Essays on Discounting Behavior and Gambling Behavior

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HANDELSHØJSKOLEN

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"The Doctoral School of Economics and Management is an active national and international research environment at CBS for research degree students who deal with economics and management at business, industry and country level in a theoretical and empirical manner".

Preface

This thesis is the result of my work as a Ph.D. Fellow at the Department of Economics at Copenhagen Business School. I am grateful for the financial support that I received in this position.

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Summary

This thesis consists of three independent chapters on the elicitation of individual discount rates and on the estimation of gambling prevalence in Denmark.

The first chapter, "Discount Rate Sensitivity to Background Consumption and Consumption Smoothing," studies the sensitivity of individual discount rates with respect to background consumption and consumption smoothing. I use simulated choice data from standard decision tasks in time preference experiments and show that individual discount rates are sensitive to assumptions with respect to background consumption and consumption smoothing if the utility function is non-linear and exogenous. However, if discount rates and the utility function are elicited jointly, discount rates are robust to assumptions on time-invariant background consumption and consumption smoothing. The analysis clarifies mixed conclusions from previous studies and indicates which elicitation methods provide robust estimates of individual discount rates.

The second chapter, "Financial Wealth, Liquidity Constraints, and Discounting Behavior," analyzes to what extent discounting behavior in experiments is correlated with financial wealth. Life cycle models of consumption and saving behavior associate higher discount rates with lower financial wealth and present bias with lower financial liquidity. We combine data from a field experiment in Denmark with administrative data on financial wealth and estimate exponential and quasi-hyperbolic discounting models. We find significantly lower discount rates for wealthy subjects than for poor subjects, but do not find any evidence of present bias and no significant association between present bias and liquidity constraints.

The third chapter, "Gambling Problems in the General Danish Population: Survey Evidence," compares several survey instruments of gambling behavior and estimates the prevalence of problem gambling in Denmark. We administer surveys on gambling behavior together with standard survey instruments for alcohol use, anxiety, depression and impulsivity to 8,405 subjects. We estimate that 95% of the population has no detectable

gambling risk, 2.9% has an early risk, 0.8% has an intermediate risk, 0.7% has an advanced risk, and only 0.2% can be classified as problem gamblers. Moreover, we find that gambling risk is positively correlated with alcohol use, anxiety, depression, and impulsivity.

Resumé

Afhandlingen består af tre uafhængige kapitler, som handler om afsløring af tidspræferencer og udbredelsen af ludomani i Danmark.

Det første kapitel, "Discount Rate Sensitivity to Background Consumption and Consumption Smoothing" analyserer følsomheden af individuelle diskonteringsrater med hensyn til forskellige antagelser om baggrundsforbrug og forbrugsudjævning. Jeg evaluerer beslutninger i typiske økonomiske eksperimenter og viser, at de estimerede diskonteringsrater er følsomme overfor forskellige antagelser om baggrundsforbrug og forbrugsudjævning, hvis nyttefunktionen er ikke-lineær og eksogent givet. Jeg opnår derimod robuste estimater, hvis nyttefunktionen er estimeret sammen med individuelle diskonteringsrater. Analysen forklarer de forskellige resultater fra tidligere studier med hensyn til vigtigheden af forskellige antagelser om baggrundsforbrug og forbrugsudjævning og giver en indikation af, hvilke metoder til afsløring af individuelle diskonteringsrater, som fører til robuste estimater.

Det andet kapitel, "Financial Wealth, Liquidity Constraints, and Discounting Behavior" analyserer sammenhængen mellem individuelle diskonteringsrater og privat opsparing. Den teoretiske litteratur vedrørende livstidsforbrug foreslår, at højere individuelle diskonteringsrater fører til lavere opsparing og, at inkonsistente tidspræferencer (present bias) medfører lavere beholdninger af likvide aktiver. Vi kombinerer data fra felteksperimenter i Denmark med administrative data vedrørende personlig indkomst og formue fra Denmark Statistik. Vi estimerer individuelle nyttefunktioner og diskonteringsrater simultant og finder, at diskonteringsrater er signifikant lavere blandt rigere deltagere end blandt fattigere deltagere. Vi finder derimod ingen signifikant sammenhæng mellem såkaldt "present bias" og beholdninger af likvide aktiver.

Det tredje kapitel, "Gambling Problems in the General Danish Population: Survey Evidence" afdækker omfanget af ludomani i Danmark. Vi anvender forskellige populære instrumenter til at afsløre omfanget af problematisk spilleadfærd samtidig med, at vi bruger

instrumenter til at afsløre forbrug af alkohol, angst, depression og impulsivitet hos 8.405 deltagere i spørgeskemaundersøgelsen. Resultaterne viser, at 95% af befolkningen ikke har en problematisk spilleadfærd, 2,9% har en lav risiko, 0,8% har en mellemstor risiko, 0,7% har en høj risiko og kun 0,2% klassificeres som ludomaner. Analysen viser også en signifikant sammenhæng mellem ludomani og forbrug af alkohol, angst, depression og impulsivitet.

Contents

Introduction

The thesis consists of three chapters on the elicitation of individual discount rates and on the estimation of gambling prevalence rates in Denmark. Each chapter is self-contained and can be read independently. However, the three chapters are related to a common theme: they discuss experimental methods for the identification and elicitation of time preferences, and the prevalence of addictive behavior such as problem gambling.

The first two chapters discuss the elicitation of individual discount rates from choice data in economic experiments: Chapter 1 analyzes methods for eliciting time preferences and studies the robustness of individual discount rates with respect to background consumption and consumption smoothing. Chapter 2 uses choice data from a Danish field experiment to study the association between discounting behavior and financial wealth, and the association between present bias and liquidity. The third chapter estimates the prevalence of problem gambling in the general Danish population using survey instruments. Gambling related problems may be viewed as time inconsistent behavior and have been linked to discounting models that posit a passion for the present.

Many decisions in life involve tradeoffs between costs and benefits that occur at different points in time, and theories on time preferences describe how these intertemporal costs and benefits are evaluated. Two popular theories on intertemporal choice are the exponential discounting model (Samuelson, 1937) and the quasi-hyperbolic discounting model (Phelps and Pollack, 1968; Laibson, 1997). According to the exponential discounting model future costs and benefits are discounted by a constant rate per time period, and the decision model thus implies time consistent behavior. The quasi-hyperbolic discounting model incorporates the idea of present bias and captures dynamically inconsistent preferences in the sense that one may deviate from long term plans and consume more now than planned in the past (Strotz, 1955). These types of preference reversals over time have been associated with addictive behavior such as problem gambling (Dixon et al., 2003), smoking (Harrison, Lau, and Rutström, 2010) and drugs (Kirby et al., 1999).

The empirical identification and measurement of time preferences has received considerable attention in experimental economics. Frederick et al. (2002) and Andersen, Harrison, Lau, and Rutström (2014) review the extensive literature and discuss the methodological developments. The typical experimental design asks subjects to make binary choices between time delayed monetary rewards. These intertemporal choices allow one to identify the parameters of exponential and hyperbolic discounting models under assumptions on how and when these monetary rewards generate utility. An important contribution to the literature is the study by Andersen, Harrison, Lau, and Rutström (2008), which shows that controlling for non-linearity in the utility function has significant effects on estimated discount rates from choices between time delayed monetary rewards.

The first chapter, "Discount Rate Sensitivity to Background Consumption and Consumption Smoothing," analyzes the sensitivity of estimated individual discount rates with respect to alternative assumptions on the integration of experimental income with other income (background consumption) and the expenditure profile (consumption smoothing). Andersen et al. (2008) find that individual discount rates are robust to the level of background consumption but sensitive to the degree of consumption smoothing. However, Andreoni and Sprenger (2012) and Holden and Quiggin (2015) find that individual discount rates are sensitive with respect to the level of background consumption. These mixed results motivate the analysis in the first chapter. I use simulated choices from standard decision tasks in time preference experiments and show that individual discount rates are robust to background consumption and consumption smoothing if the utility function is elicited jointly. The analysis contributes to the literature on time preferences by clarifying the mixed results and conclusions from previous studies.

The second chapter, "Financial Wealth, Liquidity Constraints, and Discounting Behavior," joint with Morten I. Lau, analyzes to what extent discounting behavior in experiments is correlated with financial wealth. Life cycle models of consumption and saving behavior associate higher discount rates with lower financial wealth and present bias with small deposits of liquid assets. However, despite these clear associations between time preferences and saving behavior, and despite the policy relevance of understanding private saving and investment behavior, the empirical literature on this topic is scarce. The challenge is to obtain reliable information on both individual discount rates and financial wealth and liquidity, and this combination of data is rarely available. A few studies from developing countries (Pender, 1996; Yesuf and Bluffstone, 2008; Kirby et al., 2002) have analyzed the association between individual discounting behavior and private wealth using experimental data on time preferences, and only one study (Meier and Sprenger, 2010) has analyzed the association between present bias and financial liquidity. The second chapter combines experimental data with detailed administrative data on private financial wealth for a representative sample of the Danish population and estimates exponential and quasi-hyperbolic discounting models. We find that wealthy subjects have significantly lower exponential discount rates than poor subjects, which is consistent with theoretical predictions from life cycle models of saving and investment behavior that assume exponential discounting (e.g. Krusell and Smith, 1998; Hendricks, 2007). However, we do not find any evidence of quasi-hyperbolic discounting, and there is no significant association between present bias and financial liquidity, which is not consistent with theoretical predictions from life cycle models with quasi-hyperbolic discounting (Angeletos et al., 2001).

The third chapter, "Gambling Problems in the General Danish Population: Survey Evidence," joint with Glenn W. Harrison, Morten I. Lau, and Don Ross, compares several survey instruments of gambling behavior and estimates the prevalence of problem gambling in Denmark. Problem gambling is often identified using clinically-based instruments such as the Diagnostic and Statistical Manual of Mental Disorders (DSM IV), which measures the effects and consequences of problem gambling. We administer the Focal Adult Gambling Screen (FLAGS), which was developed by Schellinck et al. (2015), and it is a broader measure of problem gambling that seeks to detect both the presence and effects of the latent disorder. The sample consists of 8,405 adult Danes and we find that 95% of the population has no detectable risk, 2.9% has an early risk, 0.8% has an intermediate risk, 0.7% has an advanced risk, and 0.2% can be classified as problem gamblers. We also find a significant correlation with scores of other gambling risk instruments, such as the DSM IV screen, and instruments measuring alcohol use, anxiety, depression and impulsivity.

The three chapters contribute to our understanding of intertemporal decisions and provide new insights on the empirical identification of time preferences and problem gambling. The thesis concludes with a short summary and discussion of the main results in each chapter, and I provide an outlook for further research.

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Chapter 1

Discount Rate Sensitivity to Background Consumption and Consumption Smoothing

Discount Rate Sensitivity to Background Consumption and Consumption Smoothing

Lasse J. Jessen*

Abstract

The experimental literature to date suggests that individual discount rates are sensitive to assumptions regarding integration of income with background consumption and consumption smoothing, i.e., the spending period and pattern of monetary rewards in incentivized decision tasks. I analyze the sensitivity of individual discount rates elicited from choices in experiments and highlight important simulation results: If the utility function is exogenous, then discount rates are sensitive to assumptions regarding background consumption and consumption smoothing. However, if the utility function is elicited jointly with time preferences, then discount rates are robust to time-invariant background consumption and consumption smoothing. These results hold for various elicitation methods and utility specifications that are common in the experimental literature, they clarify seemingly contradictory conclusions from previous studies, and highlight the importance of joint elicitation of the utility function and discount rates.

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1 Introduction

The experimental identification of time preferences in the economics literature is, to a large extent, based on choices over time-dated monetary rewards. Indifference between smaller, sooner income and larger, later income indicates the monetary premium that respondents require to be compensated for delaying the receipt of income. However, standard models of time preferences, such as the exponential discounting model (Samuelson, 1937) and the quasi-hyperbolic discounting model (Laibson, 1997), do not describe how future *income* is discounted; instead, they specify how future *utility* is discounted. It is therefore necessary to specify how monetary income translates into utility by considering the shape of the utility function, how monetary rewards are integrated with background consumption, and whether income generates utility over one or several periods.

A common assumption in the literature suggests that experimental income is spent at the time it is received and not over several time periods (Cubitt and Read, 2007). Moreover, if utility is linear then discount rates can be elicited without concern for background consumption. Most of the early literature builds on this approach (see Frederick et al., 2002, for a review), but it carries the risk of potential confounds in the elicitation of individual discount rates. In particular, variation in responses between subjects may be interpreted as differences in individual discount rates when it actually stems from differences in utility of income, background consumption or consumption smoothing.

Andersen et al. (2008b) address these caveats. Rather than relying on specific assumptions with respect to the utility function, they elicit it from choices over lotteries and find significant concavity that reduces the estimated level of individual discount rates, a result that follows from Jensen's Inequality. Identifying the utility function jointly with discount rates (Andersen et al., 2014; Andreoni and Sprenger, 2012) has since become an important element of experimental studies on time preferences.

Although the utility function can be identified, at least two other issues remain, namely the degree to which rewards are integrated with other arguments in the utility function and the consumption pattern by which rewards generate utility. Subjects in experiments may integrate their rewards with other income or consumption flows, which often differ between individuals. Recent studies have found that discount rates are sensitive to the level of background consumption (Holden and Quiggin, 2015; Andreoni and Sprenger, 2012), whereas others report that discount rates are not sensitive (Andersen et al., 2008b). Moreover, some subjects may plan to spend their rewards over several days, whereas others may plan to spend them immediately. Both Andersen et al. (2008b) and Duquette et al. (2014) find that discount rates are sensitive to the extent of consumption smoothing.

I analyze the sensitivity of elicited discount rates with respect to background consumption and consumption smoothing. My contribution to the literature is three-fold: First, I highlight the seemingly contradictory conclusions in the recent literature addressing background consumption and consumption smoothing. Section 2 presents the different studies that have come to different conclusions on the relevance of background consumption and consumption smoothing on estimation of individual discount rates under non-linear utility.

Second, I identify the drivers underlying these mixed results via a sensitivity analysis that is based on simulations from indifference points between delayed rewards and between lotteries. Section 3 introduces the theoretical framework and presents the intertemporal utility functions. The analysis in Section 4 reveals that the previous results are driven by variations in assumptions with respect to the utility function: If the utility function is exogenous, then discount rates are sensitive to both background consumption and consumption smoothing. However, if the atemporal utility function is elicited under the same assumptions as the intertemporal utility function, individual discount rates are robust and are not affected by the level of background consumption or the extent of consumption smoothing.

Third, and finally, I show that although estimates of discount rates are more robust than previously reported in the literature, some important caveats remain. I analyze in Section 5 how time-variant background consumption and consumption smoothing are possible confounds for discount rate estimation. These can to some extent be addressed by adjustments to existing experimental designs, and I make some suggestions for future research.

2 Literature on Discount Rate Sensitivity

The sensitivity of individual discount rates to assumptions on the amount of background consumption and the extent of consumption smoothing has attracted attention since the publication by Andersen et al. (2008b), who experimentally control for non-linearity in the utility function. They show that background consumption has no effect on discount rates when utility is assumed to be linear, which explains the lack of interest in background consumption in previous studies (see reviews by Frederick et al., 2002; Andersen et al., 2014). Andersen et al. (2008b) also deviate from the standard assumption that rewards are consumed immediately after they are received. Since then, other studies have addressed these assumptions and a number of contributions have emerged that are in stark contrast to each other.

2.1 Sensitivity to Background Consumption

Andersen et al. (2008b) jointly elicit the utility function from binary choices between lotteries and individual discount rates from binary choices between time-dated rewards using a representative sample of the Danish population. In their baseline specification, experimental income is integrated with a time-invariant amount of background consumption, which is set equal to the average daily consumption level of non-durable assets in Denmark. They find that the amount of background consumption does not have a significant effect on individual discount rates. When background consumption is set to 50 kroner per day, the estimated annual discount rate is 10.2%, and when background consumption is set to 200 kroner per day, the estimated annual discount rate is marginally lower and equal to 9.8%. However, the curvature of the utility function measured by the coefficient of constant relative risk aversion increases from 0.67 to 0.82.

Later studies contradict these findings. Holden and Quiggin (2015) consider a model of bounded rationality where the level of background consumption depends on the time delay between the sooner and later rewards. Their estimates are based on an elicitation method that is similar to Andersen et al. (2008b), but they assume that the utility function is exogenous and not affected by variation in background consumption. Holden and Quiggin (2015) assume that the sooner reward and the later reward are both integrated with higher levels of background consumption when the time delay between the rewards is long compared to when the time delay between the rewards is short. They find that higher levels of background consumption increase estimated discount rates.

Andreoni and Sprenger (2012) also find that estimated discount rates are sensitive to the level of background consumption. They develop an alternative method to jointly elicit discount rates and the utility function based on intertemporal allocations of income along a budget set. They allow for the integration of rewards with background consumption and discuss the sensitivity of discount rates with respect to this exogenous variable in detail. Andreoni and Sprenger (2012) find that elicited discount rates are sensitive to the amount of daily background consumption. The results from nonlinear least square estimations show that as daily background consumption increases discount rates decrease significantly (from 36% when background consumption is 1 dollar down to 15% when background consumption is 25 dollars). They also find that the estimated utility curvature increases as daily background consumption increases. However, these results are sensitive to the underlying estimation technique, and Andreoni and Sprenger (2012) find less sensitivity of discount rates when they use a two-limit tobit specification instead of the nonlinear least squares specification.

A final related study is that of Laury et al. (2012). They develop an identification strategy that avoids any impact of background consumption. They elicit individual discount rates by asking subjects to make choices over time-dated lotteries, where the sooner and later rewards are equal and constant, but the probability of the outcome varies over time. The authors show analytically that, in their design, discount rates are independent of utility curvature, background consumption, and consumption smoothing, which they highlight as an advantage of their method over alternatives. However, the choice data reveal that subjects appear to be sensitive to small variations in probabilities between the sooner and later lotteries. The sooner option is always a 50-50 chance of receiving 0 dollar or 200 dollars, and the later option offers increasing probabilities of receiving 200 dollars. They observe a significant shift in preferences when the probability of the later reward increases from 50% to 50.1%, which indicates that not all subjects evaluate the choice tasks entirely according to the underlying discounting theory, and they may instead focus on probabilities in the time-dated lotteries without considering the time delay.

Overall, the conclusions regarding the sensitivity of individual discount rates to variation in background consumption are mixed. Andersen et al. (2008b) find no effect of the amount of background consumption on discount rates but some effect on the utility function when all rewards (from both the lottery and discounting tasks) are integrated with background consumption. In contrast, Holden and Quiggin (2015) find that individual discount rates are sensitive when the utility function is exogenous, and Andreoni and Sprenger (2012) find that discount rates and the utility function are both sensitive to variation in background consumption.

2.2 Sensitivity to Consumption Smoothing

Andersen et al. (2008b) also deviate from the standard assumption with respect to consumption smoothing, namely that rewards are spent immediately after they are paid out. Focusing on the simple case of uniform and time-invariant consumption smoothing over time periods following the receipt of income, they find a significant effect of consumption smoothing on individual discount rates. As consumption smoothing increases, the estimated discount rate tends toward the level that is obtained under linear utility, i.e. risk neutrality. However, Andersen et al. (2008b) conclude that the most appropriate assumption based on log likelihood values of the statistical models is immediate, and not delayed, consumption of rewards.

Duquette et al. (2014) follow Andersen et al. (2008b) and allow for uniform, time-invariant consumption smoothing over several time periods following the receipt of a reward. They show that utility maximization may lead to consumption smoothing over longer periods of time and up to 234 days in their analysis.[1] Like Andersen et al. (2008b),

[1]For the rewards used in their analysis, optimal consumption smoothing over 234 days means splitting 405 dollars into daily spending of 1.73 dollars. While this may be the optimal extent of consumption smoothing according to theory, Duquette et al. (2014) acknowledge that it may not be the most realistic

they find that consumption smoothing leads to higher individual discount rates, and that individual discount rates for a utility maximizing consumer are close to the level obtained under linear utility. Hence, estimated discount rates under the assumption of intertemporal utility maximization are not sensitive to the degree of utility curvature because consumption is spread across relatively long periods of time.

These are the only two studies to date that discuss the possible effects of allowing for consumption smoothing on discount rates. Interestingly, they both find that discount rate estimates are sensitive to the extent of consumption smoothing. However, neither study allows for consumption smoothing in the evaluation of lottery rewards, and I return to this issue later.

3 Theoretical Framework

3.1 Identification of Discount Rates

In most experiments on time preference, individual discount rates are identified from indifference points between smaller, sooner and larger, later monetary rewards.[2] Like Andersen et al. (2008b), I allow rewards to be integrated with background consumption and smoothed uniformly over several time periods after the payment date. I further assume that the intertemporal utility function is additively separable[3] and time preferences are represented by exponential discounting.[4]

Under these assumptions, the present value of utility from a sooner, smaller reward x_S

assumption.

[2]Different experimental designs exist for eliciting discount rates. Some rely on "fill in the blank" tasks, where participants state or reveal a sooner amount X that makes them indifferent to a later amount Y (e.g., Thaler, 1981; Benhabib et al., 2010). Others rely on ordered sets of binary choices in decision tasks (e.g., Coller and Williams, 1999; Harrison et al., 2002; Andersen et al., 2008b). Both elicitation methods have the same aim: to identify (approximate) indifference between smaller, sooner and larger, later rewards.

[3]The assumption of additive separability is standard in the experimental literature on time preferences. To date, few studies have attempted to identify non-additive intertemporal utility specifications from experimental choice data. One exception is the identification of correlation aversion over income in Andersen et al. (2011). In this paper, I focus on the standard utility framework that has been applied in most time preference experiments.

[4]The theory of exponential discounting has been challenged by non-standard discounting theories, such as quasi-hyperbolic discounting, which capture a possible bias toward present consumption. I discuss to what extent present bias is sensitive to background consumption and consumption smoothing in Section 4.3.

received at time $t = S$ is specified as

$$DU_S = \sum_{t=0}^{S-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot u(\omega_t) + \underbrace{\sum_{t=S}^{S+\lambda_S-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot u\left(\omega_t + \frac{x_S}{\lambda_S}\right)}_{\substack{\text{Utility from background consumption} \\ \text{plus experimental reward } x_S}} + \sum_{t=S+\lambda_S}^{T} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot u(\omega_t), \quad (1)$$

where δ is the annual exponential discount rate, u defines the atemporal utility function, λ_S is the number of time periods over which consumption is smoothed, ω_t is daily background consumption, and T is the planning horizon.

Equation (1) initially appears complicated, but it is analogous to the framework applied in Andersen et al. (2008b) and Duquette et al. (2014). Without any income from the experiment, a subject would consume her background consumption ω_t in every period. If she receives a reward x_S at time $t = S$, she will increase her consumption uniformly over λ_S days, allowing her to increase consumption from ω_t to $\omega_t + \frac{x_S}{\lambda_S}$ on those days. On all other days, she will continue to consume ω_t.[5]

The discounted utility from receiving a larger, later reward x_L is

$$DU_L = \sum_{t=0}^{L-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot u(\omega_t) + \underbrace{\sum_{t=L}^{L+\lambda_L-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot u\left(\omega_t + \frac{x_L}{\lambda_L}\right)}_{\substack{\text{Utility from background consumption} \\ \text{plus experimental reward } x_L}} + \sum_{t=L+\lambda_L}^{T} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot u(\omega_t), \quad (2)$$

where λ_L indicates the number of periods over which the later reward is consumed. The planning horizon T is longer than reward-based consumption, which means that $T > S + \lambda_S$ and $T > L + \lambda_L$.[6]

The indifference point between a smaller, sooner reward and a larger, later reward is

[5]Uniform consumption smoothing is a simplifying assumption that is different from the optimal consumption path under intertemporal utility maximization when individual discount rates deviate from the growth adjusted market interest rate (e.g., the Euler equation in neoclassical growth models). However, this assumption simplifies the analysis significantly.

[6]It is not necessary to assume that consumption from the sooner reward ends before consumption from the later reward begins, i.e. $S + \lambda_S < L$ is not a necessary restriction.

given by

$$\underbrace{\sum_{t=S}^{S+\lambda_S-1}\left(\frac{1}{1+\delta}\right)^{\frac{t}{360}}\cdot\left[u\left(\omega_t+\frac{x_S}{\lambda_S}\right)-u(\omega_t)\right]}_{\text{Added utility from consuming } x_S \text{ over } \lambda_S \text{ days}}=\underbrace{\sum_{t=L}^{L+\lambda_L-1}\left(\frac{1}{1+\delta}\right)^{\frac{t}{360}}\cdot\left[u\left(\omega_t+\frac{x_L}{\lambda_L}\right)-u(\omega_t)\right]}_{\text{Added utility from consuming } x_L \text{ over } \lambda_L \text{ days}}. \quad (3)$$

The additional utility from consuming the sooner, smaller reward is equal to the additional utility from consuming the larger, later reward. To identify the discount rate δ from the indifference point between two rewards x_S and x_L, one needs to know: (1) the functional form of the utility function u, (2) the level of background consumption ω_t in each period, and (3) the extent of consumption smoothing λ_S and λ_L for the sooner and later rewards, respectively.

Equation (3) is a general specification of discount rate identification found in the experimental literature. Assuming linear utility and excluding consumption smoothing by setting $\lambda_S = \lambda_L = 1$, equation (3) is simplified and the discount rate δ is given by

$$\delta = \left(\frac{x_L}{x_S}\right)^{\frac{360}{L-S}} - 1. \quad (4)$$

Before the contribution by Andersen et al. (2008b), many studies on individual discount rates based their identification on equation (4) (e.g., Thaler, 1981; Coller and Williams, 1999; Frederick et al., 2002, for a review). Under linear utility, integration of rewards with background consumption does not affect estimated discount rates, and neither does time-invariant consumption smoothing.

Allowing for non-linear utility, integration with constant background consumption ω and time-invariant uniform consumption smoothing λ gives the specification used by Andersen et al. (2008b).[7] The exponential discount rate is then identified by

$$\delta = \left[\frac{u(\omega+\frac{x_L}{\lambda})-u(\omega)}{u(\omega+\frac{x_S}{\lambda})-u(\omega)}\right]^{\frac{360}{L-S}} - 1. \quad (5)$$

[7] Using a different identification method, as discussed in Appendix D, Andreoni and Sprenger (2012) also allow for the integration of rewards with background consumption ω. They do not allow for consumption smoothing over several time periods and keep $\lambda = 1$. Holden and Quiggin (2015) allow only for variation in background consumption in their model of bounded rationality applied to time preference experiments.

In Section 4, I analyze the sensitivity of individual discount rates to time-invariant levels of background consumption and to time-invariant degrees of consumption smoothing, and I use Equation (5) in the analysis for different specifications of the utility function.

3.2 Identification of the Utility Function

The sensitivity of individual discount rates with respect to consumption smoothing and background consumption depends on the specification of the atemporal utility function and how it is identified. Duquette et al. (2014) take the utility function as given and assume constant relative risk aversion over consumption.[8] The same approach is followed by Holden and Quiggin (2015). Andersen et al. (2008b) and Andreoni and Sprenger (2012) jointly elicit the utility function and individual discount rates based on choice data but use different methods to identify the utility function.

Andersen et al. (2008b) use seperate decision tasks to elicit the utility function. Binary choices between lotteries, as in Holt and Laury (2002), identify a utility function with constant relative risk aversion under the assumption of expected utility theory.[9]

Allowing for integration of lottery rewards with background consumption and consumption smoothing, the indifference point between a safe lottery paying x_{A1} or x_{A2} with probabilities p and $(1-p)$, respectively, and a riskier lottery paying x_{B1} or x_{B2} with probabilities p and $(1-p)$, respectively, is specified as

$$\begin{aligned} p \cdot u\left(\omega_{RA} + \frac{x_{A1}}{\lambda_{RA}}\right) + (1-p) \cdot u\left(\omega_{RA} + \frac{x_{A2}}{\lambda_{RA}}\right) \\ = p \cdot u\left(\omega_{RA} + \frac{x_{B1}}{\lambda_{RA}}\right) + (1-p) \cdot u\left(\omega_{RA} + \frac{x_{B2}}{\lambda_{RA}}\right). \end{aligned} \tag{6}$$

Lottery A is safer than lottery B because the payouts x_{A1} and x_{A2} have lower variance than x_{B1} and x_{B2}. Each lottery reward is integrated with background consumption ω_{RA} and

[8] Although Duquette et al. (2014) state that their elicitation of the utility function is based on data from lottery choices, they do not discuss the identification strategy and underlying assumptions.

[9] Alternative specifications such as rank-dependent utility theory, as in Quiggin (1982), could also be applied if the experimental design allows. Only the component related to utility curvature would then affect individual discount rates, and the component related to probability weighting would not have a direct influence.

smoothed over λ_{RA} periods.[10]

In all studies to date that elicit individual discount rates and allow for nonlinear utility, the utility function $u(c)$ is represented by a constant relative risk aversion specification. I use the specification $u(c) = \frac{(c)^{1-r}-1}{1-r}$, where the coefficient of constant relative risk aversion with respect to consumption (r) describes the utility curvature. Linear utility is nested when $r = 0$, $r > 0$ indicates risk aversion and concavity of the utility function, and $r < 0$ indicates risk lovingness and convex utility.[11] I apply this specification for the sensitivity analysis in the following section.[12]

Andreoni and Sprenger (2012) elicit the utility function from intertemporal allocations of income along a convex budget set without relying on seperate decision tasks to identify the utility function. They find a discrepancy between utility curvature elicited from binary choices between lotteries and the curvature elicited from intertemporal allocations of income. I rely primarily on the identification of utility from binary choices between lotteries; however, I show that my conclusions also hold when the utility function is elicited from intertemporal allocations of income.

4 Time-invariant Background Consumption and Consumption Smoothing

The review of the literature in Section 2 shows mixed effects of background consumption and consumption smoothing on elicited discount rates. Using the framework introduced in the previous section, I illustrate the effect of varying background consumption and consumption smoothing on elicited discount rates.

I begin by restricting background consumption and consumption smoothing to be constant over time and independent of reward size. Andersen et al. (2008b) set background consumption equal to average daily consumption of non-durable goods using household

[10]I assume that consumption smoothing λ_{RA} does not vary with reward size. I comment on the case where consumption smoothing depends on reward size in Section 5.2.

[11]When $r = 1$, utility is defined by the logarithmic function, since $\lim_{r\to 1} \frac{(c)^{1-r}-1}{1-r} = ln(c)$.

[12]I analyze the robustness of the results to alternative specifications of utility, such as exponential (CARA) and expo-power utility, in Section 4.3.

expenditure data, whereas Andreoni and Sprenger (2012) elicit average daily consumption by asking subjects about their spending habits in a questionnaire. It is likely that average daily background consumption is constant over the time delays considered in experiments, which typically range from a few days to one year. By assuming a constant and uniform λ, Andersen et al. (2008b, p. 596) indicate that their approach can be viewed as "...the simplest possible way in which one could add structure...," and I follow their example with respect to consumption smoothing.[13]

Given the theoretical framework in Section 3, if background consumption ω and consumption smoothing λ are constant, the discount rate is given by

$$\delta = \left[\frac{(\omega + \frac{x_L}{\lambda})^{1-r} - \omega^{1-r}}{(\omega + \frac{x_S}{\lambda})^{1-r} - \omega^{1-r}}\right]^{\frac{360}{L-S}} - 1. \tag{7}$$

To illustrate the effects of background consumption and consumption smoothing on elicited discount rates, I use parameter values that correspond to those that are reported in Andersen et al. (2008b). In their baseline specification, they set daily background consumption equal to 118 kroner and assume no consumption smoothing, i.e. $\lambda = 1$. The estimated discount rate is 25.1% per annum when the utility function is assumed to be linear. Indifference between a smaller, sooner payment x_S of 3,000 kroner at t=30 and a larger, later payment x_L of 3,750 kroner at t=390 corresponds to a discount rate of 25% per annum when the utility function is linear, and I use these values in the sensitivity analysis.

I investigate individual discount rates under non-linear utility and differentiate between two estimation methods: (1) one method where the utility function is exogenous, and (2) another method where the utility function is elicited from binary choices between lotteries.

[13]If longer time delays are considered, or subjects expect significant changes in their private or professional life, then background consumption and consumption smoothing may not be constant over time. I discuss both possibilities in Section 5.

4.1 Individual Discount Rates and Exogenous Utility

I start by assuming that the utility function is exogenous and r=0.77.[14] The discount rate δ is then identified by

$$\delta = \left[\frac{(\omega + \frac{3{,}750}{\lambda})^{1-0.77} - \omega^{1-0.77}}{(\omega + \frac{3{,}000}{\lambda})^{1-0.77} - \omega^{1-0.77}}\right]^{\frac{360}{L-S}} - 1. \tag{8}$$

I first analyze the sensitivity of discount rates with respect to background consumption when λ is equal to 1, and then I look at the association between elicited discount rates and consumption smoothing when ω is equal to 118 kroner per day.

Background Consumption

Figure 1 shows the solutions to equation (8) for different levels of background consumption ω between 0 kroner and 10,000 kroner per day when $\lambda = 1$.[15] The horizontal line shows the level of discounting under linear utility given by the indifference point between the sooner and later rewards. As background consumption increases, the discount rate increases and tends toward the level under linear utility. In Appendix A I show analytically that the discount rate given by equation (7) tends toward the level under linear utility as ω approaches infinity, and the limit is given by

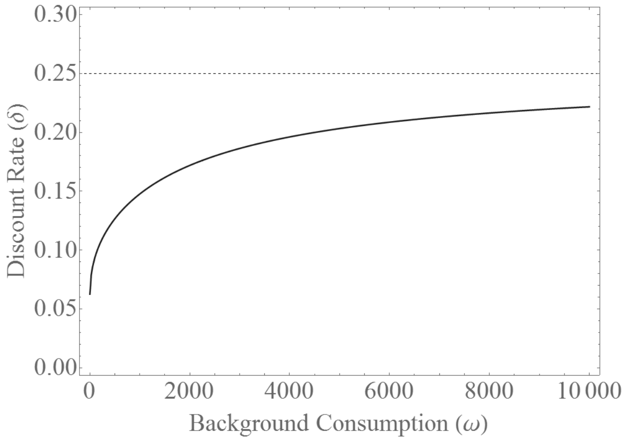
$$\lim_{\omega\to\infty} \delta = \left[\frac{x_L}{x_S}\right]^{\frac{360}{L-S}} - 1. \tag{9}$$

If the utility function is exogenous and non-linear, then the elicited discount rate is sensitive to the level of background consumption. Marginal utility with respect to the reward is positive and diminishing when the utility function is concave, and the curvature of the utility function over rewards can be measured by the ratio between the second and first order derivatives. This is the Arrow Pratt measure of absolute risk aversion with respect

[14]This coefficient is chosen from an indifference point in the choice set by Andersen et al. (2008b) and is close to the estimated mean value of r = 0.74 from all observations in their analysis.

[15]A daily background consumption level of 10,000 kroner is unrealistically high, however, it is possible that rewards and utility are not identified over days but instead weeks, months, or years, in which case integration of rewards with 10,000 kroner would be reasonable.

Figure 1: Individual Discount rates and Background Consumption under Exogenous Utility



to income, which under the specification here is equal to

$$A_x = -\frac{u_{xx}}{u_x} = \frac{r}{x + \omega\lambda}. \tag{10}$$

A_x is decreasing in ω as well as λ for a given parameter r, which implies that the utility curvature with respect to income is decreasing and the discount rate increases toward the level under linear utility.

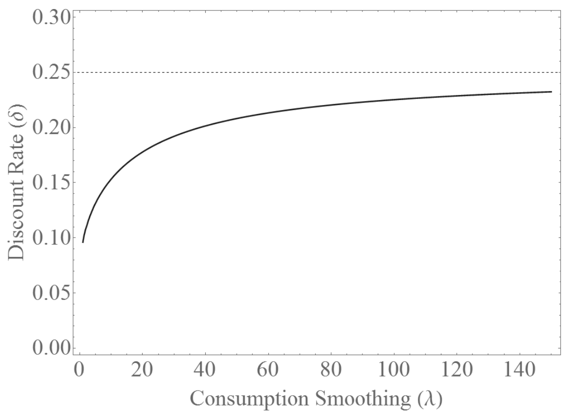
The implications of this sensitivity to changes in background consumption can be significant. For example, if I want to identify discount rates for a wealthy and a poor participant, who both choose the same indifference point and for whom I assume the same utility function and the same level of background consumption, I will estimate the same discount rate. If, however, I ask both participants to reveal their background consumption, which is likely to be higher for the wealthy participant, I would find a higher discount rate for the wealthy participant than for the poor participant. This means that the identification of discount rates across individuals depends on the ability to identify differences in background consumption when the utility function is exogenous and constant.

Consumption Smoothing

Figure 2 shows the solutions to equation (7) for different degrees of consumption smoothing between 1 day and 150 days when $\omega = 118$ kroner per day. The horizontal line shows the level of discounting under linear utility, and as consumption smoothing increases the discount rate tends toward the linear utility level. In Appendix A I show this property analytically for individual discount rates given by equation (7), and the limit with respect to consumption smoothing is given by

$$\lim_{\lambda \to \infty} \delta = \left[\frac{x_L}{x_S} \right]^{\frac{360}{L-S}} - 1. \tag{11}$$

Figure 2: Individual Discount rates and Consumption Smoothing under Exogenous Utility



Given a constant utility function, discount rates are sensitive to the degree of consumption smoothing. The utility curvature with respect to x, measured by the coefficient of absolute risk aversion in equation (10), is decreasing in λ. Consumption smoothing over longer periods of time reduces the impact of the concavity of the utility function, and elicited discount rates move closer to the linear utility level. The implications are the same as before: When the utility function is exogenous, identification of individual discount rates depends on the ability to accurately identify the extent of consumption smoothing.

