LL rewards and proceed as before.

6. Results

We present the results from a set of risk and time preference models so as to explore the relationship between risk preferences, time preferences and smoking behavior. We begin with the risk preference results because they provide a natural segue to the time preference results which are conditional on the utility function curvature identified by the risk preference task.

Risk Preferences

We estimate an EU model employing a power utility function and the CU behavioral error specification; see Supporting Information Appendix E for more details. We find a relatively high level of risk aversion in the sample; a statistically significant estimate of the behavioral error parameter, implying that subjects make behavioral errors in the risk preference task; and no substantive differences in the risk preferences of smokers and nonsmokers. We also estimate a model which allows risk preferences to vary as a quadratic function of smoking intensity as measured by the number of cigarettes smoked per day: risk preferences are not significantly related to smoking intensity. These results are robust to the assumption that Saha's (1993) expo-power utility function—which admits increasing relative risk aversion, decreasing relative risk aversion, and CRRA—characterizes choice under risk.

The EU results suggest that there are no significant differences in the risk preferences of smokers and nonsmokers. However, this analysis, by assumption, ignores the role of probability weighting and it may be the case that smokers perceive probabilities differently to nonsmokers. For example, smokers may underweight moderate to high probabilities more so than nonsmokers, and may, therefore, underestimate the likelihood of the negative consequences associated with smoking. To explore this possibility, we estimate RDU models.

One of the key components of an RDU model is the specification of the PWF. We estimate the power PWF, the PWF popularized by Tversky and Kahneman (1992) (TK), and the Prelec (1998) two-parameter PWF which exhibits considerable flexibility; see Supporting Information Appendix D for more details. The functional form for the Prelec (1998) PWF is:

$$\pi(p) = \exp[-\eta(-\ln p)^{\varphi}] \tag{5}$$

which is defined for $1 > p > 0$, $\eta > 0$, and $\varphi > 0$. This function allows independent specification of location and curvature in probability weighting. It also nests the power PWF when $\varphi = 1$ and nests a one-parameter function when $\eta = 1$, which is similar to the TK function and admits linear, inverse S-shaped, and S-shaped forms.

We find statistically significant evidence of inverse S-shaped probability weighting. To investigate the possibility that smokers perceive probabilities differently to nonsmokers we estimate a RDU model with a power utility function, the CU behavioral error specification, and the Prelec (1998) PWF, and allow the parameters to vary as a function of observable characteristics and task parameters. Results are presented in Table 4.[22] Smokers do not differ significantly from nonsmokers in the shape of their utility functions (i.e., in the estimate of r) nor in the way they perceive probabilities (i.e., in the estimates of φ and η). In addition, tests of the joint hypothesis that the coefficients for smokers across r, φ, and η are equal to zero, cannot be rejected ($p = 0.823$).[23,24]

Thus, at least in this sample, there are no significant differences in risk preferences according to smoking behavior. This result is robust to different theories of choice under risk, different PWFs, and a utility function that admits varying relative risk aversion.

Time Preferences

We estimate four time preference models: the E model, the quasi-hyperbolic (QH) model, Mazur's (1984) hyperbolic (H) model, and the Weibull (WB) model; see Supporting Information

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[22] Supporting Information Appendix E also presents results from a RDU model employing the TK PWF; the results are qualitatively identical to those in Table 4.

[23] We also estimate a RDU model with the expo-power utility function, the Prelec (1998) PWF, and the full set of covariates from Table 4. The smoker coefficient is not significantly different from zero for any of the parameters in the model. In addition, a test of the joint hypothesis that the coefficients for smokers across r, α, φ, and η are equal to zero, cannot be rejected ($p = 0.967$).

[24] We also investigate the relationship between smoking intensity and risk preferences by estimating the model in Table 4 and allowing the parameters of interest to vary as a quadratic function of number of cigarettes smoked per day. None of the linear or quadratic terms are statistically significant in any of the equations and a joint test of the linear *and* quadratic terms across all equations is not statistically significant either ($p = 0.576$).

Table 4. RDU Theory ML Estimates, Heterogenous Preferences

	Model Prelec	
	Estimate	Std Error
Power function parameter (r)		
Age	−0.004	0.011
White	0.029	0.051
Male	0.062	0.049
Commerce faculty	0.030	0.062
Financial aid	−0.051	0.058
Risk task first	−0.015	0.050
Smoker	−0.005	0.055
Constant	0.366	0.230
PWF parameter (φ)		
Age	−0.003	0.006
White	0.001	0.047
Male	−0.009	0.044
Commerce faculty	−0.084	0.120
Financial aid	0.034	0.056
Risk task first	0.054	0.080
Smoker	0.028	0.049
Constant	0.871[c]	0.206
PWF parameter (η)		
Age	−0.027	0.046
White	−0.062	0.121
Male	−0.166	0.137
Commerce faculty	−0.216	0.184
Financial aid	−0.014	0.139
Risk task first	0.166	0.153
Smoker	0.146	0.153
Constant	1.425[b]	0.676
Error (μ)		
Constant	0.166[c]	0.008
N	7000	
log-likelihood	−4119.762	

Results account for clustering at the individual level.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$.

