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The social cost of smoking behavior is very high, and demands a better understanding of the determinants of smoking behavior.[1] The decision to smoke cigarettes involves a trade off between gratification in the short term and the expectation of negative health effects in the long term. Smokers would thus appear to put more weight on the short term benefits of smoking, whereas non-smokers might be presumed to be more patient and place higher weight on long term health effects. The decision to smoke may therefore be correlated with individual discount rates, where those discount rates may be constant over time but simply higher for smokers than non-smokers. The standard model of inter-temporal choice can generate dynamic inconsistencies if the discount rate is not constant over time, and individual decisions can indeed reverse as time passes if the discounting function is hyperbolic rather than exponential. In this case a forward-looking individual might make a long term plan in one period and systematically deviate from this plan in later periods. For example, people may smoke more cigarettes in the present than planned in the past if the discount rate declines over time.

We elicit measures of individual discount rates from a representative sample of the Danish population and test two substantive hypotheses. The first hypothesis is that smokers, defined here as those that "currently smoke," have higher individual discount rates than non-smokers. The second hypothesis is that smokers are more likely to have time inconsistent preferences than non-smokers, where time inconsistency is indicated by a hyperbolic discounting function. We follow the elicitation method by Andersen, Harrison, Lau and Rutström [2008] (AHLR) and control for the concavity of the utility function in our estimates of individual discount rates. Information on smoking behavior is obtained from a socio-demographic questionnaire that subjects answered in one part of the experiment, and is self-reported. The sample consists of 252 subjects, divided across 130 women

[1] Coller, Harrison and McInnes [2002] calculate that the Medicaid litigation in the United States only generated settlement payments that covered 30% of past and projected costs, even though it exceeded USD$250 billion. Moreover, many of those settlement funds have been diverted to cover government projects other than the additional health care costs from smoking. In Canada the costs in 1995 have been estimated by Harrison, Feehan, Edwards and Segovia [2003] to be as much as C$140 per capita; the litigation in Canada remains in process.

and 122 men, with 38 (29.2%) reported smokers among the women in the sample and 33 (27.0%) smokers among the men.

We use data from a field methodology developed by Harrison, Lau, Rutström and Sullivan [2005] (HLRS) to elicit both risk and time preferences from the same respondents. They used relatively simple experimental procedures that have evolved in the recent literature to study each. These experimental procedures are presented in Section 1 and build on the risk aversion experiments of Holt and Laury [2002] (HL) and the discount rate experiments of Coller and Williams [1999] (CW) and Harrison, Lau and Williams [2002] (HLW). Data is collected in the field in Denmark, to obtain a sample that offers a wider range of individual socio-demographic characteristics than usually found in subject pools recruited in colleges, as well as a sample that can be used to make inferences about the preferences of the adult population of Denmark. These experiments are "artefactual field experiments" in the terminology of Harrison and List [2004], since we essentially take lab experiments to field subjects.

Our statistical specification relies on a special case of the model in AHLR, which is based on the dual-self representation of latent risk and time preferences by Fudenberg and Levine [2007]. We assume that income earned from the risk and the discount rate tasks is integrated with the same level of background consumption and spent over the same period of time.[2] The relationship between risk and time preferences is initially specified by an exponential discount function and an explicit utility function that exhibits constant relative risk aversion. The latent theoretical specification is presented in Section 2, along with a formal representation of the structural maximum likelihood method.

Our estimates rely on parametric functional forms, which is just to say that some theoretical structure is needed to measure these latent preferences correctly. So it is important to consider alternative specifications and functional forms. In Section 3 we consider models that use a

[2] AHLR assume that income from the risk aversion tasks is spent in one day, and income from the discount rate tasks is spent in $\lambda \geq 1$ days. The results show that the log-likelihood value of the model is maximized when $\lambda=1$, i.e. when income from both the risk and discount rate tasks is spent over the same period of time.

hyperbolic specification of the discount rate function, and allow for more than one latent data generating process. We find that male smokers have significantly higher discount rates than male non-smokers, but smoking has no significant effect on discount rates among women. The results also suggest that smokers and non-smokers have the same fraction of their financial choices explained by the time consistent, exponential discounting specification. Thus there is no evidence that smokers are any less consistent than non-smokers in their time preferences over the monetary incentives provided in the experiment. Section 4 discusses the existing literature on the relationship between individual discount rates and smoking, and Section 5 draws some overall conclusions.

1. Experimental Procedures

Our experimental procedures are documented in detail in HLRS, so we focus here just on the basics. In brief, each subject was asked to respond to four risk aversion tasks and six discount rate tasks. Each such task involved a series of binary choices, typically 10 per task. Thus each subject typically provides 100 binary choices that can be used to infer risk and time preferences.

A. Risk Preferences: Measuring Risk Aversion

Holt and Laury [2002] devise a simple experimental measure for risk aversion using a multiple price list (MPL) design.[3] Each subject is presented with a choice between two lotteries, which we can call A or B. Table 1 illustrates the basic payoff matrix presented to subjects in our experiments. The first row shows that lottery A offered a 10% chance of receiving 2,000 DKK and a 90% chance of receiving 1,600 DKK. The expected value of this lottery, EV^A, is shown in the third-last column as 1,640 DKK, although the EV columns were not presented to subjects. Similarly, lottery B in the first row has chances of payoffs of 3,850 and 100 DKK, for an expected value of 475 DKK. Thus the two lotteries have a relatively large difference in expected values, in this case

[3] Andersen, Harrison, Lau and Rutström [2006] examine the properties of the MPL procedure in detail, and the older literature using it. Harrison and Rutström [2008] evaluate the strengths and weaknesses of alternative elicitation procedures for risk attitudes.