4.2 Joint Elicitation of Individual Discount Rate and Utility

So far, I have assumed that the utility function was exogenous. I have not considered the possibility that utility functions can be inferred from binary choice data, such as those in Andersen et al. (2008b). I analyze the sensitivity of discount rates to background consumption and consumption smoothing and allow these assumptions to also influence the inferred utility function, as identified in equation (6). In the baseline scenario I assume that $r = 0.77$, which is similar to the estimated coefficient of relative risk aversion of 0.74 in Andersen et al. (2008b). Suppose that a subject is indifferent between a relatively safe lottery that pays 2,000 kroner with a probability of 0.7 or 1,600 kroner with a probability of 0.3 and a relatively risky lottery that pays 3,850 kroner or 100 kroner with similar probabilities of 0.7 and 0.3, respectively. This is one of the decision tasks in Andersen et al. (2008b) and indifference between the two lotteries would give $r = 0.77$ when daily background consumption is 118 kroner and rewards are consumed straight away. Without loss of generality I use the rewards and probabilities from this decision task in the analysis.[16]

Background Consumption

I first keep consumption smoothing of both delayed rewards and lottery rewards constant at $\lambda = 1$ and vary the level of time-invariant background consumption ω.

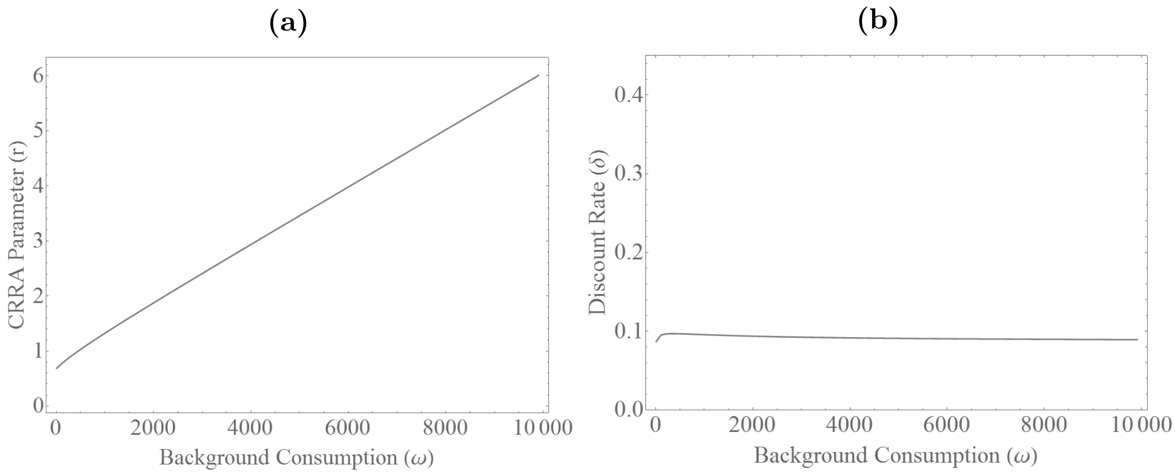
Applying the framework described in Section 3, the utility function is identified from the indifference relation

$$\left[(0.7)\cdot\frac{(\omega+2,000)^{(1-r)}}{1-r}+(1-0.7)\cdot\frac{(\omega+1,600)^{(1-r)}}{1-r}\right] = \left[(0.7)\cdot\frac{(\omega+3,850)^{(1-r)}}{1-r}+(1-0.7)\cdot\frac{(\omega+100)^{(1-r)}}{1-r}\right], \quad (12)$$

which can be uniquely solved for r but does not have a closed-form solution. The discount

[16] In Section 4.3, I show that the conclusions also hold for other decision tasks with different rewards and probabilities.

Figure 3: CRRA Utility, Individual Discount Rates, and Background Consumption



rate, given the value of r, is again identified by

$$\delta = \left[\frac{(\omega + 3,750)^{1-0.77} - \omega^{1-0.77}}{(\omega + 3,000)^{1-0.77} - \omega^{1-0.77}} \right]^{\frac{360}{L-S}} - 1. \tag{13}$$

Solving both indifference equations jointly reveals the sensitivity of individual discount rates to changes in time-invariant background consumption when identification of the utility function also depends on background consumption. Because there is no closed-form solution for the r-parameter in equation (12), I cannot show analytically how the individual discount rate varies with background consumption and I rely instead on numerical simulations.

Figure 3 (a) and (b) show the inferred values for the r-parameter and the individual discount rate δ, respectively. The results are different from those that rely on an exogenous utility function. While an increase in background consumption leads to a significant increase in the r-parameter, the inferred discount rate is stable between 8% and 10%.[17] Andersen et al. (2008b) arrive at the same conclusion when they vary the level of background consumption.

Although inferred discount rates increase with background consumption when r is constant, an increase in r has the opposite effect on elicited discount rates. The two effects

[17]Because there is no analytical solution for the r-parameter in equation (12), I cannot calculate the limit to show that discount rates are indeed robust to variation in background consumption. However, the inferred discount rate is equal to 8.7% when background consumption is equal to 1 million kroner, which shows that the results are robust to very high values of background consumption.

combined lead to little variation in elicited discount rates. Absolute risk aversion decreases with ω, as shown in Section 4.1, but it increases with r. These two effects combined lead to little variation in the absolute risk aversion over income, and thus to little variation in utility curvature with respect to x. The implication is that elicited discount rates are not sensitive to background consumption.

The robustness of discount rates to background consumption means that one can elicit individual discount rates without knowing the exact level of background consumption as long as the utility function is jointly elicited. Comparisons of discount rates for subjects with different levels of background consumption are possible without knowing the exact level for each individual. If two subjects choose the same indifference points over lotteries and over delayed rewards, the elicited discount rate will be almost the same for both subjects regardless of background consumption.

Rabin (2000) shows that expected utility theory defined over lifetime income leads to unrealistic out-of-sample predictions over gambles with large stakes if risk aversion over small stakes is observed. The same critique can be applied to this analysis, although the rewards in the decision tasks are higher than usual in the experimental literature. However, Cox and Sadiraj (2006) show that alternative models, such as rank-dependent utility theory and cumulative prospect theory, may suffer from calibration problems as well. The calibration critique points to the difficulty of making out-of-sample predictions, and I only make inferences over income levels that have been provided in previous experiments on risk and time preferences.

Consumption Smoothing

Both Andersen et al. (2008b) and Duquette et al. (2014) find discount rate sensitivity with respect to consumption smoothing. Duquette et al. (2014) treat the utility function as given, and Andersen et al. (2008b) make a subtle but important assumption that also keeps the utility function constant: While they allow for consumption smoothing of delayed rewards, they do not make the same assumption for lottery rewards that are paid out without delay. This assumption is motivated by an application of Fudenberg and Levine's (2006)'s dual self model. Andersen et al. (2008b) assume that lottery rewards are consumed immediately, and allow for differences between consumption smoothing from lottery rewards and delayed rewards.

If rewards from risk aversion tasks are received at the same time and under the same conditions as rewards from discounting tasks, it is reasonable to assume that consumption smoothing is similar for these rewards. In this case, keeping daily background consumption constant at 118 kroner per day, the CRRA coefficient r is identified by

$$\begin{aligned} p \cdot \frac{\left(118 + \frac{2{,}000}{\lambda}\right)^{(1-r)}}{1-r} + (1-p) \cdot \frac{\left(118 + \frac{1{,}600}{\lambda}\right)^{(1-r)}}{1-r} \\ = p \cdot \frac{\left(118 + \frac{3{,}850}{\lambda}\right)^{(1-r)}}{1-r} + (1-p) \cdot \frac{\left(118 + \frac{100}{\lambda}\right)^{(1-r)}}{1-r} \end{aligned} \tag{14}$$

and the discount rate given r is identified by

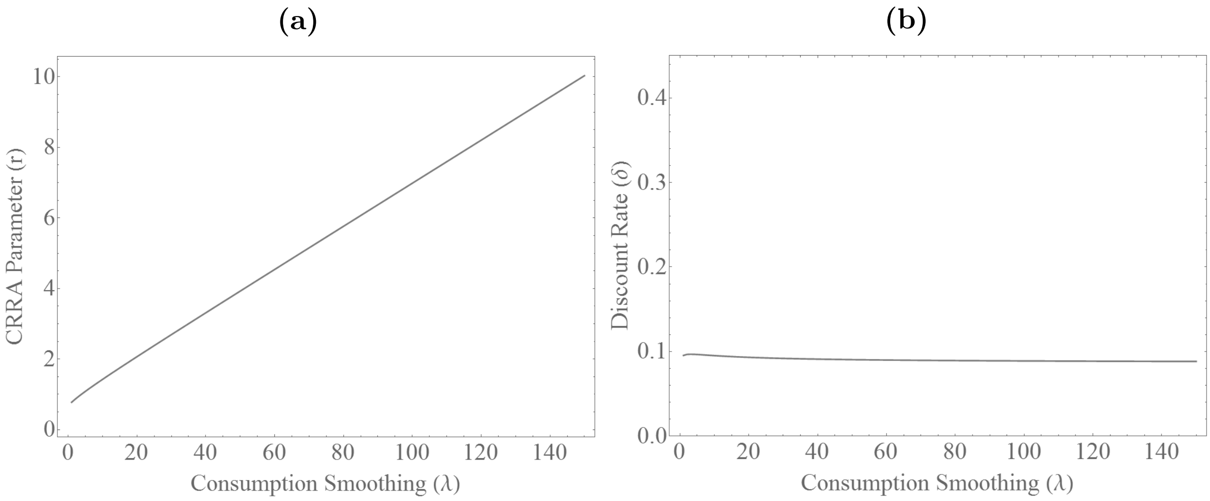
$$\delta = \left[\frac{(118 + \frac{3{,}750}{\lambda})^{1-r} - 118^{1-r}}{(118 + \frac{3{,}000}{\lambda})^{1-r} - 118^{1-r}} \right]^{\frac{360}{L-S}} - 1. \tag{15}$$

Once again, equation (14) has no closed-form solution for r. Therefore, I solve both equations numerically and illustrate the effects of consumption smoothing on the utility function and individual discount rates in Figure 4 (a) and (b).

The results show that the estimated r-parameter is increasing in λ, but the discount rates remain flat between 8% and 10%.[18] The curvature of the utility function, measured by absolute risk aversion over income x, increases with r, but decreases with λ, and the combined effect leads to little variation in absolute risk aversion over income and elicited discount rates. This result implies that one can elicit individual discount rates without knowing the exact level of time-invariant consumption smoothing for subjects in the sample.

[18]Because there is no analytical solution for the the r-parameter, I cannot calculate the limit of discount rates with respect to consumption smoothing. However, the inferred discount rate is equal to 8.7% for very high degrees of consumption smoothing.

Figure 4: CRRA Utility, Individual Discount Rates, and Consumption Smoothing



4.3 Extensions of the Sensitivity Analysis

The analysis shows that discount rates are robust to different levels of background consumption and consumption smoothing if the utility function is elicited from binary choice data and estimated under the same assumptions as individual discount rates. However, I have made a number of simplifying assumptions: (i) I only consider inferences from a single lottery choice task, (ii) the atemporal utility function is characterized by constant relative risk aversion, (iii) the discounting function is exponential, and (iv) I only consider identification of utility curvature from binary choices between lotteries. Here I discuss these assumptions and consider the most common alternatives.

Alternative Degrees of Risk Aversion

I previously chose an arbitrary indifference point between two lotteries that implies $r = 0.77$ under the baseline assumptions. However, individuals differ in their risk preferences. Are individual discount rates also robust to variation in background consumption and consumption smoothing for other values of the r-parameter?

I repeat the analysis from Section 4.2 and vary the probability p and (1-p) of receiving the highest and lowest reward in each lottery, respectively. In particular, I assume that $p = \{$ 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 $\}$, which gives the following coefficients of relative risk aversion, $r = \{ -1.84, -1.03, -0.53, -0.16, 0.16, 0.47, 0.77, 1.12, \text{ and } 1.61 \}$, respectively.

Figure 5 and 6 show the numerical solutions for r and δ to changes in background consumption and consumption smoothing, respectively. Whereas the r-parameter is sensitive to these changes in both the risk-loving and risk-averse domains, the individual discount rate δ is generally robust with respect to changes in background consumption and consumption smoothing. The results do show some variation in individual discount rates for highly convex utility functions, but such risk-loving behavior is rarely observed empirically. The level of the discount rate δ varies with the degree of risk aversion, which is consistent with the results in Andersen et al. (2008b): a higher degree of utility curvature reduces the discount rate.

Figure 5: Individual Discount Rates and Background Consumption for Various Degrees of Risk Aversion

(a) **(b)**

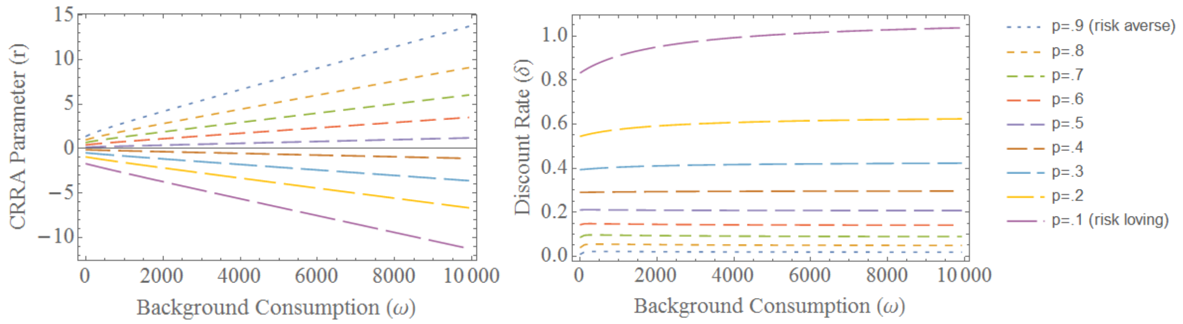
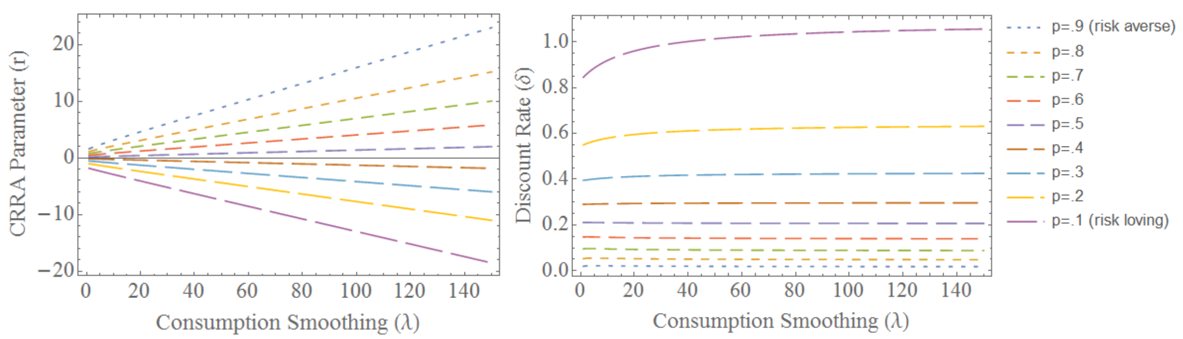


Figure 6: Individual Discount Rates and Consumption Smoothing for Various Degrees of Risk Aversion



(a) **(b)**

Alternative Utility Specifications

The main analysis is based on the identification of a power utility function, which is the most commonly applied specification in the experimental literature on time preferences. However, a natural question arises: Does this utility specification drive the results?

The constant absolute risk aversion (CARA) utility specification is a popular alternative representation of individual risk attitudes and belongs to the family of exponential functions: $u(x) = 1 - e^{-ax}$. Using this specification of the utility function, I show analytically in Appendix B that background consumption has no effect on absolute risk aversion or inferred discount rates. Consumption smoothing has the same effect as before: Higher consumption smoothing increases the estimated a-parameter of the utility function, but discount rates remain constant.

A flexible one-parameter utility specification introduced by Abdellaoui et al. (2007), which allows for increasing relative risk aversion and decreasing absolute risk aversion, is the expo-power utility function $u(x) = -e^{-\frac{x^s}{s}}$. I repeat the analysis for this specification and confirm the results in Section 4.2. Increasing background consumption and the extent of consumption smoothing have a significant effect on the s-parameter in the utility function but small effects on elicited individual discount rates (see Appendix B).

Quasi-Hyperbolic Discounting

I consider an exponential discounting function in the sensitivity analysis, but alternative discounting models that capture present bias have become popular. The quasi-hyperbolic discounting model, popularized by Laibson (1997), introduces an additional parameter to the standard exponential discounting model. According to exponential discounting, future utility is discounted by the factor $\frac{1}{(1+\delta)^{\frac{t}{360}}}$, where δ is the discount rate per annum and t is measured in days. According to the quasi-hyperbolic discounting model, future utility is discounted by the factor $\frac{\beta}{(1+\delta)^{\frac{t}{360}}}$, where β is a new parameter that indicates present bias. If $\beta < 1$, then future utility is discounted by an additional fixed premium that gives a weaker preference for delayed rewards compared to the exponential discounting model.

Quasi-hyperbolic discounting can also be identified from indifference points between time delayed rewards. I assume indifference points from two decision tasks to identify both δ and β: One decision task where both rewards are paid out in the future, and another decision task where the sooner reward is paid out immediately. The first decision task identifies the parameter δ, and the second decision task identifies the parameter β conditional on δ.

In Appendix C I analyze the sensitivity of both δ and β to changes in background consumption and consumption smoothing. The discount rate δ is robust when the utility function is jointly elicited. Because the δ-parameter in the quasi-hyperbolic discounting model is identified in the same way as δ in the exponential discounting model, the sensitivity results are similar. The β-parameter is robust to background consumption when the utility function is jointly elicited. However, β is sensitive to consumption smoothing, both when the utility function is exogenous and when the utility function is jointly elicited.

Consumption smoothing over longer periods of time decreases the fraction of an immediate reward that is consumed immediately. Part of the utility of the immediate reward is realized in the future and also discounted by β. As a consequence the estimated present bias inferred from a given indifference point becomes stronger, i.e. β decreases, as consumption smoothing increases. Appendix C illustrates this effect in detail. The result implies that quasi-hyperbolic discounting cannot be inferred from decision tasks on binary lotteries and delayed rewards without knowing the extent of time-invariant consumption smoothing for the subjects in the sample.

Individual Discount Rates and Intertemporal Allocations of Income

So far I have focused on joint elicitation of the utility function and individual discount rates from two separate decision tasks. One might suspect that the results discussed here are specific to this elicitation approach.

An alternative procedure is suggested by Andreoni and Sprenger (2012). In their design subjects allocate tokens (income) across two dates, and these tokens are transformed by exchange rates into earnings that are paid out on those dates. Tokens allocated to the later date have a higher value than tokens allocated to the sooner date. At least two of these decision tasks with different exchange rates are needed to uniquely identify the individual discount rate and the utility function. I review this identification procedure in detail in Appendix D and repeat the sensitivity analysis with respect to background consumption and consumption smoothing. The results show that discount rates are robust to changes in background consumption and consumption smoothing, and only the elicited utility function is affected by these changes.

Andreoni and Sprenger (2012) arrive at different conclusions in their analysis. They estimate the parameter of the CRRA utility function and the individual discount rate at levels of background consumption between 1 dollar per day and 25 dollars per day. The estimation results using nonlinear least squares reveal, that the parameter of the utility function is sensitive to the level of background consumption. However, Andreoni and Sprenger (2012) also find that exponential discount rates are sensitive and decreasing with background consumption (from 36% at ω=1 dollar to 15% at ω=25 dollars) and conclude, that "...the method of determining the ω parameters is potentially of great relevance" (p. 3348). This finding contradicts the simulation results in Appendix D. It is likely that the sensitivity of discount rates found by Andreoni and Sprenger (2012) is caused by their estimation method. When they use a Tobit estimator instead of a nonlinear least squares estimator, they find considerably less sensitivity of individual discount rate estimates to the level of background consumption, consistent with the results in Appendix D.

5 Non-Constant Background Consumption and Consumption Smoothing

Discount rates are robust to background consumption and consumption smoothing if the utility function is jointly elicited. However, this result holds only if background consumption and consumption smoothing are time-invariant and independent of reward size. What happens to estimates of individual discount rates if the level of background consumption and the extent of consumption smoothing are not constant over time and rewards? I analyze the sensitivity of individual discount rates when the level of background consumption and the extent of consumption smoothing vary over time, and I discuss how individual discount rates can be elicited if consumption smoothing varies with rewards.

5.1 Time-Variant Background Consumption and Consumption Smoothing

Unlike the results in the previous section, discount rates are highly sensitive to time-variant background consumption and consumption smoothing. I illustrate this sensitivity by keeping background consumption and consumption smoothing of the sooner reward constant and vary both assumptions for the later reward. I assume that the utility function is constant over time and identified from the same decision task as before, which implies that $r = 0.77$. When the level of background consumption and the extent of consumption smoothing can vary over time, the individual discount rate is identified by

$$\sum_{t=30}^{30+\lambda_S-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left(\frac{\left(\omega_t + \frac{3{,}000}{\lambda_S}\right)^{(1-0.77)}}{1-0.77} - \frac{(\omega_t)^{(1-0.77)}}{1-0.77} \right)$$
$$= \sum_{t=390}^{390+\lambda_L-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left(\frac{\left(\omega_t + \frac{3{,}750}{\lambda_L}\right)^{(1-0.77)}}{1-0.77} - \frac{(\omega_t)^{(1-0.77)}}{1-0.77} \right). \quad (16)$$

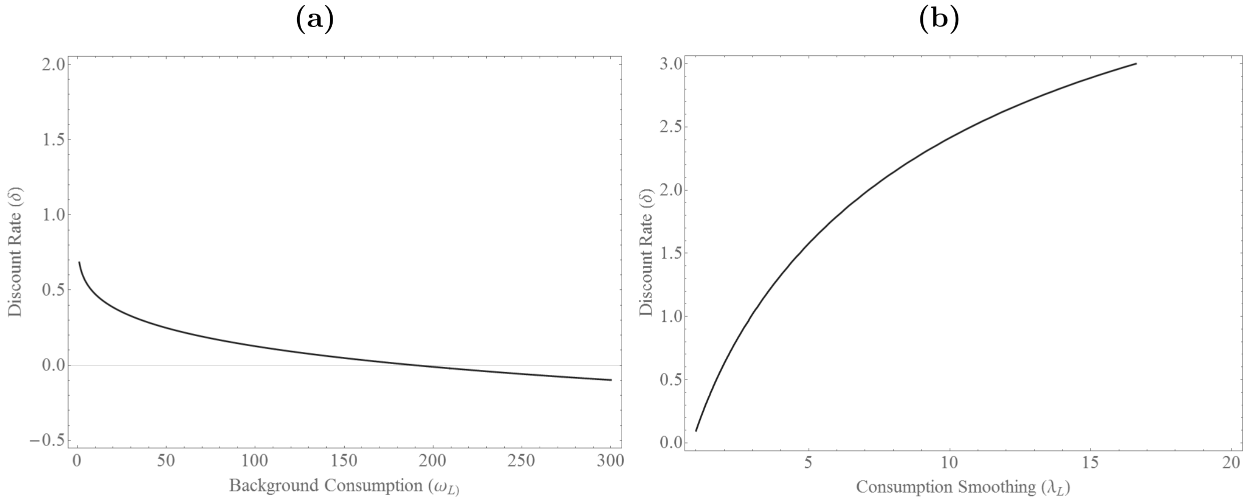
In Figure 7 (a), I vary background consumption on the later date assuming that $\lambda_S = \lambda_L = 1$ and background consumption on the sooner date is equal to 118 kroner. As background consumption on the later date ω_L increases, the discount rate decreases. For example, an increase in ω_L from 118 kroner to 150 kroner implies that the elicited discount rate falls from 9.5% to 4.8%. When the level of background consumption on the later date is 200 kroner or more per day, the elicited discount rate is negative.[19]

In Figure 7 (b), I vary consumption smoothing on the later date and assume that $\lambda_S = 1$. Background consumption is kept constant at 118 kroner. As the degree of consumption smoothing λ_L increases, the elicited discount rate also increases. For example, the individual discount rate increases from 9.5% when $\lambda_L = 1$ to more than 50% when $\lambda_L = 2$.[20]

[19]When the utility function is concave, higher background consumption leads to lower marginal utility of income, and the implied individual discount rate falls when background consumption on the later date increases.

[20]When the utility function is concave, consumption smoothing leads to higher marginal utility of income, and the implied discount rate increases when λ_L increases.

Figure 7: Individual Discount Rates and Time-Variant Consumption Smoothing and Background Consumption



The sensitivity of individual discount rates to time-variant consumption smoothing and background consumption has interesting consequences. For example, an expected increase in background consumption can be one explanation for seemingly present biased preferences. Suppose a person is indifferent between 3,000 kroner now and 4,000 kroner in one year and is indifferent between 3,000 kroner in one year and 3,750 kroner in two years.[21] Under the assumption of time-invariant background consumption and consumption smoothing, the first indifference point would imply a higher discount rate than the second, which is consistent with quasi-hyperbolic discounting. However, the two indifference points are also consistent with exponential discounting and time-varying background consumption. A subject may expect an increase in future background consumption, which implies that the discount rate inferred from the first indifference point would decrease and could become the same as the discount rate inferred from the second indifference point. In this scenario, present bias is not the result of quasi-hyperbolic discounting but the result of an expected increase in background consumption on later dates.

This example illustrates that time-varying background consumption and consumption smoothing are relevant to consider in future research. How one best identifies variation in the level of background consumption and the extent of consumption smoothing is an open

[21] See, for example, Thaler (1981), where the subjects reveal similar preferences over delayed rewards with and without a front end delay to the sooner reward.

question. One suggestion is to elicit risk preferences at different points in time and infer variation in background consumption or consumption smoothing from variation in absolute risk aversion. However, this method requires that the underlying utility function is the same for all subjects and constant over time, and one cannot separate effects from background consumption and consumption smoothing.

Andersen et al. (2008b), Andersen et al. (2014) and Andreoni and Sprenger (2012) identify the atemporal utility function at a single point in time. Other studies have investigated to what extent risk aversion changes with the timing of lotteries. For example, Noussair and Wu (2006) find that 38.6% of the subjects in their sample are more risk averse over lotteries that are paid out in the present compared to similar lotteries that are paid out in the future. The observed decrease in risk aversion could be influenced by an increase in background consumption or consumption smoothing (or both) over time. Abdellaoui et al. (2011) also find that risk aversion is sensitivity to the timing of lottery rewards, but attribute this behavior to changes in probability weighting. Andersen et al. (2008a) elicit risk preferences from binary choices between lotteries, and repeat the same decision task with the same subjects after 17 months. They do not assume that rewards are integrated with background consumption, and find no general tendencey for risk attitudes to increase or decrease. It will be an interesting avenue for future research to further investigate time-varying risk aversion, and analyze to what extent risk aversion varies with expected future income.

5.2 Consumption Smoothing that Varies with Rewards

It is likely that the extent of consumption smoothing depends on reward size. For example, small rewards may be consumed straight away, whereas large rewards may be consumed over longer periods of time. Suppose that a subject converts the rewards into days he can buy an additional coffee, and that a cup of coffee costs 30 kroner. When the subject is indifferent between 300 kroner today or 360 kroner in a year from now, the sooner reward is converted into an extra coffee on 10 subsequent days and the later reward is converted into an extra coffee on 12 subsequent days. This indifference point is given by

$$\underbrace{\sum_{t=S}^{S+\frac{x_S}{z}-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left(u\left(\omega_t + z\right) - u(\omega_t)\right)}_{\text{Added utility from consuming } z \text{ over } \frac{x_S}{z} \text{ days}} = \underbrace{\sum_{t=L}^{L+\frac{x_L}{z}-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left(u\left(\omega_t + z\right) - u(\omega_t)\right)}_{\text{Added utility from consuming } z \text{ over } \frac{x_L}{z} \text{ days}}. \quad (17)$$

where z is the price of coffee, x_S is the sooner reward at $t = S$ and x_L is the later reward at $t = L$. If background consumption ω_t is constant over time, then equation (17) simplifies to

$$\sum_{t=S}^{S+\frac{x_S}{z}-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} = \sum_{t=L}^{L+\frac{x_L}{z}-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \quad (18)$$

such that identification of the discount rate becomes independent of the utility function.

One can use this insight and consider an alternative experimental design that elicits individual discount rates over annuities. Instead of offering a choice between two rewards x_S and x_L at different points in time, one can offer a choice between two annuities with different start dates and durations. By varying the duration of the annuities one can identify the indifference point and the implied individual discount rate without identifying the utility function.

6 Summary and Conclusion

I use simulated indifference points from decision tasks in time preference experiments to analyze the sensitivity of individual discount rates with respect to background consumption and consumption smoothing. I control for the curvature of the utility function and differentiate between two estimation methods that are applied in previous studies: (1) when the utility function is non-linear and exogenous, and (2) when the utility function is inferred from choice data.

When the utility function is exogenous and non-linear, then individual discount rates are sensitive to the level of background consumption and to the extent of consumption smoothing. Previous experimental studies assume that the atemporal utility function is described by the CRRA specification, and I show both analytically and in numerical simulations that the individual discount rate tends toward the level under linear utility as consumption smoothing or background consumption increase.

When the utility function is instead jointly elicited with discount rates from choice data, then discount rates are robust to time-invariant background consumption and consumption smoothing. The inferred utility function is sensitive to these assumptions, but the curvature with respect to income and the inferred individual discount rates are stable. The result holds for alternative specifications of the utility function and for the alternative elicitation method in Andreoni and Sprenger (2012). Considering alternative discounting functions, I find that the β-parameter of the quasi-hyperbolic discounting model is only robust to background consumption, but not to consumption smoothing.

The different conclusions with respect to the sensitivity of discount rates under joint elicitation and under the assumption of an exogenous utility function explain why previous studies have found mixed results. Moreover, the results imply that exponential discount rates can be identified without knowing the exact level of time-invariant background consumption or the extent of time-invariant consumption smoothing as long as the utility function is jointly elicited.

A possibility that has not been discussed by several previous studies is that background consumption and consumption smoothing may vary over time. I show that individual discount rates are highly sensitive to time-variant background consumption and consumption smoothing. Moreover, expected increases in future background consumption can be an alternative explanation for present biased preferences. To date little is known about time-varying background consumption and how this affects preferences and could be an area for future research.

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Appendix A

Analytical Solutions for Discount Rate Sensitivity

Given the theoretical framework in Section 3, if background consumption ω and consumption smoothing λ are time-invariant, the discount rate is given by

$$\delta = \left[\frac{\left(\frac{\left(\omega + \frac{x_S}{\lambda}\right)^{(1-r)}}{1-r} - \frac{(\omega)^{(1-r)}}{1-r} \right)}{\left(\frac{\left(\omega + \frac{x_L}{\lambda}\right)^{(1-r)}}{1-r} - \frac{(\omega)^{(1-r)}}{1-r} \right)} \right]^{\frac{360}{L-S}} - 1 \tag{19}$$

I present the analytical properties of individual discount rates identified by equation (19).

A.1 Discount Rates in the Limit as ω Approaches Infinity

As background consumption ω approaches infinity for a given r-parameter, the discount rate δ tends toward the level under linear utility. The limit is given by

$$\lim_{\omega \to \infty} \delta = \left[\frac{\lim_{\omega \to \infty} \left(\left(\omega + \frac{x_L}{\lambda}\right)^{(1-r)} - (\omega)^{(1-r)} \right)}{\lim_{\omega \to \infty} \left(\left(\omega + \frac{x_S}{\lambda}\right)^{(1-r)} - (\omega)^{(1-r)} \right)} \right]^{\frac{360}{L-S}} - 1.$$

I divide both the numerator and denominator by $\omega^{(1-r)}$ and simplify the expression. The limit is then given by

$$\lim_{\omega \to \infty} \delta = \left[\frac{\lim_{\omega \to \infty} \left(\left(1 + \frac{\left(\frac{x_L}{\lambda}\right)}{\omega} \right)^{1-r} - 1 \right)}{\lim_{\omega \to \infty} \left(\left(1 + \frac{\left(\frac{x_S}{\lambda}\right)}{\omega} \right)^{1-r} - 1 \right)} \right]^{\frac{360}{L-S}} - 1.$$

Both the limit of the numerator and the limit of the denominator tend to 0, which allows me to use L'Hôpital's rule. I replace the limits of the numerator and denominator with the limits of the first order derivatives, respectively,

$$\lim_{\omega\to\infty} \delta = \left[\frac{\lim_{\omega\to\infty}\left((1-r)\left(1+\frac{\left(\frac{x_L}{\lambda}\right)}{\omega}\right)^{-r}\left(-\frac{\left(\frac{x_L}{\lambda}\right)}{\omega^2}\right)\right)}{\lim_{\omega\to\infty}\left((1-r)\left(1+\frac{\left(\frac{x_S}{\lambda}\right)}{\omega}\right)^{-r}\left(-\frac{\left(\frac{x_S}{\lambda}\right)}{\omega^2}\right)\right)}\right]^{\frac{360}{L-S}} - 1,$$

and simplify the equation further, so that the limit of δ is given by

$$\lim_{\omega\to\infty} \delta = \left[\frac{\lim_{\omega\to\infty}\left(\left(1+\frac{\left(\frac{x_L}{\lambda}\right)}{\omega}\right)^{-r} x_L\right)}{\lim_{\omega\to\infty}\left(\left(1+\frac{\left(\frac{x_S}{\lambda}\right)}{\omega}\right)^{-r} x_S\right)}\right]^{\frac{360}{L-S}} - 1.$$

The limits of the numerator and denominator tend toward x_L and x_S, respectively, as background consumption ω approaches infinity. The limit of the individual discount rate δ is then given by

$$\lim_{\omega\to\infty} \delta = \left[\frac{x_L}{x_S}\right]^{\frac{360}{L-S}} - 1,$$

which is the individual discount rate under linear utility.

A.2 Individual Discount Rates in the Limit as λ Approaches Infinity

As consumption smoothing λ approaches infinity for a given r-parameter, the discount rate δ tends toward the level under linear utility. The limit is given by

$$\lim_{\lambda\to\infty} \delta = \left[\frac{\lim_{\lambda\to\infty}\left(\left(\omega+\frac{x_L}{\lambda}\right)^{(1-r)} - (\omega)^{(1-r)}\right)}{\lim_{\lambda\to\infty}\left(\left(\omega+\frac{x_S}{\lambda}\right)^{(1-r)} - (\omega)^{(1-r)}\right)}\right]^{\frac{360}{L-S}} - 1,$$

Both the limit of the numerator and the limit of the denominator tend to 0 and I apply L'Hôpital's rule. I replace the limits of the numerator and denominator with the limits of the first order derivatives, respectively,

$$\lim_{\lambda\to\infty} \delta = \left[\frac{\lim_{\lambda\to\infty} \left((1-r) \left(\omega + \frac{x_L}{\lambda} \right)^{(-r)} \left(-\frac{x_L}{\lambda^2} \right) \right)}{\lim_{\lambda\to\infty} \left((1-r) \left(\omega + \frac{x_S}{\lambda} \right)^{(-r)} \left(-\frac{x_S}{\lambda^2} \right) \right)} \right]^{\frac{360}{L-S}} - 1.$$

The limits of the numerator and denominator tend toward $\omega^{-r} x_L$ and $\omega^{-r} x_S$, respectively, and the limit of the individual discount rate δ is then given by

$$\lim_{\lambda\to\infty} \delta = \left[\frac{x_L}{x_S} \right]^{\frac{360}{L-S}} - 1,$$

which is the individual discount rate under linear utility.

Appendix B

Alternative Utility Specifications

The analysis in Section 4 is based on the identification of a power utility function, and I show that individual discount rates are robust to background consumption and consumption smoothing if the utility function is jointly elicited. This result holds for other specifications of the atemporal utility function that are applied in the experimental literature: Discount rates are also robust to background consumption and consumption smoothing under exponential and expo-power utility specifications.

B.1 Exponential Utility Specification

A popular alternative representation of the utility function is the constant absolute risk aversion (CARA) specification of the form $u(x) = 1 - e^{-ax}$. Allowing for integration of rewards x with background consumption ω and consumption smoothing λ gives the atemporal utility function $u(x) = 1 - e^{-a\left(\frac{x}{\lambda}+\omega\right)}$. Absolute risk aversion with respect to income is equal to

$$A_x = \frac{a}{\lambda}.$$

Absolute risk aversion is independent of background consumption ω, decreasing with consumption smoothing λ, and increasing with the a-parameter.