Appendix F for more details and Andersen et al. (2014) for a review of all of the major discounting models. We use a Fechner error term and jointly estimate the parameters of these models with the curvature of the utility function, assuming RDU[25] and the Prelec (1998) PWF to characterize choice under risk, to focus on the discounting of utility flows, not flows of money. In the context of addiction, the crucial difference between these time preference specifications is that under the

[25] Given the presence of probability weighting in this dataset, we employ RDU theory to apportion risk preferences into their concave utility and probability weighting components so as to draw accurate inferences about discounting behavior. If one ignores probability weighting when it is present, this would lead to biased estimates of utility function curvature and, hence, biased estimates of discounting parameters. In Supporting Information Appendix G we test the robustness of our results by estimating these models assuming EU theory characterises choice under risk; the results are *qualitatively* identical to those reported in the main text.

assumption of an additively separable intertemporal utility function, the E model implies time-consistent preferences whereas the other models can yield time-inconsistent preferences.[26]

The estimate of the E discount rate $\delta = 0.493$ implies an annual discount rate of approximately 49%, which is a marked decline in comparison to the estimate of $\delta = 3.234$ under the assumption of linear utility (see Supporting Information Appendix F). Similar declines are evident across all of the discounting specifications which highlights the point, now familiar from Andersen et al. (2008), that incorporating concavity of the utility function leads to substantial declines in inferred discount rates.

In the QH model, the estimate of $\beta = 0.988$, which captures a "present-bias" or a "passion for the present" in discounting behavior, is statistically significantly less than 1 ($p = 0.002$), which provides evidence of quasi-hyperbolic discounting and declining discount rates. The same is true in the WB results: the estimate of $\beta = 1.611$, which "expands" or "contracts" time, is statistically significantly greater than 1 ($p < 0.001$) which leads us to infer that people perceive time as "slowing down," generating declining discount rates. Thus, both the QH and WB results suggest that discount rates decline over time, which, when coupled with an additively separable intertemporal utility function, raises the spectre of time-inconsistent choices. However, the two discounting functions provide competing explanations for this result: a present-bias in the case of the QH model and subjective time perception in the case of the WB model.

As a descriptive prelude to the formal statistical results, Figure 4 shows a kernel-weighted local polynomial regression, with a 95% confidence interval, of the fraction of LL choices by smokers and nonsmokers for the nominal annual interest rates on offer in the time preference task. At each interest rate, the point estimate of the fraction of LL choices by smokers is less than the point estimate of the fraction of LL choices by nonsmokers, and the 95% confidence intervals do not overlap. This suggests that smokers discount more heavily than nonsmokers, but clearly this result must be subjected to closer statistical scrutiny before any definitive conclusions are reached.

Consequently, we estimate the four time preference models, assuming RDU and the Prelec (1998) PWF, where risk and discounting parameters are allowed to vary by smoking status, other observable characteristics, and task parameters; see Supporting Information Appendix F for the results. Across all specifications, the effect of smoking on the estimate of δ is positive and statistically significant at the 1% level, implying that smokers tend to discount the future more heavily than nonsmokers. The magnitude of this difference in discounting behavior is economically significant. In the E model, for example, smokers have an annual discount rate which is 26 percentage points higher than nonsmokers. Thus, the positive relationship between smoking and discounting identified in Table 1 has been replicated using a full set of covariates and a joint estimation approach to time preferences which controls for utility function curvature and probability weighting.[27]

The estimates of β in the QH and WB models, by contrast, do not vary according to smoking status. Thus, smokers are no more present-biased than nonsmokers in the QH model nor are they more likely to perceive time as slowing down in the WB model. It is only the long-term discount rate δ which differs between smokers and nonsmokers in these models.

[26] Time consistency, or the lack thereof, is central to economic models of addiction. Time-inconsistent agents may fail to carry out plans they make for the future, which provides a possible explanation for the behavioral puzzles listed earlier: addicts expend resources to acquire their targets of addiction but then incur real costs to try to reduce or limit their consumption of these goods; and the fact that the typical course of addiction is characterised by repeated unsuccessful attempts to quit prior to final abstention.

[27] Supporting Information Appendix G presents results from the four time preference models where EU theory is assumed to characterise choice under risk: the results are virtually identical to the models which assume RDU and the Prelec (1998) PWF.

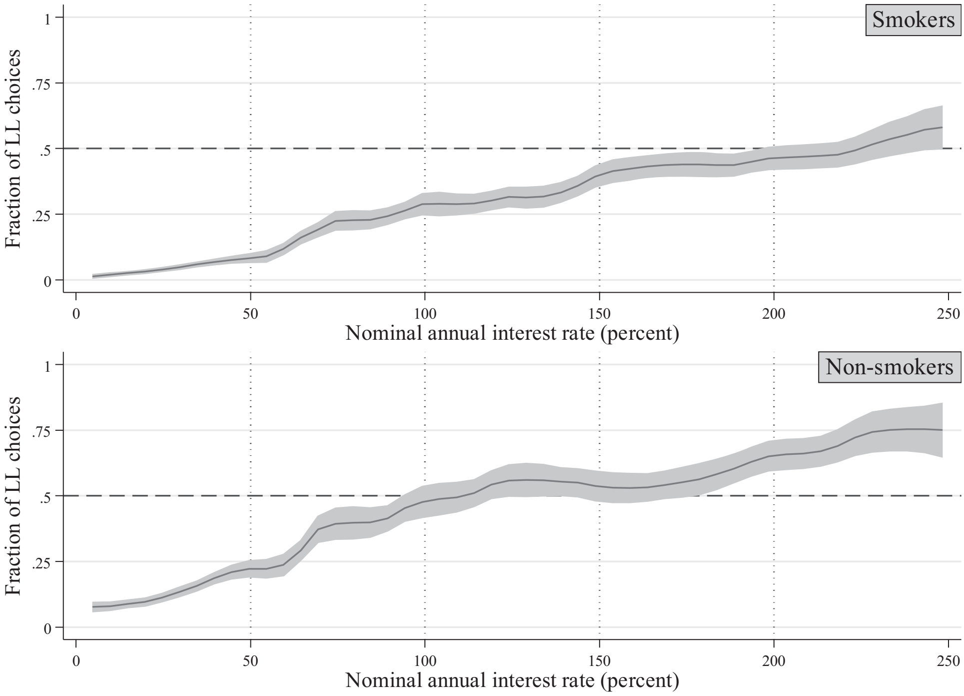

Figure 4. Fraction of LL Choices and Interest Rate Offered.