1,165 DKK. As one proceeds down the matrix, the expected value of both lotteries increases, but the expected value of lottery B becomes greater relative to the expected value of lottery A.

The subject chooses A or B in each row, and one row is later selected at random for payout for that subject. The logic behind this test for risk aversion is that only risk-loving subjects would take lottery B in the first row, and only very risk-averse subjects would take lottery A in the second last row. Arguably, the last row is simply a test that the subject understood the instructions, and has no relevance for risk aversion at all. A risk neutral subject should switch from choosing A to B when the EV of each is about the same, so a risk-neutral subject would choose A for the first four rows and B thereafter.

We take each of the binary choices of the subject as the data, and estimate the parameters of a latent utility function that explains those choices using an appropriate error structure to account for the panel nature of the data. Once the utility function is defined, for a candidate value of the parameters of that function, we can construct the expected utility of the two gambles, and then use a linking function to infer the likelihood of the observed choice. We discuss statistical specifications in more detail in section 2.

We undertake four separate risk aversion tasks with each subject, each with different prizes designed so that all 16 prizes span the range of income over which we seek to estimate risk aversion. The four sets of prizes are as follows, with the two prizes for lottery A listed first and the two prizes for lottery B listed next: (A1: 2000 DKK, 1600 DKK; B1: 3850 DKK, 100 DKK), (A2: 2250 DKK, 1500 DKK; B2: 4000 DKK, 500 DKK), (A3: 2000 DKK, 1750 DKK; B3: 4000 DKK, 150 DKK), and (A4: 2500 DKK, 1000 DKK; B4: 4500 DKK, 50 DKK). At the time of the experiments, the exchange rate was approximately 6.55 DKK per U.S. dollar, so these prizes range from approximately $7.65 to $687.

We ask the subject to respond to all four risk aversion tasks and then randomly decide which task and row to play out. In addition, the large incentives and budget constraints precluded paying all subjects, so each subject is given a 10% chance to actually receive the payment associated with his decision.[4]

B. Time Preferences: Measuring Individual Discount Rates

The basic experimental design for eliciting individual discount rates (IDRs) was introduced in CW and expanded in HLW. Subjects in our experiments were given payoff tables such as the one illustrated in Table 2, with 10 symmetric intervals. In this example, Option A offered 3000 DKK in one month and Option B paid 3000 DKK + x DKK in seven months, where x ranged from annual rates of return of 5% to 50% on the principal of 3000 DKK, compounded quarterly to be consistent with general Danish banking practices on overdraft accounts. The payoff tables provided the annual and annual effective interest rates for each payment option, and the experimental instructions defined these terms by way of example.[5] Subjects were asked to choose between Option A and B for each of the 10 payoff alternatives, and one decision row was selected at random to be paid out at the chosen date. If a risk-neutral subject prefers the 3000 DKK in one month then we can infer that the annual discount rate is higher than x%; otherwise, we can infer that it is x% or less.[6] We examine the theoretical basis for these direct inferences about discount rates in section 2.

We use the multiple-horizon treatment from HLW. From the perspective of the task faced by the subjects, the only variations are that the instrument is now computerized, and subjects are presented with 6 discount rate tasks, corresponding to 6 different time horizons: 1 month, 4 months, 6 months, 12 months, 18 months, and 24 months.[7] In each task subjects are provided two future

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[4] There is considerable behavioral evidence that rewarding subjects by selecting one task at random for payment does not distort choices, even though it does make the overall experiment a compound lottery. See Harrison, Lau and Rutström [2007; fn.16] for evidence on this issue for the risk aversion instrument we used here, and Harrison and Rutström [2008; §2.6] for similar evidence in comparable lottery choice tasks.

[5] CW and HLW provided annual and annual effective interest rates to help subjects compare lab and field investments. This feature may reduce comparison errors and CW find that providing information on interest rates has a significant negative effect on elicited discount rates.

[6] We assume that the subject does not have access to perfect capital markets, as explained in CW (p.110) and HLW (p.1607ff.). This assumption is plausible, but also subject to checks from responses to the financial questionnaire that CW, HLW and we ask each subject to complete. The effects of allowing for field borrowing and lending opportunities on elicited discount rates for risk neutral subjects are discussed by CW and HLW; Harrison, Harstad and Rutström [2004] discuss the general implications of allowing for extra-experimental trading opportunities on inferences from experimental responses.

[7] The design mimics the format used by HL in their risk aversion experiments: in that case the rows

income options rather than one "instant income" option and one future income option. We follow HLW and use a delay of one month to the early income option in all tasks. For example, they were offered 3000 DKK in one month and 3000 DKK + x DKK in 7 months, so that we interpret the revealed discount rate as applying to a time horizon of 6 months. This avoids the potential problem of the subject facing extra risk or transactions costs with the future income option, as compared to the "instant" income option.[8] If the delayed option were to involve such additional transactions costs, then the revealed discount rate would include these subjective transactions costs. By having both options presented as future income we hold these transactions costs constant.