Under exponential utility, indifference between binary lotteries is given by

$$\begin{aligned}
&\sum_{t=0}^{\lambda_{RA}-1}\left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left[p \cdot \left(1 - e^{-a\left(\omega_t + \frac{x_{A1}}{\lambda_{RA}}\right)}\right) + (1-p) \cdot \left(1 - e^{-a\left(\omega_t + \frac{x_{A2}}{\lambda_{RA}}\right)}\right)\right] \\
&\quad = \sum_{t=0}^{\lambda_{RA}-1}\left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left[p \cdot \left(1 - e^{-a\left(\omega_t + \frac{x_{B1}}{\lambda_{RA}}\right)}\right) + (1-p) \cdot \left(1 - e^{-a\left(\omega_t + \frac{x_{B2}}{\lambda_{RA}}\right)}\right)\right] \qquad (20)
\end{aligned}$$

which can be uniquely solved for a.

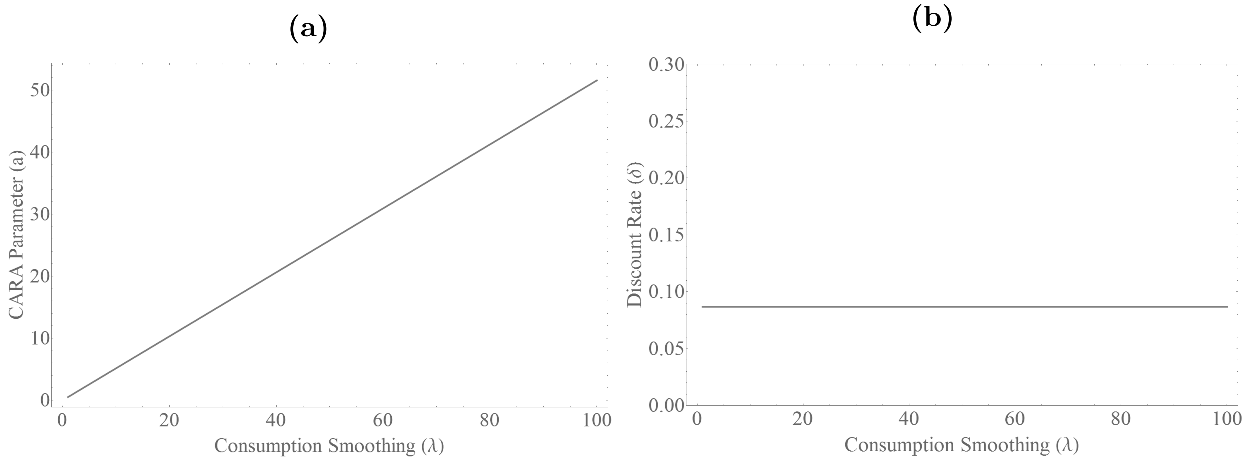
The indifference point between delayed rewards is given by

$$\sum_{t=S}^{S+\lambda_S-1}\left(\frac{1}{1+\delta}\right)^{\frac{t}{360}}\cdot\left(\left(1-e^{-a\left(\omega_t+\frac{x_S}{\lambda_S}\right)}\right)-\left(1-e^{-a\omega_t}\right)\right)$$
$$=\sum_{t=L}^{L+\lambda_L-1}\left(\frac{1}{1+\delta}\right)^{\frac{t}{360}}\cdot\left(\left(1-e^{-a\left(\omega_t+\frac{x_L}{\lambda_L}\right)}\right)-\left(1-e^{-a\omega_t}\right)\right)\quad(21)$$

Equations (20) and (21) simplify and ω_t cancels out. The utility function and the discount rate identified from Equations (20) and (21), respectively, are independent of background consumption.

I assume time-invariant consumption smoothing ($\lambda_{RA} = \lambda_S = \lambda_L$) and solve both equations numerically for the same decision tasks as in Section 4. Figure 8 (a) and (b) show the inferred values for the a-parameter and the individual discount rate δ, respectively. The a-parameter is increasing in λ, but the discount rate δ remains flat. The curvature of the utility function, measured by absolute risk aversion over income x, increases with a, but decreases with λ, and the combined effect leads to no changes in absolute risk aversion over income and elicited discount rates.

Figure 8: CARA Utility, Individual Discount Rates, and Consumption Smoothing



B.2 Expo-Power Utility Function

A flexible specification of the utility function is the expo-power utility function introduced by Abdellaoui et al. (2007). The utility function is $u(x) = -e^{-\frac{x^s}{s}}$, and it allows for both concave and convex utility and has desirable features such as a combination of increasing relative risk aversion and decreasing absolute risk aversion.

Under this utility function, indifference between binary lotteries is given by

$$\sum_{t=0}^{\lambda_{RA}-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left[p \cdot \left(-e^{-\frac{\left(\omega_t + \frac{x_{A1}}{\lambda_{RA}}\right)^s}{s}}\right) + (1-p) \cdot \left(-e^{-\frac{\left(\omega_t + \frac{x_{A2}}{\lambda_{RA}}\right)^s}{s}}\right)\right]$$
$$= \sum_{t=0}^{\lambda_{RA}-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left[p \cdot \left(-e^{-\frac{\left(\omega_t + \frac{x_{B1}}{\lambda_{RA}}\right)^s}{s}}\right) + (1-p) \cdot \left(-e^{-\frac{\left(\omega_t + \frac{x_{B2}}{\lambda_{RA}}\right)^s}{s}}\right)\right], \quad (22)$$

and the indifference point between delayed rewards is given by

$$\sum_{t=S}^{S+\lambda_S-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left(\left(-e^{-\frac{\left(\omega_t + \frac{x_S}{\lambda_S}\right)^s}{s}}\right) - \left(-e^{-\frac{\omega_t^s}{s}}\right)\right)$$
$$= \sum_{t=L}^{L+\lambda_L-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \cdot \left(\left(-e^{-\frac{\left(\omega_t + \frac{x_L}{\lambda_L}\right)^s}{s}}\right) - \left(-e^{-\frac{\omega_t^s}{s}}\right)\right). \quad (23)$$

I assume time-invariant background consumption and consumption smoothing and solve Equations (20) and (21) numerically for the same decision tasks as in Section 4. Figures 9 and 10 show the inferred values for the s-parameter and the individual discount rate δ for different levels of background consumption and consumption smoothing, respectively. The parameter of the utility function s decreases with background consumption ω and consumption smoothing λ, and elicited discount rates remain stable.[22]

[22] The value of s that solves the indifference equation (22) is very small for large values of λ and cannot be identified precisely. Discount rates are robust for values of λ between 1 and 16.

Figure 9: Expo-Power Utility, Individual Discount Rates, and Background Consumption

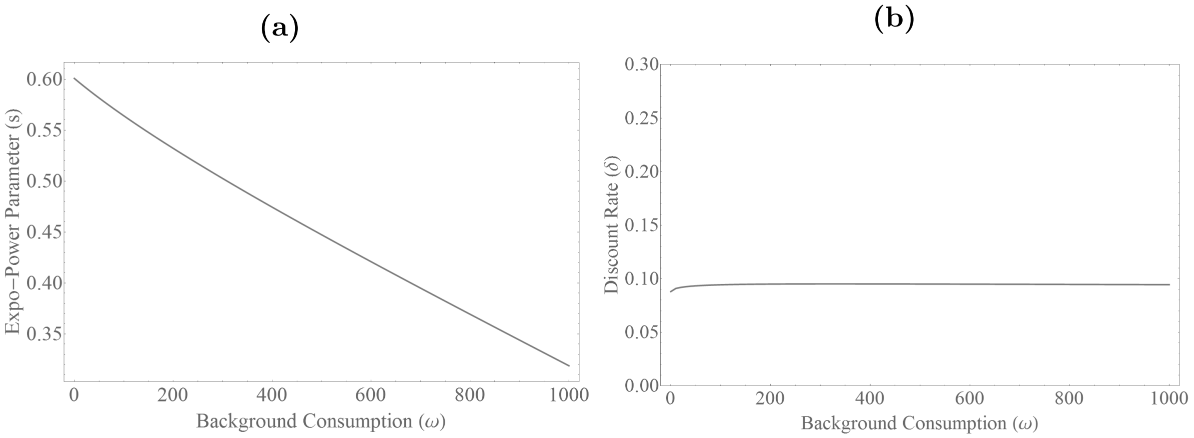
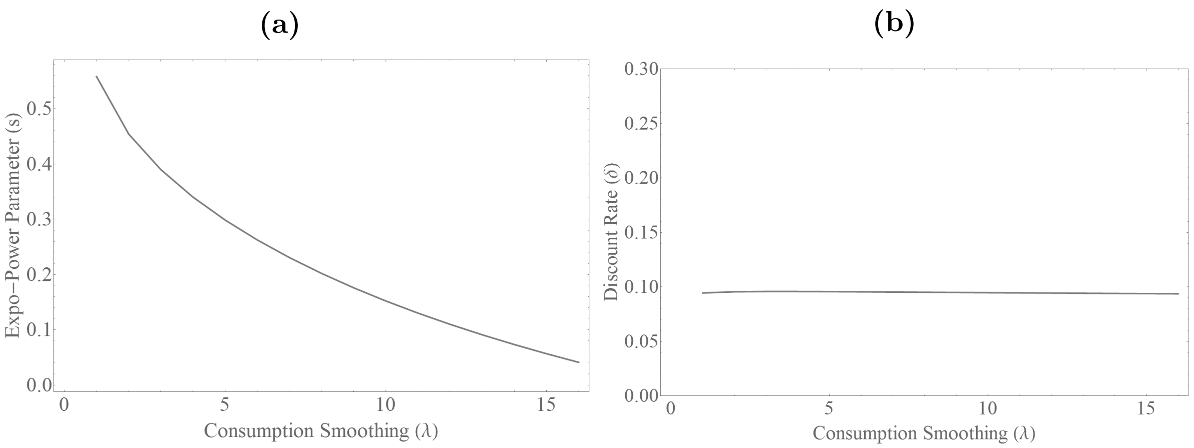


Figure 10: Expo-Power Utility, Individual Discount Rates, and Consumption Smoothing



Appendix C

Quasi-Hyperbolic Discounting

According to exponential discounting, future utility is discounted by the factor $\frac{1}{(1+\delta)^{\frac{t}{360}}}$, where δ is the discount rate per annum and t is measured in days. According to the quasi-hyperbolic discounting model, future utility is discounted by the factor $\frac{\beta}{(1+\delta)^{\frac{t}{360}}}$, where β is a new parameter that indicates present bias. If $\beta < 1$, then future utility is discounted by an additional fixed premium that gives a weaker preference for delayed rewards compared to the exponential discounting model.

Under quasi-hyperbolic discounting, the indifference point between a smaller, sooner and a larger, later reward depends on the delay of the later reward. In a decision task where both rewards are paid out in the future ($S > 0$ and $L > 0$), the indifference point is given by

$$\underbrace{\sum_{t=S}^{S+\lambda_S-1} \frac{\beta}{(1+\delta)^{\frac{t}{360}}} \cdot \left[u\left(\omega_t + \frac{x_S}{\lambda_S}\right) - u(\omega_t)\right]}_{\text{Added utility from consuming } x_S \text{ over } \lambda_S \text{ days}} = \underbrace{\sum_{t=L}^{L+\lambda_L-1} \frac{\beta}{(1+\delta)^{\frac{t}{360}}} \cdot \left[u\left(\omega_t + \frac{x_L}{\lambda_L}\right) - u(\omega_t)\right]}_{\text{Added utility from consuming } x_L \text{ over } \lambda_L \text{ days}} \quad (24)$$

and β cancels out on both sides of the equation, so that equation (24) simplifies to the same equation as under exponential discounting. A decision task where both rewards are paid out in the future identifies the δ-parameter of the quasi-hyperbolic discounting model.

In a decision task where the sooner reward is paid out immediately ($S = 0$), I differentiate between two scenarios. First, when rewards are consumed straight away so that $\lambda_S = \lambda_L = 1$, the indifference point is given by

$$\underbrace{\left[u\left(\omega_S + x_S\right) - u(\omega_S)\right]}_{\text{Added utility from consuming } x_S} = \underbrace{\frac{\beta}{(1+\delta)^{\frac{L}{360}}} \cdot \left[u\left(\omega_L + x_L\right) - u(\omega_L)\right]}_{\text{Added utility from consuming } x_L}. \quad (25)$$

The additional utility from the immediate reward is not discounted because the reward is spent at $t = 0$.

Second, when rewards are smoothed over more than one period, such that $\lambda_S > 1$ and $\lambda_L > 1$, the indifference point is given by

$$\underbrace{\left(1 + \sum_{t=1}^{\lambda_S - 1} \frac{\beta}{(1+\delta)^{\frac{t}{360}}}\right) \cdot \left[u\left(\omega_t + \frac{x_S}{\lambda_S}\right) - u(\omega_t)\right]}_{\text{Added utility from consuming } x_S \text{ over } \lambda_S \text{ days}}$$
$$= \underbrace{\sum_{t=L}^{L+\lambda_L - 1} \frac{\beta}{(1+\delta)^{\frac{t}{360}}} \cdot \left[u\left(\omega_t + \frac{x_L}{\lambda_L}\right) - u(\omega_t)\right]}_{\text{Added utility from consuming } x_L \text{ over } \lambda_L \text{ days}} \quad (26)$$

The additional utility from the fraction of the sooner reward that is spent immediately at $t = 0$ is not discounted. However, the additional utility from the fraction of the sooner reward that is spent later due to consumption smoothing is discounted by the factor $\frac{\beta}{(1+\delta)^{\frac{t}{360}}}$.

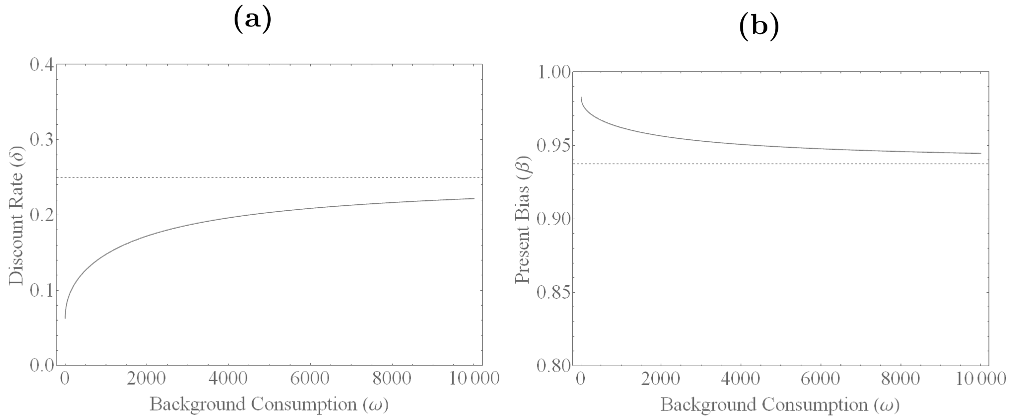
I analyze the effect of background consumption and consumption smoothing on the estimates of β and δ with these equations. I assume indifference between a smaller, sooner payment x_S of 3,000 kroner at t=30 and a larger, later payment x_L of 3,750 kroner after a 1-year delay at t=390. I assume a second indifference point between a smaller, immediate payment x_{S0} of 3,000 kroner at t=0 and a larger, later payment x_{L0} of 4000 kroner after a 1-year delay at t=360. These indifference points correspond to an individual discount rate δ of 25% and present bias $\beta = 0.9375$ under the assumption of linear utility, and they imply $\delta = 0.096$ and $\beta = 0.974$ when utility is represented by the CRRA specification with $r = 0.77$ under background consumption of 118 kroner per day and no consumption smoothing.

C.1 Quasi-Hyperbolic Discounting and Exogenous Utility

I start by assuming that the utility function is exogenous and $r = 0.77$. I first analyze the sensitivity of δ and β with respect to background consumption when λ is equal to 1, and then I look at the sensitivity with respect to consumption smoothing when ω is equal to 118 kroner per day.

Figure 11 (a) and (b) show the solutions for δ and β for different levels of background

Figure 11: CRRA Utility, Quasi-Hyperbolic Discounting and Background Consumption



consumption, respectively. The horizontal lines indicate the parameter values under linear utility. When r is exogenous and constant, both parameters tend toward the level under linear utility as background consumption increases.

Figure 12: CRRA Utility, Quasi-Hyperbolic Discounting and Consumption Smoothing

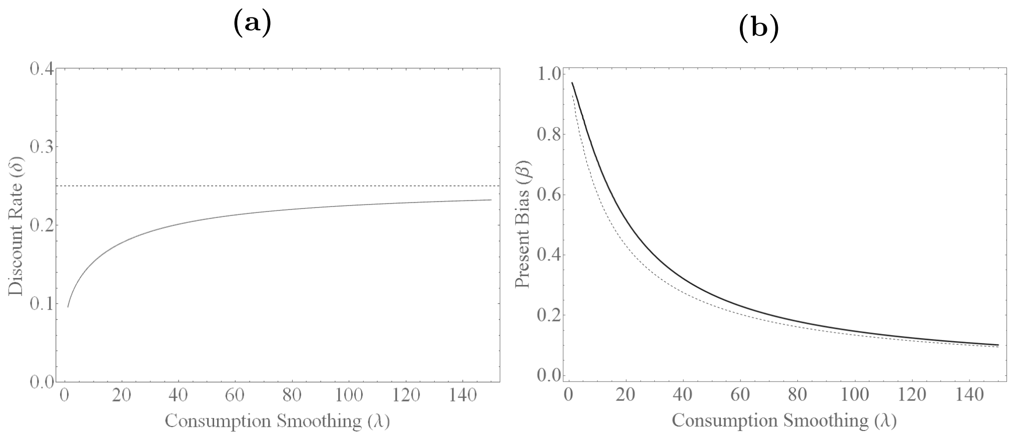
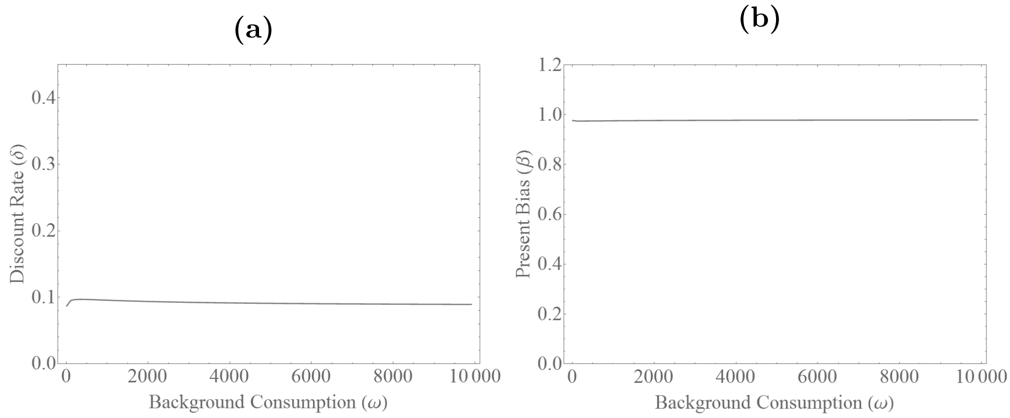


Figure 12 (a) and (b) show the solutions for δ and β for different degrees of consumption smoothing, respectively. The result for the discount rate δ is the same as before: the individual discount rate tends toward the level of discounting under linear utility.

In contrast, the β-parameter decreases significantly. The dashed curve shows that the β-parameter under the assumption of linear utility is also decreasing in λ. Consumption smoothing over longer periods of time reduces the fraction of the sooner reward that is spent immediately and present bias thus has an effect on utility from the immediate reward.

Figure 13: Quasi-Hyperbolic Discounting and Background Consumption under Joint Elicitation of the Utility Function



Hence, the degree of present bias identified from the indifference points becomes stronger.

C.2 Joint Elicitation of Quasi-Hyperbolic Discounting and Utility

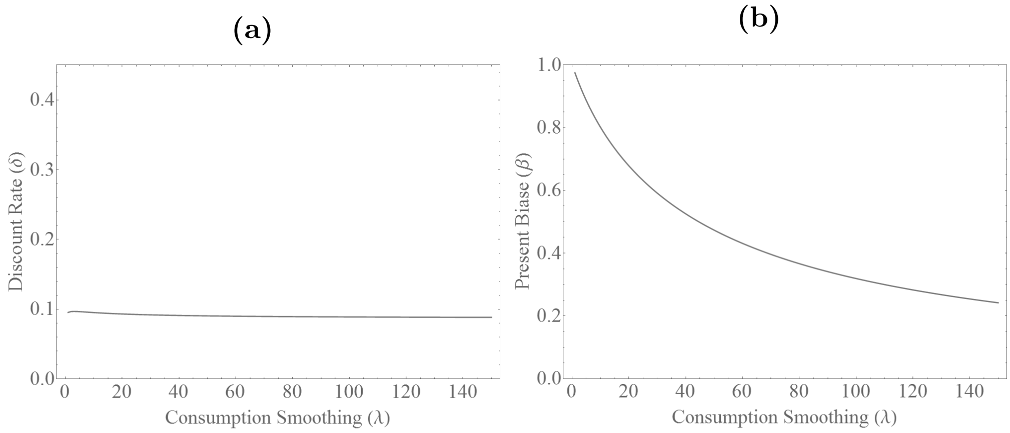
I next analyze the sensitivity of δ and β to assumptions on background consumption and consumption smoothing when the utility function is inferred from binary lottery choices.

I first keep consumption smoothing of both delayed rewards and lottery rewards constant at $\lambda = 1$ and vary the level of time-invariant background consumption ω. Figure 13 (a) and (b) show the inferred values for δ and β for different levels of background consumption ω.[23] The inferred δ-parameter is stable, and the inferred β-parameter is constant.

Figure 14 (a) and (b) show the inferred values for δ and β when I keep the amount of background consumption constant at 118 kroner per day, but vary the extent of time-invariant, uniform consumption smoothing. The inferred δ-parameter is stable as λ increases, but the inferred β-parameter is decreasing in λ even when the utility function is jointly elicited.

[23] The results for r are not shown but are equivalent to those reported in Figure 3.

Figure 14: Quasi-Hyperbolic Discounting to Consumption Smoothing under Joint Elicitation of the Utility Function



Appendix D

Sensitivity of Discount Rates from Convex Budget Set Allocations

In the design by Andreoni and Sprenger (2012), subjects allocate 100 tokens across two dates, where they are transformed by exchange rates into earnings that are paid out on those dates. Tokens allocated to the later date have a higher value than tokens allocated to the sooner date. The utility function and the individual discount rate can be inferred from at least two of these decision tasks with different exchange rates.

D.1 Background Consumption

Andreoni and Sprenger's (2012) assume integration of income with background consumption and no consumption smoothing. The utility function is represented by the CRRA specification. The decision of allocating the shares of tokens α and $1-\alpha$ between two dates $t = S$ and $t = L$ is described by the maximization problem

$$\max_{\alpha} U = \left(\frac{1}{1+\delta}\right)^{\frac{S}{360}} \frac{[\alpha \cdot X_S + \omega]^{1-r}}{1-r} + \left(\frac{1}{1+\delta}\right)^{\frac{L}{360}} \frac{[(1-\alpha) \cdot X_L + \omega]^{1-r}}{1-r}. \tag{27}$$

At the sooner date, each token has a value of $\frac{X_S}{100}$, and at the later date, each token has a value of $\frac{X_L}{100}$. If all 100 tokens are allocated to the sooner date ($\alpha = 1$), the subject receives X_S at $t = S$ and nothing at $t = L$, and vice versa.

Solving for the first-order condition with respect to α gives

$$FOC: \left(\frac{1}{1+\delta}\right)^{\frac{S}{360}} \cdot X_S \cdot [\alpha \cdot X_S + \omega]^{-r} = \left(\frac{1}{1+\delta}\right)^{\frac{L}{360}} \cdot X_L \cdot [(1-\alpha) \cdot X_L + \omega]^{-r} \quad (28)$$

which has a closed form solution for the discount rate, and δ is given by

$$\delta = \left(\frac{X_L \cdot [(1-\alpha) \cdot X_L + \omega]^{-r}}{X_S \cdot [\alpha \cdot X_S + \omega]^{-r}}\right)^{\frac{360}{L-S}} - 1 \quad (29)$$

An allocation in a single decision task identifies δ as a function of r, and together with an allocation in a second decision task with different exchange rates the discount rate δ and the r-parameter are uniquely identified. Figure 15 plots the first-order condition for two arbitrary allocations: (1) a 50:50 allocation of tokens between the sooner and later date, where $X_S = 17$ dollars at $t = 0$ and $X_L = 20$ dollars at $t = 360$ and (2) a 30:70 allocation between the sooner and later date, where $X_S = 15$ dollars at $t = 0$ and $X_L = 20$ dollars at $t = 360$. I assume that all earnings are integrated with background consumption ω, which is set equal to 7.05.[24] These particular allocations identify a discount rate $\delta = 15\%$ and a utility function with $r = 0.26$.

I analyze the sensitivity of the inferred r-parameter and the individual discount rate δ to different levels of time-invariant background consumption. Figure 16 shows the inferred values for r and δ for different levels of ω between 0 and 1,000. The r-parameter increases with background consumption while the individual discount rate is constant at 15%.

Most respondents in Andreoni and Sprenger (2012) do not make interior allocations to both dates. 70% of respondents allocate all tokens to either date. Andreoni and Sprenger (2012) estimate individual discount rates and the utility function for the pooled sample and find a similar discount rate and a similar r-parameter as I use in this analysis. Harrison

[24]This is the amount (in dollars) that Andreoni and Sprenger's (2012) elicit from the subjects via a survey question probing average daily consumption.

Figure 15: Identification of Individual Discount Rates from Intertemporal Allocations

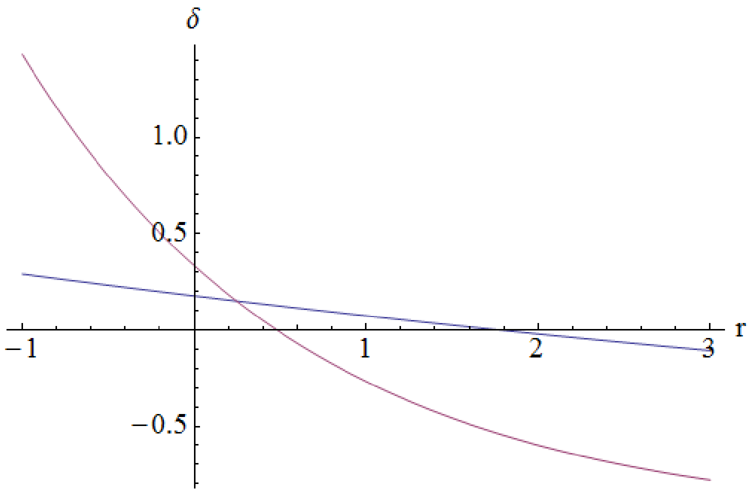
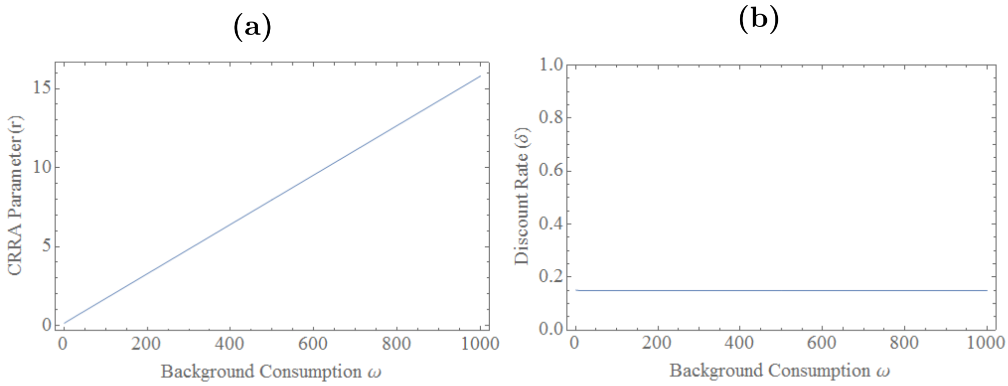


Figure 16: CRRA Utility, Exponential Discount Rates and Background Consumption from Intertemporal Allocations



et al. (2013, p. 4) comment on Andreoni and Sprenger (2012) and state that the majority of respondents that make only corner allocations "...*must* either have linear or convex utility functions." If the utility function is convex, the decision tasks in Andreoni and Sprenger (2012) cannot uniquely identify the discount rate and the utility function: A subject with a slightly convex utility function and a subject with a highly convex utility function would both make the same corner allocations.

D.2 Consumption Smoothing

Andreoni and Sprenger (2012) do not consider consumption smoothing in their analysis. I adapt equations (27) and (28) to include consumption smoothing. The choice problem, when the sooner (later) earnings are smoothed over λ_S (λ_L) periods, is given by

$$\max_{\alpha} U = \sum_{t=S}^{S+\lambda_S-1} \left(\frac{1}{1+\delta}\right)^{\frac{t}{360}} \frac{\left[\alpha \cdot \frac{X_S}{\lambda_S} + \omega\right]^{1-r}}{1-r} + \sum_{t=L}^{L+\lambda_L-1} \left(\frac{1}{1+\delta}\right)^{\frac{L}{360}} \frac{\left[(1-\alpha) \cdot \frac{X_L}{\lambda_L} + \omega\right]^{1-r}}{1-r} \tag{30}$$

and the first-order condition is given by

$$FOC: \sum_{t=S}^{S+\lambda_S-1} \left(\frac{1}{1+\delta}\right)^{\frac{S}{360}} \cdot \frac{X_S}{\lambda_S} \cdot \left[\alpha \cdot \frac{X_S}{\lambda_S} + \omega\right]^{-r}$$
$$= \sum_{t=S}^{L+\lambda_L-1} \left(\frac{1}{1+\delta}\right)^{\frac{L}{360}} \cdot \frac{X_L}{\lambda_L} \cdot \left[(1-\alpha) \cdot \frac{X_L}{\lambda_L} + \omega\right]^{-r} \tag{31}$$

If $\lambda_S = \lambda_L = \lambda$, equation (31) simplifies to

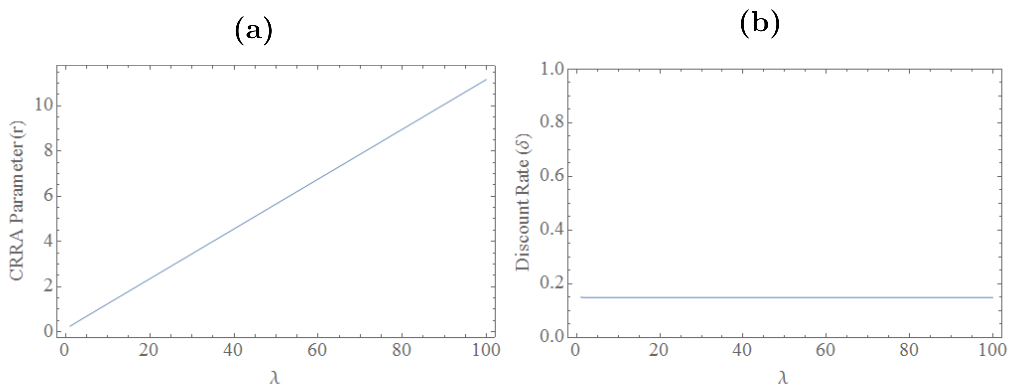
$$FOC: \left(\frac{1}{1+\delta}\right)^{\frac{S}{360}} \cdot \frac{X_S}{\lambda} \cdot \left[\alpha \cdot \frac{X_S}{\lambda} + \omega\right]^{-r} = \left(\frac{1}{1+\delta}\right)^{\frac{L}{360}} \cdot \frac{X_L}{\lambda} \cdot \left[(1-\alpha) \cdot \frac{X_L}{\lambda} + \omega\right]^{-r} \tag{32}$$

The individual discount rate δ is identified by

$$\delta = \left(\frac{\frac{X_L}{\lambda} \cdot \left[(1-\alpha) \cdot \frac{X_L}{\lambda} + \omega\right]^{-r}}{\frac{X_S}{\lambda} \cdot \left[\alpha \cdot \frac{X_S}{\lambda} + \omega\right]^{-r}} \right)^{\frac{360}{L-S}} - 1 \tag{33}$$

Figure 17 shows the inferred values for δ and r from the two allocations described previously for different values of consumption smoothing λ between 1 day and 100 days. The inferred r-parameter is increasing in λ, but the individual discount rate δ is flat.

Figure 17: CRRA Utility, Exponential Discount Rates and Consumption Smoothing from Intertemporal Allocations



Chapter 2

Financial Wealth, Liquidity Constraints, and Discounting Behavior

Financial Wealth, Liquidity Constraints, and Discounting Behavior

Lasse J. Jessen* and Morten I. Lau†

Abstract

Life cycle models of consumption and saving behavior associate higher discount rates with lower financial wealth and present bias with liquidity constraints. We test these associations and analyze whether discounting behavior in time preference experiments is correlated with wealth and liquidity. We combine choice data from a field experiment in Denmark with detailed administrative data on individual income and financial wealth and estimate exponential and quasi-hyperbolic discounting models. Our results reveal no evidence of present bias for either affluent or liquidity constrained subjects. However, subjects in the lowest wealth quartiles exhibit exponential discount rates that are nearly twice as high as those we estimate for subjects in the highest wealth quartiles.

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1 Introduction

Each day we make decisions that have some future effects on our wellbeing. The tradeoff between sooner and later payoffs influences our choices with respect to what we eat, how long we invest in education, how hard we work, consumption of alcohol, cigarettes or drugs, etc. In an economic context, the concept of time preferences is particularly important in one area: intertemporal decisions regarding consumption, saving, and investment. John Rae's (1834) *The Sociological Theory of Capital* suggests that differences in the wealth of nations are related to psychological factors that influence patience, and calibrations of modern life cycle models to aggregate consumption and income data assume that individual discount rates are correlated with private saving decisions and financial wealth (e.g. Krusell and Smith, 1998; Hendricks, 2007).

The identification and measurement of time preferences has received considerable attention in experimental economics. The typical experimental design involves choices over time delayed rewards from which individual discount rates are identified (for reviews, see Frederick et al., 2002, and Andersen et al., 2014). There is an extensive experimental literature on the association between individual discount rates and behavior with potential long-term negative health effects, such as smoking, obesity, or drug addiction.[1] However, there is a distinct lack of empirical evidence on the association between time preferences and saving behavior, and only a few experimental studies, namely Meier and Sprenger (2010), Pender (1996), Yesuf and Bluffstone (2008), and Kirby et al. (2002), have investigated the association between individual discounting behavior and wealth.

We contribute to the experimental literature on individual discounting and saving behavior with new empirical evidence. We combine data on income and financial wealth from registers at Statistics Denmark with data from a field experiment on risk and time preferences. The sample of 413 subjects is representative of the adult Danish population and is stratified according to population size in each region of the country. Using maximum likelihood estimation, we identify differences in individual discount rates with respect to

[1]See for example Khwaja et al. (2007) and Harrison et al. (2010) on smoking behavior, Kirby et al. (1999) on drug addiction, and Komlos et al. (2004) on obesity.

financial wealth while controlling for relevant socio-demographic characteristics. Subjects with high wealth reveal lower discount rates than subjects with low or negative wealth. This result suggests that heterogeneity in individual discount rates and financial wealth are associated.

Life cycle models that apply the quasi-hyperbolic discounting function predict that present biased consumers will hold fewer deposits of liquid assets and are more likely to accumulate consumer debt than otherwise. We test this prediction by estimating the quasi-hyperbolic discounting model and study the correlation between present bias and deposits of liquid assets. We find no evidence of present bias in the sample and reject the quasi-hyperbolic model in favor of exponential discounting. We also find that present bias is not significantly correlated with liquidity constraints measured by deposits of liquid assets. These results stand in sharp contrast to previous empirical results by Meier and Sprenger (2010) who find a significant association between present bias and consumer debt.

The paper proceeds as follows: In Section 2, we review the theoretical and empirical literature on the association between individual discount rates and financial wealth and formulate the hypotheses we will test with our data. We present the experimental design and data in Section 3 and discuss the structural econometric specifications. We introduce the administrative data in Section 4 and explain the measurement of wealth and liquidity that we use in the analysis. The estimation results and sensitivity analysis are presented in Section 5 before we conclude the analysis.

2 Theoretical and Empirical Literature

The discussion on time preferences in the economics literature originates from studies on saving and wealth across nations. We review the theoretical and empirical literature on time preferences and private saving decisions.

2.1 Wealth and Exponential Discounting

John Rae (1834) directly links time preferences to accumulation of private wealth, and he suggests that psychological attitudes toward delayed gratification and self-restraint are associated with private saving. Private saving leads to accumulation of capital and is thus an important factor in economic growth theory. Using Samuelson's (1937) exponential specification of individual discounting in an additive life cycle model of intertemporal consumption (e.g., Hall, 1978) captures the effect of time preferences on private saving. The solution to the intertemporal maximization problem is characterized by the Euler equation, which specifies the relation between the (expected) marginal utility of consumption in period t and $t+1$, respectively, by

$$E_t\left[u'(c_{t+1})\right] = \left(\frac{1+\delta}{1+i}\right) u'(c_t), \tag{1}$$

where i is the market interest rate between period t and $t+1$, and δ is the individual discount rate. Equation (1) shows the optimal consumption profile, which is determined by the relative difference between the discount rate and market interest rate: a higher discount rate δ is associated with lower consumption growth. The model predicts that higher discount rates reduce private saving for future consumption and thus have a negative impact on consumption growth, *ceteris paribus*.