It is inferentially risky to try to boil down smoking to a binary covariate (e.g., smoker, nonsmoker) because one runs the risk of mischaracterizing the full effects of smoking behavior if there are differences between nonsmokers, light smokers, moderate smokers, and heavy smokers. Thus, to extend our analysis, we investigate whether smoking intensity and discounting behavior are related by estimating the four time preference models and allowing the parameters of interest to vary as a quadratic function of the number of cigarettes smoked per day, other observable characteristics, and task parameters.

In all models, both the linear and quadratic terms are statistically significant in the estimate of δ: the linear term is positive and significant whereas the quadratic term is negative and significant. Thus, there is a concave relationship between discounting behavior and number of cigarettes smoked per day: every additional cigarette is associated with an increase in discounting, but at a decreasing rate until a maximum is reached, after which every additional cigarette is associated with a decrease in discounting.[28]

Table 5 maps out the response surface for estimates of δ in the four-time preference models evaluated at different values of number of cigarettes smoked per day. At low values of number of cigarettes, the conditional marginal effect of additional cigarettes is positive. By 15 cigarettes, however, the conditional marginal effect of additional cigarettes is negative. Table 5 highlights the nonlinear effect of smoking intensity on discounting behavior. To our knowledge, this is the first study of time preferences and smoking behavior which has identified this effect.

[28] In the QH model, smoking intensity is not significantly related to the extent of present-bias. In the WB model, though, the number of cigarettes' linear term is negative and significant in the estimate of β, albeit at the 10% level. Thus, the more cigarettes smoked per day, the less likely people are to perceive time as slowing down.

Table 5. Number of Cigarettes Conditional Marginal Effects for δ

	Model 1 Exponential	Model 2 Hyperbolic	Model 3 Quasihyperbolic	Model 4 Weibull
Number of cigarettes				
0	0.051 (0.015)	0.044 (0.013)	0.053 (0.014)	0.018 (0.006)
5	0.031 (0.009)	0.025 (0.007)	0.032 (0.009)	0.011 (0.003)
10	0.010 (0.006)	0.006 (0.005)	0.011 (0.005)	0.004 (0.002)
15	−0.011 (0.009)	−0.013 (0.010)	−0.010 (0.008)	−0.003 (0.002)
20	−0.032 (0.015)	−0.032 (0.016)	−0.030 (0.014)	−0.010 (0.004)
25	−0.053 (0.022)	−0.051 (0.023)	−0.051 (0.020)	−0.017 (0.006)

Standard errors in parentheses.

Mixture Models of Discounting Behavior

The analyses conducted thus far have been based on the implicit assumption that the observations are produced by only one discounting data generating process (DGP): either E, H, QH, or WB. However, the data may be a result of more than one DGP. For example, the E model may explain some discounting choices better than the H model whereas the H model may explain other choices better than the E model. The assumption that only one DGP characterizes all of the data precludes such a possibility.

Finite mixture models[29] allow two or more DGPs to account for the data and also provide a measure of the proportion of the data which is best explained by each process. In the current context, one can estimate a mixture model of, say, the E and H discounting functions and then ask the data to determine each function's level of support. To do so one specifies a "grand likelihood" function which is just a probability-weighted average of the likelihoods of the two models; see Supporting Information Appendix H for more details.

We estimate a mixture model of the E and H discounting functions and both functions find statistically significant support in the data.[30] In addition, the mixture model shows that discounting parameter estimates are distorted when the E or H models have to account for all of the data. We also use the mixture model to explore the factors that may affect the likelihood of discounting according to the E and H functions.

Given that the typical pattern of addiction is characterized by choice behavior that implies time-inconsistent preferences, it is of particular importance to determine whether smoking behavior is associated with a greater likelihood of discounting according to the time-inconsistent H model as opposed to the time-consistent E model. Given our interest in smoking intensity, rather than a binary classification of smoking status, we estimate a mixture model of the E and H discounting functions and allow the risk and time preference parameters to vary as a quadratic function of number of cigarettes smoked per day. In addition, we include a full set of covariates in the mixture probability equation and a number of cigarettes smoked

[29] For detailed discussions of mixture models see McLachlan and Peel (2000), Harrison and Rutström (2009), and Conte, Hey and Moffatt (2011). Mixture models have been applied to discounting behavior by Andersen et al. (2008), Coller, Harrison and Rutström (2012) and Andersen et al. (2014).

[30] Supporting Information Appendix H contains the results from all of the two-process mixture models that can be estimated from the four discounting specifications. We only discuss the results from the E and H mixture model in this section because these are the most commonly used discounting functions in the addiction literature and they are representative of the results from the other mixture models.