Each subject responded to all six discount rate tasks and one task and row was chosen at random to be played out. Future payments to subjects were guaranteed by the Danish Ministry of Economic and Business Affairs, and made by automatic transfer from the Ministry's bank account to the subject's bank account. This payment procedure is similar to a post-dated check, and automatic transfers between bank accounts are a common procedure in Denmark. Finally, each subject was given a 10% chance to receive actual payment. Thus, each subject faced a 10% chance of receiving payment in the risk preference task as well as a 10% chance in the time preference task.

Our estimation strategy is the same as for the lottery task. We take each of the binary choices of the subject as data, and estimate the parameters with an error structure that recognizes the panel nature of the data. Risk attitudes and discount rates are estimated jointly. In effect, the lottery tasks identify risk attitudes and the intertemporal tasks identify discount rates.

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reflected different probabilities of each prize, and in this case the rows reflect different annual effective rates of return. We exploit this similarity of format in the design of our computerized interface to subjects, and in the use of trainers in the risk aversion task as a generic substitute for trainers in the discount rate task.

[8] These transactions costs are discussed in CW, and they include simple things such as remembering to pick up the delayed payment as well as more complex things such as the credibility of the money actually being paid in the future. As discussed in HLRS the design of our experiment was intended to make sure that the credibility of receiving the money in the future was high. These considerations may be important in a field context, particularly in less developed countries.

C. Experimental Procedures and Data

The sample for the field experiments was designed to generate a representative sample of the adult Danish population between 19 and 75 years of age. The experiments were conducted over 20 sessions, between June 2 and June 24, 2003, in 19 locations spread over Denmark, and a total of 252 subjects provided data.

The experiment was conducted in four parts. Part I consisted of a questionnaire collecting subjects' socio-demographic characteristics. Specifically, we collected information on age, sex, size of town the subject resided in, type of residence, primary occupation during the last 12 months, highest level of education, household type (viz., marital status and presence of younger or older children), number of people employed in the household, total household income before taxes, whether the subject is a smoker, and the number of cigarettes smoked per day. Part IV consisted of another questionnaire which elicits information on the subject's financial market instruments, and probes the subject for information on their expectations about their future economic conditions and their own future financial position. The questionnaires are rather long, so we chose to divide them across Parts I and IV in order to reduce subject fatigue and boredom. Part II consisted of the four risk aversion tasks, and Part III presented subjects with the six discount rate tasks.

2. Identifying Risk and Time Preferences

Consider the identification of risk and time preferences in the canonical case of mainstream economic theory. Specifically, if we assume that Expected Utility Theory (EUT) holds for the choices over risky alternatives and that discounting is exponential then the subject is indifferent between two income options M_t and $M_{t+\tau}$ if and only if

$$U(\omega+M_t) + (1/(1+\delta)^\tau)\ U(\omega) = U(\omega) + (1/(1+\delta)^\tau)\ U(\omega+M_{t+\tau}) \tag{1}$$

where $U(\omega+M_t)$ is the utility of monetary outcome M_t for delivery at time t plus some measure of background consumption ω, δ is the discount rate, τ is the horizon for delivery of the later monetary outcome at time $t+\tau$, and the utility function U is separable and stationary over time. The left hand side of equation (1) is the sum of the discounted utilities of receiving the monetary outcome M_t at time t (in addition to background consumption) and receiving nothing extra at time $t+\tau$, and the right hand side is the sum of the discounted utilities of receiving nothing over background consumption at time t and the outcome $M_{t+\tau}$ (plus background consumption) at time $t+\tau$. Thus (1) is an indifference condition and δ is the discount rate that equalizes the present value of the utility of the two monetary outcomes M_t and $M_{t+\tau}$, after integration with an appropriate level of background consumption ω.

We can quickly put some familiar parametric structure on this statement of the identification problem. Let the utility function be the constant relative risk aversion (CRRA) specification

$$U(M) = (\omega+M)^{(1-r)}/(1-r) \tag{2}$$

for $r\neq1$, where r is the CRRA coefficient. Background consumption, ω, is assumed to be zero in some studies and to represent lifetime wealth in other studies. We assume that $\omega>0$ and view this specification as a "reduced form" model that is consistent with a variety of structural models. With this functional form, $r=0$ denotes risk neutral behavior, $r>0$ denotes risk aversion, and $r<0$ denotes risk loving behavior.

To relate this specification to the risk aversion choices in our experiment, one can calculate the implied bounds on the CRRA coefficient for each row in Table 1, and these are in fact reported by HL [2002; Table 3]. These intervals are shown in the final column of Table 1, assuming that background consumption ω is zero. Thus, for example, a subject that made 5 safe choices and then switched to the risky alternatives would have revealed a CRRA interval between 0.14 and 0.41, and a subject that made 7 safe choices would have revealed a CRRA interval between 0.68 and 0.97, and so on. Thus the binary choices of the subject can be explained by different values of the CRRA coefficient, and the coefficient estimated using standard maximum likelihood procedures (explained in detail below). For positive background consumption levels the same observed choices would imply higher absolute values of the CRRA coefficients, i.e. more curvature of the utility functions.