Heterogeneity in individual discount rates has important theoretical implications for private saving and capital accumulation. In a simple economy with two households, Becker (1980) shows that all capital eventually will be held by the most patient household. Using that model, Becker asserts Ramsey's (1928) conjecture on "...a division of society into two classes, the thrifty enjoying bliss and the improvident at the subsistence level." These extreme wealth distributions that are predicted by early life cycle models do not conform to aggregate data on consumption and private saving, and alternative specifications with non-additive intertemporal utility functions lead to more realistic wealth distributions. These models still predict that there is a significant effect of individual discount rates on private saving and wealth (e.g., Lucas Jr and Stokey, 1984; Epstein and Hynes, 1983).

The empirical evidence on the association between individual discount rates and private saving implied by theoretical life cycle models is scarce. Lawrance (1991) estimates individual discount rates using administrative panel data on consumption, income, and savings. The results indicate that discount rates are lower for individuals with high permanent income compared to those with low income, but she does not study the association between individual discount rates and private saving rates. Furthermore, her identification approach is not appropriate when prudence and precautionary measures against income fluctuations are added as motives for private saving (see Deaton, 1991; Carroll, 1997). In this case, individual discount rates cannot be identified from administrative consumption and saving data because patience and prudence cannot be disentangled (Carroll, 1997).

Krusell and Smith (1998) use a model that incorporates precautionary saving motives and show in a calibration exercise that heterogeneity in individual discount rates help explain the distribution of private wealth in U.S. consumption data. In particular, consumers with high discount rates hold significantly less wealth than those with lower discount rates. Hendricks (2007) confirms these results, applying a different model with a finite planning horizon to the same administrative data instead of the model with an infinite planning horizon that is applied in Krusell and Smith (1998).

The theoretical implications of individual discounting behavior on private saving and wealth are clear: Patience in the form of lower discount rates is associated with higher private saving and wealth. The first hypothesis we test is:

> *Hypothesis 1: Individual discount rates are significantly correlated with private financial wealth: subjects with high financial wealth have significantly lower discount rates than subjects with low financial wealth.*

To date, the experimental evidence that tests this hypothesis is limited, as it is rare to have reliable information on both individual discount rates and financial wealth. Some studies using data from developing countries have collected information on household assets from surveys and conducted time preference experiments with subjects from the same sample, whereas other studies rely entirely on proxies of private saving and wealth.

Pender (1996) tests different models of credit supply and imperfect capital markets in India. He runs intertemporal choice experiments with a sample of subjects from two villages, who are asked to make binary choices over a smaller amount of rice received at a sooner date or a larger amount received at a later date. The front-end delay to the sooner reward was 1 month, 4 months, and 8 months, and the time delay between the sooner and later rewards was 7, 12, 19, and 24 months. Data on socio-demographic characteristics and information on private assets and debt from a related study are used to test the association between individual discount rates and private wealth.[2] Positive wealth is significantly correlated with the observed willingness to wait for the larger, later reward when there is a front-end delay of 1 month, but not when the front-end delay is 4 months or 8 months.

Yesuf and Bluffstone (2008) conduct a comparable study with 262 farm households in Ethiopia and find that private wealth is negatively correlated with elicited discount rates.[3] The subjects made binary choices over rewards that were paid out in cash, where the sooner reward was paid out immediately and the time delay between the sooner and later rewards was 3, 6 and 12 months. Interestingly, they find that cash holdings are not correlated with individual discount rates, despite the significant correlation between discount rates and private wealth.

A third study, also conducted in a developing country, is by Kirby et al. (2002). They analyze the association between individual discount rates and information on health, education, age, and private wealth using a sample of 154 subjects between 10 and 80 years of an indigenous society from the Bolivian rain forest. They collect data on individual discount rates from incentivized decision tasks, as well as data on socio-demographic characteristics that includes a measure of private wealth based on the monetary value of physical assets owned by the person.[4] The subjects made choices between immediate and delayed rewards,

[2] Private wealth is measured as the cash value of land, buildings, livestock, farming tools, stocks of agricultural products, inputs, household items and consumer durables, plus financial assets and minus financial debt.

[3] Wealth is measured as the cash value of land, oxen and capital.

[4] These assets include cattle, ducks, chickens, pigs, rifles, radios, canoes, mosquito nets, dogs, machetes

and the time delay between the sooner and later rewards varied between 7 and 157 days. Kirby et al. (2002) do not find a significant association between individual discount rates and private wealth, but they do find a significant negative correlation between individual discount rates and income.

While the results are mixed, there is some support for the hypothesis that individual discount rates are significantly correlated with private wealth. However, the previous studies consider only empirical evidence from developing countries and there is no empirical evidence yet for developed countries.[5] Moreover, none of the previous studies elicit discount rates over utility of income, and we return to this issue later.

2.2 Liquidity and Present Bias

Several experimental studies show that the assumption of constant individual discount rates in the exponential discounting model may be violated (see reviews by Frederick et al., 2002; Andersen et al., 2014). In particular, individual discount rates may be declining over time and some subjects may have a preference for the present that cannot be explained by the exponential discounting model. A discounting model that captures present bias was introduced by Phelps and Pollak (1968) and popularized by Laibson (1997), and it is known as the quasi-hyperbolic discounting model.[6] Laibson (1997) applies this discounting function to a model of life cycle consumption and saving behavior and the intertemporal utility function is specified as

$$U_t = E_t \left[u(c_t) + \beta \sum_{\tau=1}^{T-t} \left(\frac{1}{1+\delta} \right)^{\tau} u(c_{t+\tau}) \right]. \tag{2}$$

In the quasi-hyperbolic model future utiliy is discounted by the discount rate, δ, and an additional parameter β that measures present bias. The exponential discounting model is

and axes.

[5]Dohmen et al. (2015) use survey instruments to measure time preferences across several countries and they find a positive relationship between their measure of patience and a country's capital stock, gross savings, net savings and household savings rate. However, they do not have measures of private wealth at the individual level and instead consider proxies such as income and education. Moreover, their measure of time preferences is based on hypothetical survey questions and not on incentivized decision tasks.

[6]The structural model was introduced by Phelps and Pollak (1968) in an overlapping-generations context in which current generations discount the utility of future generations.

nested in equation (2) when $\beta = 1$. A lower value of β implies that future rewards are discounted more, and $\beta < 1$ indicates a present bias. One implication of present bias is that time preferences are dynamically inconsistent in the sense that one may systematically deviate from long-term plans and consume more in the present than planned in the past.

Quasi-hyperbolic discounting may also have important implications for portfolio choice. Because liquid assets allow an individual to succumb to temptation and consume more than initially planned, Laibson asserts that a present biased consumer, who is more likely to give in to temptation, will hold fewer liquid assets than a consumer who is not present biased but otherwise has the same preferences. Holding fewer liquid assets is either the result of giving in to temptation as just described or the result of holding larger stocks of illiquid assets as a commitment device to prevent falling for temptation. Laibson furthermore asserts that easy access to consumer debt against illiquid assets and future income, such as credit cards, may undermine the commitment aspect of holding illiquid assets, which results in higher borrowing by present biased individuals with access to consumer credit.

Angeletos et al. (2001) incorporate quasi-hyperbolic discounting into a life cycle model with precautionary savings and simulate portfolio choice between liquid and illiquid assets. They find that the quasi-hyperbolic model is more appropriate than the exponential discounting model in explaining aggregate data from the US Survey of Consumer Finances.[7] We formulate our second hypothesis based on this literature:

> *Hypothesis 2: Present bias is significantly correlated with portfolio choice and the allocation of financial wealth between liquid and illiquid assets. Subjects who are present biased hold significantly fewer liquid assets than subjects who are not present biased.*

While model calibrations and simulations such as those in Angeletos et al. (2001) or Laibson et al. (2007) are valuable, and the concept of quasi-hyperbolic discounting is intuitive, the empirical evidence from experimental economics that supports the association

[7] Angeletos et al. (2001) assume that present biased individuals are sophisticated and correctly anticipate tempting consumption opportunities. As a result, the consumption profiles and wealth levels of quasi-hyperbolic and exponential discounters are similar but quasi-hyperbolic discounters hold fewer liquid assets than exponential discounters.

between present bias and portfolio choice is scarce. The only study to our knowledge that examines the correlation between present bias and financial wealth is that by Meier and Sprenger (2010). They conduct a field experiment with predominantly low-income people seeking assistance in filing their annual income tax statements. Each subject made choices between smaller, sooner rewards and a larger, later reward that was fixed. The sooner and later dates in the experimental design were: (a) immediately and in 1 month, (b) immediately and in 6 months, and (c) in 6 months and in 7 months. This design allows one to identify exponential and quasi-hyperbolic discounting functions.[8]

Meier and Sprenger (2010) combine data from the field experiment with administrative data on income and credit records, which allows them to generate reliable measures of credit card debt and credit ratings.[9] The analysis reveals that present biased subjects have significantly higher credit card debt than otherwise, and the exponential discount rate δ is not significantly correlated with the debt balance. These results support the assertion by Laibson (1997) that present bias may be significantly correlated with consumer debt, but the study is limited by only looking at short term liabilities and leaving out (liquid and illiquid) assets.

3 Experimental Design and Identification of Time Preferences

In this section, we describe the experimental data, underlying theoretical assumptions, and procedures for the identification of individual discount rates from choices over monetary rewards that are paid out at different points in time.

[8]Meier and Sprenger (2010) note that differences in utility curvature across subjects may confound their conclusions with respect to individual discount rates. They address this issue by eliciting a survey measure of risk tolerance and use it as a control variable in their estimations. The results are not influenced by this control variable and remain unchanged.

[9]Meier and Sprenger (2010) do not have access to administrative data on liquid and illiquid assets and only have limited survey information on liabilities other than credit card debt. They can only analyze the correlation between discount rates (or present bias) and borrowing behavior, and not the correlation between discount rates (or present bias) and total wealth.

3.1 Experimental Choice Data

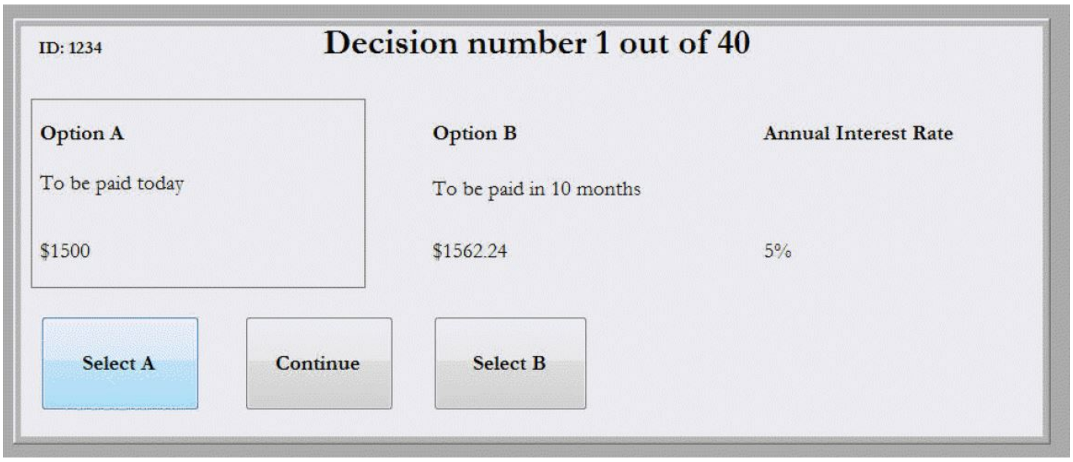
We use choice data from a field experiment by Andersen et al. (2014) with a representative sample of the Danish population consisting of 413 subjects. We refer to the original publication for details on experimental procedures, sample selection, payment procedures and implementation of treatments. In our analysis, we use data from two standard experimental decision tasks: The first decision task identifies discounting behavior from binary choices between smaller, sooner and larger, later rewards. The second decision task identifies the utility function (risk aversion) from binary choices between lotteries. In both decision tasks, subjects had a 10% chance of being paid according to one of their decisions.

Discounting Task

Andersen et al. (2014) ask subjects to make a series of choices over two certain outcomes. For example, one option can be 3,000 kroner in 1 month, and another option can be 3,300 kroner in 13 months. If the subject selects the earlier option, we can infer that his or her discount rate over one year is more than 10%, and if the subject picks the later option, we can infer that his or her discount rate over one year is less than 10%. By varying the amount of the later option, we can identify the individual discount rate.

The time horizon between the sooner and later payments and the front-end delay to the sooner payment were varied to identify the shape of the discounting function and present bias. The time delays were .5, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 or 12 months. Each subject made 40 decisions in total, with 10 decisions for each of 4 randomly assigned time delays, and the interest rate in the decision tasks varied between 5% and 50% per annum. The front-end delay was assigned between subjects and the sooner reward was either paid out immediately or 1 month after the experiment. Four other treatments were assigned between subjects: (i) the sooner reward was either 1,500 kroner or 3,000 kroner, (ii) the time horizons were presented in ascending or descending order, (iii) information on implied interest rates was either provided or not provided, and (iv) the discounting task came either before or after the risk aversion task. The decision tasks were displayed one at a time and the subjects were asked to select their preferred option (Figure 1).

Figure 1: Example of Discounting Task (Source: Andersen et al., 2014)



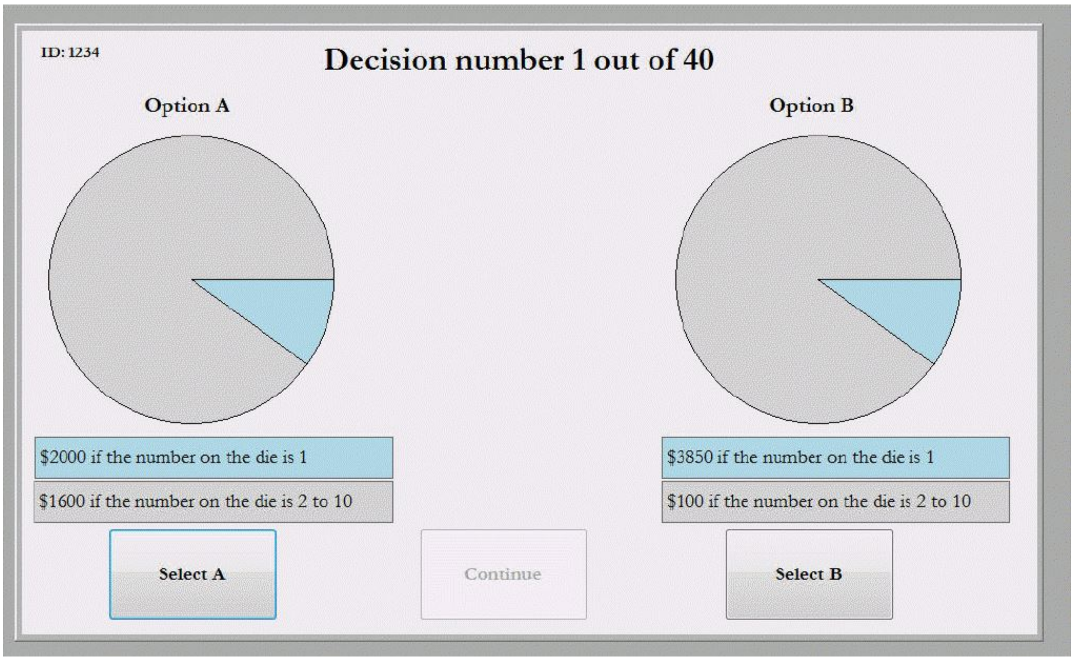
Risk Aversion Task

Risk attitudes are evaluated by asking subjects to make a series of choices over outcomes that involve some uncertainty. The decision tasks allow us to identify the utility function, and thus discount rates over the utility of income. The experimental design is based on the risk aversion experiments by Holt and Laury (2002) and poses a series of binary lottery choices. For example, lottery A might give the subject a 50-50 chance of receiving 1,600 kroner or 2,000 kroner to be paid today, and lottery B might have a 50-50 chance of receiving 3,850 kroner or 100 kroner today. The subject picks A or B. One series of 10 choices would offer these prize sets, where the probability of the highest prize in each lottery starts at 0.1 in the first decision task, it increases by 0.1 to 0.2 in the next decision task, and so on until the last decision task is between two certain amounts of money (2,000 kroner and 3,850 kroner in this example).

The experimental procedures in Holt and Laury (2002) provided a single decision sheet with all 10 decision tasks displayed at once and presented in an ordered manner. Andersen et al. (2014) iused a similar experimental design but presented the decision tasks one at a time and used pie charts to display the probabilities in each lottery (as in Figure 2). Each subject made 40 decisions in total, with 10 decisions for each of 4 randomly assigned prize sets.[10]

[10]These prize sets were [A1: 2,000 and 1,600; B1: 3,850 and 100], [A2: 1,125 and 750; B2: 2,000 and 250], [A3: 1,000 and 875; B3: 2,000 and 75] and [A4: 2,250 and 1,000; B4: 4,500 and 50].

Figure 2: Example of Risk Aversion Task (Source: Andersen et al., 2014)



3.2 Structural Specification and Identification

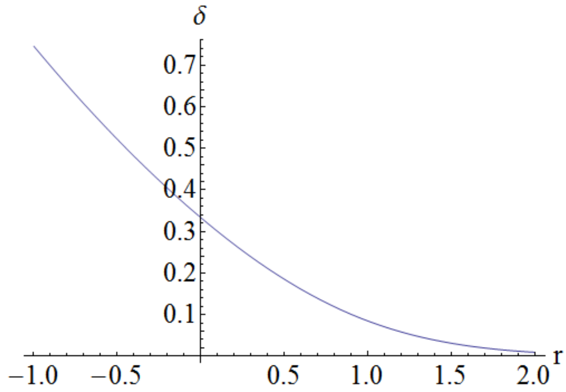
Our identification of individual discount rates relies on binary choices between sooner, smaller and larger, later monetary rewards. We follow the existing literature (e.g., Andersen et al., 2008; Andreoni and Sprenger, 2012a) and assume that utility is defined over a constant measure of background consumption (or income) ω plus the monetary reward x from the experiment. Under the assumption of constant relative risk aversion, atemporal utility is defined as

$$u(x) = \frac{(\omega + x)^{1-r}}{1-r}. \tag{3}$$

Under the assumption of exponential discounting, the added utility from a smaller sooner reward x_S at time $t = S$ is

$$DU_S = \frac{1}{1+\delta}^{S} \cdot \left(\frac{(\omega + x_S)^{1-r}}{1-r} - \frac{\omega^{1-r}}{1-r} \right), \tag{4}$$

Figure 3: (δ, r) Combinations Implied by Indifference Between Delayed Rewards



and the added utility for a larger later reward x_L at time $t = L$ is

$$DU_L = \frac{1}{1+\delta}^{L} \cdot \left(\frac{(\omega + x_L)^{1-r}}{1-r} - \frac{\omega^{1-r}}{1-r} \right). \tag{5}$$

The indifference point between the smaller, sooner and larger, later rewards identifies the discount rate δ and is given by

$$\delta = \left(\frac{\frac{(\omega+x_L)^{1-r}}{1-r} - \frac{\omega^{1-r}}{1-r}}{\frac{(\omega+x_S)^{1-r}}{1-r} - \frac{\omega^{1-r}}{1-r}} \right)^{\frac{1}{L-S}} - 1. \tag{6}$$

The experimental design also allows us to identify the quasi-hyperbolic discounting model and present bias. The quasi-hyperbolic discounting model is specified by

$$DU_t = \begin{cases} \frac{\beta}{(1+\delta)^t} \cdot \left(\frac{(\omega+x_t)^{1-r}}{1-r} - \frac{\omega^{1-r}}{1-r} \right) & \text{if } t > 0, \\ \left(\frac{(\omega+x_t)^{1-r}}{1-r} - \frac{\omega^{1-r}}{1-r} \right) & \text{if } t = 0. \end{cases} \tag{7}$$

Equation (6) shows that discount rates are a function of the relative risk aversion, r. Figure 3 plots the (δ, r) combinations that are implied by an indifference point between a sooner payment of 3,000 kroner now and and a later payment of 3,400 kroner in 1 year. Different levels of relative risk aversion result in different levels of individual discount rates, as shown by Andersen et al. (2008).

We thus control for relative risk aversion in our estimation of individual discount rates.[11] Under expected utility theory, the utility from selecting a relatively safe lottery A, which pays out the rewards x_{A1} and x_{A2} with probability p and $(1-p)$ respectively is

$$EU_A = p \cdot \frac{(\omega + x_{A1})^{1-r}}{1-r} + (1-p) \cdot \frac{(\omega + x_{A2})^{1-r}}{1-r}, \tag{8}$$

and the utility of selecting a relative more risky lottery B with rewards x_{B1} and x_{B2} is

$$EU_B = p \cdot \frac{(\omega + x_{B1})^{1-r}}{1-r} + (1-p) \cdot \frac{(\omega + x_{B2})^{1-r}}{1-r}. \tag{9}$$

The utility function is uniquely identified from the indifference point between EU_A and EU_B given the outcomes and probabilities. We assume that the utility function is constant over time, which is standard in the literature on individual discounting. Combining data from the risk aversion and discounting tasks we can identify a unique point on the graph in Figure 3.

3.3 Econometric Methodology

We use maximum likelihood to estimate individual discount rates and the utility function and follow the same statistical method as Andersen et al. (2014). We first estimate individual discount rates under the assumption that utility is linear, which is the traditional approach in the literature, and then relax this assumption and allow for non-linear utility.

Estimation of Discount Rates under Linear Utility

For each choice over delayed rewards, we define a latent index as the difference between the discounted utility from the larger, later reward DU_L and the discounted utility from the

[11] Andreoni and Sprenger (2012a) find a significant difference between utility curvature elicited from lottery choices and utility curvature elicited from intertemporal allocations along a convex budget set. They claim that "the practice of using [...] risk experiments to identify and correct for curvature in discounting may be problematic" (p. 3353) and further argue in Andreoni and Sprenger (2012b) that risk preferences are not time preferences. However, the results in Andreoni and Sprenger (2012b) can be explained by correlation aversion, which is discussed by Cheung (2015).

smaller, sooner reward DU_S

$$\Delta DU = DU_L - DU_S. \tag{10}$$

We assume that ΔDU is linked to the probability of choosing the larger, later reward over the smaller, sooner reward via the cumulative logistic distribution function, hence

$$P(choose\ later\ reward) = F(\Delta DU). \tag{11}$$

Indifference between the smaller, sooner and the larger, later reward, such that $\Delta DU = 0$, indicates that the probability of choosing either reward is equal to 0.5. When $\Delta DU > 0$, the probability of choosing the larger, later reward is higher than 0.5, and vice versa. We then define the log likelihood function, given the structural decision model and observed choices y, as

$$ln\ L(\delta;\ y,\ r = 0) = \sum_i \left[ln\left(F(\Delta DU)\right) \cdot I(y = L) + ln\left(F(-\Delta DU)\right) \cdot I(y = S)\right]. \tag{12}$$

We adopt two extensions to this basic framework. First, we introduce a parameter that controls the stochastic component in the decision-making process by adding a behavioral Fechner (1966) error term. We replace equation (10) with

$$\Delta DU' = \frac{DU_L - DU_S}{\mu_{IDR}}. \tag{13}$$

The parameter μ_{IDR} is endogenous and estimated within the maximum likelihood model and is a measure of noise in the data: as μ_{IDR} becomes larger, $\Delta DU'$ tends toward 0 and the probability of choosing either lottery tends toward 0.5. Conversely, as μ_{IDR} goes toward 0, $\Delta DU'$ becomes larger, and the choice becomes more deterministic. The variation in individual choices identifies the error term μ_{IDR} in the maximum likelihood estimation.

The second extension is to control for observable socio-demographic characteristics and treatments in the experimental design. For example, if we allow the discount rate to be a linear function of sex, we have

$$\delta = \delta_{constant} + \delta_{female} \cdot female, \tag{14}$$

which allows us to estimate the marginal effect of being a female instead of a male.

Estimation of the Utility Function

We elicit the parameter r of the utility function from the risk aversion tasks. For each binary choice in the risk aversion tasks, the difference between the expected values of the two lotteries is

$$\Delta EU = EU_B - EU_A. \tag{15}$$

The probability of choosing lottery B over lottery A is then specified by a logistic linking function, hence

$$P(choose\ lottery\ B) = F(\Delta EU). \tag{16}$$

The logistic linking function transforms the difference in expected utilities between the two lotteries into a value between 0 and 1. If both lotteries yield the same utility such that $\Delta EU = 0$, the probability of choosing either lottery is 0.5. If the utility from lottery B is higher than the utility from lottery A, such that $\Delta EU > 0$, then the probability of choosing lottery B is higher than the probability of choosing lottery A, and vice versa. The log likelihood function is then

$$ln\ L(r; y) = \sum_i \left[ln\left(F(\Delta EU)\right) \cdot I(y = B) + ln\left(F(-\Delta EU)\right) \cdot I(y = A) \right], \tag{17}$$

where y indicates the observed outcome of the binary choice and the log likelihood, which depends only on the parameter r, is summed over all i lottery choices.

We make the same two adjustments as before. First, we introduce a stochastic error term and follow Wilcox (2011) by replacing equation (15) with

$$\Delta EU' = \frac{\frac{(EU_B - EU_A)}{\nu}}{\mu_{RA}}, \tag{18}$$

where μ_{RA} is a stochastic error term, and ν is a normalizing parameter defined as the difference between the utility of the highest prize and utility of the lowest prize in the two lotteries. The normalization implies that the latent index is always between 0 and 1. Second, we allow for variation in the estimated parameters by controlling for observable characteristics in the same way as before. The log likelihood function is then

$$ln\ L(r, \mu_{RA}; y,\ Z) = \sum_i \left[ln\left(F(\Delta EU')\right) \cdot I(y = B) + ln\left(F(-\Delta EU')\right) \cdot I(y = A) \right], \tag{19}$$

where μ_{RA} is the stochastic error term, and Z is a vector of control variables.

Joint Estimation of Discount Rates and the Utility Function

We jointly estimate both the coefficient of relative risk aversion, r, and the individual discount rate, δ, from the risk aversion and discounting tasks. We define the log likelihood function as

$$\begin{aligned} ln\ L(r,\ \mu_{RA},\ \delta,\ \mu_{IDR};\ y,\ Z) = {} & ln\ L_{RA}(r,\ \mu_{RA};\ y,\ Z) \\ & + ln\ L_{IDR}(\delta,\ \mu_{IDR},\ r;\ y,\ Z), \end{aligned} \tag{20}$$

where r is estimated from the choices in the risk aversion task, and used in the estimation of discount rates by deriving the utility gain of rewards given r.

It is straightforward to allow for alternative utility and discounting functions in the statistical model. While we rely on expected utility theory to identify the utility function, we also estimate the quasi-hyperbolic discounting model as an alternative to the canonical exponential discounting model.

4 Register Data on Wealth and Income

One of the possible reasons for the lack of research on the association between individual discount rates and financial wealth is the difficulty in getting access to reliable financial information at the individual level. We overcome this challenge by combining the experimental data with detailed administrative data at Statistics Denmark. Every subject in the experiment can be linked to administrative records via her unique civil registration number. In this way, we get access to relevant economic, financial and personal information collected from different government agencies such as the Danish Civil Registration Office and the Danish Ministry of Taxation.

4.1 Control Variables for Sex, Age and Education

Socio-demographic information on sex and age is obtained from records at the Danish Civil Registration Office, and information on the highest level of completed education is obtained from the Education Register, which contains records of ongoing and completed education. We list summary statistics of these demographic variables in Table 1. In the analysis we use binary indicator variables for age and education groups. The analysis excludes 6 subjects from the original sample due to missing data on education, and the final sample consists of 407 subjects.[12]

The summary statistics show substantial variation in observed individual characteristics such as age, and the sample is more diverse than usually found in experimental studies. The data allows us to analyze the correlation between individual discount rates and private wealth, and to control for individual characteristics that may be correlated with wealth.[13]

[12]The data in the Education Register is collected from Danish Ministry of Education. For immigrants data on education, among other things, is obtained from surveys and the last survey of this kind was conducted in 2006. Our sample is drawn from the Civil Registration Office, which also contains records for immigrants, and it is likely that the 6 subjects with missing information on education are immigrants. Our results do not change if we keep the 6 subjects in the sample and use their self-reported education level to replace the missing values in the administrative data.

[13]There are several other demographic control variables that we could have included in the analysis. We focus on sex, age and education because these characteristics may be correlated with private wealth. When we control for other demographic variables, such as marital status or number of children, we do not observe significantly different results, but we do observe higher standard errors in the estimated marginal effects due to the inclusion of more covariates.

Table 1: List of Variables and Descriptive Statistics

	Mean	SD
Female	0.48	0.50
Age	47.49	15.10
below 30 years old	0.18	0.38
30-39 years old	0.12	0.32
40-49 years old	0.23	0.42
50-59 years old	0.24	0.43
60 years old and above	0.23	0.42
Years of Education	12.74	3.08
Not finished high school	0.25	0.43
High school graduate	0.41	0.49
Higher education, Bachelor	0.26	0.44
Higher education, Master and above	0.09	0.29
N	407	

4.2 Income and Wealth Data

Information on income and financial wealth is obtained from official records at the Danish Ministry of Taxation. Labor income and returns to financial assets are subject to taxation, and Danish tax authorities collect information directly from employers and financial institutions. We measure income as annual disposable income from labor and capital, and Figure 4 shows the distribution of income in the sample. For data confidentiality reasons, we calculate average values for each percentile of the distribution.[14] We also added the income distribution for the entire Danish population between 18 and 75 years, excluding the top and bottom 0.5% of the distribution, and we observe that the two distributions are similar.

The average annual disposable income in the sample is 200,000 kroner. Some subjects have negative disposable income due to financial losses. We generate binary indicator variables for each income quartile (Table 2) and use these as control variables in the statistical model of individual discount rates. We also generate a separate set of indicator variables for each income quartile over a 3-year period from January 1, 2008 to December 31, 2010, to reduce the effects of fluctuations in individual income from year to year. The income quartiles over the 3-year period are reported in Table 3.

[14]We do not have permission from the Data Protection Agency to report any information that is related to a single person, such as minimum, maximum or median values, or outliers in a histogram.

Figure 4: Distribution of Annual Disposable Income

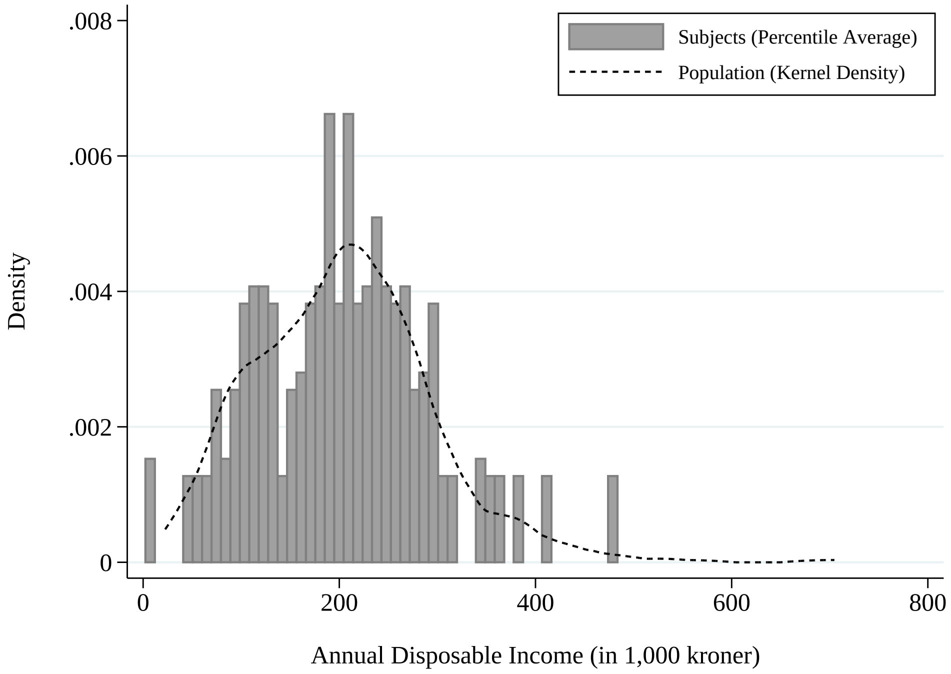


Table 2: Disposable Income Quartiles (in 1,000 kroner)

	N	Mean	SD
1	101	91.61	34.61
2	101	174.84	19.18
3	103	229.50	16.04
4	102	379.00	384.60
Total	407	219.18	219.61

Table 3: Disposable Income Quartiles over a 3-Year Period (in 1,000 kroner)

	N	Mean	SD
1	101	97.11	31.52
2	101	177.52	17.12
3	103	232.14	16.45
4	102	358.95	222.90
Total	407	216.86	147.74

The information on private wealth in the registry data is detailed and contains different types of assets and liabilities (Table 4). *Bank Assets* is balances in regular Danish bank accounts, *Stock Assets* is the market value of shares and equity held in Danish deposits, *Bond Assets* is tradable bonds and liabilities held in Danish deposits, and *Privateloan Assets* is any other non-traded financial assets held, such as private loans to friends and family. *Housingvalue* is the appraised value of property owned, which may deviate from the actual market value.[15] Unfortunately, information on contributions to pension funds is not available, which accounts for about a third of overall private wealth in Denmark.

Looking at liabilities, we have information on *Bank Debt*, which is consumer credit and debt owed to financial institutions in Denmark, *Bond Debt* is privately issued bonds (including mortgages), and *Privateloan Debt* is other liabilities such as private debt to friends and family.

Cash holdings and valuable items such as yachts, cars, art, jewelry, etc. and assets and liabilities held outside Denmark are self-reported. If assets and liabilities are reported, then it is included in the *Net Wealth* variable, which is the difference between reported assets and liabilities. There are slight differences between *Net Wealth* and the sum of all assets and liabilities listed above, but the correlation coefficient between the two measures of net wealth is 0.97, which suggests that few subjects report other wealth than already recorded by the tax authorities.

Although the data is highly detailed at the individual level, there are several weaknesses. First, not all assets are recorded and measured according to market values, particularly private property and pensions. Second, assets and liabilities are recorded once per year on December 31. Hence, we do not observe wealth at the exact date of the experiment, which was conducted in September and October 2009. Third, and finally, we cannot identify consumer debt because bank debt also includes loans for downpayments on houses and apartments. Despite these issues, the measures of private wealth that we have at our disposal are more reliable and complete than alternative measures based on survey questions.

We create several measures of private wealth for our analysis. First, we use Net Wealth as the baseline measure of accumulated wealth. The distribution of Net Wealth for our sample is shown in Figure 5, and it is similar to the distribution of net wealth for the entire

[15]Unfortunately, housing value only includes privately owned apartments and houses and does not include cooperatively owned apartments. In 2009, 7% of all housing in Denmark was cooperatively owned (Statistics Denmark, 2010).

population.[16] The average net wealth in the sample is approximately 500,000 kroner (which is roughly 100,000 dollars at the time net wealth was recorded), but we also observe that a third of the subjects in the sample have negative net wealth. If we take into account that most employees in Denmark receive their paycheck by the end of the month, then 40% of all subjects in the sample have no positive net wealth beyond their monthly disposable income.

Table 4: List of Financial Wealth Variables (in 1,000 kroner)

	Mean	SD
Bank Assets	117.36	307.41
Stock Assets	40.50	181.06
Bond Assets	30.38	174.66
Privateloan Assets	0.00	0.00
Housingvalue	88.70	2,416.68
Total Assets	1,113.71	3,110.71
Bank Debt	140.37	280.89
Bond Debt	439.02	1,073.29
Privateloan Debt	7.10	90.21
Total Debt	586.49	1,227.96
Net Wealth	527.22	2,172.91

Table 5: Net Wealth Quartiles (in 1,000 kroner)

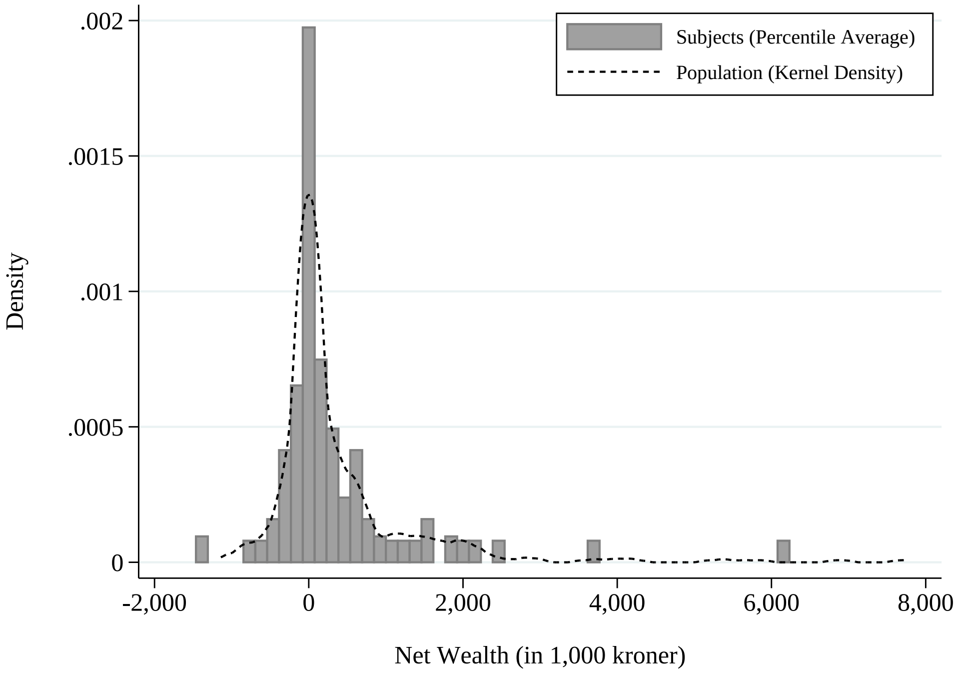
	N	Mean	SD
1	104	-337.70	361.02
2	100	-0.19	23.90
3	101	233.98	133.65
4	102	2,216.54	3,848.99
Total	407	527.22	2,172.91

Table 6: Net Wealth Quartiles over a 3-Year Period (in 1,000 kroner)

	N	Mean	SD
1	104	-297.01	296.63
2	100	5.57	26.04
3	101	274.22	148.76
4	102	2,213.91	3,631.27
Total	407	548.36	2,068.70

[16] We exclude the highest percentile in Figure 5 which had average net wealth of more than 10 million kroner.