Table 6. Mixture Model ML Estimates of E and H Discounting Functions

	Estimate	Std Error	*p*-Value	95% Confidence Interval	
Power function parameter (r)					
Number of Cigarettes	0.016[c]	0.005	0.003	0.005	0.026
Number of Cigarettes^2	−0.001[c]	0.000	0.003	−0.001	0.000
Constant	0.305[c]	0.028	0.000	0.251	0.359
PWF parameter (φ)					
Number of Cigarettes	−0.013	0.012	0.267	−0.035	0.010
Number of Cigarettes^2	0.001	0.001	0.146	0.000	0.002
Constant	0.813[c]	0.036	0.000	0.743	0.883
PWF parameter (η)					
Number of Cigarettes	0.018	0.019	0.362	−0.020	0.055
Number of Cigarettes^2	0.000	0.001	0.993	−0.002	0.002
Constant	0.818[c]	0.047	0.000	0.725	0.910
Discounting parameter (δ_E^{mix})					
Number of Cigarettes	0.031[c]	0.010	0.002	0.012	0.051
Number of Cigarettes^2	−0.002[c]	0.001	0.003	−0.003	−0.001
Constant	0.116[c]	0.019	0.000	0.078	0.153
Discounting parameter (δ_H^{mix})					
Number of Cigarettes	0.047[c]	0.017	0.005	0.014	0.079
Number of Cigarettes^2	−0.002[c]	0.001	0.002	−0.003	−0.001
Constant	0.640[c]	0.076	0.000	0.491	0.790
Mixture probability (π^E)					
Age	−0.002	0.016	0.900	−0.033	0.029
White	0.076	0.086	0.374	−0.092	0.244
Male	−0.105	0.074	0.156	−0.250	0.040
Commerce faculty	−0.017	0.089	0.850	−0.192	0.158
Financial aid	−0.118	0.084	0.160	−0.283	0.047
Risk task first	−0.049	0.080	0.541	−0.205	0.107
FED: 1 week	−0.105	0.083	0.203	−0.267	0.057
FED: 2 weeks	−0.038	0.091	0.679	−0.216	0.141
High Principal	0.186[c]	0.051	0.000	0.087	0.285
Number of Cigarettes	−0.018[c]	0.007	0.007	−0.031	−0.005
Constant	0.512	0.313	0.102	−0.101	1.125
Error terms					
Risk error (μ)	0.166[c]	0.007	0.000	0.151	0.180
Time error (ν)	0.051[c]	0.012	0.000	0.026	0.075
N	17500				
log-likelihood	−8484.767				

Results account for clustering at the individual level.
[a] $p < 0.10$
[b] $p < 0.05$
[c] $p < 0.01$.

per day linear term[31] to identify the factors that may affect the likelihood of discounting according to the E and H models.

[31] We also estimate the mixture model with a full set of covariates in the mixture probability equation and allow this equation to vary as a quadratic function of number of cigarettes smoked per day. The quadratic term is not statistically significant, implying that we do not need to incorporate higher order polynomials of this variable in the equation, and can employ the linear term by itself. As would be expected from the results in Table 6, when we incorporate both the linear and quadratic terms of number of cigarettes smoked per day, a joint test of the coefficients on these terms is statistically significant at the 5% level.

Table 6 presents the results. Of particular interest is that the number of cigarettes smoked per day is negatively and statistically significantly ($p < 0.01$) related to the likelihood of discounting according to the E model. The magnitude of this effect is large: every additional cigarette smoked per day is associated with a 2 percentage point *decrease* in the likelihood of discounting according to the E model and, hence, a 2 percentage point *increase* in the likelihood of discounting according to the H model. Thus, increases in smoking intensity are associated with a greater likelihood of discounting hyperbolically as opposed to discounting exponentially. This result has important implications for our understanding of addiction. In addition to the nonlinear effect of smoking intensity on inferred discount rates identified in the previous section, smoking intensity is also linked to the likelihood of making time-inconsistent choices, which is the hallmark of addictive consumption patterns. To our knowledge, this is the first study to have identified this effect.

7. Discussion and Conclusions

We analyse the relationship between risk preferences, time preferences and smoking behavior using an incentive-compatible experimental design and a joint estimation approach to data analysis. We find that both probability weighting and utility function curvature affect attitudes to risk in this sample but we find no statistically significant relationship between risk preferences and smoking behavior. This result is robust to different theories of choice under risk, different PWFs, and different utility functions which admit varying relative risk aversion.

To analyse the time preferences of our sample, we adopt the methodology of HLR which jointly estimates utility function curvature and discounting functions so as to characterize time preferences over utility flows, not flows of money. We find that controlling for the concavity of the utility function leads to a dramatic decline in estimates of δ, replicating the result of Andersen et al. (2008). We also allow RDU to characterize choice under risk so as to apportion risk preferences into their utility curvature and probability weighting components.

We explore the relationship between time preferences and smoking behavior in three ways. First, we focus on the marginal effect of smoking status on time preferences by estimating the discounting models and making the parameters of interest linear functions of observable characteristics and task parameters. Across all specifications, the estimate of δ for smokers is positive and statistically significant, implying that smokers discount at a higher rate than nonsmokers. In Supporting Information Appendix G, we also test to see whether these results are robust to the assumption that EU characterizes choice under risk: the results are qualitatively identical to those in section 6.

Second, to investigate whether smoking intensity is related to discounting behavior, we estimate the four-time preference models and allow the parameters of interest to vary as quadratic functions of number of cigarettes smoked per day, other observable characteristics, and task parameters. These analyses reveal a concave relationship between smoking intensity and estimates of the discounting parameter δ. Specifically, every additional cigarette is associated with an increase in discounting, but at a decreasing rate until a maximum is reached, after which every additional cigarette is associated with a decrease in discounting.

Finally, we estimate mixture models of the different discounting specifications and focus on the link between smoking intensity and the likelihood of making time-inconsistent choices. We find that smoking intensity is positively and significantly related to the likelihood of discounting hyperbolically, which suggests that smokers, and, in particular, heavier smokers, are more likely to make time-inconsistent choices.

This research makes a number of contributions to the literature. When analyzing risk preferences and smoking behavior, we allow risk attitudes to be determined both by utility function curvature and probability weighting. Prior studies in the literature either focus on utility function curvature or probability weighting, not both. Consequently, they are always open to the critique that the other source of risk attitudes, the one not explored in the study, differs according to smoking behavior. Incorporating both utility function curvature and probability weighting in estimates of risk attitudes provides us with immunity to this critique and allows us to make stronger claims about differences in risk preferences according to smoking behavior.

This is only the second study in the smoking-discounting literature to incorporate utility function curvature in the estimation of time preference models, and it is the first which allows RDU to characterize choice under risk. Although the qualitative discounting estimates do not differ significantly across the EU and RDU specifications, it is nevertheless theoretically appropriate to quantitatively apportion risk preferences into their utility curvature and probability weighting components.