There is evidence from the lab and field that subjects are risk averse over stakes ranging between pennies and several hundred dollars. Holt and Laury [2002][2005] produced the most widely cited evidence from the lab, and they show that subjects are moderately risk averse. Harrison, Lau and Rutström [2007] find comparable results with artefactual field experiments conducted with the adult Danish population used for our analysis. This literature also offers some evidence of lower estimates of relative risk aversion when the stakes in the experimental task are reduced significantly, which may cause one to question our use of the restrictive CRRA function. However, Harrison, Lau and Rutström [2007] find that CRRA holds locally over the domain of stakes offered here, and we adopt this specification because it is popular in the theoretical and empirical literature on risk preferences. We do not claim that the particular estimates provided here would hold globally if the stakes in our tasks are reduced or increased by a significant amount.

We can write out the likelihood function for the choices that our subjects made and jointly estimate the risk parameter r and the discount rate δ. Consider first the contribution to the overall likelihood from the risk aversion responses. Probabilities for each outcome M_j, $p(M_j)$, are those that are induced by the experimenter, so expected utility is simply the probability weighted utility of each outcome in each lottery. Since there were two outcomes in each lottery, the EU for lottery i is

$$EU_i = \sum_{j=1,2} [\ p(M_j) \times U(\omega+M_j)\ ]. \tag{3}$$

A simple stochastic specification from Holt and Laury [2002] is used to specify likelihoods conditional on the model. The EU for each lottery pair is calculated for candidate estimate of r and ω, and the ratio

$$\nabla EU = EU_B^{1/\mu} / (EU_A^{1/\mu} + EU_B^{1/\mu}) \tag{4}$$

calculated, where EU_A refers to Option A and EU_B refers to Option B, and μ is a structural "noise parameter" used to allow some errors from the perspective of the deterministic EUT model. The index ∇EU is in the form of a cumulative probability distribution function defined over differences in the EU of the two lotteries and the noise parameter μ.[9] Thus, as $\mu \rightarrow 0$ this specification collapses

[9] An alternative approach might be to define an index as the EU difference, and then specify some cumulative distribution function to link it to the observed choices. For example, the cumulative standard normal distribution leads to the probit specification.

to the deterministic choice EUT model, where the choice is strictly determined by the EU of the two lotteries; but as μ gets larger and larger the choice essentially becomes random. This is one of several different types of error story that could be used.[10] The index in (4) is linked to observed choices by specifying that the Option B lottery is chosen when $\nabla EU > \frac{1}{2}$.

Thus the likelihood of the risk aversion responses, conditional on the EUT and CRRA specifications being true, depends on the estimates of r and μ, and the observed choices. If we ignore the responses that reflect indifference, the conditional log-likelihood is

$$\ln L^{RA}(r, \mu; y, \omega, \mathbf{X}) = \textstyle\sum_i \left[(\ln \Phi(\nabla EU) \times \mathbf{I}(y_i = 1)) + (\ln \Phi(1 - \nabla EU) \times \mathbf{I}(y_i = -1)) \right] \qquad (5)$$

where $\mathbf{I}(\cdot)$ is the indicator function, $y_i = 1(-1)$ denotes the choice of the Option B (A) lottery in risk aversion task i, and $\mathbf{X}$ is a vector of individual characteristics reflecting age, sex, race, and so on. The parameter r is defined as a linear function of the characteristics in vector $\mathbf{X}$.

The subjects were told at the outset that any expression of indifference would mean that if that choice was selected to be played out the experimenter would toss a fair coin to make the decision for them. Hence one can modify the likelihood to take these responses into account by recognizing that such choices implied a 50:50 mixture of the likelihood of choosing either lottery

$$\ln L^{RA}(r, \mu; y, \omega, \mathbf{X}) = \textstyle\sum_i \left[(\ln \Phi(\nabla EU) \times \mathbf{I}(y_i = 1)) + (\ln \Phi(1 - \nabla EU) \times \mathbf{I}(y_i = -1)) + \right.$$
$$\left. ((\tfrac{1}{2} \ln \Phi(\nabla EU) + \tfrac{1}{2} \ln \Phi(1 - \nabla EU)) \times \mathbf{I}(y_i = 0)) \right] \qquad (5')$$

where $y_i = 0$ denotes the choice of indifference. Only 4.6% of the observed choices in our experiments were expressions of indifference, but it is appropriate to use (5′) to account for these choices.

A similar specification is employed for the discount rate choices. Equation (3) is replaced by the discounted utility of each of the two options, conditional on some assumed discount rate, and equation (4) is defined in terms of those discounted utilities instead of the expected utilities. The discounted utility of Option A is given by

$$PV_A = (\omega + M_A)^{(1-r)} + (1/(1+\delta)^{\tau})\, \omega^{(1-r)} \qquad (6)$$

[10] See Wilcox [2008] for a detailed review.

and the discounted utility of Option B is

$$PV_B = \omega^{(1-r)} + (1/(1+\delta)^{\tau})\ (\omega+M_B)^{(1-r)} \tag{7}$$

where M_A and M_B are the monetary amounts in the choice tasks presented to subjects, illustrated in Table 2, and the utility function is assumed to be stationary over time.