Figure 5: Distribution of Net Wealth



We generate binary indicators for each quartile of the net wealth distribution in 2009 (Table 5) and a separate set of indicator variables for each quartile of the (average) net wealth distribution over a 3-year period from January 1, 2008 to December 31, 2010 (Table 6).

To test the hypothesis that present biased subjects are less likely to hold liquid assets and more likely to accumulate debt, we consider several measures of liquidity. Leth-Petersen (2010) identifies individuals as being credit constrained if the value of their liquid assets is less than monthly disposable income, where liquid assets are defined as all non-housing assets.[17] We follow Leth-Petersen's (2010) approach but define liquid assets as bank deposits only and exclude deposits of stocks and bonds. This measure of liquidity is closer to Laibson's (1997) definition, whereby liquid assets can be used for consumption without significant transaction costs. We specify an indicator variable for positive bank deposits, which is equal to 1 if *Bank Assets* is higher than monthly disposable income, and 0 otherwise. Table 7 shows that two thirds of the subjects in the sample had positive bank deposits that

[17] The reason for this definition is that most wages are paid at the end of the month before rent and utility bills for the coming month have been paid, and the wealth related variables in the administrative data are recorded at the end of the year. Hence, monthly income ends up being recorded as private wealth without consideration of monthly expenses.

Table 7: Summary Statistics for Positive Bank Assets and Positive Bank Wealth (by Net Wealth Quartile)

	Positive Bank Assets %	Positive Bank Wealth %
1	0.44	0.07
2	0.61	0.37
3	0.81	0.66
4	0.81	0.65
Total	0.67	0.43

exceeded monthly income at the end of 2009. While the share of subjects with positive bank deposits increases with private wealth, we observe that 20% of the subjects in the highest net wealth quartile had fewer bank deposits than their monthly income.

While we cannot directly measure credit card debt as in Meier and Sprenger (2010), we measure consumer debt using the *Bank Debt* variable. In addition to overdrafts on bank accounts and consumer credit, this variable also includes down payments for real estate, and it is therefore not a perfect measure of consumer debt. We define *Bank Wealth* = *Bank Assets* - *Bank Debt* and generate another measure of liquidity, which is an indicator variable that is equal to 1 if *Bank Wealth* is higher than monthly disposable income, and 0 otherwise. Only 7% of the subjects in the lowest net wealth quartile had net bank wealth that exceeded monthly income, as opposed to 66% of the subjects in the highest net wealth quartile.

One concern is a high degree of multicolinearity between our measures of private wealth and other demographic variables such as income, age and education. Table 8 shows that net wealth indeed is significantly correlated with these other demographic variables. However, the estimated coefficients of correlation are not close to 1 and the results suggest that we have sufficient variation in net wealth within age, education and income groups to identify marginal effects of net wealth on individual discount rates while controlling for these other demographic factors.

Income has sometimes been used as a proxy for private wealth (e.g., Tanaka et al., 2010; Harrison et al., 2002), and we find that the coefficient of correlation between net wealth quartile and income quartile is equal to 0.33 and significantly different from 0. However, Table 9 illustrates that income is not a perfect proxy for net wealth. Within the highest net wealth quartile, some subjects fall into the lowest income quartile. Similarly, within the lowest net wealth quartile, some subjects fall into the highest income quartile. This variation in net wealth and income illustrates the value of observing private wealth directly.

Table 8: Pairwise Correlations Between Variables

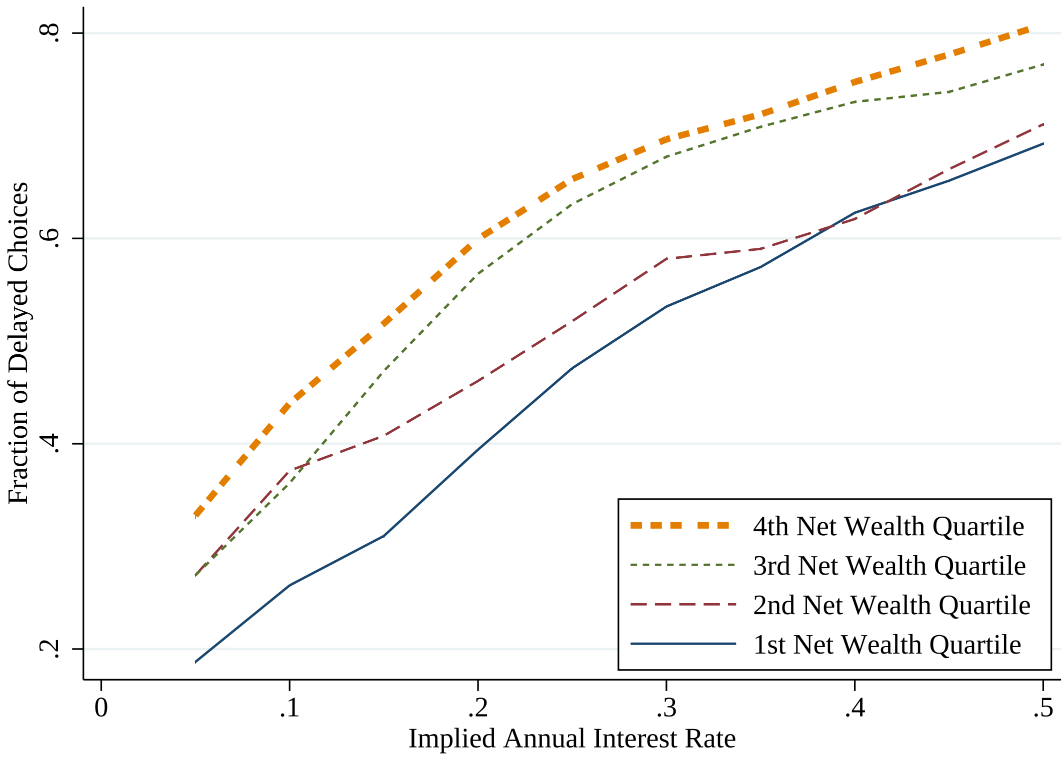
	Net Wealth Quartile	Income Quartile	Age	Years of Education	Positive Bank Assets	Positive Bank Wealth
Net Wealth Quartile	1					
Income Quartile	0.331***	1				
Age	0.301***	0.245***	1			
Years of Education	0.176***	0.446***	0.0619	1		
Positive Bank Assets	0.314***	0.0950*	0.0927*	0.112**	1	
Positive Bank Wealth	0.461***	0.0640	0.134***	0.0953*	0.618***	1

* p<0.1, ** p<0.05, *** p<0.01

Table 9: Fraction of Subjects by Income Quartile and Net Wealth Quartile (in percent)

	Income Quartile			
Net Wealth Quartile	1	2	3	4
1	5.90	8.35	6.88	4.42
2	11.79	7.86	4.42	0.49
3	5.16	4.18	0.74	7.62
4	1.97	4.42	6.14	12.53

Figure 6: Fraction of Delayed Choices by Net Wealth Quartile



5 Results

The data set provides a unique opportunity to investigate the association between individual discount rates and measures of private wealth and liquidity.

5.1 Wealth and Exponential Discounting

We first address the hypothesis that individual discount rates are significantly correlated with private net wealth. Figure 6 displays the fraction of delayed choices across net wealth quartiles and implied annual interest rate in the discounting tasks. We observe that subjects in the highest net wealth quartile are more likely to choose the larger, later reward than subjects in the lowest net wealth quartile. The descriptive data thus indicates that subjects in higher net wealth quartiles have lower discount rates than those in lower net wealth quartiles.

Table 10 reports estimated discount rates under the assumption of exponential discount-

Table 10: Exponential Discounting under Linear Utility

	Coefficient	Standard Error	p-Value	95% Confidence Interval
Discount Rate δ				
Constant	0.282	0.072	0.000	{ 0.141; 0.423 }
2nd Net Wealth Quartile	-0.028	0.069	0.689	{-0.162; 0.107 }
3rd Net Wealth Quartile	-0.094	0.048	0.050	{-0.187; -0.000 }
4th Net Wealth Quartile	-0.114	0.057	0.045	{-0.225; -0.002 }
2nd Income Quartile	-0.057	0.069	0.408	{-0.192; 0.078 }
3rd Income Quartile	-0.049	0.062	0.427	{-0.171; 0.072 }
4th Income Quartile	-0.098	0.065	0.132	{-0.227; 0.030 }
Female	-0.009	0.044	0.836	{-0.096; 0.077 }
30-39 Years	0.080	0.060	0.185	{-0.038; 0.198 }
40-49 years	0.030	0.058	0.609	{-0.084; 0.144 }
50-59 Years	0.005	0.074	0.949	{-0.141; 0.150 }
60 Years and older	-0.060	0.071	0.395	{-0.199; 0.079 }
Highschool Graduate	0.051	0.049	0.302	{-0.046; 0.147 }
Higher Education, Bachelor	0.049	0.058	0.400	{-0.065; 0.164 }
Higher Education, Master a.a.	0.036	0.071	0.610	{-0.103; 0.176 }

Note: We estimate exponential discount rates using maximum likelihood under the assumption of linear utility. The full set of of estimates including stochastic error terms is documented in Appendix A.

ing and linear utility. The results show that individual discount rates vary significantly with net wealth: the marginal effects of being in the two highest net wealth quartiles are negative and significantly different from 0 relative to the lowest net wealth quartile, which is omitted. To our surprise we do not find any significant marginal effects of other control variables such as income, sex, age and education on estimated discount rates.

To control for the curvature of the utility function we jointly elicit individual risk attitudes and discount rates. The results are presented in Table 11. We reject the assumption that utility is linear and find empirical support for concave utility, but we do not find any significant correlation between relative risk aversion and net wealth.[18] Controlling for utility curvature does not change our previous conclusions: we continue to find a significant negative association between individual discount rates and net wealth. The estimated marginal effect for the highest net wealth quartile is -0.054 with a p-value of 0.064, and the estimated marginal effect for the second highest net wealth quartile is also -0.054 with a p-value of 0.038. These marginal effects are measured relative to the lowest net wealth quartile. We

[18]We do find that women are significantly more risk averse than men. All other control variables are not significant at the 5% level.

do not find any significant marginal effects of other control variables such as income, sex, age and education on estimated discount rates.

Table 11: Exponential Discounting under Non-Linear Utility

	Coefficient	Standard Error	p-Value	95% Confidence Interval
Discount Rate δ				
Constant	0.185	0.039	0.000	{ 0.109; 0.261 }
2nd Net Wealth Quartile	-0.027	0.033	0.406	{-0.091; 0.037 }
3rd Net Wealth Quartile	-0.054	0.026	0.038	{-0.106; -0.003 }
4th Net Wealth Quartile	-0.054	0.029	0.064	{-0.111; 0.003 }
2nd Income Quartile	-0.031	0.036	0.391	{-0.101; 0.040 }
3rd Income Quartile	-0.047	0.033	0.163	{-0.112; 0.019 }
4th Income Quartile	-0.044	0.035	0.204	{-0.113; 0.024 }
Female	-0.027	0.023	0.246	{-0.073; 0.019 }
30-39 Years	0.045	0.034	0.193	{-0.023; 0.112 }
40-49 Years	0.024	0.031	0.438	{-0.037; 0.085 }
50-59 Years	0.014	0.036	0.700	{-0.057; 0.085 }
60 Years and older	-0.033	0.037	0.371	{-0.106; 0.039 }
Highschool Graduate	-0.006	0.027	0.824	{-0.060; 0.047 }
Higher Education, Bachelor	-0.016	0.032	0.621	{-0.079; 0.047 }
Higher Education, Master a.a.	-0.023	0.041	0.574	{-0.104; 0.058 }
Utility Curvature r				
Constant	0.295	0.085	0.001	{ 0.127; 0.462 }
2nd Net Wealth Quartile	0.077	0.077	0.318	{-0.075; 0.229 }
3rd Net Wealth Quartile	0.086	0.077	0.260	{-0.064; 0.237 }
4th Net Wealth Quartile	-0.054	0.091	0.557	{-0.232; 0.125 }
2nd Income Quartile	0.032	0.083	0.696	{-0.130; 0.194 }
3rd Income Quartile	0.148	0.103	0.150	{-0.053; 0.349 }
4th Income Quartile	-0.007	0.100	0.944	{-0.204; 0.189 }
Female	0.174	0.056	0.002	{ 0.065; 0.284 }
30-39 Years	-0.005	0.098	0.958	{-0.197; 0.186 }
40-49 Years	-0.003	0.093	0.972	{-0.185; 0.178 }
50-59 Years	0.058	0.087	0.503	{-0.112; 0.228 }
60 Years and older	0.189	0.120	0.115	{-0.046; 0.424 }
Highschool Graduate	0.132	0.078	0.088	{-0.020; 0.284 }
Higher Education, Bachelor	0.167	0.088	0.058	{-0.006; 0.339 }
Higher Education, Master a.a.	0.181	0.116	0.117	{-0.045; 0.407 }

Note: We jointly estimate exponential discount rates and utility curvature using maximum likelihood and use frequency weights (fweight=50) with respect to observations from the risk aversion task. The full set of of estimates including stochastic error terms is documented in Appendix A.

Figure 7: Predicted Discount Rates by Net Wealth Quartile

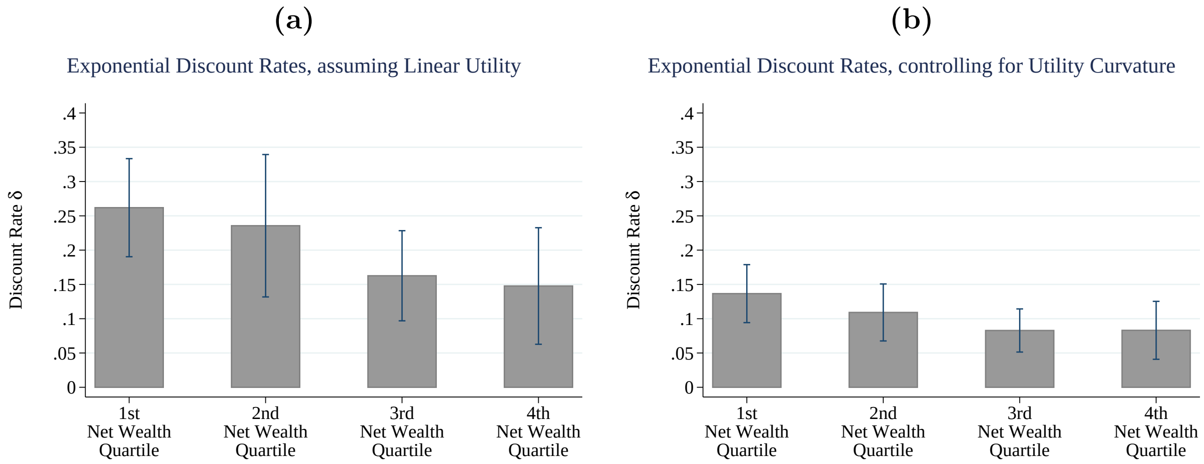


Figure 7 shows the distribution of predicted discount rates across the four net wealth quartiles. The height of the box indicates the mean estimate and the vertical line indicates the 95% significance interval. Panel (a) shows the predicted values under linear utility, and panel (b) shows the predicted values under non-linear utility. The association between individual discount rates and net wealth is negative under both assumptions, and predicted discount rates are significantly lower in the highest net wealth quartile compared to the lowest net wealth quartile. Under concave utility, the predicted discount rates for the lowest and highest net wealth quartiles is 14% and 8.5%, respectively.

We now investigate the association between individual discount rates and alternative measures of net wealth and liquidity. Table 12 reports the results from those estimations, which control for utility curvature and include covariates for income, sex, age and education.

First, we test to what extent liquidity is correlated with individual discount rates. Table 12 panels (A) and (B) show that the binary indicators for *Positive Bank Assets* and *Positive Bank Wealth* have no significant effect on individual discount rates, and including these measures of liquidity do not change our conclusions regarding the significant negative correlation between net wealth and individual discount rates.

Table 12: Exponential Discounting - Sensitivity Analysis

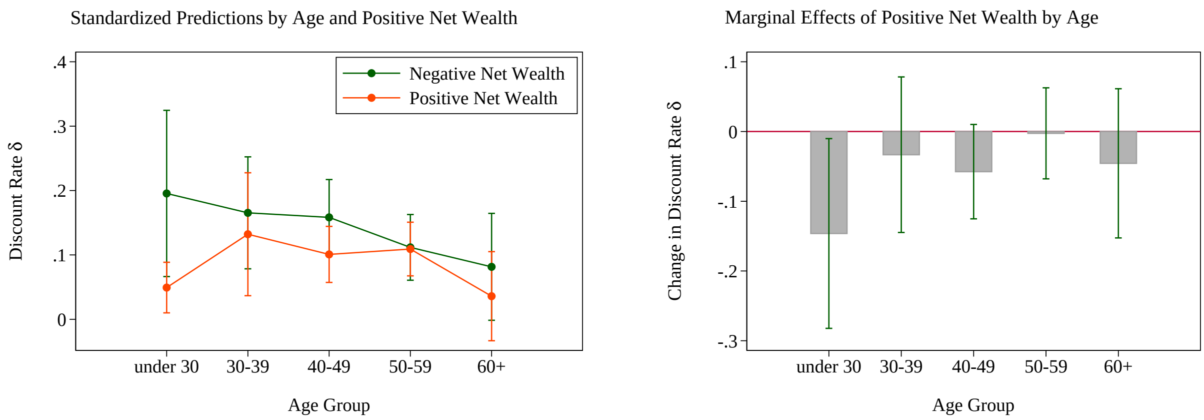
	Coefficient	Standard Error	p-Value	95% Confidence Interval
(A) Discount Rate δ: Net Wealth Quartiles and Positive Bank Assets				
Constant	0.176	0.039	0.000	{ 0.100; 0.252 }
Positive Bank Assets	0.013	0.020	0.524	{-0.026; 0.052 }
2nd Net Wealth Quartile	-0.027	0.033	0.413	{-0.091; 0.038 }
3rd Net Wealth Quartile	-0.058	0.028	0.040	{-0.113;-0.003 }
4th Net Wealth Quartile	-0.057	0.031	0.065	{-0.117; 0.004 }
(B) Discount Rate δ: Net Wealth Quartiles and Positive Bank Wealth				
Constant	0.186	0.041	0.000	{ 0.105; 0.267 }
Positive Bank Wealth	0.003	0.026	0.911	{-0.048; 0.053 }
2nd Net Wealth Quartile	-0.028	0.035	0.423	{-0.097; 0.041 }
3rd Net Wealth Quartile	-0.057	0.026	0.032	{-0.109; -0.005 }
4th Net Wealth Quartile	-0.056	0.031	0.071	{-0.117; 0.005 }
(C) Discount Rate δ: Positive Net Wealth				
Constant	0.186	0.032	0.000	{ 0.123; 0.248 }
Positive Net Wealth	-0.054	0.021	0.010	{-0.095;-0.013 }
(D) Discount Rate δ: Positive Net Wealth interacted with Age				
Constant	0.265	0.079	0.001	{ 0.110; 0.421 }
Pos. Net Wealth	-0.146	0.071	0.041	{-0.285;-0.006 }
30-39 Years	-0.029	0.062	0.640	{-0.151; 0.093 }
40-49 Years	-0.033	0.067	0.624	{-0.163; 0.098 }
50-59 Years	-0.078	0.076	0.305	{-0.228; 0.071 }
60+ Years	-0.095	0.096	0.324	{-0.283; 0.093 }
Pos. Net Wealth * 30-39 Years	0.121	0.088	0.169	{-0.051; 0.293 }
Pos. Net Wealth * 40-49 Years	0.089	0.076	0.243	{-0.060; 0.238 }
Pos. Net Wealth * 50-59 Years	0.141	0.082	0.088	{-0.021; 0.302 }
Pos. Net Wealth * 60+ Years	0.086	0.109	0.430	{-0.127; 0.299 }
(E) Discount Rate δ: 3 Year Average Net Wealth Quartiles				
Constant	0.209	0.042	0.000	{ 0.127; 0.292 }
2nd Net Wealth Quartile	-0.067	0.034	0.048	{-0.132;-0.001 }
3rd Net Wealth Quartile	-0.086	0.031	0.005	{-0.146;-0.026 }
4th Net Wealth Quartile	-0.075	0.032	0.020	{-0.139;-0.012 }

Note: We jointly estimate exponential discount rates and utility curvature using maximum likelihood and use frequency weights (fweight=50) with respect to observations from the risk aversion task. The variables included in the estimations are similar to those in Table 11, and the full set of of estimates is available upon request.

When net wealth quartiles are replaced by a binary indicator for positive net wealth, we continue to observe a significant negative correlation between net wealth and discount rates. Table 12 panel (C) shows that the estimated coefficient for positive net wealth is equal to -0.054 with a p-value of 0.010. We can also consider interaction effects between positive net wealth and age groups, and the estimated coefficients are reported in panel (D). We find a significant effect of net wealth on predicted discount rates for the youngest

Figure 8: Association between Discount Rates and Net Wealth by Age Group

(a) (b)



age group, but we do not find a significant association between individual discount rates and positive net wealth for any of the other age groups. Figure 8 (a) shows the predicted discount rates across net wealth and age groups, and Figure 8 (b) illustrates the marginal effects of net wealth on discount rates across age groups. We do not know to what extent individual discount rates vary over the life cycle and across generations, and it is therefore difficult to say whether the significant correlation between individual discount rates and net wealth that we observe for the youngest age group is transitory or persists throughout life. It is also possible that older subjects are more likely to experience exogenous shocks to their net wealth than younger subjects, which makes it harder to identify the association between net wealth and discounting behavior.

Finally, in panel (E) of Table 12 we replace the measures of net wealth, liquidity, and income with alternative measures that are based on average net wealth, liquditiy, and income over a 3-year period instead of 1 year. The negative correlation between net wealth and individual discount rates is now more pronounced, and subjects in the lowest net wealth quartile have significantly higher discount rates than otherwise. These results suggest that subjects who consistently find themselves in the lowest net wealth quartile over the 3-year period are significantly less patient than subjects who are consistently more wealthy over the same period. Hence, variation in net wealth over longer periods of time appears to have a stronger association with individual discount rates than short-term variation in net wealth.

5.2 Present Bias and Liquidity

We now consider the second hypothesis that present bias is significantly correlated with financial liquidity. The two treatments with respect to the front-end delay to the smaller, sooner reward allow us to identify the quasi-hyperbolic discounting model and present bias. Andersen et al. (2014) do not find any evidence of present bias in their estimations of individual discount rates on the full sample, but we may still find a significant association between present bias and bank deposits. Recall that our binary indicator of financial liquidity is based on bank deposits and does not include stocks and bonds. It is equal to 1 if bank deposits exceed monthly income, and 0 otherwise.

We estimate the quasi-hyperbolic discounting model and control for net wealth and liquidity along with the other control variables for demographic characteristics. Table 13 shows the estimated coefficients of the quasi-hyperbolic discounting model under non-linear utility. We find no evidence of present bias, and there is no significant association between present bias and our measure of liquidity constraints: the marginal effect of positive bank deposits on the estimated parameters in the discounting function are small and close to 0 and we cannot reject the null hypothesis of no significant association with discounting behavior.[19] Figure 9 shows the predicted values of the β-parameter across net wealth quartiles for subjects with and without liquidity constraints, respectively. We observe some variation in the estimated β-parameter, but it is not significantly different from 1 for any of the net wealth quartiles or liquidity constraints. Hence, there is no evidence of present bias, and no significant association with net wealth and financial liquidity.[20]

[19]The p-value of a one-sided t-test that $\beta = 1$ against the alternative hypothesis that $\beta < 1$ is equal to 0.209 for the constant term in the equation, and we cannot reject the null hypothesis of exponential discounting.

[20]We do observe significant effects of net wealth on the estimated δ-parameter in the quasi-hyperbolic model, and the results are similar to those in the exponential discounting model.

Table 13: Quasi-Hyperbolic Discounting and Positive Bank Assets

	Coefficient	Standard Error	p-Value	95% Confidence Interval
Present Bias β				
Constant	0.989	0.013	0.000	{ 0.963; 1.015 }
Positive Bank Assets	-0.002	0.007	0.761	{-0.016; 0.012 }
2nd Net Wealth Quartile	0.010	0.013	0.451	{-0.016; 0.036 }
3rd Net Wealth Quartile	0.005	0.013	0.683	{-0.020; 0.031 }
4th Net Wealth Quartile	-0.004	0.011	0.748	{-0.026; 0.018 }
2nd Income Quartile	0.001	0.013	0.953	{-0.024; 0.025 }
3rd Income Quartile	0.001	0.015	0.930	{-0.028; 0.031 }
4th Income Quartile	0.003	0.016	0.859	{-0.028; 0.034 }
Female	-0.001	0.013	0.958	{-0.025; 0.024 }
30-39 Years	-0.002	0.014	0.904	{-0.030; 0.027 }
40-49 Years	-0.004	0.021	0.849	{-0.046; 0.038 }
50-59 Years	0.008	0.023	0.716	{-0.036; 0.053 }
60 Years and older	0.019	0.020	0.354	{-0.021; 0.058 }
Highschool Graduate	0.004	0.009	0.617	{-0.013; 0.022 }
Higher Education, Bachelor	-0.004	0.014	0.770	{-0.032; 0.024 }
Higher Education, Master a.a.	-0.003	0.023	0.912	{-0.048; 0.043 }
Discount Rate δ				
Constant	0.158	0.040	0.000	{ 0.080; 0.235 }
Positive Bank Assets	0.008	0.019	0.650	{-0.028; 0.045 }
2nd Net Wealth Quartile	-0.016	0.039	0.686	{-0.093; 0.061 }
3rd Net Wealth Quartile	-0.050	0.030	0.100	{-0.109; 0.009 }
4th Net Wealth Quartile	-0.081	0.049	0.098	{-0.177; 0.015 }
2nd Income Quartile	-0.036	0.033	0.281	{-0.101; 0.029 }
3rd Income Quartile	-0.038	0.037	0.310	{-0.111; 0.035 }
4th Income Quartile	-0.036	0.039	0.356	{-0.112; 0.040 }
Female	-0.034	0.025	0.164	{-0.082; 0.014 }
30-39 Years	0.036	0.031	0.252	{-0.026; 0.098 }
40-49 Years	0.026	0.030	0.396	{-0.033; 0.084 }
50-59 Years	0.025	0.037	0.509	{-0.049; 0.098 }
60 Years and older	0.001	0.055	0.989	{-0.106; 0.108 }
Highschool Graduate	0.011	0.047	0.823	{-0.082; 0.103 }
Higher Education, Bachelor	-0.016	0.051	0.747	{-0.117; 0.084 }
Higher Education, Master a.a.	-0.045	0.083	0.591	{-0.208; 0.118 }

Note: We jointly estimate exponential discount rates and utility curvature using maximum likelihood and use frequency weights (fweight=50) with respect to observations from the risk aversion task. The full set of of estimates including stochastic error terms is documented in Appendix A.

Figure 9: Predicted Present Bias by Net Wealth and Positive Bank Assets

The only other study that looks at the association between present bias and financial outcomes is Meier and Sprenger (2010). They do not consider financial assets but instead investigate the correlation between present bias and consumer debt. We include consumer debt in an alternative measure of liquidity which is based on positive bank wealth instead of bank deposits. Table 14 shows the estimated coefficients of the quasi-hyperbolic discounting model when we control for positive bank wealth. The conclusions do not change: we find no evidence of present bias, and no significant association with net wealth or liquidity.[21] In fact, none of the control variables are significantly correlated with present bias. Figure 10 shows the predicted values of the β-parameter across net wealth quartiles and liquidity constraints. We observe some variation in the estimated β-parameter, but it is not significantly different from 1 for any of the net wealth quartiles or liquidity constraints.

[21]The p-value of a one-sided t-test that $\beta = 1$ against the alternative hypothesis that $\beta < 1$ is equal to 0.237 for the constant term in the equation, and we cannot reject the null hypothesis of exponential discounting.

Table 14: Quasi-Hyperbolic Discounting and Positive Bank Wealth

	Coefficient	Standard Error	p-Value	95% Confidence Interval
Present Bias β				
Constant	0.978	0.031	0.000	{ 0.917; 1.039 }
Positive Bank Wealth	0.013	0.017	0.461	{-0.021; 0.047 }
2nd Net Wealth Quartile	0.012	0.014	0.401	{-0.016; 0.040 }
3rd Net Wealth Quartile	0.004	0.013	0.761	{-0.022; 0.030 }
4th Net Wealth Quartile	-0.011	0.018	0.556	{-0.047; 0.025 }
2nd Income Quartile	0.010	0.028	0.715	{-0.045; 0.066 }
3rd Income Quartile	0.014	0.036	0.700	{-0.056; 0.084 }
4th Income Quartile	0.017	0.043	0.704	{-0.069; 0.102 }
Female	0.004	0.018	0.808	{-0.031; 0.040 }
30-39 Years	-0.006	0.020	0.751	{-0.045; 0.033 }
40-49 Years	-0.009	0.025	0.703	{-0.058; 0.039 }
50-59 Years	0.004	0.023	0.874	{-0.041; 0.048 }
60 Years and older	0.023	0.019	0.228	{-0.014; 0.059 }
Highschool Graduate	0.003	0.010	0.750	{-0.016; 0.023 }
Higher Education, Bachelor	-0.014	0.028	0.615	{-0.069; 0.041 }
Higher Education, Master a.a.	-0.012	0.036	0.733	{-0.082; 0.058 }
Discount Rate δ				
Constant	0.159	0.044	0.000	{ 0.074; 0.244 }
Positive Bank Wealth	0.020	0.027	0.462	{-0.033; 0.072 }
2nd Net Wealth Quartile	-0.015	0.037	0.690	{-0.088; 0.058 }
3rd Net Wealth Quartile	-0.053	0.027	0.052	{-0.106; 0.000 }
4th Net Wealth Quartile	-0.113	0.104	0.276	{-0.316; 0.090 }
2nd Income Quartile	-0.027	0.040	0.500	{-0.105; 0.051 }
3rd Income Quartile	-0.028	0.047	0.542	{-0.120; 0.063 }
4th Income Quartile	-0.026	0.049	0.597	{-0.122; 0.070 }
Female	-0.037	0.020	0.061	{-0.076; 0.002 }
30-39 Years	0.032	0.039	0.416	{-0.045; 0.109 }
40-49 years	0.026	0.027	0.344	{-0.028; 0.079 }
50-59 Years	0.029	0.035	0.411	{-0.040; 0.097 }
60 Years and older	0.013	0.061	0.829	{-0.106; 0.133 }
Highschool Graduate	0.002	0.043	0.964	{-0.083; 0.087 }
Higher Education, Bachelor	-0.034	0.061	0.581	{-0.153; 0.086 }
Higher Education, Master a.a.	-0.070	0.114	0.536	{-0.293; 0.153 }

Note: We jointly estimate quasi-hyperbolic discounting and utility curvature using maximum likelihood and use frequency weights (fweight=50) with respect to observations from the risk aversion task. The full set of of estimates including stochastic error terms is documented in Appendix A.

Figure 10: Predicted Present Bias by Net Wealth and Positive Bank Wealth

Finally, we investigate the association between present bias and alternative measures of net wealth and liquidity. Table 15 reports the results from those estimations, which control for utility curvature and include covariates for income, sex, age and education. In panels (A) and (B), we replace the net wealth quartiles with a binary indicator for positive net wealth. The conclusions are the same as before: the β-coefficient is not significantly different from 1, and the measure of liquidity has no significant effect on present bias. In panels (C) and (D) we replace the measures of net wealth and income with alternative measures that are based on average net wealth and income over a 3-year period instead of 1 year. The results do not change and we continue to find no evidence in favor of present bias and no significant correlation with net wealth and liquidity.[22]

[22] The marginal effects of net wealth on the estimated δ-parameter are robust in these estimations, with the exception of panel D.

Table 15: **Quasi-Hyperbolic Discounting - Sensitivity Analysis**

	Coefficient	Standard Error	p-Value	95% Confidence Interval
(A) Positive Net Wealth and Positive Bank Assets				
Present Bias β:				
Constant	1.003	0.019	0.000	{ 0.965; 1.041 }
Positive Bank Assets	-0.002	0.008	0.822	{ -0.018; 0.014 }
Positive Net Wealth	-0.003	0.008	0.726	{ -0.019; 0.013 }
Discount Rate δ:				
Constant	0.173	0.030	0.000	{ 0.113; 0.232 }
Positive Bank Assets	0.015	0.019	0.439	{ -0.023; 0.053 }
Positive Net Wealth	-0.062	0.026	0.015	{ -0.112; -0.012 }
(B) Positive Net Wealth and Positive Bank Wealth				
Present Bias β:				
Constant	0.999	0.013	0.000	{ 0.974; 1.024 }
Positive Bank Wealth	0.005	0.007	0.518	{ -0.010; 0.019 }
Positive Net Wealth	-0.005	0.008	0.566	{ -0.021; 0.012 }
Discount Rate δ:				
Constant	0.182	0.031	0.000	{ 0.122; 0.242 }
Positive Bank Wealth	0.023	0.028	0.411	{ -0.031; 0.077 }
Positive Net Wealth	-0.071	0.026	0.007	{ -0.123; -0.019 }
(C) 3yr Average Net Wealth Quartile and Positive Bank Assets				
Present Bias β:				
Constant	0.993	0.015	0.000	{ 0.963; 1.023 }
Positive Bank Assets	-0.003	0.010	0.797	{ -0.023; 0.018 }
2nd Net Wealth Quartile	0.008	0.016	0.630	{ -0.023; 0.039 }
3rd Net Wealth Quartile	0.012	0.019	0.548	{ -0.026; 0.049 }
4th Net Wealth Quartile	0.003	0.022	0.905	{ -0.041; 0.046 }
Discount Rate δ:				
Constant	0.196	0.043	0.000	{ 0.112; 0.279 }
Positive Bank Assets	0.007	0.023	0.752	{ -0.038; 0.052 }
2nd Net Wealth Quartile	-0.058	0.054	0.287	{ -0.164; 0.048 }
3rd Net Wealth Quartile	-0.075	0.040	0.061	{ -0.152; 0.003 }
4th Net Wealth Quartile	-0.084	0.043	0.052	{ -0.169; 0.001 }
(D) 3yr Average Net Wealth Quartile and Positive Bank Wealth				
Present Bias β:				
Constant	0.995	0.012	0.000	{ 0.972; 1.018 }
Positive Bank Wealth	-0.002	0.007	0.824	{ -0.015; 0.012 }
2nd Net Wealth Quartile	0.002	0.012	0.872	{ -0.022; 0.026 }
3rd Net Wealth Quartile	0.007	0.007	0.304	{ -0.007; 0.021 }
4th Net Wealth Quartile	-0.001	0.008	0.868	{ -0.017; 0.015 }
Discount Rate δ:				
Constant	0.228	0.075	0.002	{ 0.081; 0.375 }
Positive Bank Wealth	-0.045	0.080	0.574	{ -0.203; 0.112 }
2nd Net Wealth Quartile	-0.085	0.055	0.120	{ -0.193; 0.022 }
3rd Net Wealth Quartile	-0.065	0.040	0.103	{ -0.143; 0.013 }
4th Net Wealth Quartile	-0.042	0.079	0.590	{ -0.197; 0.112 }

Note: We jointly estimate quasi-hyperbolic discounting and utility curvature using maximum likelihood and use frequency weights (fweight=50) with respect to observations from the risk aversion task. The variables included in the estimations are similar to those in Tables 13 and 14, and the full set of of estimates is available upon request.

6 Conclusion

We use a unique combination of data on individual discount rates from a field experiment with a representative sample of the Danish population and administrative data on income and financial wealth. Our analysis leads to two important insights. First, we find a negative association between net wealth and individual discount rates, with wealthier subjects having significantly lower individual discount rates than less wealthy subjects. Second, we do not find a significant association between present bias and deposits of liquid asset.

The first result of our analysis, a negative correlation between net wealth and individual discount rates, is consistent with economic theory on saving and capital accumulation; more patient individuals accumulate more savings and capital than less patient individuals. No other study has so far combined experimental data on individual discount rates from a broad sample of a population with reliable administrative data on accumulated financial wealth and asset classes. Our results confirm the findings by Pender (1996) and Yesuf and Bluffstone (2008), who combine experimental data on discount rates with survey data on broad definitions of wealth in developing countries.