This is the first study to identify a nonlinear effect of smoking intensity on discounting behavior. Smoking more cigarettes is associated with an increase in discounting but only up to a point, after which each additional cigarette is associated with a decrease in discounting. This nonlinear effect may explain why some studies, which only recruited heavy smokers and never-smokers, fail to find a difference in discounting behavior between these groups.

In addition, this nonlinear effect of smoking intensity may provide an explanation for patterns of cigarette consumption. It has long been assumed that the marked modal clustering around 20 cigarettes per day in mature smokers simply reflects the fact that cigarettes are typically sold in packs of 20. It may be the case, though, that cigarette companies learned to sell cigarettes in packs of 20 because that is where the psychofunctional, and not merely the homeostatic, equilibrium lies for the majority of mature smokers.

This research also reiterates the point that multiple decision processes characterize the discounting of delayed rewards. It is crucial for researchers to be cognizant of this fact when exploring the smoking-discounting relationship. Smoking intensity increases the likelihood of discounting hyperbolically, which may be an important factor in tobacco addiction and explain recalcitrance to treatment. To our knowledge, this is the first study in the literature to identify this effect in a sample of smokers and nonsmokers.

This research naturally involves some limitations. Clearly our sample of young South African university students is not representative of a general population, and the smokers among them are not representative of smokers in general. But the significance of our findings, we suggest, does not depend on supporting inferences about general populations. Existing theories of addiction focus on differences between addicts and nonaddicts. As people who smoke as few as five cigarettes every day can be addicted, our observation of effects of smoking intensity on key variables in the economic structure of choice is novel. The "clean" conditions of the laboratory often furnish, as here, the best initial environment for detecting effects not predicted by established theory. The next step in follow-up research is obviously to use larger, more representative samples, along with field studies, to determine whether the effects are robust.

Another potential issue with the sample is the extent of possible selection bias. As discussed earlier, a large number of people applied to take part in the study, so people in the smoking and nonsmoking groups were randomly selected to form the study pool. It may be the case that those who were selected were not representative of their group. Ideally, we would use information on the population of smokers and nonsmokers at UCT to correct for any sample selection issues present in the data.[32] Unfortunately, we do not have any additional information on the population of smokers and nonsmokers at UCT.

A question that arises naturally in this line of research is whether risk and time preferences are domain- or context-specific. A noteworthy feature of the limited existing empirical literature on addiction and risk and time preferences is that the latter are invariably measured in the domain of responses to monetary rewards, despite the fact that the most directly relevant arguments of utility functions where addiction is concerned refer to social and health status. While it is possible that most people's risk and time preferences are closely related across domains, this cannot be assumed, especially in a population that is already atypical in being characterized by addiction.

It is practically challenging to address the question of cross-domain preference structure consistency in the laboratory using hypothetical rewards because one loses salience and dominance without money as a reward medium when trying to induce value. Arguably, the best long-run methodology for handling this difficulty will be to use laboratory work on choices over money as a baseline for extensions into the field where participants' choices affect their real health and social well-being. In that case, the first stage research involving monetary rewards is the immediate priority.

We stress that our results refer to correlations between smoking behavior and preferences. It is apparent that causality can run in both directions, even if we have priors that favor the causal effect of preferences on smoking behavior as being more prominent. There are several ways to go beyond statements about correlation, which should be considered in future work. One is to mimic a randomized control trial, by matching smokers and nonsmokers using some metric such as a propensity score (see Rubin 1998, 2001), and then evaluating the risk and time preferences of these matched samples. This approach avoids the obvious ethical problem of randomizing "smoking" to a sample. One problem with this approach is the need for much larger samples than we have available. A more fundamental problem is that it requires that we reduce "smoking" to a coarse representation of the full characterization of smoking behavior (e.g., to a binary variable, an ordered discrete variable, or a single continuous variable). This would blunt the very nonlinearity of smoking intensity that is one of our major findings.

These issues notwithstanding, we provide a rigorous framework within which to analyze risk preferences, time preferences and smoking behavior. Future experimental research should abandon binary classifications of smoking status and seek to replicate the nonlinear effect of smoking intensity on discounting behavior, and the link between smoking intensity and the likelihood of making time-inconsistent choices. If these results hold in other samples, our understanding of smoking specifically, and addiction generally, will be sharpened.

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[32] Harrison, Lau and Rutström (2009) and Harrison and Lau (2014) analyse the effect of sample selection bias on estimated risk preference parameters. They used the Danish Registry to gather information on people who were invited to participate in their experiment but who did not take part and this allowed them to make sample selection corrections for the sample of people who were invited and who did participate in the experiment. Harrison, Lau and Rutström (2009) find that correcting for sample selection bias leads to attenuated risk aversion estimates, implying that their sample was more risk averse than the population from which it was drawn. Similarly, Harrison and Lau (2014) find that sample selection corrections lead to lower estimates of risk aversion.

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References

Adams, J., and D. Nettle. 2009. Time perspective, personality and smoking, body mass, and physical activity: An empirical study. *British Journal of Health Psychology* 14:83–105

Ainslie, G. 1992. *Picoeconomics: The Interaction of Successive Motivational States within the Individual*. Cambridge: Cambridge University Press.