An index of the difference between these present values, conditional on r and δ, can then be defined as

$$\nabla PV = PV_B^{1/\nu} / (PV_A^{1/\nu} + PV_B^{1/\nu}) \tag{8}$$

where ν is a noise parameter for the discount rate choices, just as μ was a noise parameter for the risk aversion choices. It is not obvious that $\mu=\nu$, since these are cognitively different tasks. Our own priors are that the risk aversion tasks are harder, since they involve four outcomes compared to two outcomes in the discount rate tasks, so we would expect $\mu>\nu$. Error structures are things one should always be agnostic about since they capture one's modeling ignorance, and we allow the error terms to differ between the risk and discount rate tasks.

Thus the likelihood of the discount rate responses, conditional on the EUT, CRRA and exponential discounting specifications being true, depend on the estimates of r, δ, μ and ν, given the assumed value of ω, λ and the observed choices. If we ignore the responses that reflect indifference, the conditional log-likelihood is

$$\ln L^{DR}(r, \delta, \mu, \nu; y, \omega, \lambda, \mathbf{X}) = \textstyle\sum_i [\ (\ln \Phi(\nabla PV)\times\mathbf{I}(y_i=1)) + (\ln \Phi(1-\nabla PV)\times\mathbf{I}(y_i=-1))\ ] \tag{9}$$

where $y_i = 1(-1)$ again denotes the choice of Option B (A) in discount rate task i, and $\mathbf{X}$ is a vector of individual characteristics. We can easily add responses that reflect indifference to the log-likelihood function and get

$$\ln L^{DR}(r, \delta, \mu, \nu; y, \omega, \lambda, \mathbf{X}) = \textstyle\sum_i [\ (\ln \Phi(\nabla PV)\times\mathbf{I}(y_i = 1)) + (\ln \Phi(1-\nabla PV)\times\mathbf{I}(y_i = -1)) + ((\tfrac{1}{2} \ln \Phi(\nabla PV) + \tfrac{1}{2} \ln \Phi(1-\nabla PV))\times\mathbf{I}(y_i = 0))\ ] \tag{9$'$}$$

where $y_i = 0$ denotes the choice of indifference.

The joint likelihood of the risk aversion and discount rate responses can then be written as

$$\ln L\ (r, \delta, \mu, \nu; y, \omega, \lambda, \mathbf{X}) = \ln L^{RA} + \ln L^{DR} \tag{10}$$

and maximized using standard numerical methods. Our implementation uses version 10 of *Stata*.[11] The statistical specification allows for the possibility of correlation between responses by the same subject.[12]

We assume that income from the risk aversion and discount rate tasks is spent in one day. Andersen, Harrison, Lau and Rutström [2008] and Fudenberg and Levine [2007] consider a similar time horizon for the short-run self, and this assumption seems reasonable given the stakes in the experimental tasks and our payment methods. Using data from the household expenditure survey at Statistics Denmark we find that per capita consumption of private non-durable goods on an average daily basis was equal to 118 DKK in 2003. We use this value of daily background consumption ω in our estimations.

The data consists of observations from 252 subjects, with 7,888 risk aversion choices and 15,120 discount rate choices.

3. Results

A. Discount Rates of Smokers and Non-Smokers

Table 3 presents maximum likelihood estimates from our experiments. Panel A presents the estimates allowing for risk aversion, and panel B presents the effects of constraining the model to assume risk neutrality. Both sets of estimates allow for the complex survey design and sample weights that reflect the adult population of Denmark, as well as the possibility that observations on

[11] We document the *Stata* syntax for this estimation at http://exlab.bus.ucf.edu. We also provide all source code and data for the estimates reported here.

[12] The use of clustering to allow for "panel effects" from unobserved individual effects is common in the statistical survey literature. Clustering commonly arises in national field surveys from the fact that physically proximate households are often sampled to save time and money, but it can also arise from more homely sampling procedures. For example, Williams [2000; p.645] notes that it could arise from dental studies that "collect data on each tooth surface for each of several teeth from a set of patients" or "repeated measurements or recurrent events observed on the same person." The procedures for allowing for clustering allow heteroskedasticity between and within clusters, as well as autocorrelation within clusters. They are closely related to the "generalized estimating equations" approach to panel estimation in epidemiology (see Liang and Zeger [1986]), and generalize the "robust standard errors" approach popular in econometrics (see Rogers [1993]). Wooldridge [2003] reviews some issues in the use of clustering for panel effects, in particular noting that significant inferential problems may arise with small numbers of panels.

choices made by the subject are not independent.

We consider interaction effects between smoking and sex and test for the absence of interaction effects formally. The results in Panel A show that smokers have significantly higher discount rates than non-smokers among men, but not among women. All discount rates are stated in annualized form. Male smokers have an estimated discount rate of 12.3% whereas the estimated discount rate for non-smoking males is 9.2%. This difference of 3.1 percentage points is significantly different from zero with a *p*-value of 0.033. However, female smokers do not appear to have significantly higher discount rates than female non-smokers. Female smokers have an estimated discount rate of 10.6% while the discount rate for non-smoking females is 9.2%. The difference of 1.4 percentage points is not significantly different from zero at conventional levels (*p*-value of 0.345).

The risk neutral results in Panel B suggest that smoking has a significant effect on individual discount rates for both men and women. The estimated coefficient for smokers is 30.8% for men and 30.1% for women, and the coefficient for non-smokers is 22.7% and 23.6% for men and women, respectively. We reject the hypothesis that smokers and non-smokers provided the same individual discount rates for both men and women (*p*-values of 0.049 and 0.067, respectively). One would thus incorrectly infer from the risk neutral estimates that female smokers have higher discount rates than non-smokers.