We cannot identify the direction of causality but only estimate the correlation between net wealth and individual discount rates. Pender (1996) suggests that differences in individual discount rates across different levels of wealth are due to differences in financial liquidity constraints and opportunity interest rates. This interpretation follows Fisher's (1930) *Theory of Interest*, in which choices over time delayed rewards identify opportunity interest rates. Under the alternative interpretation that intertemporal choices in experiments are made irrespective of capital market opportunities, individual discount rates may be a cause of wealth accumulation, which is consistent with the assumptions in life cycle models of individual saving and investment behavior.

To identify the extent to which financial wealth leads to more patient decisions in experiments, one would require exogenous changes in net wealth and measure discount rates before and after these exogenous changes at the individual level. A recent study related to this question is Dean and Sautmann (2014). They combine data on weekly income and consumption from a household survey in Mali with data from repeated incentivized discounting tasks and find that the marginal rate of substitution over delayed rewards is correlated with financial shocks. This result indicates that there is a causal effect from net wealth on individual discount rates.

The second result of our analysis, that there is no significant association between present bias and financial liquidity, has important theoretical and policy implications. In particular, our results challenge the assumption of present bias in discounting models: we find no evidence of present biased time preferences. Laibson (1997) highlights the risks posed by easy access to consumer credit via financial instruments such as credit cards, since these instruments allow subjects to consume more in the short term at the expense of future consumption. However, we do not observe a significant association between consumer debt and present bias, which does not provide support for restricting access to consumer credit.

Our results stand in contrast to the conclusions by Meier and Sprenger (2010), but there are several important differences to consider between their study and ours. First, the two samples are very different: our sample is representative of the adult Danish population, whereas the sample in Meier and Sprenger (2010) is predominantly low-income individuals from the United States seeking assistance with their tax returns. Second, while we consider assets and liabilities in our measures of wealth and liquidity, they only consider liabilities. To make definite conclusions regarding the connection between present bias and financial wealth, further empirical evidence will be useful.

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Appendix A

Complete Estimation Results

We present estimation results for Tables 10 11, 13, and 14, including the estimates for stochastic errors and curvature.[23] We describe the estimation models in Section 3.2. For risk choices, we include a contextual stochastic error, and for discounting choices, we include a Fechner error.

We include covariates for the time delay of the discounting choice in the stochastic error for discounting choices. The higher the delay, the higher the stochastic error in all estimations.[24] This result is consistent with the fact that a higher time delay results in a higher latent index. The higher stochastic error for these choices normalizes the magnitude of the latent index to comparable levels across treatments.

Table 16: Exponential Discounting under Linear Utility - Complete Set of Estimates

	Coefficient	Standard Error	p-Value	95% Confidence Interval
Discount Rate δ				
Constant	0.282	0.072	0.000	{ 0.141; 0.423 }
2nd Net Wealth Quartile	-0.028	0.069	0.689	{-0.162; 0.107 }
3rd Net Wealth Quartile	-0.094	0.048	0.050	{-0.187; -0.000 }
4th Net Wealth Quartile	-0.114	0.057	0.045	{-0.225; -0.002 }
2nd Income Quartile	-0.057	0.069	0.408	{-0.192; 0.078 }
3rd Income Quartile	-0.049	0.062	0.427	{-0.171; 0.072 }
4th Income Quartile	-0.098	0.065	0.132	{-0.227; 0.030 }
Female	-0.009	0.044	0.836	{-0.096; 0.077 }
30-39 Years	0.080	0.060	0.185	{-0.038; 0.198 }
40-49 years	0.030	0.058	0.609	{-0.084; 0.144 }
50-59 Years	0.005	0.074	0.949	{-0.141; 0.150 }
60 Years and older	-0.060	0.071	0.395	{-0.199; 0.079 }
Highschool Graduate	0.051	0.049	0.302	{-0.046; 0.147 }
Higher Education, Bachelor	0.049	0.058	0.400	{-0.065; 0.164 }
Higher Education, Master a.a.	0.036	0.071	0.610	{-0.103; 0.176 }

[23]The complete estimation results for all robustness checks in Tables 12 and 15 are available from the authors upon request.

[24]In the quasi-hyperbolic discounting estimates, the estimates are not statistically significantly different form zero but have the same point estimates as in the other estimations.

Stochastic Error Discounting $ln(\mu_{IDR})$				
Constant	3.841	0.601	0.000	{ 2.663; 5.019 }
2nd Net Wealth Quartile	0.173	0.371	0.641	{-0.554; 0.901 }
3rd Net Wealth Quartile	-0.061	0.260	0.815	{-0.570; 0.448 }
4th Net Wealth Quartile	-0.002	0.248	0.994	{-0.488; 0.484 }
2nd Income Quartile	-0.230	0.338	0.495	{-0.892; 0.431 }
3rd Income Quartile	-0.211	0.346	0.542	{-0.888; 0.467 }
4th Income Quartile	-0.603	0.398	0.130	{-1.384; 0.177 }
Female	0.272	0.207	0.189	{-0.134; 0.677 }
30-39 Years	0.280	0.256	0.274	{-0.221; 0.782 }
40-49 years	0.224	0.275	0.414	{-0.314; 0.762 }
50-59 Years	0.271	0.368	0.462	{-0.450; 0.992 }
60 Years and older	0.764	0.316	0.015	{ 0.146; 1.383 }
Highschool Graduate	-0.179	0.239	0.452	{-0.647; 0.288 }
Higher Education, Bachelor	0.076	0.307	0.804	{-0.525; 0.677 }
Higher Education, Master a.a.	-0.015	0.346	0.965	{-0.692; 0.662 }
T: Low Stakes	-0.551	0.206	0.008	{-0.956; -0.147 }
T: 1 Month Horizon	0.280	0.333	0.401	{-0.373; 0.933 }
T: 2 Month Horizon	0.659	0.352	0.061	{-0.032; 1.350 }
T: 3 Month Horizon	0.648	0.450	0.150	{-0.234; 1.530 }
T: 4 Month Horizon	1.140	0.385	0.003	{ 0.385; 1.895 }
T: 5 Month Horizon	1.298	0.420	0.002	{ 0.475; 2.121 }
T: 6 Month Horizon	1.357	0.423	0.001	{ 0.529; 2.186 }
T: 7 Month Horizon	1.463	0.446	0.001	{ 0.588; 2.338 }
T: 8 Month Horizon	1.607	0.423	0.000	{ 0.778; 2.436 }
T: 9 Month Horizon	1.717	0.482	0.000	{ 0.772; 2.662 }
T: 10 Month Horizon	1.777	0.440	0.000	{ 0.915; 2.638 }
T: 11 Month Horizon	1.783	0.434	0.000	{ 0.932; 2.633 }
T: 12 Month Horizon	1.900	0.441	0.000	{ 1.036; 2.765 }

Table 17: Exponential Discounting controlling for Utility Curvature - Complete Set of Estimates

	Coefficient	Standard Error	p-Value	95% Confidence Interval
Discount Rate δ				
Constant	0.185	0.039	0.000	{ 0.109; 0.261 }
2nd Net Wealth Quartile	-0.027	0.033	0.406	{-0.091; 0.037 }
3rd Net Wealth Quartile	-0.054	0.026	0.038	{-0.106; -0.003 }
4th Net Wealth Quartile	-0.054	0.029	0.064	{-0.111; 0.003 }
2nd Income Quartile	-0.031	0.036	0.391	{-0.101; 0.040 }
3rd Income Quartile	-0.047	0.033	0.163	{-0.112; 0.019 }
4th Income Quartile	-0.044	0.035	0.204	{-0.113; 0.024 }
Female	-0.027	0.023	0.246	{-0.073; 0.019 }
30-39 Years	0.045	0.034	0.193	{-0.023; 0.112 }
40-49 Years	0.024	0.031	0.438	{-0.037; 0.085 }
50-59 Years	0.014	0.036	0.700	{-0.057; 0.085 }
60 Years and older	-0.033	0.037	0.371	{-0.106; 0.039 }
Highschool Graduate	-0.006	0.027	0.824	{-0.060; 0.047 }
Higher Education, Bachelor	-0.016	0.032	0.621	{-0.079; 0.047 }
Higher Education, Master a.a.	-0.023	0.041	0.574	{-0.104; 0.058 }

Utility Curvature r				
Constant	0.295	0.085	0.001	{ 0.127; 0.462 }
2nd Net Wealth Quartile	0.077	0.077	0.318	{-0.075; 0.229 }
3rd Net Wealth Quartile	0.086	0.077	0.260	{-0.064; 0.237 }
4th Net Wealth Quartile	-0.054	0.091	0.557	{-0.232; 0.125 }
2nd Income Quartile	0.032	0.083	0.696	{-0.130; 0.194 }
3rd Income Quartile	0.148	0.103	0.150	{-0.053; 0.349 }
4th Income Quartile	-0.007	0.100	0.944	{-0.204; 0.189 }
Female	0.174	0.056	0.002	{ 0.065; 0.284 }
30-39 Years	-0.005	0.098	0.958	{-0.197; 0.186 }
40-49 Years	-0.003	0.093	0.972	{-0.185; 0.178 }
50-59 Years	0.058	0.087	0.503	{-0.112; 0.228 }
60 Years and older	0.189	0.120	0.115	{-0.046; 0.424 }
Highschool Graduate	0.132	0.078	0.088	{-0.020; 0.284 }
Higher Education, Bachelor	0.167	0.088	0.058	{-0.006; 0.339 }
Higher Education, Master a.a.	0.181	0.116	0.117	{-0.045; 0.407 }
Stochastic Error Discounting $ln(\mu_{IDR})$				
Constant	1.681	0.952	0.077	{-0.184; 3.546 }
2nd Net Wealth Quartile	-0.581	0.752	0.440	{-2.055; 0.894 }
3rd Net Wealth Quartile	-0.834	0.692	0.228	{-2.190; 0.522 }
4th Net Wealth Quartile	0.375	0.800	0.640	{-1.194; 1.944 }
2nd Income Quartile	-0.437	0.735	0.552	{-1.877; 1.004 }
3rd Income Quartile	-1.312	0.840	0.118	{-2.957; 0.334 }
4th Income Quartile	-0.568	0.897	0.526	{-2.326; 1.189 }
Female	-1.135	0.495	0.022	{-2.104; -0.165 }
30-39 Years	0.233	0.743	0.754	{-1.224; 1.689 }
40-49 Years	0.132	0.798	0.869	{-1.432; 1.697 }
50-59 Years	-0.335	0.800	0.676	{-1.902; 1.233 }
60 Years and older	-0.930	1.079	0.389	{-3.044; 1.185 }
Highschool Graduate	-1.117	0.629	0.076	{-2.350; 0.115 }
Higher Education, Bachelor	-1.058	0.757	0.162	{-2.542; 0.425 }
Higher Education, Master a.a.	-1.293	0.983	0.188	{-3.219; 0.634 }
T: Low Stakes	-0.103	0.240	0.668	{-0.573; 0.368 }
T: 1 Month Horizon	0.099	0.411	0.810	{-0.707; 0.904 }
T: 2 Month Horizon	0.519	0.400	0.195	{-0.266; 1.303 }
T: 3 Month Horizon	0.415	0.492	0.398	{-0.548; 1.379 }
T: 4 Month Horizon	0.929	0.422	0.028	{ 0.103; 1.756 }
T: 5 Month Horizon	1.094	0.469	0.020	{ 0.174; 2.014 }
T: 6 Month Horizon	1.188	0.456	0.009	{ 0.294; 2.082 }
T: 7 Month Horizon	1.213	0.483	0.012	{ 0.266; 2.159 }
T: 8 Month Horizon	1.364	0.487	0.005	{ 0.410; 2.318 }
T: 9 Month Horizon	1.424	0.515	0.006	{ 0.415; 2.433 }
T: 10 Month Horizon	1.529	0.485	0.002	{ 0.579; 2.478 }
T: 11 Month Horizon	1.544	0.478	0.001	{ 0.607; 2.480 }
T: 12 Month Horizon	1.609	0.485	0.001	{ 0.659; 2.559 }
Stochastic Error Risk $ln(\mu_{RA})$				
Constant	-2.237	0.133	0.000	{-2.498; -1.976 }
2nd Net Wealth Quartile	0.058	0.119	0.628	{-0.175; 0.290 }
3rd Net Wealth Quartile	-0.032	0.113	0.774	{-0.254; 0.189 }
4th Net Wealth Quartile	-0.121	0.125	0.333	{-0.366; 0.124 }
2nd Income Quartile	0.013	0.115	0.908	{-0.213; 0.239 }
3rd Income Quartile	0.151	0.135	0.264	{-0.114; 0.416 }

4th Income Quartile	-0.157	0.151	0.299	{-0.453; 0.139 }
Female	-0.007	0.079	0.925	{-0.162; 0.147 }
30-39 Years	0.254	0.138	0.065	{-0.016; 0.524 }
40-49 Years	0.416	0.118	0.000	{ 0.184; 0.648 }
50-59 Years	0.381	0.121	0.002	{ 0.143; 0.618 }
60 Years and older	0.859	0.126	0.000	{ 0.611; 1.106 }
Highschool Graduate	-0.161	0.103	0.118	{-0.362; 0.041 }
Higher Education, Bachelor	-0.249	0.121	0.040	{-0.486; -0.011 }
Higher Education, Master a.a.	-0.201	0.164	0.220	{-0.521; 0.120 }

Table 18: Quasi-Hyperbolic Discounting and Positive Bank Assets - Complete Set of Estimates

	Coefficient	Standard Error	p-Value	95% Confidence Interval
Present Bias β				
Constant	0.989	0.013	0.000	{ 0.963; 1.015 }
Positive Bank Assets	-0.002	0.007	0.761	{-0.016; 0.012 }
2nd Net Wealth Quartile	0.010	0.013	0.451	{-0.016; 0.036 }
3rd Net Wealth Quartile	0.005	0.013	0.683	{-0.020; 0.031 }
4th Net Wealth Quartile	-0.004	0.011	0.748	{-0.026; 0.018 }
2nd Income Quartile	0.001	0.013	0.953	{-0.024; 0.025 }
3rd Income Quartile	0.001	0.015	0.930	{-0.028; 0.031 }
4th Income Quartile	0.003	0.016	0.859	{-0.028; 0.034 }
Female	-0.001	0.013	0.958	{-0.025; 0.024 }
30-39 Years	-0.002	0.014	0.904	{-0.030; 0.027 }
40-49 Years	-0.004	0.021	0.849	{-0.046; 0.038 }
50-59 Years	0.008	0.023	0.716	{-0.036; 0.053 }
60 Years and older	0.019	0.020	0.354	{-0.021; 0.058 }
Highschool Graduate	0.004	0.009	0.617	{-0.013; 0.022 }
Higher Education, Bachelor	-0.004	0.014	0.770	{-0.032; 0.024 }
Higher Education, Master a.a.	-0.003	0.023	0.912	{-0.048; 0.043 }
Discount Rate δ				
Constant	0.158	0.040	0.000	{ 0.080; 0.235 }
Positive Bank Assets	0.008	0.019	0.650	{-0.028; 0.045 }
2nd Net Wealth Quartile	-0.016	0.039	0.686	{-0.093; 0.061 }
3rd Net Wealth Quartile	-0.050	0.030	0.100	{-0.109; 0.009 }
4th Net Wealth Quartile	-0.081	0.049	0.098	{-0.177; 0.015 }
2nd Income Quartile	-0.036	0.033	0.281	{-0.101; 0.029 }
3rd Income Quartile	-0.038	0.037	0.310	{-0.111; 0.035 }
4th Income Quartile	-0.036	0.039	0.356	{-0.112; 0.040 }
Female	-0.034	0.025	0.164	{-0.082; 0.014 }
30-39 Years	0.036	0.031	0.252	{-0.026; 0.098 }
40-49 Years	0.026	0.030	0.396	{-0.033; 0.084 }
50-59 Years	0.025	0.037	0.509	{-0.049; 0.098 }
60 Years and older	0.001	0.055	0.989	{-0.106; 0.108 }
Highschool Graduate	0.011	0.047	0.823	{-0.082; 0.103 }
Higher Education, Bachelor	-0.016	0.051	0.747	{-0.117; 0.084 }
Higher Education, Master a.a.	-0.045	0.083	0.591	{-0.208; 0.118 }

Utility Curvature r				
Constant	0.347	0.089	0.000	{ 0.173; 0.521 }
Positive Bank Assets	-0.101	0.056	0.072	{-0.211; 0.009 }
2nd Net Wealth Quartile	0.091	0.077	0.235	{-0.059; 0.242 }
3rd Net Wealth Quartile	0.119	0.076	0.119	{-0.031; 0.269 }
4th Net Wealth Quartile	-0.023	0.090	0.801	{-0.198; 0.153 }
2nd Income Quartile	0.034	0.083	0.681	{-0.129; 0.197 }
3rd Income Quartile	0.153	0.103	0.138	{-0.049; 0.355 }
4th Income Quartile	-0.003	0.102	0.975	{-0.202; 0.196 }
Female	0.174	0.056	0.002	{ 0.064; 0.283 }
30-39 Years	-0.012	0.096	0.901	{-0.201; 0.177 }
40-49 Years	-0.021	0.092	0.817	{-0.201; 0.158 }
50-59 Years	0.052	0.087	0.546	{-0.118; 0.223 }
60 Years and older	0.192	0.122	0.114	{-0.046; 0.430 }
Highschool Graduate	0.127	0.079	0.109	{-0.028; 0.281 }
Higher Education, Bachelor	0.172	0.089	0.054	{-0.003; 0.347 }
Higher Education, Master a.a.	0.185	0.116	0.112	{-0.043; 0.413 }
Stochastic Error Risk $ln(\mu_{RA})$				
Constant	-2.180	0.144	0.000	{-2.463; -1.897 }
Positive Bank Assets	-0.076	0.093	0.415	{-0.259; 0.107 }
2nd Net Wealth Quartile	0.064	0.120	0.594	{-0.171; 0.298 }
3rd Net Wealth Quartile	-0.005	0.119	0.964	{-0.239; 0.228 }
4th Net Wealth Quartile	-0.092	0.132	0.484	{-0.350; 0.166 }
2nd Income Quartile	0.022	0.116	0.848	{-0.205; 0.249 }
3rd Income Quartile	0.163	0.135	0.225	{-0.101; 0.427 }
4th Income Quartile	-0.150	0.150	0.317	{-0.444; 0.144 }
Female	-0.013	0.079	0.868	{-0.168; 0.142 }
30-39 Years	0.218	0.139	0.115	{-0.054; 0.490 }
40-49 Years	0.378	0.118	0.001	{ 0.147; 0.609 }
50-59 Years	0.363	0.122	0.003	{ 0.124; 0.601 }
60 Years and older	0.849	0.127	0.000	{ 0.600; 1.098 }
Highschool Graduate	-0.174	0.104	0.094	{-0.377; 0.030 }
Higher Education, Bachelor	-0.253	0.121	0.037	{-0.490; -0.016 }
Higher Education, Master a.a.	-0.210	0.165	0.203	{-0.533; 0.113 }
Stochastic Error Discounting $ln(\mu_{IDR})$				
Constant	1.572	1.388	0.257	{-1.149; 4.293 }
Positive Bank Assets	0.871	0.542	0.108	{-0.192; 1.934 }
2nd Net Wealth Quartile	-0.693	1.156	0.549	{-2.959; 1.573 }
3rd Net Wealth Quartile	-1.173	0.827	0.156	{-2.794; 0.449 }
4th Net Wealth Quartile	0.375	0.940	0.690	{-1.468; 2.218 }
2nd Income Quartile	-0.465	0.812	0.567	{-2.057; 1.126 }
3rd Income Quartile	-1.465	1.285	0.254	{-3.983; 1.052 }
4th Income Quartile	-0.776	1.105	0.483	{-2.942; 1.391 }
Female	-1.071	0.576	0.063	{-2.200; 0.058 }
30-39 Years	0.228	0.975	0.815	{-1.684; 2.140 }
40-49 Years	0.323	1.096	0.768	{-1.824; 2.470 }
50-59 Years	-0.156	1.081	0.885	{-2.275; 1.963 }
60 Years and older	-1.059	1.148	0.356	{-3.309; 1.190 }
Highschool Graduate	-1.323	0.705	0.061	{-2.705; 0.059 }
Higher Education, Bachelor	-1.265	0.816	0.121	{-2.864; 0.334 }
Higher Education, Master a.a.	-1.145	1.194	0.338	{-3.486; 1.197 }

T: Low Stakes	0.048	0.642	0.940	{-1.211; 1.307 }
T: 1 Month Horizon	-0.096	0.653	0.883	{-1.377; 1.184 }
T: 2 Month Horizon	0.194	0.906	0.831	{-1.583; 1.970 }
T: 3 Month Horizon	0.144	0.930	0.877	{-1.680; 1.967 }
T: 4 Month Horizon	0.683	0.914	0.455	{-1.108; 2.475 }
T: 5 Month Horizon	0.885	0.917	0.335	{-0.913; 2.683 }
T: 6 Month Horizon	0.934	0.936	0.318	{-0.901; 2.769 }
T: 7 Month Horizon	0.999	0.918	0.276	{-0.800; 2.798 }
T: 8 Month Horizon	1.107	0.912	0.225	{-0.681; 2.895 }
T: 9 Month Horizon	1.146	0.937	0.221	{-0.690; 2.982 }
T: 10 Month Horizon	1.267	0.969	0.191	{-0.633; 3.167 }
T: 11 Month Horizon	1.245	0.942	0.187	{-0.602; 3.092 }
T: 12 Month Horizon	1.385	0.925	0.134	{-0.428; 3.198 }
T: Front End Delay	0.023	0.298	0.939	{-0.561; 0.607 }

Table 19: Quasi-Hyperbolic Discounting and Positive Bank Wealth - Complete Set of Estimates

	Coefficient	Standard Error	p-Value	95% Confidence Interval
Present Bias β				
Constant	0.978	0.031	0.000	{ 0.917; 1.039 }
Positive Bank Wealth	0.013	0.017	0.461	{-0.021; 0.047 }
2nd Net Wealth Quartile	0.012	0.014	0.401	{-0.016; 0.040 }
3rd Net Wealth Quartile	0.004	0.013	0.761	{-0.022; 0.030 }
4th Net Wealth Quartile	-0.011	0.018	0.556	{-0.047; 0.025 }
2nd Income Quartile	0.010	0.028	0.715	{-0.045; 0.066 }
3rd Income Quartile	0.014	0.036	0.700	{-0.056; 0.084 }
4th Income Quartile	0.017	0.043	0.704	{-0.069; 0.102 }
Female	0.004	0.018	0.808	{-0.031; 0.040 }
30-39 Years	-0.006	0.020	0.751	{-0.045; 0.033 }
40-49 Years	-0.009	0.025	0.703	{-0.058; 0.039 }
50-59 Years	0.004	0.023	0.874	{-0.041; 0.048 }
60 Years and older	0.023	0.019	0.228	{-0.014; 0.059 }
Highschool Graduate	0.003	0.010	0.750	{-0.016; 0.023 }
Higher Education, Bachelor	-0.014	0.028	0.615	{-0.069; 0.041 }
Higher Education, Master a.a.	-0.012	0.036	0.733	{-0.082; 0.058 }
Discount Rate δ				
Constant	0.159	0.044	0.000	{ 0.074; 0.244 }
Positive Bank Wealth	0.020	0.027	0.462	{-0.033; 0.072 }
2nd Net Wealth Quartile	-0.015	0.037	0.690	{-0.088; 0.058 }
3rd Net Wealth Quartile	-0.053	0.027	0.052	{-0.106; 0.000 }
4th Net Wealth Quartile	-0.113	0.104	0.276	{-0.316; 0.090 }
2nd Income Quartile	-0.027	0.040	0.500	{-0.105; 0.051 }
3rd Income Quartile	-0.028	0.047	0.542	{-0.120; 0.063 }
4th Income Quartile	-0.026	0.049	0.597	{-0.122; 0.070 }
Female	-0.037	0.020	0.061	{-0.076; 0.002 }
30-39 Years	0.032	0.039	0.416	{-0.045; 0.109 }
40-49 years	0.026	0.027	0.344	{-0.028; 0.079 }
50-59 Years	0.029	0.035	0.411	{-0.040; 0.097 }

60 Years and older	0.013	0.061	0.829	{-0.106; 0.133 }
Highschool Graduate	0.002	0.043	0.964	{-0.083; 0.087 }
Higher Education, Bachelor	-0.034	0.061	0.581	{-0.153; 0.086 }
Higher Education, Master a.a.	-0.070	0.114	0.536	{-0.293; 0.153 }
Utility Curvature r				
Constant	0.297	0.088	0.001	{ 0.126; 0.469 }
Positive Bank Wealth	-0.039	0.066	0.553	{-0.167; 0.090 }
2nd Net Wealth Quartile	0.088	0.079	0.265	{-0.067; 0.243 }
3rd Net Wealth Quartile	0.111	0.082	0.177	{-0.050; 0.271 }
4th Net Wealth Quartile	-0.032	0.097	0.742	{-0.222; 0.158 }
2nd Income Quartile	0.029	0.083	0.725	{-0.133; 0.192 }
3rd Income Quartile	0.148	0.103	0.154	{-0.055; 0.350 }
4th Income Quartile	-0.011	0.101	0.915	{-0.210; 0.188 }
Female	0.177	0.056	0.002	{ 0.067; 0.287 }
30-39 Years	-0.011	0.099	0.908	{-0.206; 0.184 }
40-49 years	-0.006	0.095	0.953	{-0.191; 0.180 }
50-59 Years	0.056	0.089	0.528	{-0.118; 0.230 }
60 Years and older	0.191	0.121	0.113	{-0.045; 0.427 }
Highschool Graduate	0.135	0.078	0.083	{-0.018; 0.288 }
Higher Education, Bachelor	0.168	0.088	0.058	{-0.006; 0.341 }
Higher Education, Master a.a.	0.187	0.116	0.106	{-0.040; 0.413 }
Stochastic Error Risk $ln(\mu_{RA})$				
Constant	-2.226	0.137	0.000	{-2.493; -1.958 }
Positive Bank Wealth	0.015	0.099	0.879	{-0.179; 0.209 }
2nd Net Wealth Quartile	0.055	0.120	0.649	{-0.181; 0.290 }
3rd Net Wealth Quartile	-0.047	0.127	0.711	{-0.296; 0.202 }
4th Net Wealth Quartile	-0.132	0.141	0.348	{-0.408; 0.144 }
2nd Income Quartile	0.017	0.116	0.885	{-0.211; 0.245 }
3rd Income Quartile	0.159	0.136	0.244	{-0.108; 0.426 }
4th Income Quartile	-0.149	0.153	0.329	{-0.449; 0.150 }
Female	-0.011	0.080	0.890	{-0.168; 0.146 }
30-39 Years	0.242	0.145	0.095	{-0.042; 0.527 }
40-49 years	0.406	0.123	0.001	{ 0.166; 0.647 }
50-59 Years	0.366	0.125	0.003	{ 0.121; 0.611 }
60 Years and older	0.851	0.126	0.000	{ 0.604; 1.098 }
Highschool Graduate	-0.168	0.103	0.102	{-0.369; 0.033 }
Higher Education, Bachelor	-0.254	0.122	0.037	{-0.492; -0.015 }
Higher Education, Master a.a.	-0.210	0.163	0.199	{-0.529; 0.110 }
Stochastic Error Discounting $ln(\mu_{IDR})$				
Constant	2.577	1.806	0.154	{-0.963; 6.117 }
Positive Bank Wealth	0.248	0.655	0.705	{-1.035; 1.531 }
2nd Net Wealth Quartile	-1.043	1.391	0.454	{-3.770; 1.684 }
3rd Net Wealth Quartile	-1.257	0.899	0.162	{-3.020; 0.505 }
4th Net Wealth Quartile	0.621	1.040	0.551	{-1.418; 2.660 }
2nd Income Quartile	-0.766	1.182	0.517	{-3.081; 1.550 }
3rd Income Quartile	-2.055	1.871	0.272	{-5.723; 1.612 }
4th Income Quartile	-1.221	1.837	0.506	{-4.821; 2.380 }
Female	-1.133	0.547	0.038	{-2.205; -0.061 }
30-39 Years	0.609	1.257	0.628	{-1.855; 3.073 }
40-49 years	0.536	1.223	0.661	{-1.860; 2.933 }

50-59 Years	0.257	1.462	0.860	{-2.608; 3.122 }
60 Years and older	-0.766	1.193	0.520	{-3.104; 1.571 }
Highschool Graduate	-1.411	0.666	0.034	{-2.716; -0.106 }
Higher Education, Bachelor	-1.255	0.765	0.101	{-2.754; 0.244 }
Higher Education, Master a.a.	-1.054	1.175	0.370	{-3.358; 1.249 }
T: Low Stakes	0.200	0.710	0.779	{-1.192; 1.592 }
T: 1 Month Horizon	-0.287	0.552	0.603	{-1.370; 0.795 }
T: 2 Month Horizon	-0.063	0.738	0.932	{-1.509; 1.383 }
T: 3 Month Horizon	-0.136	0.766	0.859	{-1.637; 1.365 }
T: 4 Month Horizon	0.431	0.755	0.568	{-1.050; 1.911 }
T: 5 Month Horizon	0.530	0.841	0.529	{-1.119; 2.179 }
T: 6 Month Horizon	0.656	0.803	0.414	{-0.917; 2.230 }
T: 7 Month Horizon	0.728	0.766	0.342	{-0.773; 2.229 }
T: 8 Month Horizon	0.754	0.888	0.396	{-0.988; 2.495 }
T: 9 Month Horizon	0.878	0.776	0.258	{-0.643; 2.399 }
T: 10 Month Horizon	1.017	0.774	0.189	{-0.500; 2.534 }
T: 11 Month Horizon	0.932	0.833	0.264	{-0.702; 2.565 }
T: 12 Month Horizon	1.157	0.748	0.122	{-0.309; 2.623 }
T: Front End Delay	-0.022	0.336	0.949	{-0.680; 0.637 }

Chapter 3

Gambling Problems in the General Danish Population: Survey Evidence

Gambling Problems in the General Danish Population: Survey Evidence

Glenn W. Harrison, Lasse J. Jessen, Morten Lau and Don Ross †

Abstract

We compare several popular survey instruments of gambling behavior and gambling propensity to assess if they differ in their classification of individuals in the general adult Danish population. We also examine correlations with standard survey instruments for alcohol use, anxiety, depression and impulsiveness. A feature of our design is that nobody was excluded on the basis of their response to a "trigger," "gateway" or "diagnostic item" question about previous gambling history. Our sample consists of 8,405 adult Danes. We administered the Focal Adult Gambling Screen to all subjects and find that 95% of the population has no detectable risk, 2.9% has an early risk, 0.8% has an intermediate risk, 0.7% has an advanced risk, and 0.2% can be classified as problem gamblers. There is a significant correlation with the scores of other gambling risk instruments and the instruments measuring alcohol use, anxiety, depression and impulsivity. We also find that controlling for sample selection has a significant effect on prevalence rates: we observe a significant decrease in prevalence rates of detectable gambling risk groups when we control for endogenous sample selection, since gambling behavior is positively correlated with the decision to participate in gambling survey instruments.

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1 Introduction

Gambling surveys have provided measures of the extent of gambling problems in the general population, but have proven to be controversial. Several concerns with these surveys derive from the goal of mimicking prevalence estimates obtained from "face to face" assessments by trained clinicians. Indeed, these concerns motivated, in part, the revisions to the Diagnostic and Statistical Manual of Mental Disorders (DSM) between editions III, III-R and IV, to emphasize the criteria for clinically significant distress or impairment. Many of the survey instruments of mental health to come out of that period reflected those criteria.[1]

It is worthwhile listing the DSM-IV criteria, to get a sense of the type of gambling problems that these survey instruments seek to identify:

1. Have you found yourself thinking about gambling (e.g. reliving past gambling experiences, planning the next time you will play or thinking of ways to get money for gambling)?
2. Have you needed to gamble with more and more money to get the amount of excitement you are looking for?
3. Have you become restless or irritable when trying to cut down or stop gambling?
4. Have you gambled to escape from problems or when you are feeling depressed, anxious or bad about yourself?
5. After losing money gambling, have you returned another day in order to get even?
6. Have you lied to your family, or others, to hide the extent of your gambling?
7. Have you made repeated unsuccessful attempts to control, cut back or stop gambling?
8. Have you been forced to go beyond what is strictly legal, in order to finance gambling or to pay gambling debts?
9. Have you risked or lost a significant relationship, job, educational or career opportunity because of gambling?
10. Have you sought help from others to provide money to relieve a desperate financial situation caused by gambling?

If someone meets 5 or more of these 10 criteria they are deemed to be a "pathological gambler."[2]

These criteria seek to identify and screen someone one might expect to be seeking help from

[1] As Kessler et al. (2004; p. 123) noted, in explanations of the extensive efforts they undertook to clinically calibrate the instruments used in NCS-R, "The initial reaction to these results among health policy analysts was one of disbelief. The most obvious interpretation was that the lay administered diagnostic interviews [...] were upwardly biased."

[2] The term "pathological gambler" was introduced in DSM-III, and has been replaced in DSM-V with the term "gambling disorder." The old expression was regarded by some clinicians as being "outdated and pejorative", to borrow the words of the Working Group that changed the name (Petry et al., 2014; p.494). The new terminology might also be regarded as improving on the situation in which the terms "problem

gambling outcomes, and who might well exhibit some other psychiatric disorder, such as anxiety, panic attacks or depression.[3] All survey instruments, as far as we are aware, employ a "screener," "gateway" or "diagnostic stem" question to filter out individuals that have never engaged in certain gambling behavior. In many cases the filter is whether they have ever lost a certain amount of money in any one day of gambling, and in other cases it is whether they have ever gambled more than a certain number of times in any year.[4]

There are several issues with these criteria. The first for us is that they place emphasis solely on meeting clinical criteria, in effect predicting whether someone is likely to "present" for treatment or should "present" for treatment. This is certainly not wrong *per se*, but it is only one criterion for deciding if someone has a gambling problem.

The second issue is that these measures could easily skip someone who one might reasonably view as having a gambling problem. To take an extreme example, somebody who builds up a considerable debt from gambling that burdens them for years, but who is not in denial or wanting to get back into the casino in the optimistic hope of winning the money back.

The third issue is that there could be someone with serious symptoms of 4 of these criteria, but not 5. This is more a criticism of the binary threshold applied to the criteria than the criteria themselves, and of the fact that the criteria are unweighted.[5]

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gambling" and "pathological gambling" were not used consistently and contributed to confusion in comparing different prevalence estimates.

[3] The DSM-IV explicitly excludes someone whose gambling behavior might be better diagnosed as due to a Manic Episode.

[4] For example, the NCS-R has gateway questions that ask if the individual has gambled 11 or more times ever in any one of a wide range of activities *and* ever lost $365 or more in a year; the NESARC has a gateway question that asks if the individual has ever gambled in any organized form 5 times in one year; and the CCHS Cycle 1.2 survey asked, *inter alia*, "In the past 12 months, how often have you bet or spent more money than you wanted on gambling?" and excluded anyone that responded "I am not a gambler."

[5] The DSM-V has removed the 8th criterion to do with illegal activities associated with gambling, and lowered the threshold to 4 of 9, but the point we make is a more general one. One might also imagine a clinician being able to apply weights to the criteria, even if this might be frowned on by some (e.g., insurance companies covering reimbursable psychiatric expenses). There have been evaluations of "subclinical" sets of criteria, which means individuals meeting between 1 and 4 of the DSM-IV criteria other than the threshold defining pathological gambling: see Blanco et al. (2006), for example, who stress gender differences in comorbidities when comparing subclinical and clinical gambling problems.

The fourth issue is the fact that according to the criteria someone has to have *engaged* in gambling in order to have a *potential* gambling problem. It is not self-evident that everyone with the potential for a gambling problem has had the opportunity to legally exercise that opportunity.

The fifth issue has to do with the gateway question. One of the *possible* criteria for the disorder is that the respondent has lied to family or others to hide the extent of their gambling, but is magically assumed not to do this when asked if they gamble in a survey, particularly in response to the gateway question. The possibility that someone might lie in response to the gateway question, to avoid being asked questions about their gambling behavior is well documented in clinical test-retest interview settings: see Kessler et al. (2004; p.125). One simply does not know *a priori* if this applies to survey instruments.[6]

A final issue is that clinical criteria can fuel political battles when applied in general population surveys. It is not hard to discern from discussions of revisions to the DSM criteria for pathological gambling and clinically-based instruments that a major concern has been that prevalence estimates cannot be allowed to get "too high" because that would imply a shortage of funding for mental health treatment. Clear (enough) statements of this "tail wags dog" problem can be easily found, and the issue is well known in the research folklore.[7]

Another dimension to this final issue is that the operators in the gambling industry welcome prevalence measures for pathological gambling or gambling disorders that are very low. For instance, the lobbying association The American Gambling Association notes that "Although the

[6] There exist econometric methods for evaluating "sample selection" issues such as these. Harrison, Lau and Ross (2016) show that correction for sample selection makes a significant difference to inferences drawn from large-scale surveys of gambling disorders of the general population in the United States and Canada.