Ainslie, G. 2001. *Breakdown of Will*. Cambridge: Cambridge University Press.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström. 2008. Eliciting risk and time preferences. *Econometrica* 76:583–618

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström. 2014. Discounting behavior: A reconsideration. *European Economic Review* 71:15–33

Anderson, L. R., and J. M. Mellor. 2008. Predicting Health Behaviors With An Experimental Measure Of Risk Preference. *Journal of Health Economics* 27:1260–74

Audrain-McGovern, J., D. Rodriguez, L. H. Epstein, J. Cuevas, K. Rodgers, and E. P. Wileyto. 2009. Does delay discounting play an etiological role in smoking or is it a consequence of smoking? *Drug and Alcohol Dependence* 103: 99–106

Baker, F., M. W. Johnson, and W. K. Bickel. 2003. Delay discounting in current and never-before cigarette smokers: Similarities and differences across commodity, sign, and magnitude. *Journal of Abnormal Psychology* 112:382–92

Balevich, E. C., N. D. Wein, and J. D. Flory. 2013. Cigarette smoking and measures of impulsivity in a college sample. *Substance Abuse* 34:256–62

Becker, G. S., and K. M. Murphy. 1988. A theory of rational addiction. *Journal of Political Economy* 96:675–700

Bénabou, R., and J. Tirole. 2004. Willpower and personal rules. *Journal of Political Economy* 112:848–86

Benhabib, J., and A. Bisin. 2004. Modeling internal commitment mechanisms and self-control: A neuroeconomics approach to consumption-saving decisions. *Games and Economic Behavior* 52:460–92

Bernheim, B. D., and A. Rangel. 2004. Addiction and cue-triggered decision processes. *American Economic Review* 94: 1558–90

Bickel, W. K., D. P. Jarmolowicz, E. T. Mueller, C. T. Franck, C. Carrin, and K. M. Gatchalian 2012. Altruism in time: Social temporal discounting differentiates smokers from problem drinkers. *Psychopharmacology* 224:109–20

Bickel, W. K., A. L. Odum, and G. J. Madden. 1999. Impulsivity and cigarette smoking: Delay discounting in current, never, and ex-smokers. *Psychopharmacology* 146:447–54

Bickel, W. K., R. Yi, B. P. Kowal, and K. M. Gatchalian. 2008. Cigarette smokers discount past and future rewards symmetrically and more than controls: Is discounting a measure of impulsivity? *Drug and Alcohol Dependence* 96:256–62

Bradford, W. D. 2010. The association between individual time preferences and health maintenance habits. *Medical Decision Making* 30:99–112

Businelle, M. S., M. A. McVay, D. Kendzor, and A. Copeland. 2010. A comparison of delay discounting among smokers, substance abusers, and non-dependent controls. *Drug and Alcohol Dependence* 112:247–50

Chabris, C., D. Laibson, C. L. Morris, J. P. Schuldt, and D. Taubinsky. 2008. Individual laboratory-measured discount rates predict field behavior. *Journal of Risk and Uncertainty* 37:237–69

Choi, A., and J. Cawley. 2018. Health disparities across education: The role of differential reporting error. *Health Economics.* 27:e1–e29

Clark, A. 1997. *Being there.* Cambridge, MA: MIT Press.

Coller, M., G. W. Harrison, and M. M. McInnes. 2002. Evaluating the tobacco settlement damage awards: Too much or not enough? *American Journal of Public Health* 92:1–6

Coller, M., G. W. Harrison, and E. E. Rutström. 2012. Latent process heterogeneity in discounting behavior. *Oxford Economic Papers* 64:375–91

Coller, M., and M. B. Williams. 1999. Eliciting individual discount rates. *Experimental Economics* 2:107–27

Conte, A., J. D. Hey, and P. G. Moffat. 2011. Mixture models of choice under risk. *Journal of Econometrics* 162:79–88

Cox, J. C., V. Sadiraj, and U. Schmidt. 2015. Paradoxes and mechanisms for choice under risk. *Experimental Economics* 18:215–50

Dallery, J., and B. R. Raiff. 2007. Delay discounting predicts cigarette smoking in a laboratory model of abstinence reinforcement. *Psychopharmacology* 190:485–96

Epstein, L. H., J. B. Richards, F. G. Saad, R. A. Paluch, J. N. Roemmich, and C. Lerman. 2003. Comparison between two measures of delay discounting in smokers. *Experimental and Clinical Psychopharmacology* 11:131–8

Eriksen, M., J. Mackay, N. Schluger, F. I. Gomeshtapeh, and J. Drope. 2015. *The tobacco atlas*. Atlanta, GA: American Cancer Society.

Fechner, G. T. 1966/1860. *Elements of psychophysics*. New York, NY: Holt, Rinehart and Winston.

Field, M., M. Santarcangelo, H. Sumnall, A. Goudie, and J. Cole. 2006. Delay discounting and the behavioural economics of cigarette purchases in smokers: The effects of nicotine deprivation. *Psychopharmacology* 186:255–63

Fudenberg, D., and D. K. Levine. 2006. A dual-self model of impulse control. *American Economic Review* 96:1449–76

Fudenberg, D., and D. K. Levine. 2011. Risk, delay and convex self-control costs. *American Economic Journal: Microeconomics* 3:34–68

Fudenberg, D., and D. K. Levine. 2012. Timing and self-control. *Econometrica* 80:1–42

Gorber, S. C., S. Schofield-Hurwitz, J. Hardt, G. Levasseur, and M. Tremblay. 2009. The accuracy of self-reported smoking: A systematic review of the relationship between self-reported and cotinine-assessed smoking status. *Nicotine & Tobacco Research* 11:12–24

Gruber, J., and B. Köszegi. 2001. Is addiction "rational"? Theory and evidence. *Quarterly Journal of Economics* 116: 1261–303

Gul, F., and W. Pesendorfer. 2007. Harmful addiction. *The Review of Economic Studies* 74:147–72

Harrison, G. W., and M. I. Lau. 2014. Risk attitudes, sample selection and attrition in a longitudinal field experiment. Working Paper 2014-04.