We do not find a significant effect of smoking on individual risk attitudes among men: the estimated coefficient of constant relative risk aversion is 0.729 for smokers and 0.746 for non-smokers. However, smokers are significantly *more* risk averse than non-smokers among women: the estimated *r*-coefficient is 0.811 for smokers and 0.755 for non-smokers, and we reject the hypothesis that the two coefficients are identical at the 5.4% significance level. Anderson and Mellor [2008] apply the same method to elicit individual risk attitudes, albeit with monetary incentives in the income range between $0.30 and $11.55. They find that smokers are significantly *less* risk averse than non-smokers using a sample of 1,094 adult subjects from the greater Williamsburg, Virginia area. We thus observe different qualitative effects of smoking on risk attitudes in our sample of Danish adults compared to the results from the sample of American adults in Anderson and Mellor [2008].

B. Hyperbolic Discounting by Smokers

The exponential discounting function is canonical, and important in its own right given its place in the literature. Can we say that our results are robust to alternative specifications and functional forms? One concern is with alternative discounting functions, such as those assumed in hyperbolic discounting models, which is popular in the existing literature on the relationship between smoking and time preferences.

The earliest hyperbolic specifications assumed that individuals had discount rates that declined with the horizon they faced, in contrast to later quasi-hyperbolic specifications that posit an initial decline and then constant (per period) discount rates. Our use of a front end delay on receipt of the earlier option implies that we cannot test the quasi-hyperbolic specification against the standard exponential specification, unless one assumes that the "passion for the present" lasted longer than our front end delay. We therefore focus on the earlier hyperbolic specifications. The most common functional form of the older literature is due to Herrnstein [1981], Ainslie [1992] and Mazur [1987], and would replace (6) and (7) with

$$PV_A = (\omega+M_A)^{(1-r)} + (1/(1+\gamma\cdot\tau))\ \omega^{(1-r)} \tag{6'}$$

$$PV_B = \omega^{(1-r)} + (1/(1+\gamma\cdot\tau))\ (\omega+M_B)^{(1-r)} \tag{7'}$$

for γ>0, and with discounted utility to the time of decision, t=0.

Maximum likelihood estimates using the hyperbolic specification in (6′) and (7′) can be obtained using the same methods used for the exponential specification, and the results are reported in Table 4. We find similar qualitative results for the hyperbolic discounting model. Panel A shows that smokers have significantly higher discount rates than non-smokers among men, but not among women when we control for the concavity of the utility function (*p*-values of 0.030 and 0.327, respectively). The results in Panel A do not reveal a significant effect of smoking on individual risk attitudes among men (*p*-value of 0.602), but smokers are more risk averse than non-smokers among women (*p*-value of 0.053). The risk neutral results in Panel B show that smokers have significantly higher discount rates than non-smokers for both men and women (*p*-values of 0.043 and 0.067, respectively).

C. Are Smokers Less Dynamically Consistent than Non-Smokers?

Finally, we consider the sensitivity of our conclusions to a statistical specification that allows each observation to potentially be generated by more than one latent data-generating process. Our motivation is to better identify the effect of smoking behavior on the weight of evidence for exponential and hyperbolic discounting. How can we use the data to inform us about the relative importance of the exponential and hyperbolic specification for smokers and non-smokers?

Finite mixture models provide an ideal statistical framework to address this question.[13] Consider the mixture of exponential discounting models and hyperbolic models, defined by (8′) and (8″). We assume that EUT characterizes behavior in all other respects. The mixture likelihood function is then

$$\ln L\,(r, \delta, \gamma, \mu, \nu, \pi; y, \omega, \lambda, \mathbf{X}) = \ln L^{RA} + [\pi \times \ln L^{DR\text{-}E}] + [(1-\pi) \times \ln L^{DR\text{-}H}] \tag{11}$$

where π is a parameter, to be estimated and constrained such that $0 \leq \pi \leq 1$, giving the probability that a given observation[14] is generated by the exponential discounting model. In (11) the likelihood contributions $L^{DR\text{-}E}$ and $L^{DR\text{-}H}$ refer to the exponential and hyperbolic specifications given by (7′) and (7″), respectively.

[13] Mixture models have an astonishing pedigree in statistics: Pearson [1894] examined data on the ratio of forehead to body length of 1000 crabs to illustrate "the dissection of abnormal frequency curves into normal curves." In modern parlance he was allowing the observed data to be generated by two distinct Gaussian processes, and estimated the two means and two standard deviations. Modern surveys of the evolution of mixture models are provided by Everitt [1996] and McLachlan and Peel [2000]. Harrison and Rutström [2009] review the literature on mixture models in experimental economics, and discuss the interpretation of alternative mixture specifications.

[14] One could alternatively define a grand likelihood in which observations or subjects are completely classified as following one model or the other on the basis of the latent probability π. El-Gamal and Grether [1995] illustrate this approach in the context of identifying behavioral strategies in Bayesian updating experiments.