[7] For example, Regier et al. (1998; p. 110) commented that "Both the scientific and political implications of these high prevalence rates were highlighted by the timing of this release during the national debate on health reform. Major policy questions were raised about the need for mental health services that were implied by these high rates, along with concerns about possible insurance cost-benefit consequences. Some major media commentators identified such high rates as indicating a bottomless pit of possible demand for mental health services." More recently, from Petry et al., (2014; p.497): "The American Psychiatric Association requires strong empirical data in support of changes to DSM-5 that would substantially increase the base rate of a disorder." But the only motivation then mentioned is the circular argument that reducing the number of threshold criteria would empirically make the base rate increase.

vast majority of Americans are able to gamble responsibly, a small percentage of people – approximately 1 percent of the adult population – cannot."[8] These prevalence estimates come from measures of pathological gambling as defined by clinical criteria. The thrust of the industry's comments on responsible gambling is that 99 out of 100 gamblers are just having fun, and should be left alone, and regulators should only worry about the 1-in-a-100 who is not gambling responsibly.

Again, we stress that these concerns arise for a simple reason: the general purpose survey instruments were intended, by design, to mimic and correlate with the screening that would occur in a clinical setting. Whether that setting is a "gold standard" for some mental health screening purposes or not, it simply differs from other reasons for wanting to measure gambling problems. Society may take a broader view of what constitutes a gambling problem, and certainly economists take a broader view.

Our primary objective is to evaluate for a general population surveys of gambling problems that did not restrict themselves to clinical criteria. We want to see how well these measures correlated with traditional clinically-oriented surveys, of course, if for no other reason than to build a bridge to the type of instrument that has dominated the scene. We stress that we do not see any problem in finding low correlations between a non-clinical instrument and a clinical instrument, and indeed this would be informative.

Our secondary objective is to have a "wide screen" for subjects to be recruited to subsequent experiments to evaluate gambling behavior in controlled gambling tasks. Our view is that the "proof of the pudding" for these instruments is whether they can predict, or be reweighted or calibrated to predict, actual gambling problems. In effect, we agree with the thrust of the movement to have psychiatric disorders measured by clinical tests (e.g. Kapur, Phillips, and Insel, 2012), but

[8] On http://www.americangaming.org/social-responsibility/responsible-gaming, accessed on 9/21/2014.

differ in what we call a "clinical test." For us, any controlled experiment, whether it is the evaluation of a physical tissue specimen in a laboratory setting or the evaluation of gambling choice behavior in a laboratory setting, can potentially serve as an appropriate measure.

In Section 1 we review several instruments for measuring gambling problems, with an eye to widening the screens beyond *ex post* evaluation of clinical metrics of gambling behavior to consider *ex ante* measures of gambling propensity. We also build some bridges to clinically-motivated measures of gambling problems. In Section 2 we review several instruments for detecting psychiatric disorders that are widely linked to gambling disorders through numerous comorbidity studies. In our case we focus on alcohol abuse, anxiety, depression and impulsiveness.

Our overall survey design is intended to evaluate several methodological questions. One, as noted, is the extent of correlation between different survey instruments of gambling behavior, particularly instruments designed to identify different latent factors relevant to gambling behavior. Another methodological issue is the use of randomization of question order, and in some cases instrument order. Another methodological issue is whether one uses lifetime gambling behavior or the last year's gambling behavior as the time frame for responses. A final methodological issue is the role of the "trigger" or "gateway" question. We discuss this design in Section 3, along with specifics of our sample frame and procedures. Section 4 reviews the survey results, and Section 5 presents implications and conclusions.

2 Survey Instruments of Gambling Problems

We examine several survey instruments designed to measure gambling problems. We focus on the Focal Adult Gambling Screen (FLAGS) designed by Schellinck et al. (2015a, 2015b) to span both reflective and formative constructs. A reflective construct is an instrument that seeks to reflect the effects and consequences of some latent variable, and a formative construct is an instrument that seeks to detect the presence of the latent variable. In this case the latent variable is "problem gambling," which we keep in quotation marks because that term can mean different things to different people. The idea from psychometrics is that these two types of constructs provide insights into two different types of causal statements. In the one case problem gambling causes certain behaviors and attributes, and in the other case certain attributes cause problem gambling to arise. The attributes in each case are the traits and beliefs probed by the survey instruments.

Most of the major surveys of gambling behavior based on clinical criteria rely solely on reflective constructs. There have been surveys of gambling propensity building on formative constructs, most notably Breen and Zuckerman (1999). They administered their own Gambling Beliefs and Attitudes Survey (GABS) to college students, and then studied their actual gambling behavior in laboratory card-game. A formal psychometric evaluation of the reflective construct of GABS was undertaken by Strong et al. (2004a), boiling the original 35-item instrument down to a preferred 15-item instrument.[9]

The latest version of FLAGS contains 64 questions designed to measure 10 latent constructs. As applied to machine gambling, these constructs are:

[9] The same general psychometric methods can in principle be used to re-tool clinically based instruments to identify a continuum of gambling types rather than just the binary classification into pathological gamblers and others: see Strong et al. (2003, 2004b) for an application to the South Oaks Gambling Screen (SOGS), Strong and Kahler (2007) for an application to the Alcohol Use Disorder and Associated Disability Interview Schedule – DSM-IV (AUDADIS-IV), and Sharp et al. (2012) for an application to the PGSI. The efforts for SOGS and AUDADIS-IV did not met with great success, suggesting that more fundamental *ex ante* survey design methods are needed as a complement to *ex post* statistical forensics.

1. **Risky Cognitions: Beliefs (RCB)**, such as irrational or inaccurate beliefs about machine gambling.
2. **Risky Cognitions: Motives (RCM)**, such as risky reasons for gambling (e.g., to pay off bills, to escape problems, for self-esteem or status).
3. **Preoccupation: Desire (POD)**, such as a strong drive to play the machines as much as possible.
4. **Impaired Control: Continue (ICC)**, such as the inability to stop playing slots/machines once started.
5. **Risky Practices: Earlier (RBE)**, such as less extreme types of risky practices that usually precede more harmful practices (e.g., using bank card to get more money to play).
6. **Risky Practices: Later (RBL)**, such as more extreme or harmful types of risky practices (e.g., using credit to finance play).
7. **Impaired Control: Begin (ICB)**, such as an inability to resist or stop oneself from going to play slots/machines.
8. **Preoccupation: Obsessed (POO)**, such as excessive preoccupation, constantly thinking about slot gambling or finding ways to gamble on machines.
9. **Negative Consequences (NGC)**, such as negative impacts in at least 3 of 14 different areas of life including financial, personal, family, work, health, social.
10. **Persistence (PST)**: such as continuing to gamble, over an extended period, in a risky manner that leads to harms.

Five of these constructs are formative (items 1, 2 5, 6 and 9), and the other five are reflective. The complete list of statements can be found in Appendix A.

We consider two other popular survey instruments for existing gambling problems. One is the 9-item scored component of the 12-item Canadian Problem Gambling Inventory (CPGI) developed by Ferris and Wynne (2001), and known as the Problem Gambling Severity Index (PGSI). The other is based on the DSM-IV criteria. Both the PGSI and DSM-IV are reflective constructs. We also evaluate three survey instruments of *potential* gambling problems, each stressing formative constructs. One is the Gambling Craving Scale (GACS) developed by Young and Wohl (2009), another is the Gambling Urge Screen (GUS) developed by Raylu and Oei (2004a), and the third is the Gambling Related Cognitions Scale (GRCS) developed by Raylu and Oei (2004b).[10] Each instrument is listed in Appendix A, and Appendix B explains how each instrument was scored. In most cases the scores follow the standard algorithms, but in some instances the scoring is not obvious.

[10] We also considered the Gambling Beliefs and Attitudes Survey (GABS) developed in 1994 by Breen and Zuckerman in unpublished research, and listed in Breen and Zuckerman (1999; p. 1109).

To evaluate the effects of order we only evaluated one instrument along with FLAGS for any one person, and randomized the order of presentation. Thus one randomly selected subject received FLAGS and then PGSI, another received PGSI then FLAGS, another received FLAGS and then DSM-IV, and another received DSM-IV then FLAGS, etc.

In addition, we asked several questions to identify past gambling behavior, since we did not use these as a "trigger" question. Subjects were separately asked, in the lifetime frame, if they had ever lost more than 40 kroner or 500 kroner on gambling in a single day. The lower amount corresponds to the amount of a common state lottery ticket, and the larger amount to a naturally larger denomination that a Dane would likely recall. We also asked these questions for 50% of the sample in the time frame that spanned the last 12 months.

3 Survey Instruments for Other Problems

There is a long history of interest in comorbidities of gambling disorders. Indeed, some research points to virtually *every* measured psychiatric disorder as being correlated with pathological gambling.[11] The implication of much of this research is to focus attention on common causes of several psychiatric disorders. Our evaluation cannot be that exhaustive, but we do consider instruments to measure certain other psychiatric disorders.

These survey instrument are the Beck Anxiety Index (BAI) developed by Beck, Epstein, Brown and Steer (1988) and Beck and Steer (1990), the Beck Depression Inventory (BDI) developed by Beck et al. (1961), and the Barratt Impulsivity Scale (BIS) developed by Patton, Stanford and Barratt (1995). Because alcohol is often highly correlated with gambling, and of particular concern in

[11] For instance, evaluating data from the NESARC Petry et al., (2005; Table 3, p. 570; model 3) report 95% confidence interval lower bounds of Odds Ratio in excess of 1 for alcohol dependence, any drug abuse, any drug dependence, nicotine dependence, major depressive episodes, dysthymic disorders, manic episodes, panic disorders, social phobia, specific phobia, generalized anxiety, and every personality disorder considered (avoidant, dependent, obsessive-compulsive, paranoid, schizoid, histrionic and antisocial). Kessler et al. (2008; Table 2, p.1357) report a similar list from the NCS-R.

Denmark, we implemented the Alcohol Use Disorders Identification Test (AUDIT) of Babor, Higgins-Biddle, Saunders and Monteiro (2001). We also asked if the individual currently smoked, and if so how many cigarettes per day.

To allow for the effects of recent life events, we asked if the individual had experienced the death of an immediate family member (partner, child, parent or sibling) in the past 12 months, or been hospitalized for a major medical problem during the past 12 months.

4 Survey Design

4.1 Treatments

We split our sample into 10 treatments:

1. **FLAGS**, PGSI, BIS
2. PGSI, **FLAGS**, BIS
3. **FLAGS**, DSM-IV, BAI, AUDIT
4. DSM-IV, **FLAGS**, BAI, AUDIT
5. **FLAGS**, GACS, AUDIT
6. GACS, **FLAGS**, AUDIT
7. **FLAGS**, GUS, BDI, AUDIT
8. GUS, **FLAGS**, BDI, AUDIT
9. **FLAGS**, GRCS, AUDIT
10. GRCS, **FLAGS**, AUDIT

The only difference between the odd and even treatments here is the order of the gambling instrument, to assess if comparisons of FLAGS with the other instruments are affected by subjects having already completed the more expansive FLAGS.[12]

We further split each treatment equally into cases in which the timeframe for the gambling instruments FLAGS, PGSI and DSM are lifetime or just the past 12 months. This only affects the introductory text to each instrument.

[12] We do not randomize the order of the sub-blocks of questions for each of the 10 constructs within FLAGS. There is a natural aggregation of these 10 sub-blocks into three groupings, often used in the field implementation of FLAGS (§1: RCB, RCM and POD, §2: ICC, RBE and RBL, and §3: ICB, POO, NGC and PST), and we do not randomize across those groupings either.

Finally, for 50% of the subjects we randomize within each block, when possible, and otherwise present the questions in the standard order. The software used to implement the survey did not allow randomization within a block unless the responses were all the same, so we could *not* randomize the order for AUDIT, the BDI, and our few concluding questions.

4.2 Sample Frame

We contracted with *Analyse Danmark* (http://www.analysedanmark.dk/english) to obtain 10,000 completed survey responses from the adult population of Denmark. This sample was to be assigned equally to all treatments. Our completed sample consisted of 8,405 respondents, which is 12.8% of the sample frame of 65,592 Danes contacted. Of those contacted that did not complete the survey, 3,331 started but gave up. The cost of these surveys was 272,425 DKK, which was just over $45,400 at the time they were implemented.

The sample was stratified according to sex and age across three regions in Denmark: (i) greater Copenhagen, (ii) Jutland, and (iii) Funen and Zealand. We assigned different weights to the three regions, with a 50% weight on the sample from greater Copenhagen and a 25% weight on each sample from the two other regions. This design allows us to recruit subjects for later experiments from a relatively large sample in greater Copenhagen. The respondents in our survey were recruited from two internet-based panels with 165,000 active members.[13] Invitations were sent out by email and the respondents could answer the survey questions on the internet using personal computers or mobile devices (phones and tablets). They were told in the invitation letter that 40 respondents who completed the survey would be randomly chosen to receive a gift card of 500 kroner.[14] Summary statistics for all participants and non-participants are provided in Appendix C.

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[13] *Analyse Danmark* have a panel of 25,000 active members, and *Userneeds* have a panel of 140,000 members. The two internet panels are regularly updated and members are recruited via the internet (banners, newsgroups, etc.), email, and by phone.

[14] The gift cards were issued by www.gavekortet.dk, which is an internet based portal for gift cards.

5 Results

We are interested in answering several questions with these data. First, what is the distribution over the Danish adult population of gambling risk as assessed using the FLAGS instrument? The answer to this question provides the sampling frame for subsequent experimental evaluation of actual gambling behavior by individuals who were recruited into incentivized experiments. We want to evaluate the raw distribution, based on the sample that completed our surveys, since that is the basis that is typically used to assess population gambling risk.

Second, how is the distribution of gambling risks affected by the treatments we considered? Does it matter if FLAGS comes first or second, or if we randomize question order? And how does the lifetime frame affect the distribution of gambling risk?

Third, what is the inferred population distribution after correcting for sample weights and sample selection? The correction for sample weights, based on observable differences in the demographic mix of the sample and the population, is familiar in many survey settings, but is not always applied in assessments of gambling risk. The correction for sample selection, based on unobservable differences of the sampled and non-sampled population, has never been applied in published assessments of gambling risk.

Fourth, what is the effect on inferences about the distribution of gambling risks of applying a threshold trigger question based on past gambling history? These trigger questions are usually applied *ex ante* the administration of the survey, and some status then assumed for the individual. Our design deliberately avoided such assumptions, allowing us to impose them *ex post* the administration of the survey to study their effect.

Finally, what are the correlates of gambling risk, as assessed by FLAGS? We examine the correlation between different instruments, and when possible the partial correlation holding constant the effect of a third instrument.

5.1 Gambling Risk in the Danish Sample

Table 1 shows the distribution of gambling risks in the Danish sample based on the FLAGS instrument. We do not apply here any gambling history threshold, which was in fact asked after the individual had completed all instruments. We find that 80% of the sample has no detectable risk, 12% has an early risk, 3.9% has an intermediate risk, 3.3% has an advanced risk, and 1.1% is classified as a problem gambler. Out of 8,405 in the sample, we detect 95 problem gamblers with this instrument.

Table 1 also shows the distribution of FLAGS risk levels broken down by comparison with the risk levels implied by the DSM and PGSI instruments. Note that the samples here are smaller, at 1,671 and 1,757 respectively, but these were assigned at random within the complete sample. For the DSM comparison, the biggest difference in classification in percentage terms is for those that FLAGS classifies as problem gamblers. Although the sample of 12 is small, DSM classifies 5 of these as non-gamblers and 6 as problem gamblers, and only 1 of the 12 is classified by DSM as a pathological gambler. The other DSM mismatch is for those that FLAGS classifies as being at advanced risk: DSM classifies 86% of those 56 individuals as being non-gamblers. The PGSI has a better match with FLAGS for the highest risk level, but a significant difference in classification for those that FLAGS classifies as being at advanced risk. In that case 27.7% and 25.5% of the 47 are classified by PGSI as being non-gamblers or low risk, respectively. Similarly, for those 62 individuals that FLAGS classifies as being an intermediate risk, the PGSI classifies 43.6% as being non-gamblers.

Table 1: Sample Tabulations of FLAGS Risk Levels

(A) FLAGS Risk Level

	N	Percent
No Detectable Risk	6,698	79.69%
Early Risk	1,010	12.02%
Intermediate Risk	328	3.90%
Advanced Risk	274	3.26%
Problem Gambler	95	1.13%
Total	8,405	100%

(B) FLAGS Risk Level

			DSM Risk Level		
	N	Percent	Non-Gambler	Problem Gambler	Pathological Gambler
No Detectable Risk	1,360	81.39%	1,353	7	0
Early Risk	177	10.59%	174	3	0
Intermediate Risk	66	3.95%	64	2	0
Advanced Risk	56	3.35%	48	7	1
Problem Gambler	12	0.72%	5	6	1
Total	1,671	100%	1,644	25	2

(C) FLAGS Risk Level

			PGSI Risk Level			
	N	Percent	Non-Gambler	Low Risk	Moderate Risk	Problem Gambler
No Detectable Risk	1,399	79.62%	1,291	93	14	1
Early Risk	229	13.03%	161	53	15	0
Intermediate Risk	62	3.53%	27	25	10	0
Advanced Risk	47	2.68%	13	12	19	3
Problem Gambler	20	1.14%	0	0	2	18
Total	1,757	100%	1,492	183	60	22

5.2 Effects of Treatments

The effects of treatments on gambling risk levels determined by FLAGS can be gauged by standard measures of association applied to a 5×2 contingency table, but for more informative analysis we develop an Ordered Probit statistical model. The statistical model allows us to estimate the size and significance of the effect of a variable on the probability of each gambling risk level. It also allows us to examine the marginal effect of the treatment, controlling for other correlated effects. For some inferential purposes we want to know the total (unconditional) effect, but typically we are interested in the marginal effect. Appendix D documents this statistical model and the first column of Table 3 documents the estimation results.

Figure 1 shows the marginal effect of FLAGS being the first survey instrument on the inferred probabilities of different gambling risk levels. The lines show the point estimates of the effect, and the shaded bars show the 95% confidence interval, so one can quickly ascertain if the effect is statistically significant. The vertical axis is the change in probability, so a value of +0.02 implies a change of 2 percentage points. We find that when FLAGS is presented first it does increase the likelihood of someone being classified as having a detectable risk, particularly an early risk.[15] Of course, these marginal effects must sum to zero across all of the possible levels, so there is a corresponding decline in the likelihood of someone being classified as having no detectable risk.

The opposite qualitative effect occurs when we randomize question order within the FLAGS instrument. Figure 2 shows that randomization significantly lowers the likelihood of being classified with a detectable risk, again with the biggest effect on the early risk level.[16]

Perhaps the most surprising treatment effect comes from using a lifetime gambling frame rather than just the past year, shown in Figure 3. Here one might have expected *a priori* to find

[15] A Pearson χ^2 test of the hypothesis of no association has a *p*-value less than 0.001.
[16] A Pearson χ^2 test of the hypothesis of no association has a *p*-value less than 0.001.

Figure 1: Marginal Effect of FLAGS Being First
on Probability of FLAGS Gambling Risk Level
Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval

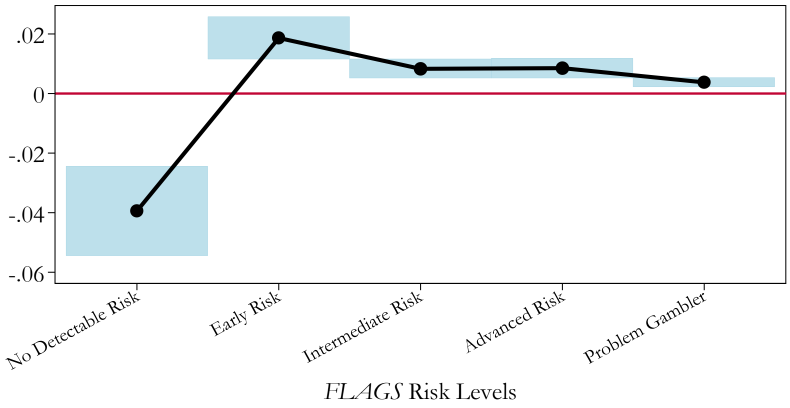


Figure 2: Marginal Effect of Randomized Questions
on Probability of FLAGS Gambling Risk Level
Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval

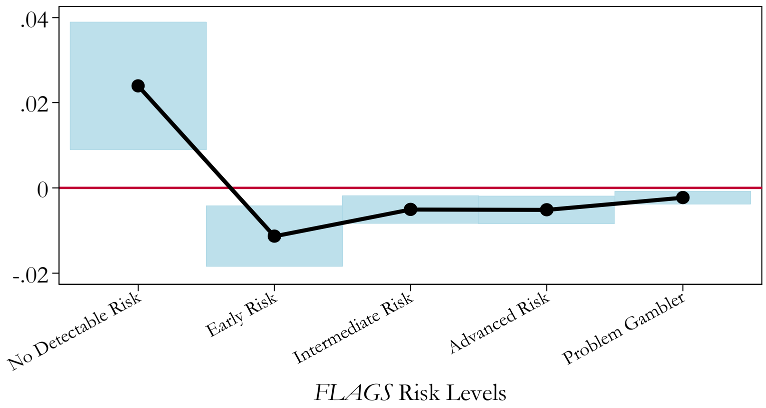
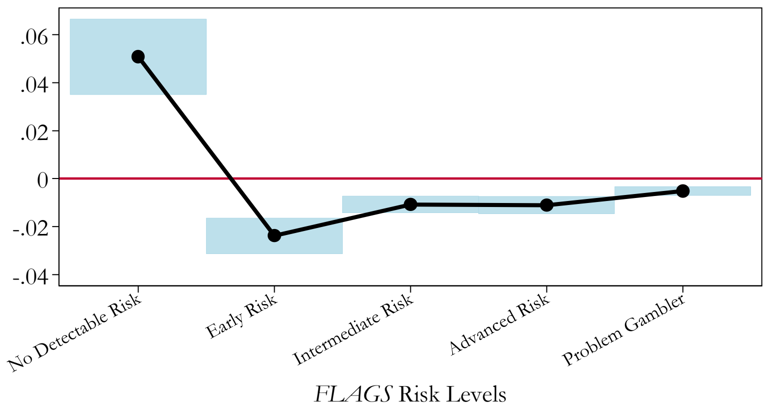


Figure 3: Marginal Effect of Lifetime Frame
on Probability of FLAGS Gambling Risk Level
Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval



greater gambling risk, since it cannot be less as a logical matter. However, we find a significant and large *reduction* in detectable risk using the statistical model.[17] We implement the lifetime gambling frame by asking the respondents to "…think about your lifetime gambling experiences," as opposed to "…think about your gambling experiences in the last year." It is likely that some respondents answer "yes" to a question when they are asked to consider their behavior in the last year and no when they are asked to consider their lifetime behavior. For example, the respondents are asked to consider the following question "I would like to gamble almost every day" and answer yes or no. Someone who recently has developed a gambling problem might answer "yes" when the question is framed over the last year and answer "no" when it is framed over the lifetime. Predicted gambling prevalence rates could therefore be lower when the respondents are asked to consider their lifetime behavior instead of their most recent behavior.

5.3 Gambling Risk in Denmark

We focus next on gambling risk in Denmark and address two questions. What is the inferred distribution of gambling risk in the population after controlling for sample selection into the survey instrument? Are individual characteristics correlated with gambling risk?

We estimate an Ordered Probit model with and without controls for sample selection to gauge the effect of selection bias from the sample frame of 65,592 Danes in the two internet-based panels. Sample weights are constructed from administrative data at Statistics Denmark on the population size of men and women in various age groups and regions in Denmark, and these weights are included in the predicted distributions of gambling risk. We control for endogenous sample selection bias using full information maximum likelihood estimation of the Ordered Probit model,

[17] A Pearson χ^2 test of the hypothesis of no association has a *p*-value less than 0.001. This is a two-sided test, but the direction of the effect is in the opposite of the alternative hypothesis that lifetime risks can be no smaller than recent risks.

and follow the direct likelihood approach due to Heckman (1976), Hausman and Wise (1979) and Diggle and Kenward (1994). The statistical model is documented in Appendix D.

Table 2 shows the predicted distribution of gambling risk in the adult Danish population. The predictions in the first column are based on the Ordered Probit model without sample weights and without controls for sample selection. They are similar to those reported in Table 1. Roughly 80% of the sample has no detectable risk, 12% has an early risk, 3.9% has an intermediate risk, 3.3% has an advanced risk, and 1.1% is classified as a problem gambler.

Adding sample weights *increases* the prevalence of detectable risk as opposed to no detectable risk. The second column in Table 2 shows that roughly 76% of the sample has no detectable risk, 13.3% has an early risk, 4.2% has an intermediate risk, 4.6% has an advanced risk, and 1.9% is classified as a problem gambler. We thus observe an increase from 1.1% to 1.9% in the prevalence of problem gambling when sample weights are added to the model.

Finally, controlling for sample selection has a significant *negative* effect on prevalence rates. The third column in Table 2 shows that more than 95% of the sample has no detectable risk, 2.9% has an early risk, 0.8% has an intermediate risk, 0.7% has an advanced risk, and only 0.2% is classified as a problem gambler. Thus we see a significant drop in prevalence rates of detectable risk compared to non-detectable risk, since respondents in detectable risk groups are more likely to answer the survey questions than those in the non-detectable risk group.

Table 3 shows the estimated parameter values that generate the predicted distributions of gambling risk in Table 2. The Ordered Probit models control for treatment variables and demographic characteristics such as sex, age, income and smoking behavior. Indicators for trigger questions and subcontractor are also added as control variables in the models. In the first model with no sample weights and controls for sample selection, demographic characteristics are significantly correlated with gambling risk. The marginal effect of being female is negative and equal to -0.28, which indicates that women are less likely to have a higher level of gambling risk. This estimated coefficient for women is significantly different from 0 and has a p-value < 0.001. We also confirm the conventional findings that young people are more likely to have a detectable gambling risk than older age groups; and those with low income are more likely to have a detectable gambling risk than people with higher income. The results also show that smokers are more likely to be classified in a detectable risk group than non-smokers.

The second model with sample weights shows similar marginal effects of the treatment variables and demographic characteristics. However, the estimated coefficients for medium and high income groups are smaller and no longer significantly different from 0.

Table 2: Predicted FLAGS Level

	(1) No Sample Weights	(2) Sample Weights	(3) Sample Weights and Sample Selection Correction
No Risk	79.71%	76.04%	95.39%
Early Risk	11.98%	13.25%	2.87%
Intermediate Risk	3.93%	4.24%	0.82%
Advanced Risk	3.25%	4.62%	0.70%
Problem Gambler	1.13%	1.86%	0.21%

Note: The predicted distributions of gambling risk are based on the estimated parameters that are reported in Table 3. Standard errors and 95% confidence intervals of the predicted gambling risk distributions for each model are reported in Appendix E.

Table 3: Ordered Probit With and Without Sample Selection Correction

	(1) No Sample Weights			(2) Sample Weights			(3) Sample Weights and Sample Selection Correction		
	Coef.	Std. Err.	*p*-value	Coef.	Std. Err.	*p*-value	Coef.	Std. Err.	*p*-value
A. FLAGS Level									
Lifetime	-0.208	0.033	0.000	-0.208	0.044	0.000	-0.172	0.037	0.000
Randomized	-0.098	0.031	0.002	-0.129	0.044	0.004	-0.090	0.031	0.003
FLAGS first	0.162	0.032	0.000	0.125	0.044	0.004	0.134	0.029	0.000
Female	-0.280	0.036	0.000	-0.311	0.045	0.000	-0.200	0.043	0.000
Young	0.194	0.057	0.001	0.257	0.076	0.001	0.068	0.051	0.184
Ripe Aged	-0.237	0.052	0.000	-0.206	0.060	0.001	-0.107	0.055	0.051
Older	-0.358	0.047	0.000	-0.292	0.054	0.000	0.107	0.073	0.142
Low Inc.	0.108	0.049	0.028	0.168	0.066	0.011	0.103	0.047	0.029
Medium Inc.	-0.089	0.051	0.084	-0.007	0.068	0.921	-0.034	0.050	0.498
High Inc.	-0.134	0.063	0.034	-0.054	0.086	0.526	-0.060	0.059	0.309
Very High Inc.	-0.042	0.107	0.693	-0.082	0.130	0.529	-0.033	0.098	0.739
40 kr. Trigger	0.671	0.035	0.000	0.655	0.050	0.000	0.513	0.049	0.000
500 kr. Trigger	1.032	0.059	0.000	1.007	0.077	0.000	0.786	0.080	0.000
Smoker	0.169	0.038	0.000	0.151	0.048	0.002	0.108	0.036	0.003
Subcontractor	0.015	0.033	0.640	0.085	0.046	0.066	0.021	0.033	0.521
Cut 1	0.829	0.075	0.000	0.892	0.097	0.000	2.021	0.129	0.000
Cut 2	1.479	0.076	0.000	1.541	0.100	0.000	2.501	0.104	0.000
Cut 3	1.868	0.078	0.000	1.880	0.104	0.000	2.782	0.093	0.000
Cut 4	2.571	0.086	0.000	2.598	0.128	0.000	3.354	0.094	0.000
B. Selection									
Constant							-1.348	0.025	0.000
Female							0.002	0.016	0.906
Young							-0.135	0.025	0.000
Ripe Aged							0.115	0.022	0.000
Older							0.606	0.021	0.000
Subcontractor							-0.002	0.016	0.911
Midtjyylland							-0.023	0.021	0.267
Nordjyland							-0.037	0.030	0.219
Sjælland							-0.038	0.023	0.107
Syddanmark							-0.018	0.021	0.391
P							0.766	0.075	

Note: We estimate an Ordered Probit model in (1), an Ordered Probit model with sample weights in (2), and an Ordered Probit model with sample weights and sample selection correction in (3). The omitted age category is *Middle Aged* (those between 30 and 39 years of age); the omitted income category is *Silent About Income* (those who did not report annual income); and the omitted region is *Hovedstaden* (those living in the Greater Copenhagen area). The four cut points refer to the thresholds along the cumulative standard normal distribution that distinguish the five ordered outcomes of gambling risk. The first cut point refers to the probability threshold between no detectable risk and early risk, the second cut point refers to the probability threshold between early risk and intermediate risk, and so on.

The third model adds controls for endogenous sample selection. Estimated coefficients in the selection equation are reported in Panel B of Table 3, and we find a significant association between response rates and age groups: subjects younger than 30 have significantly lower response rates than middle aged between 30 and 39; middle aged subjects have significantly lower response rates than ripe aged between 40 and 49; and subjects older than 50 have significantly higher response rates than ripe aged. We also find evidence of significant sample selection bias: the estimated correlation coefficient, ϱ, is equal to 0.77 and is significantly different from 0 (p-value < 0.001). Hence there is a significant positive correlation between the error terms in the main equation and in the selection equation, and we observe a significant increase in the gambling risk thresholds that are given by the cut points along the cumulative standard normal distribution. The first cut point identifies the probability of no detectable gambling risk, the second cut point identifies the probability of early risk, and so on. We continue to observe significant marginal effects of being a female and a smoker. However, we do not find a significant effect on gambling risk of being young or old compared to the omitted age group of respondents between 30 and 39. The estimated coefficient of being young is equal to 0.068 and has a p-value of 0.184, and the estimated coefficient of being older is positive and equal to 0.107 with a p-value of 0.142. The results suggest that ripe aged people between 40 and 49 are less likely than any other age group of having a detectable gambling risk, followed by middle aged people between 30 and 39. People younger than 30 and older than 50 are most likely to have a detectable gambling risk. Low income continues to be associated with significantly higher gambling risk than other income groups.

Figure 4 shows the marginal effect of being female on inferred probabilities for each FLAGS risk level. The probability of having no detectable gambling risk is 2 percentage points higher for women than for men, and women are significantly less likely than men to be classified in one of the detectable risk groups. Figure 5 shows the marginal effect of reporting low income compared to those who did not report their income. The probability of having no detectable gambling risk decreases by 1 percentage point for respondents in the low income group compared to the control group that did not report any income, and the probability of having a detectable gambling risk consequently increases for the low income group compared to the control group. We present additional figures in Appendix E that show marginal effects on gambling risk of the remaining demographic characteristics.

Figure 4: Marginal Effect of Being Female
on Probability of *FLAGS* Gambling Risk Level
Ordered Probit Model, population weights, with sample selection correction
Point estimate of effect and 95% confidence interval

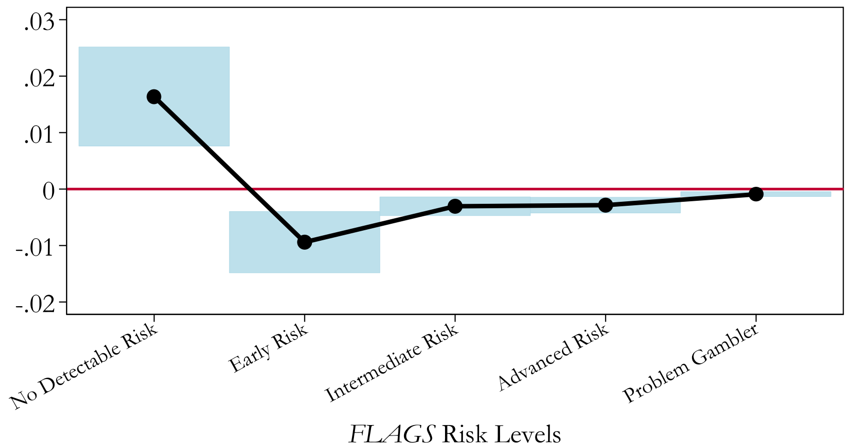
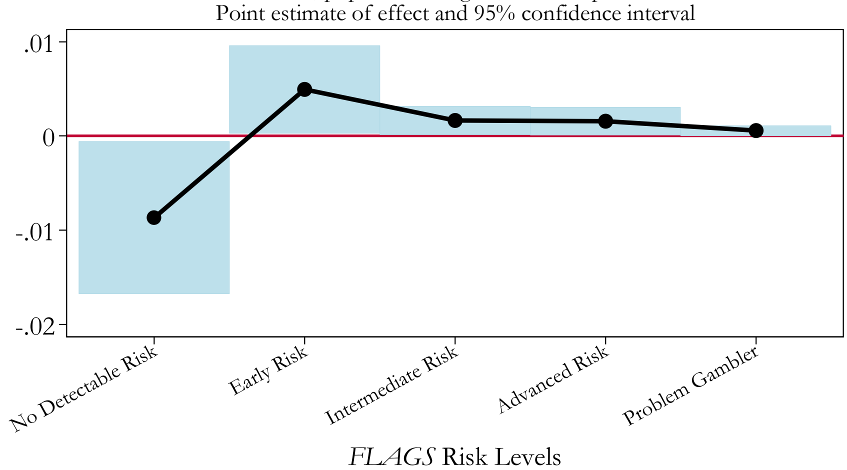


Figure 5: Marginal Effect of Having Low Income
on Probability of *FLAGS* Gambling Risk Level
Ordered Probit Model, population weights, with sample selection correction
Point estimate of effect and 95% confidence interval



We can compare our results to the existing Danish gambling prevalence studies by Bonke and Borregard (2006, 2009) and Ekholm et al. (2012). These two gambling prevalence studies do not control for sample selection bias, and we therefore compare our uncorrected prevalence rates of gambling risk with the prevalence rates reported in the existing studies.

The predicted prevalence rates of gambling risk (without controls for sample selection) in our study are significantly higher than those reported for Denmark by Bonke and Borregard (2006, 2009). They use the *National Opinion Research Center DSM* (NODS) screen to estimate prevalence of gambling risk in a sample of 8,153 Adult Danes between 18 and 74 years of age.[18] The sample frame of 11,737 people was randomly drawn from the Danish Central National Register and stratified according to sex, age, geographical information and marital status. The survey was conducted mainly by telephone and in some cases by face-to-face interviews, and the overall response rate to the survey instrument was 69.5%. Bonke and Borregard (2006, 2009) ask the respondents to consider their lifetime (past-year) gambling behavior and identify 0.26% (0.14%) of the sample as being a pathological gambler, 0.42% (0.23%) of the sample as being a problem gambler, and 3.14% (1.85%) as having some gambling risk.[19] They also report higher prevalence rates of gambling risk for men than for women, lower prevalence rates for respondents older than 45, and lower prevalence rates for respondents in the highest income quartile than in lower quartiles. Despite the researchers having had access to administrative data for the full sample frame, the estimated coefficients by Bonke and Borregard (2006, 2009) are not corrected for endogenous sample selection and the corrected prevalence rates may be smaller than those reported.

Ekholm et al. (2012) use data from the Danish Health Interview Survey in 2005 and the Danish Health and Morbidity Survey in 2010. The two samples are nationally representative and

[18] The NODS was developed by Gerstein et al. (1999) and builds on the DSM IV gambling screen. It is a reflective construct with 17 questions that measure lifetime and past-year prevalence of gambling risk. Bonke and Borregard (2006) compare the NODS instrument with the South Oaks Gambling Screen (SOGS) in a pre-test with 1,232 subjects and find that the NODS detects a lower prevalence of gambling risk.

[19] The respondents were first asked whether they had ever lost 35 kroner in a single day, and those who gave a positive answer were asked the same question considering past-year instead of lifetime experience.

include 10,916 respondents in 2005 and 23,405 respondents in 2010. After the main face-to-face interview the respondents were asked to complete a self-administered questionnaire that, among things, included two questions that are related to gambling behavior. The so-called lie/bet questionnaire, which consists of two questions from the DSM IV screen, was used in the survey, and those respondents who answered yes to at least one of the two questions are classified as problem gamblers.[20] The final sample contains 5,686 respondents in 2005 and 14,670 respondents in 2010. Ekholm et al. (2012) find that the prevalence rate of lifetime (past-year) problem gambling is 2.6% (0.9%) in 2005, and falls to 2.0% (0.8%) in 2010. Prevalence rates are higher among men than women and decrease with age. They do not report any estimates that control for endogenous sample selection, but mention that "non-response adjusted prevalence estimates did not indicate that non-response bias affects the conclusion of the present study."