Harrison, G. W., M. I. Lau, and E. E. Rutström. 2009. Risk attitudes, randomization to treatment, and self-selection into experiments. *Journal of Economic Behavior and Organization* 70:498–507

Harrison, G. W., M. I. Lau, and E. E. Rutström. 2010. Individual discount rates and smoking: Evidence from a field experiment in Denmark. *Journal of Health Economics* 29:708–17

Harrison, G. W., and E. E. Rutström. 2009. Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics* 12:133–58

Harrison, G. W., and J. T. Swarthout. 2014. Experimental payment protocols and the bipolar behaviorist. *Theory and Decision* 77:423–38

Heatherton, T. F., L. T. Kozlowski, R. C. Frecker, and K. Fagerström. 1991. The Fagerström test for nicotine dependence: A revision of the Fagerström tolerance questionnaire. *British Journal of Addiction* 86:1119–27

Hey, J. D., and C. Orme. 1994. Investigating generalizations of expected utility theory using experimental data. *Econometrica* 62:1291–326

Heyman, G. M. 2009. *Addiction: A disorder of choice*. Cambridge, MA: Harvard University Press.

Heyman, G. M., and S. P. Gibb. 2006. Delay discounting in college cigarette chippers. *Behavioural Pharmacology* 17: 669–79

Hofmeyr, A., J. Monterosso, A. C. Dean, A. M. Morales, R. M. Bilder, F. W. Sabb, and E. D. London. 2017. Mixture models of delay discounting and smoking behavior. *The American Journal of Drug and Alcohol Abuse* 43:271–80

Johnson, M. W., W. K. Bickel, and F. Baker. 2007. Moderate drug use and delay discounting: A comparison of heavy, light, and never smokers. *Experimental and Clinical Psychopharmacology* 15:187–94

Jones, B. A., R. D. Landes, R. Yi, and W. K. Bickel. 2009. Temporal horizon: Modulation by smoking status and gender. *Drug and Alcohol Dependence* 104(Suppl. 1):S87–93

Jusot, F., and M. Khlat. 2013. The role of time and risk preferences in smoking inequalities: A population-based study. *Addictive Behaviors* 38:2167–73

Kang, M. I., and S. Ikeda. 2014. Time discounting and smoking behavior: Evidence from a panel survey. *Health Economics* 23:1443–64

Kirby, K. N., N. M. Petry, and W. K. Bickel. 1999. Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *Journal of Experimental Psychology: General* 128 (1):78–87

Kobiella, A., S. Ripke, N. B. Kroemer, C. Vollmert, S. Vollstadt-Klein, D. E. Ulshofer, and M. N. Smolka. 2014. Acute and chronic nicotine effects on behaviour and brain activation during intertemporal decision making. *Addiction Biology* 19:918–30

Laibson, D. 1997. Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics* 112:443–77

Laibson, D. 2001. A cue-theory of consumption. *Quarterly Journal of Economics* 116:81–119

Lawyer, S. R., F. Schoepflin, R. Green, and C. Jenks. 2011. Discounting of hypothetical and potentially real outcomes in nicotine-dependent and nondependent samples. *Experimental and Clinical Psychopharmacology* 19:263–74

Loewenstein, G., T. O'Donoghue, and M. Rabin. 2003. Projection bias in predicting future utility. *Quarterly Journal of Economics* 118:1209–48

Loomes, G., and R. Sugden. 1998. Testing different stochastic specifications of risky choice. *Economica* 65:581–98

Mazur, J. E. 1984. Tests of an equivalence rule for fixed and variable reinforcer delays. *Journal of Experimental Psychology: Animal Behavior Processes* 10:426–37

McLachlan, G., and D. Peel. 2000. *Finite mixture models*. New York, NY: Wiley.

Melanko, S., K. Leraas, C. Collins, S. Fields, and B. Reynolds. 2009. Characteristics of psychopathy in adolescent nonsmokers and smokers: relations to delay discounting and self reported impulsivity. *Experimental and Clinical Psychopharmacology* 17:258–65

Mitchell, S. H. 1999. Measures of impulsivity in cigarette smokers and non-smokers. *Psychopharmacology* 146:455–64

Mitchell, S. H., and V. B. Wilson. 2012. Differences in delay discounting between smokers and nonsmokers remain when both rewards are delayed. *Psychopharmacology* 219:549–62

Myerson, J., L. Green, and M. Warusawitharana. 2001. Area under the curve as a measure of discounting. *Journal of the Experimental Analysis of Behavior* 76:235–43

Odum, A. L., and A. A. Baumann. 2007. Cigarette smokers show steeper discounting of both food and cigarettes than money. *Drug and Alcohol Dependence* 91:293–6

Odum, A. L., G. J. Madden, and W. K. Bickel. 2002. Discounting of delayed health gains and losses by current, never- and ex-smokers of cigarettes. *Nicotine & Tobacco Research* 4:295–303

Ohmura, Y., T. Takahashi, and N. Kitamura. 2005. Discounting delayed and probabilistic monetary gains and losses by smokers of cigarettes. *Psychopharmacology* 182:508–15

Orphanides, A., and D. Zervos. 1995. Rational addiction with learning and regret. *Journal of Political Economy* 103:739–58

Poltavski, D. V., and J. N. Weatherly. 2013. Delay and probability discounting of multiple commodities in smokers and never-smokers using multiple-choice tasks. *Behavioural Pharmacology* 24:659–67

Pratt, J. W. 1964. Risk aversion in the small and in the large. *Econometrica* 32:122–36

Prelec, D. 1998. The probability weighting function. *Econometrica* 66:497–527

Quiggin, J. 1982. A theory of anticipated utility. *Journal of Economic Behavior and Organization* 3:323–43

Redish, A. D., S. Jensen, and A. Johnson. 2008. A unified framework for addiction: Vulnerabilities in the decision process. *Behavioral and Brain Sciences* 31:415–87

Reynolds, B. 2004. Do high rates of cigarette consumption increase delay discounting? A cross-sectional comparison of adolescent smokers and young-adult smokers and nonsmokers. *Behavioural Processes* 67:545–9