Table 5 provides maximum likelihood estimates of the model that allows for a concave utility function, and Figure 1 displays the predicted discounting functions for this model. From Table 5 we see that 62.1% of the choices by smokers can be characterized as being generated by the exponential specification with a discount rate of 7.3%, and the remaining 37.9% of the observations as being generated by the hyperbolic specification with γ=0.267. This value of γ implies the discounting function shown in the top, right panel of Figure 1: a discount rates of 29.5% p.a for a 3-month horizon, and 26.7% p.a. for a 1-year horizon. Table 5 also shows that 72.8% of the choices by non-smokers can be characterized by the exponential specification with a discount rate of 5.9%, and the remaining 27.3% of the choices can be characterized by the hyperbolic discounting function with γ=0.327. The bottom, right panel of Figure 1 shows the hyperbolic discounting function for non-smokers: the discount rate is 36.9% p.a. for a 3-month horizon, and 32.7% p.a. for a 1-year horizon. We cannot reject the hypothesis that smokers and non-smokers have the same δ-value (*p*-value of 0.143) or the same γ-values (*p*-value of 0.202).

The mixture specification therefore suggests that assuming that behavior is completely exponential *or* hyperbolic is in error. Both specifications have some support, even if one has greater support than the other. The estimated coefficient of the π-parameter is 0.621 for smokers and 0.728 for non-smokers, and each is significantly different from 0 or 1 (*p*-value<0.001). We cannot reject the hypothesis that smokers and non-smokers have the same distribution of the latent time preference structures (*p*-value of 0.349). Hence we conclude that smokers and non-smokers are best characterized by having the *same* propensity to employ hyperbolic discounting: they are no more or no less dynamically inconsistent than each other.

4. Related Literature

There are surprisingly few studies that use real monetary incentives to study the relationship between individual discount rates and smoking. None control for the concavity of the utility function in the elicitation of discount rates, although Blondel, Lohéac and Rinaudo [2007] do conduct experiments to elicit risk and time preferences from the same subjects.[15] Moreover, in all previous studies latent time preferences are only represented by exponential or hyperbolic discounting functions, whereas we allow for a mixture of types of discounting functions in the population. Another common feature of most of the literature is that the discount rate tasks offer a choice between an immediate payment option and a delayed payment option, and the delay to the later payment option is then varied to better characterize the discounting function. Again, the only exception is Blondel, Lohéac and Rinaudo [2007; Table 1, p.650], who consider the effect of a front end delay on discounting choices.

The existing studies generally find a negative relationship between individual discount rates and smoking: that is, that smokers actually have *lower* discount rates than non-smokers (Mitchell [1999], Reynolds, Richards, Horn and Karraker [2004] and Chabris, Laibson, Morris, Schuldt and Taubinsky [2008]). In contrast, Reynolds, Karraker, Horn and Richards [2003] do not find a significant effect from smoking on individual discount rates, even though they used the same elicitation method and monetary incentives as Reynolds, Richards, Horn and Karraker [2004]. However, the subject group is different across the two studies: the latter study has a sample of 54 subjects between 19 and 21 years of age from West Virginia University, and the earlier study has a sample of 55 subjects between 14 and 16 years of age from a rural high school in West Virginia. Hence, the use of different student samples can lead to very different conclusions on the relationship between smoking and impatience as measured by individual discount rates.

The only study that does not rely on a student sample, but does use real incentives, is Chabris, Laibson, Morris, Schuldt and Taubinsky [2008]. They use a sample of 126 subjects from the Greater Boston area and find that smokers have significantly higher discount rates than non-smokers. The subjects are asked to make decisions in 27 binary choice tasks that are used to elicit

[15] They do not use the risk aversion tasks to infer discount rates defined over temporally dated utility streams, as proposed by Andersen, Harrison, Lau and Rutström [2008] and implemented here. Their interest was in the empirical correlation between risk attitudes and discount rates, where the latter were defined by assuming that the subject was risk neutral.

discount rates. The early payment option is always framed as an immediate payment, although checks were mailed to subjects approximately two weeks after the session. The delay to the later payment varies between 7 and 186 days, and is interpreted as the time horizon between the two payments in the statistical analysis.[16] However, an internet study is also reported, in which the monetary payments are replaced by Amazon gift certificates of similar value. The results from this sample of 326 subjects do not indicate a significant effect of smoking on discount rates.

5. Conclusions

We elicit individual discount rates from a sample of individuals representative of the general adult population using real economic commitments. We find that there is a significant correlation between individual discount rates and smoking among the men in our sample, but no significant correspondence between time preferences and smoking among women in the sample. Male smokers have significantly higher discount rates than non-smokers, but we can not reject the hypothesis that smokers and non-smokers have similar discount rates among women. We do not find evidence that non-smokers are significantly more consistent in their financial behavior compared to smokers, in terms of the exponential discounting function explaining a larger share of the financial choices.

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Table 1: Typical Payoff Matrix in the Risk Aversion Experiments

Lottery A				Lottery B				EV^A	EV^B	Difference	Open CRRA Interval if Subject Switches to Lottery B and ω=0
p	DKK	p	DKK	p	DKK	p	DKK	DKK	DKK	DKK	
0.1	2000	0.9	1600	0.1	3850	0.9	100	1640	475	1165	-∞, -1.71
0.2	2000	0.8	1600	0.2	3850	0.8	100	1680	850	830	-1.71, -0.95
0.3	2000	0.7	1600	0.3	3850	0.7	100	1720	1225	495	-0.95, -0.49
0.4	2000	0.6	1600	0.4	3850	0.6	100	1760	1600	160	-0.49, -0.15
0.5	2000	0.5	1600	0.5	3850	0.5	100	1800	1975	-175	-0.15, 0.14
0.6	2000	0.4	1600	0.6	3850	0.4	100	1840	2350	-510	0.14, 0.41
0.7	2000	0.3	1600	0.7	3850	0.3	100	1880	2725	-845	0.41, 0.68
0.8	2000	0.2	1600	0.8	3850	0.2	100	1920	3100	-1180	0.68, 0.97
0.9	2000	0.1	1600	0.9	3850	0.1	100	1960	3475	-1515	0.97, 1.37
1	2000	0	1600	1	3850	0	100	2000	3850	-1850	1.37, ∞

Note: The last four columns in this table, showing the expected values of the lotteries and the implied CRRA intervals, were not shown to subjects.

Table 2: Payoff Table for 6 Month Time Horizon in the Discount Rate Experiments

Payoff Alternative	**Payment Option A** (pays amount below in 1 month)	**Payment Option B** (pays amount below in 7 months)	**Annual Interest Rate** (AR, in percent)	**Annual Effective Interest Rate** (AER, in percent)	**Preferred Payment Option** (Circle A or B)	
1	3,000 DKK	3,075 DKK	5	5.09	A	B
2	3,000 DKK	3,152 DKK	10	10.38	A	B
3	3,000 DKK	3,229 DKK	15	15.87	A	B
4	3,000 DKK	3,308 DKK	20	21.55	A	B
5	3,000 DKK	3,387 DKK	25	27.44	A	B
6	3,000 DKK	3,467 DKK	30	33.55	A	B
7	3,000 DKK	3,548 DKK	35	39.87	A	B
8	3,000 DKK	3,630 DKK	40	46.41	A	B
9	3,000 DKK	3,713 DKK	45	53.18	A	B
10	3,000 DKK	3,797 DKK	50	60.18	A	B

Table 3. Estimates of Risk and Time Preferences Assuming Exponential Discounting

	Estimate	Standard Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
	A. Allowing a Concave Utility Function (Risk Aversion)			
CRRA coefficient (r):				
Male smokers	0.729	0.064	0.604	0.854
Male non-smokers	0.746	0.052	0.643	0.848
Female smokers	0.811	0.047	0.718	0.904
Female non-smokers	0.755	0.048	0.661	0.848
Individual discount rate (δ):				
Male smokers	0.123	0.016	0.093	0.153
Male non-smokers	0.092	0.011	0.071	0.113
Female smokers	0.106	0.013	0.080	0.131
Female non-smokers	0.093	0.009	0.075	0.111
μ_{RA}	0.080	0.015	0.051	0.110
μ_{IDR}	0.021	0.005	0.011	0.031
	B. Assuming a Linear Utility Function (Risk Neutrality)			
Individual discount rate (δ):				
Male smokers	0.308	0.035	0.238	0.377
Male non-smokers	0.227	0.021	0.186	0.267
Female smokers	0.301	0.030	0.243	0.360
Female non-smokers	0.236	0.020	0.197	0.275
μ_{IDR}	0.131	0.008	0.116	0.146

Table 4. Estimates of Risk and Time Preferences Assuming Hyperbolic Discounting

	Estimate	Standard Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
	A. Allowing a Concave Utility Function (Risk Aversion)			
CRRA coefficient (r):				
Male smokers	0.735	0.064	0.609	0.861
Male non-smokers	0.753	0.052	0.651	0.856
Female smokers	0.817	0.047	0.725	0.909
Female non-smokers	0.762	0.048	0.669	0.855
Individual discount rate (γ):				
Male smokers	0.127	0.017	0.094	0.160
Male non-smokers	0.093	0.011	0.071	0.115
Female smokers	0.109	0.014	0.082	0.136
Female non-smokers	0.095	0.010	0.076	0.114
μ_{RA}	0.078	0.015	0.049	0.108
μ_{IDR}	0.020	0.005	0.010	0.031
	B. Assuming a Linear Utility Function (Risk Neutrality)			
Individual discount rate (γ):				
Male smokers	0.341	0.044	0.255	0.426
Male non-smokers	0.240	0.024	0.192	0.287
Female smokers	0.329	0.036	0.258	0.401
Female non-smokers	0.250	0.023	0.205	0.296
μ_{IDR}	0.133	0.008	0.118	0.149

Table 5. Mixture Model Estimates of Risk and Time Preferences

	Estimate	Standard Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
CRRA coefficient (r):				
Smokers	0.837	0.053	0.732	0.942
Non-smokers	0.792	0.053	0.688	0.895
Exponential discount rate (δ):				
Smokers	0.073	0.010	0.054	0.092
Non-smokers	0.059	0.008	0.043	0.075
Hyperbolic discount rate (γ):				
Smokers	0.267	0.049	0.171	0.364
Non-smokers	0.327	0.044	0.241	0.413
Exponential mixture share (π)				
Smokers	0.621	0.106	0.414	0.829
Non-smokers	0.728	0.045	0.640	0.817
μ_{RA}	0.067	0.016	0.036	0.010
μ_{IDR}	0.010	0.003	0.003	0.016

Figure 1: Predicted Discount Rates for Smokers and Non-Smokers

Mixture model of exponential and hyperbolic functions