Reynolds, B. 2006. The experiential discounting task is sensitive to cigarette-smoking status and correlates with a measure of delay discounting. *Behavioural Pharmacology* 17:133–42

Reynolds, B., and S. Fields. 2012. Delay discounting by adolescents experimenting with cigarette smoking. *Addiction* 107:417–24

Reynolds, B., K. Karraker, K. Horn, and J. B. Richards. 2003. Delay and probability discounting as related to different stages of adolescent smoking and non-smoking. *Behavioural Processes* 64:333–44

Reynolds, B., M. Patak, P. Shroff, R. B. Penfold, S. Melanko, and A. M. Duhig. 2007. Laboratory and self-report assessments of impulsive behavior in adolescent daily smokers and nonsmokers. *Experimental and Clinical Psychopharmacology* 15:264–71

Reynolds, B., J. B. Richards, K. Horn, and K. Karraker. 2004. Delay discounting and probability discounting as related to cigarette smoking status in adults. *Behavioural Processes* 65:35–42

Richards, J. B., L. Zhang, S. H. Mitchell, and H. de Wit. 1999. Delay or probability discounting in a model of impulsive behavior: effect of alcohol. *Journal of the Experimental Analysis of Behavior* 71 (2):121–43

Ross, D. 2010. Economic models of pathological gambling. In *What Is Addiction*? edited by D. Ross, H. Kincaid, D. Spurrett, and P. Collins. Cambridge, MA: MIT Press, pp. 131–158.

Ross, D. 2011. Estranged parents and a schizophrenic child: Choice in economics, psychology and neuroeconomics. *Journal of Economic Methodology* 18:215–29

Ross, D. 2014a. *Philosophy of economics*. Basingstoke: Palgrave Macmillan.

Ross, D. 2014b. Psychological versus economic models of bounded rationality. *Journal of Economic Methodology* 21: 411–27

Ross, D., C. Sharp, R. Vuchinich, and D. Spurrett. 2008. *Midbrain mutiny: The behavioural economics and neuroeconomics of disordered gambling*. Cambridge, MA: MIT Press.

Rubin, D. B. 1998. What does it mean to estimate the causal effects of 'smoking'? *Proceedings of the Section on Statistics in Epidemiology of the American Statistical Association*, pp. 18–27.

Rubin, D. B. 2001. Estimating the causal effects of smoking. *Statistics in Medicine* 20:1395–414

Saha, A. 1993. Expo-power utility: A 'flexible' form for absolute and relative risk aversion. *American Journal of Agricultural Economics* 75:905–13

Schelling, T. C. 1984. *Choice and consequence*. Cambridge, MA: Harvard University Press.

Sheffer, C. E., M. Mennemeier, R. D. Landes, W. K. Bickel, S. Brackman, J. Dornhoffer, T. Kimbrell, and G. Brown. 2013. Neuromodulation of delay discounting, the reflection effect, and cigarette consumption. *Journal of Substance Abuse Treatment* 45:206–14

Shisana, O., D. Labadarios, T. Rehle, L. Simbayi, K. Zuma, A. Dhansay, P. Reddy, W. Parker, E. Hoosain, P. Naidoo, C. Hongoro, Z. Mchiza, N. P. Steyn, N. Dwane, M. Makoae, T. Maluleke, S. Ramlagan, S. Zungu, M. G. Evans, L. Jacobs, M. Faber, and Sanhanes-1 Team. 2013. *South African national health and nutrition examination survey (SANHANES-1)*. Cape Town: HSRC Press.

Stillwell, D. J., and R. J. Tunney. 2012. Effects of measurement methods on the relationship between smoking and delay reward discounting. *Addiction* 107:1003–12

Sweitzer, M. M., E. C. Donny, L. C. Dierker, J. D. Flory, and S. B. Manuck. 2008. Delay discounting and smoking: Association with the Fagerstrom test for nicotine dependence but not cigarettes smoked per day. *Nicotine & Tobacco Research* 10:1571–5

Szrek, H., L. W. Chao, S. Ramlagan, and K. Peltzer. 2012. Predicting (Un)healthy behavior: A Comparison of risk-taking propensity measures. *Judgment and Decision Making* 7:716–27

Thaler, R. H., and H. M. Shefrin. 1981. An economic theory of self-control. *Journal of Political Economy* 89:392–406

Tversky, A., and D. Kahneman 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5:297–323

U.S. Department of Health and Human Services. 2014. *The Health Consequences of Smoking: 50 Years of Progress. A Report of the Surgeon General*. Atlanta, GA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion, Office on Smoking and Health.

van der Pol, M., and M. Ruggeri. 2008. Is risk attitude outcome specific within the health domain? *Journal of Health Economics* 27:706–17

West, R. 2006. *Theory of addiction*. Oxford: Blackwell Publishing.

Wilcox, N. T. 2011. ‘Stochastically more risk averse’: A contextual theory of stochastic discrete choice under risk. *Journal of Econometrics* 162:89–104

Wing, V. C., T. G. Moss, R. A. Rabin, and T. P. George. 2012. Effects of cigarette smoking status on delay discounting in schizophrenia and healthy controls. *Addictive Behaviors* 37:67–72

Winston, G. C. 1980. Addiction and backsliding: A theory of compulsive consumption. *Journal of Economic Behavior and Organization* 1:295–324

Wong, S. L., M. Shields, S. Leatherdale, E. Malaison, and D. Hammond. 2012. Assessment of validity of self-reported smoking status. *Health Reports* 23:47–53

Yaari, M. E. 1987. The dual theory of choice under risk. *Econometrica* 55:95–115

Yi, R., W. D. Chase, and W. K. Bickel. 2007. Probability discounting among cigarette smokers and nonsmokers: Molecular analysis discerns group differences. *Behavioural Pharmacology* 18:633–9

Supporting Information

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