5.4 Effects of Trigger Questions Based on Gambling History

Our design allows an immediate data-only comparison of the effects of using trigger questions based on gambling *history* to make inferences about *future* gambling risk. The usual tabulations do not do justice to the careful language used in scoring FLAGS when gambling history is used. An individual is classified as a Non-Gambler in FLAGS if the threshold gambling history is applied, with this explanation of that category:

> FLAGS instrument categorizes a person's risk based on their perceptions about and behaviors associated with gambling. It cannot therefore categorize a person's risk if they do not have gambling experience within the last year. There is a long list of correlates that have been shown to be associated with risk of problem gambling that we have left out of FLAGS that if possessed by an individual could indicate risk for problem gambling should they start to gamble. It was decided that in order to keep the instrument to a reasonable size its constructs would only be gambling specific; from the point of view of FLAGS these risk factors are therefore latent or unobservable. (Schellinck et al., 2011)

[20] The two questions are: "Have you ever lied to people important to you about how much you gambled?" and "Have you ever felt the need to bet more and more money?" The possible answers were: Yes, in the past 12 months; Yes, previously; No, I never gamble.

This is saying that one *could* develop a different instrument if the intention was to ignore gambling history as a determining factor of future gambling risk, as we do here. On the other hand, FLAGS contains many more formative constructs for detecting latent risk than the popular alternative instruments (DSM and PGSI) for detecting future gambling risk. Thus the above statement is exactly correct, and well-stated in terms of latent and unobservable tendencies. But we know how readers of measures of gambling prevalence will often slide over this statement, particularly if they are conditioned by other reflective-construct instruments to just assume outright that historical non-gamblers must have no clinical risk of "presenting."

The same qualifications apply to the lowest FLAGS "risk" level, "No Detectable Risk." This is defined as follows:

> Those at No Detectable Risk do not flag on any of the risk indicators although it is possible that they answered yes to one or more statements making up some of the constructs. For those who answered yes to at least one statement there was insufficient certainty for us to say there was an indication on one of the dimensions. These people may still have unobservable or latent characteristics that would make them susceptible to becoming a problem gambler should the right conditions exist. (Schellinck et al., 2011)

Again, the emphasis is on latent tendencies to exhibit gambling risk, which we seek to measure.

The tabulations we present below are unfair to these nuanced statements, and follow the standard approach by just assuming that historical non-gamblers are not at future risk. In effect, in terms of FLAGS categories, we assume that individuals that *should* be classified as non-gamblers are in fact classified as having no detectable risk.

With these qualifications, Table 4 and Figure 6 shows the dramatic effects of imposing a threshold gambling history on the classification of gambling risk. With the 500 kroner and 40 kroner threshold applied, we overstate the fraction of Danes that have no detectable risk, and understate those that have detectable gambling risk levels. Hence the standard practice in surveys of using these thresholds leads to an underestimate of the prevalence of gambling problems in the general population. The bottom panel of Figure 5 rescales just on the detectable gambling risks, to provide more information on these effects.

Table 4 shows that 95% of the sample had *not* lost 500 kroner in gambling in one day, and that 18.1% (= 100% - 81.9% = 11.5% + 3.5% + 2.3% + 0.6%) of those 7,991 had *some* detectable risk. Certainly those that had lost 500 kroner from gambling had a higher likelihood of exhibiting some gambling risk according to FLAGS, as one would expect. But the crucial point is that it is not the case that individuals with *no* historical gambling losses of 500 kroner can be safely assigned to have no risk, nor can those individuals *with* these losses be assumed to have some detectable risk. We stress again that the FLAGS classifications, when read in full, are clear on this point. Out of the complete sample, 46 individuals are deemed by the FLAGS instrument to be problem gamblers, but did not say that they had lost 500 kroner in the past year. In terms of numbers, this is almost exactly the same number of individuals (49) deemed to be problem gamblers but who did say that they had lost 500 kroner.

The 40 kroner threshold has a predictably smaller effect, since many Danes would have met this threshold compared to the 500 kroner threshold. In fact, 3,206 of the sample say that they had lost 40 kroner, compared to only 414 saying that they had lost 500 kroner. The fraction is less than a majority in the sample: 38% in fact.

Figure 7 and 8 show the effect of the thresholds for the classification of risk levels using the DSM and PGSI instruments, respectively. Since the DSM instrument assigns so many people to the lowest risk non-gambler category, and is very conservative compared to FLAGS about assigning any higher risk, there is a smaller effect than with FLAGS. This could be mitigated if one adopted a more "continuous" scoring of the DSM, as proposed in the British Gambling Prevalence Study of 2007 (p. 135) and 2010 (p. 154). The PGSI instrument shows more effect from the threshold.

Table 4: Effect of Gambling History Thresholds on *FLAGS* Risk Levels

(A) Have you ever lost more than 500 DKK in one day?

FLAGS Risk Level	No N	No Percent	Yes N	Yes Percent	Total N	Total Percent
No Detectable Risk	6,557	82.05%	141	34.06%	6,698	79.69%
Early Risk	922	11.54%	88	21.26%	1010	12.02%
Intermediate Risk	283	3.54%	45	10.87%	328	3.90%
Advanced Risk	183	2.29%	91	21.98%	274	3.26%
Problem Gambler	46	0.58%	49	11.84%	95	1.13%
Total	7,991	100%	414	100%	8,405	100%

(B) Have you ever lost more than 40 DKK in one day?

FLAGS Risk Level	No N	No Percent	Yes N	Yes Percent	Total N	Total Percent
No Detectable Risk	4,600	88.48%	2,098	65.44%	6,698	79.69%
Early Risk	404	7.77%	606	18.90%	1010	12.02%
Intermediate Risk	109	2.10%	219	6.83%	328	3.90%
Advanced Risk	61	1.17%	213	6.64%	274	3.26%
Problem Gambler	25	0.48%	70	2.18%	95	1.13%
Total	5,199	100%	3,206	100%	8,405	100%

Figure 6: Comparison of True *FLAGS* Responses and Inferred Responses if Using Gambling History Triggers

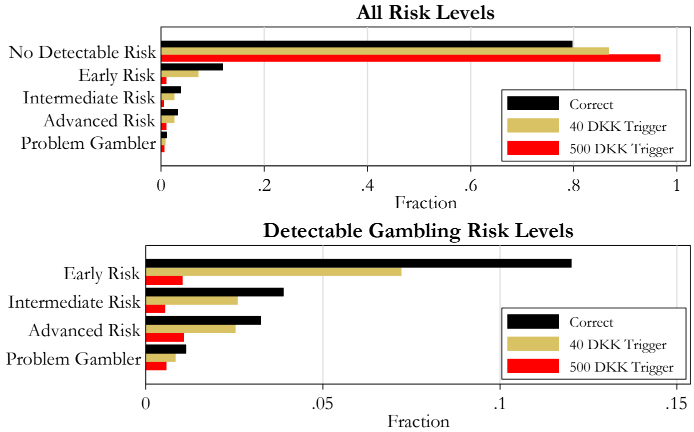


Figure 7: Comparison of True *DSM-IV* Responses and Inferred Responses if Using Gambling History Triggers

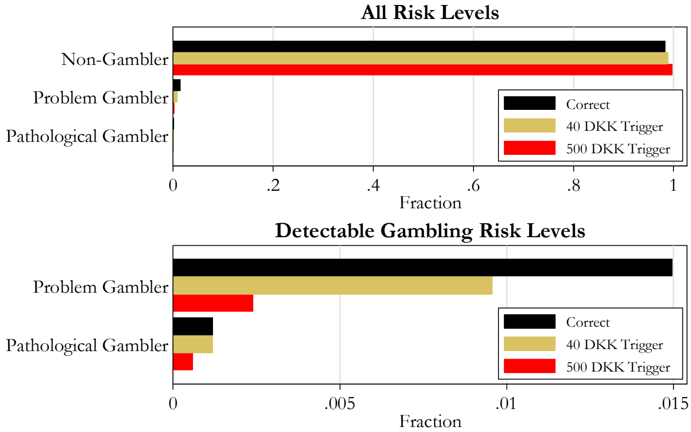
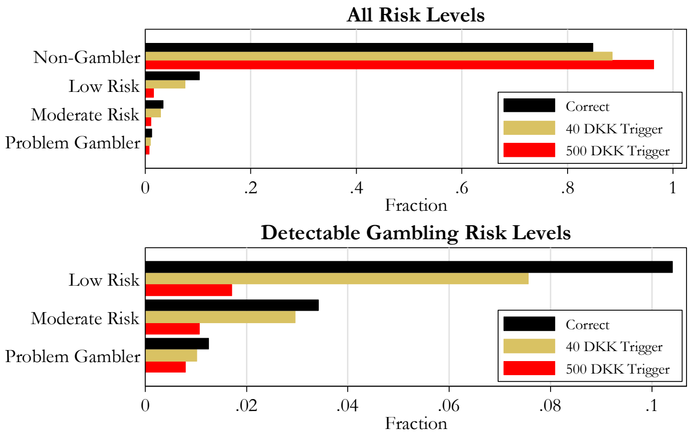


Figure 8: Comparison of True *PGSI* Responses and Inferred Responses if Using Gambling History Triggers



5.5 Correlates of Gambling Risk

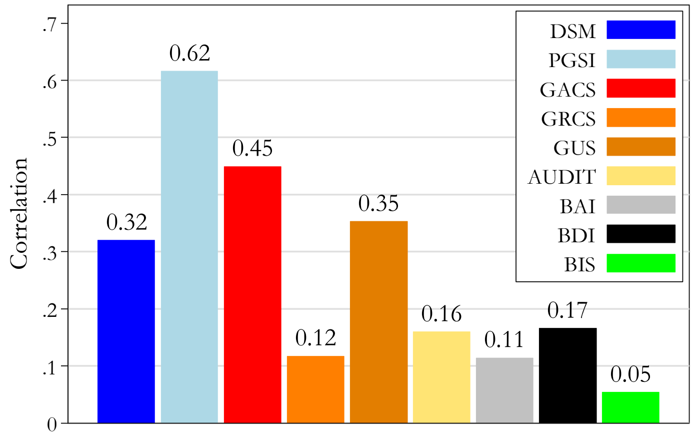
Figure 9 shows the unconditional correlations of the FLAGS gambling risk levels with the levels of other gambling risk instruments (DSM and PGSI), related instruments measuring formative gambling risk (GACS, GRCS and GUS), an instrument measuring alcohol use (AUDIT), and instruments measuring anxiety, depression and impulsiveness (BAI, BDI and BIS). All correlations are statistically significantly different than zero at *p*-values less than 0.001, except the correlation with the BIS which has a *p*-value of 0.094.

In terms of the popular instruments for gambling risk, FLAGS is more correlated with PGSI than DSM, although both have positive and large correlation coefficients. The correlation of FLAGS with GACS and GUS, respectively, is very high, but the correlation with GRCS is quite low. The correlation coefficient between FLAGS and the substance abuse instrument for alcohol is very low, as are the pairwise correlation coefficients with the measures of anxiety, depression and impulsiveness.

We find a different pattern of correlation when we examine each of the instruments in the context of our statistical model of the determinants of FLAGS gambling risk levels. This model controls for all the observable demographics and treatments considered earlier: we just add the score or level of the instrument being studied and re-estimate. In each case the detailed impact varies with the FLAGS risk level, but the pattern is by now familiar from other marginal effects considered. The impact on the "no detectable risk" level is the opposite sign as the impact on the 4 detectable risk levels, and the largest impact on a detectable risk is for early risk.

Detailed results for these marginal effects from the statistical model are shown in Appendix F. In summary, they show the predicted effects in terms of direction: someone that scores more highly on DSM or PGSI also scores more highly on FLAGS. They also show much higher connections between the formative constructs and personality instruments for anxiety, depression and impulsiveness than the unconditional correlations discussed above, and there is now a positive association between gambling risk and the measure of impulsivity.

Figure 9: Correlation of *FLAGS* Scores with Other Instruments



6 Summary and Conclusions

We compare several popular survey instruments of gambling behavior and gambling propensity to assess whether they differ in their classification of individuals in the general adult Danish population. We also examine correlations with standard survey instruments for alcohol use, anxiety, depression and impulsivity. A feature of our design is that nobody was excluded on the basis of their response to a "trigger," "gateway" or "diagnostic item" question about previous gambling history.

Our sample consists of 8,405 adult Danes and is stratified according to age and sex across three regions in Denmark. We estimate an Ordered Probit model with and without controls for sample selection to gauge the effect of selection bias from the overall sample frame of 65,592 Danes. Sample weights are constructed from administrative data at Statistics Denmark on the population size of men and women in various age groups and regions in Denmark, and these weights are included in the predicted distributions of gambling risk. We control for endogenous sample selection bias using full information maximum likelihood estimation of the Ordered Probit model. The FLAGS instrument was administered to all subjects, and we find that roughly 80% of the sample has no detectable risk, 12% has an early risk, 3.9% has an intermediate risk, 3.3% has an advanced risk, and 1.1% is classified as a problem gambler. Controlling for sample selection has a significant *negative* effect on prevalence rates, and the corrected estimates of gambling risk show that more than 95% of the population has no detectable risk, 2.9% has an early risk, 0.8% has an intermediate risk, 0.7% has an advanced risk, and only 0.2% is classified as a problem gambler.

There are significant (unconditional and conditional) correlations of the FLAGS gambling risk levels with the levels of other gambling risk instruments (DSM and PGSI), related instruments measuring formative gambling risk (GACS, GRCS and GUS), an instrument measuring alcohol use (AUDIT), and instruments measuring anxiety, depression and impulsiveness (BAI, BDI and BIS). All correlations are positive and statistically significantly different than zero: for example, someone that scores more highly on DSM or PGSI also scores more highly on FLAGS.

Finally, we administered two "trigger" questions based on past gambling history that asked subjects if they had ever lost more than 40 kroner or 500 kroner on gambling in a single day. These questions are common in gambling prevalence studies and the survey instruments are administered if the answer is affirmative. We find significant effects of imposing a threshold gambling history on the classification of gambling risk. With the 500 kroner and 40 kroner threshold, we understate the fraction of Danes with detectable gambling risk levels. Hence the standard practice in surveys of using these thresholds leads to an underestimate of the prevalence of gambling problems in the general population.

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Appendix A
Survey Instruments

The instruments listed below were employed for use in our surveys. The format displayed below is the easiest to document the blocks and response formats, but is not literally the text given to respondents. For instance, the block headings with the FLAGS instrument were not given to respondents, but make it easier to see which questions go together.

A.1 Focal Adult Gambling Screen (FLAGS)

Please read the following list of statements about gambling, and for each please indicate whether or not this statement is true for you. A simple YES or NO response is all you need to provide. If some statement does not apply to you, just respond NO. The statements are in no particular order. Think about your lifetime gambling experiences [OR: your gambling experiences in the last year].

Risky Cognition: Belief (RCB)

RCB01 People who are good at gambling get more respect from others.
RCB02 Gambling is an easy way to get extra money when you need it.
RCB03 Using a system or a strategy when you play games like lottery draws, roulette, slots or other gambling machines improves your chances of winning.
RCB04 After you have been gambling and losing for a while your chances of winning improve.
RCB05 If you are on a winning streak it makes sense to keep gambling to take advantage of your luck.
RCB06 Once someone has been gambling and losing for a while they should keep playing so they don’t miss out on the chance to win back their money.
RCB07 Some people are luckier than others and so they have a better chance of winning when they gamble.
RCB08 I had a big win when I first started to gamble.
RCB09 I used to win a lot when I gambled but it seems like the odds aren’t as good anymore.

Risky Cognition: Motives (RCM)

RCM01 I find things a lot more interesting when I have a bet or wager riding on the outcome.
RCM02 I sometimes gamble when I am feeling down or depressed.
RCM03 I gamble when I want money.
RCM04 Even if I don’t have much money I gamble to try to get a big win.
RCM05 Gambling helps me to fit in better with others.
RCM06 I want people to think I am good at gambling.
RCM07 I gamble because it feels good to beat others at the game.

Preoccupation: Desire (POD)

POD01 I would like to gamble almost every day.
POD02 Compared to many other things I can do I would rather gamble.
POD03 I wish I could gamble more often.

Impaired Control: Continue (ICC)

ICC01 Even when I only wanted to spend a few dollars gambling, I often ended up spending much more.
ICC02 Once I start gambling I sometimes find it difficult to stop.
ICC03 When I gambled I usually exceeded the amount of money I intended to spend.
ICC04 I often had trouble stopping/quitting play when I was ahead.

Risky Practices: Earlier (RBE)

RBE01 When I won big I usually kept playing rather than stop.
RBE02 I usually played at maximum bet or bet the most I could afford when I was on a winning streak.
RBE03 I often spend more time gambling than I intended.
RBE04 I am making bigger bets than I used to.
RBE05 I gamble or make bets when I get a good luck sign or I am feeling lucky.
RBE06 When I am gambling I am interested in the game, not socializing with others.

Risky Practices: Later (RBL)

RBL01 I sometimes borrowed money from others so I could go and gamble.
RBL02 I often used my credit card to get more money so I could keep gambling.
RBL03 I sometimes exceeded the amount of money I intended to spend in order to win back money I had lost.
RBL04 I gambled at work or when I was supposed to be doing something else.
RBL05 I have a strategy to improve my luck when I gamble.
RBL06 I have gambled using money that I was supposed to spend on other things.
RBL07 When gambling I usually played fast or made as many bets as quickly as I could.
RBL08 I sometimes bet when I believe I can predict the outcome of an event.

Impaired Control: Begin (ICB)

ICB01 If I have the opportunity to gamble I can't stop myself from taking it.
ICB02 There have been times I started to gamble despite my desire not to.
ICB03 I tried unsuccessfully to stop or reduce my gambling.
ICB04 I gamble more often than I want to.

Preoccupation: Obsession (POO)

POO01 I plan my life around my gambling.
POO02 I am obsessed with gambling thinking about when I will next gamble all the time.
POO03 I spend a lot of my time thinking about gambling or how to get money to gamble.
POO04 Thoughts of gambling or playing the games fill my mind day and night.

Negative Consequences (NGC)

NGC01 When I finished gambling, I sometimes did not have enough money for parking, food, a ride home or other things I was supposed to buy for myself.
NGC02 Sometimes I had to juggle money and bills to cover the cost of my gambling.
NGC03 My performance at work was negatively affected by my gambling.
NGC04 My goals in life were jeopardized by my gambling.

NGC05 I sometimes had trouble sleeping thinking about gambling.
NGC06 I missed social events with my friends and family because I was gambling.
NGC07 I sometimes neglected family or friends in order to gamble.
NGC08 My gambling caused problems for my relationship with my spouse or partner.
NGC09 I have become somewhat of a loner because of my gambling.
NGC10 My gambling caused me to have a falling out with people I used to hang out with.
NGC11 Sometimes I felt depressed over my gambling.
NGC12 I regret that I gambled as much as I did.
NGC13 I have lied to others about my gambling.

Persistence (PST)
PST01 Regardless of negative consequences, I kept gambling whenever I had the opportunity.
PST02 I have continued to gamble for some time despite the negative way gambling has affected my life.
PST03 I kept gambling last year even though I knew it was causing major problems for me.

A.2 The Problem Gambling Severity Index (PGSI)

[It is easy to confuse the acronyms of the PGSI and the CPGI. The PGSI is a scored 9-item component of the CPGI, which contains 12 items]

Some of the next 9 questions may not apply to you, but please try to be as accurate as possible. Think about your lifetime gambling experiences [OR: your gambling experiences in the last year].

Answer possibilities:
0 = Never
-1 = Sometimes
-2 = Most of the time
-3 = Almost always
-9 = Don't know

1. Have you bet more than you could really afford to lose?
2. Have you needed to gamble with larger amounts of money to get the same feeling of excitement?
3. When you gambled, did you go back on another day to try to win back the money you lost?
4. Have you borrowed money or sold anything to get money to gamble?
5. Have you felt that you might have a problem with gambling?
6. Has gambling caused you any health problems, including stress or anxiety?
7. Have people criticized your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?
8. Has your gambling caused any financial problems for you or your household?
9. Have you felt guilty about the way you gamble or what happens when you gamble?

A.3 The Diagnostic & Statistical Manual of Mental Disorders – Edition IV (DSM-IV)

Some of the next 10 questions may not apply to you, but please try to be as accurate as possible. Think about your lifetime gambling experiences [OR: your gambling experiences in the last year].

Answer possibilities:
0 = No
-1 = Once or twice
-2 = Sometimes
-3 = Often
-4 = Don't know

1. Have you found yourself thinking about gambling (e.g. reliving past gambling experiences, planning the next time you will play or thinking of ways to get money for gambling)?
2. Have you needed to gamble with more and more money to get the amount of excitement you are looking for?
3. Have you become restless or irritable when trying to cut down or stop gambling?
4. Have you gambled to escape from problems or when you are feeling depressed, anxious or bad about yourself?
5. After losing money gambling, have you returned another day in order to get even?
6. Have you lied to your family, or others, to hide the extent of your gambling?
7. Have you made repeated unsuccessful attempts to control, cut back or stop gambling?
8. Have you been forced to go beyond what is strictly legal, in order to finance gambling or to pay gambling debts?
9. Have you risked or lost a significant relationship, job, educational or career opportunity because of gambling?
10. Have you sought help from others to provide money to relieve a desperate financial situation caused by gambling?

A.4 The Gambling Craving Scale (GACS)

Please indicate how much you agree or disagree with the statements.

Answer possibilities:
1 = strongly disagree
2 = moderately disagree
3 = mildly disagree
4 = neither agree or disagree
5 = mildly agree
6 = moderately agree
7 = strongly agree

1 Gambling would be fun right now.
2 If I had an opportunity to gamble right now, I probably would take it.
3 If I were offered an opportunity to gamble right now, I would gamble.
4 If it were possible, I probably would gamble now.
5 I would not enjoy gambling right now.
6 Gambling would be very satisfying now.

7 Gambling now would make things seem just perfect.
8 All I want right now is to gamble.
9 I crave gambling right now.
10 My desire to gamble seems overpowering.
11 I need to gamble now.
12 I have an urge to gamble.
13 I would do almost anything to gamble now.
14 Nothing would be better than gambling now.
15 If I were gambling now, I could think more clearly.
16 I could control things better right now if I could gamble.
17 Gambling would make me less depressed.
18 I would be less irritable right now if I could gamble.

A.5 The Gambling Related Cognition Scale (GRCS)

Please indicate how much you agree or disagree with the statements.

Answer possibilities:
1 = strongly disagree
2 = moderately disagree
3 = mildly disagree
4 = neither agree or disagree
5 = mildly agree
6 = moderately agree
7 = strongly agree

1 Gambling makes me happier.
2 I can't function without gambling.
3 Praying helps me win.
4 Losses when gambling, are bound to be followed by a series of wins.
5 Relating my winnings to my skill and ability makes me continue gambling.
6 Gambling makes things seem better.
7 It is difficult to stop gambling as I am so out of control.
8 Specific numbers and colours can help increase my chances of winning.
9 A series of losses will provide me with a learning experience that will help me win later.
10 Relating my losses to bad luck and bad circumstances makes me continue gambling.
11 Gambling makes the future brighter.
12 My desire to gamble is so overpowering.
13 I collect specific objects that help increase my chances of winning.
14 When I have a win once, I will definitely win again.
15 Relating my losses to probability makes me continue gambling.
16 Having a gamble helps reduce tension and stress.
17 I'm not strong enough to stop gambling.
18 I have specific rituals and behaviours that increase my chances of winning.
19 There are times that I feel lucky and thus, gamble those times only.
20 Remembering how much money I won last time makes me continue gambling.
21 I will never be able to stop gambling.
22 I have some control over predicting my gambling wins.

23 If I keep changing my numbers, I have less chances of winning than if I keep the same numbers every time.

A.6 The Gambling Urge Screen (GUS)

The next 8 questions have to do with your feelings and thoughts right now. Please indicate how much you agree or disagree with the statements.

Answer possibilities:
1 = strongly disagree
2 = moderately disagree
3 = mildly disagree
4 = neither agree or disagree
5 = mildly agree
6 = moderately agree
7 = strongly agree

1 All I want to do now is to gamble.
2 It would be difficult to turn down a gamble this minute.
3 Having a gamble now would make things seem just perfect.
4 I want to gamble so bad that I can almost feel it.
5 Nothing would be better than having a gamble right now.
6 I crave a gamble right now.
7 I don't need to have a gamble now.
8 If I had the chance to have a gamble, I don't think I would gamble.

A.7 The Alcohol Use Disorders Identification Test (AUDIT)

Now I am going to ask you some questions about your use of alcoholic beverages during the past year. Because alcohol use can affect many areas of health, and may interfere with certain medications, it is important for us to know how much you usually drink and whether you have experienced any problems with your drinking. Please try to be as honest and as accurate as you can be.

1 How often do you have a drink containing alcohol?
0 - Never
1 - Monthly or less
2 - 2-4 times a month
3 - 2-3 times a week
4 - 4 or more times a week

2 How many drinks containing alcohol do you have on a typical day when you are drinking?
0 - 1 or 2
1 - 3 or 4
2 - 5 or 6
3 - 7 to 9
4 - 10 or more

3 How often do you have six or more drinks on one occasion?

0 - Never
1 - Less than monthly
2 - Monthly
3 - Weekly
4 - Daily or almost daily

4 How often during the last year have you found that you were not able to stop drinking once you had started?

0 - Never
1 - Less than monthly
2 - Monthly
3 - Weekly
4 - Daily or almost daily

5 How often during the last year have you failed to do what was normally expected of you because of drinking?

0 - Never
1 - Less than monthly
2 - Monthly
3 - Weekly
4 - Daily or almost daily

6 How often during the last year have you needed a first drink in the morning to get yourself going after a heavy drinking session?

0 - Never
1 - Less than monthly
2 - Monthly
3 - Weekly
4 - Daily or almost daily

7 How often during the last year have you had a feeling of guilt or remorse after drinking?

0 - Never
1 - Less than monthly
2 - Monthly
3 - Weekly
4 - Daily or almost daily

8 How often during the last year have you been unable to remember what happened the night before because of your drinking?

0 - Never
1 - Less than monthly
2 - Monthly
3 - Weekly
4 - Daily or almost daily

9 Have you or someone else been injured because of your drinking?

0 - No
2 - Yes, but not in the last year
4 - Yes, during the last year

10 Has a relative, friend, doctor, or other health care worker been concerned about your drinking or suggested you cut down?

0 - No
2 - Yes, but not in the last year
4 - Yes, during the last year

A.8 Beck Anxiety Index (BAI)

Over their entire life, some people have had a time in their life when they were a "worrier," in the sense that they worried a lot more about things than other with the same problems. Some people have also had a time when they were much more nervous or anxious than most other people with the same problems. And some people have had a time lasting 6 months or longer when they were anxious and worried most days. The next block of statements are common symptoms of people having these experiences. Please indicate how much you have been bothered by that symptom during the worst of these experiences in your life.

Answer possibilities:
1 = Not at all
2 = Mildly but it didn't bother me much.
3 = Moderately - it wasn't pleasant at times.
4 = Severely - it bothered me a lot.

1 Numbness or tingling
2 Feeling hot
3 Wobbliness in legs
4 Unable to relax
5 Fear of worst happening
6 Dizzy or lightheaded
7 Heart pounding/racing
8 Unsteady
9 Terrified or afraid
10 Nervous
11 Feeling of choking
12 Hands trembling
13 Shaky / unsteady
14 Fear of losing control
15 Difficulty in breathing
16 Fear of dying
17 Scared
18 Indigestion
19 Faint / lightheaded
20 Face flushed
21 Hot/cold sweats

A.9 Beck Depression Inventory (BDI)

Over their entire life, some people have had a time when they felt sad, blue, depressed or down most of the time for at least 2 weeks. Some people have also had a time over their entire life, lasting 2 weeks or more, when they didn't care about the things they usually cared about, or when they didn't enjoy the things they usually enjoyed. The next block of statements are about experiences that you might have had during one of those times, when your mood was the lowest, or you enjoyed or cared the least about things. Please pick out the one statement that best describes the way you have been feeling during that period. If none of the statements apply, just select the first one.

1 Sadness
- 0 - I do not feel sad.
- 1 - I feel sad much of the time.
- 2 - I am sad all the time.
- 3 - I am so sad or unhappy that I can't stand it.

2 Pessimism
- 0 - I am not discouraged about my future.
- 1 - I feel more discouraged about my future than I used to be.
- 2 - I do not expect things to work out for me.
- 3 - I feel my future is hopeless and will only get worse.

3 Past Failure
- 0 - I do not feel like a failure.
- 1 - I have failed more than I should have.
- 2 - As I look back, I see a lot of failures.
- 3 - I feel I am a total failure as a person.

4 Loss of Pleasure
- 0 - I get as much pleasure as I ever did from the things I enjoy.
- 1 - I don't enjoy things as much as I used to.
- 2 - I get very little pleasure from the things I used to enjoy.
- 3 - I can't get any pleasure from the things I used to enjoy.

5 Guilty Feelings
- 0 - I don't feel particularly guilty.
- 1 - I feel guilty over many things I have done or should have done.
- 2 - I feel quite guilty most of the time.
- 3 - I feel guilty all of the time.

6 Punishment Feelings
- 0 - I don't feel I am being punished.
- 1 - I feel I may be punished.
- 2 - I expect to be punished.
- 3 - I feel I am being punished.

7 Self-Dislike

0 - I feel the same about myself as ever.
1 - I have lost confidence in myself.
2 - I am disappointed in myself.
3 - I dislike myself.

8 Self-Criticalness

0 - I don't criticize or blame myself more than usual.
1 - I am more critical of myself than I used to be.
2 - I criticize myself for all of my faults.
3 - I blame myself for everything bad that happens.

9 Suicidal Thoughts or Wishes

0 - I don't have any thoughts of killing myself.
1 - I have thoughts of killing myself, but I would not carry them out.
2 - I would like to kill myself.
3 - I would kill myself if I had the chance.

10 Crying

0 - I don't cry any more than I used to.
1 - I cry more than I used to.
2 - I cry over every little thing.
3 - I feel like crying, but I can't.

11 Agitation

0 - I am no more restless or wound up than usual.
1 - I feel more restless or wound up than ususal.
2 - I am so restless or agitated that it's hard to stay still.
3 - I am so restless or agitated that have to keep moving or doing something.

12 Loss of Interest

0 - I have not lost interest in other people or activities.
1 - I am less interested in other people or things than before.
2 - I have lost most of my interest in other people.
3 - It's hard to get interested in anything.

13 Indecisiveness

0 - I make decisions about as well as ever.
1 - I find it more difficult to make decisions than usual.
2 - I have much greater difficulty in making decisions than I used to.
3 - I have trouble making any decisions.

14 Worthlessness

0 - I do not feel I am worthless.
1 - I don't consider myself as worthwhile and useful as I used to.
2 - I feel more worthless as compared to other people.
3 - I feel utterly worthless.

15 Loss of Energy

0 - I have as much energy as ever.
1 - I have less energy than I used to have.
2 - I don't have enough energy to do very much.
3 - I don't have enough energy to do anything.

16 Changes in Sleeping Pattern

0 - I have not experienced any change in my sleeping pattern.
1a - I sleep somewhat more than usual.
1b - I sleep somewhat less than usual.
2a - I sleep a lot more than usual.
2b - I sleep a lot less than usual.
3a - I sleep most of the day.
3b - I wake up 1-2 hours early and can't get back to sleep.

17 Irritability

0 - I am no more irritable than usual.
1 - I am more irritable than usual.
2 - I am much more irritable than usual.
3 - I am irritable all the time.

18 Changes in Appetite

0 - I have not experienced any change in my appetite.
1a - My appetite is somewhat less than usual.
1b - My appetite is somewhat greater than usual.
2a - My appetite is much less than before.
2b - My appetite is much greater than before.
3a - I have no appetite at all.
3b - I crave food all the time.

19 Concentration Difficulty

0 - I can concentrate as well as ever.
1 - I can't concentrate as well as usual.
2 - It's hard to keep my mind on anything for very long.
3 - I find I can't concentrate on anything.

20 Tiredness or Fatigue

0 - I am no more tired or fatigued than usual.
1 - I get more tired or fatigued more easily than usual.
2 - I am too tired or fatigued to do a lot of the things I used to do.
3 - I am too tired or fatigued to do most of the things I used to do.

21 Loss of Interest in Sex

0 - I have not noticed any recent change in my interest in sex.
1 - I am less interested in sex than I used to be.
2 - I am much less interested in sex now.
3 - I have lost interest in sex completely.

A.10 Barratt Impulsivity Scale (BIS)

People differ in the ways they act and think in different situations. The next block of questions are designed to measure some of the ways in which you act and think. Read each statement and select the best answer.

Answer possibilities:
1 = Rarely / Never
2 = Occasionally.
3 = Often
4 = Almost Always / Always

1 I plan tasks carefully.
2 I do things without thinking.
3 I make-up my mind quickly.
4 I am happy-go-lucky.
5 I don't "pay attention."
6 I have "racing" thoughts.
7 I plan trips well ahead of time.
8 I am self controlled.
9 I concentrate easily.
10 I save regularly.
11 I "squirm" at plays or lectures.
12 I am a careful thinker.
13 I plan for job security.
14 I say things without thinking.
15 I like to think about complex problems.
16 I change jobs.
17 I act "on impulse."
18 I get easily bored when solving thought problems.
19 I act on the spur of the moment.
20 I am a steady thinker.
21 I change residences.
22 I buy things on impulse.
23 I can only think about one thing at a time.
24 I change hobbies.
25 I spend or charge more than I earn.
26 I often have extraneous thoughts when thinking.
27 I am more interested in the present than the future.
28 I am restless at the theater or lectures.
29 I like puzzles.
30 I am future oriented.

A.11 Additional Questions

1. Have you experienced the death of an immediate family member (partner, child, parent or sibling) in the past 12 months? (Yes/No)

2. Have you been hospitalized for a major medical problem during the past 12 months? (Yes/No)

3a. In the past 12 months have you lost more than 40 kroner on gambling in a single day? (Yes/No)
3b. Have you ever lost more than 40 kroner on gambling in a single day? (Yes/No)

4a. In the past 12 months have you lost more than 500 kroner on gambling in a single day? (Yes/No)
4b. Have you ever lost more than 500 kroner on gambling in a single day? (Yes/No)

5. Do you currently smoke cigarettes?
6. If yes, how much do you smoke in one day?

Thank you very much for your participation in the survey. Your answers are valuable to us.

Appendix B
Scoring the Survey Instruments

In this appendix we document how we have scored each instrument.

B.1 FLAGS

We have 8,422 valid survey respondents that completed the survey, and of course everyone did FLAGS. The FLAGS documentation (Schellinck et al., 2011) explains the scoring:

Construct	Abrev.	Chosen Cut-Off
Persistence	(PST)	2
Negative Consequences	(NGC)	3
Preoccupation: Obsession	(POO)	2
Impaired Control: Begin	(ICB)	2
Risky Practices: Later	(RBL)	3
Risky Practices: Earlier	(RBE)	3
Impaired Control: Continue	(ICC)	2
Preoccupation: Desire	(POD)	2
Risky Cognitions: Motives	(RCM)	2
Risky Cognitions: Beliefs	(RCB)	3

Constructs Scoring

- $\sum_i RCBi \geq 3 \rightarrow RCB$
- $\sum_i RCMi \geq 2 \rightarrow RCM$
- $\sum_i PODi \geq 2 \rightarrow POD$
- $\sum_i ICCi \geq 2 \rightarrow ICC$
- $\sum_i RBEi \geq 3 \rightarrow RBE$
- $\sum_i RBLi \geq 3 \rightarrow RBL$
- $\sum_i ICBi \geq 2 \rightarrow ICB$
- $\sum_i POOi \geq 2 \rightarrow POO$
- $\sum_i NGCi \geq 3 \rightarrow NGC$
- $\sum_i PSTi \geq 2 \rightarrow PST$

Here is the raw tabulation:

FLAGS Risk Level	Freq.	Percent	Cum.
No Detectable Risk	6,698	79.69	79.69
Early Risk	1,010	12.02	91.71
Intermediate Risk	328	3.90	95.61
Advanced Risk	274	3.26	98.87
Problem Gambler	95	1.13	100.00
Total	8,405	100.00	

B.2 PGSI

We have 1,757 valid survey respondents that completed the PGSI survey questions, and of course everyone in that 1,757 also did FLAGS.

The PGSI is directly scored from the responses, once we conservatively assign a Don't Know response as a No. The classification is then to assign anyone with a score of 1 or 2 to Low Risk, a score between 3 and 7 to Moderate Risk, and a score of 8 or more to Problem Gambler.

Here is the raw tabulation:

PGSI Risk Level	Freq.	Percent	Cum.
Non-Gambler	1,492	84.92	84.92
Low Risk	183	10.42	95.33
Moderate Risk	60	3.41	98.75
Problem Gambler	22	1.25	100.00
Total	1,757	100.00	

	Lifetime prevalence		
PGSI Risk Level	0	1	Total
Non-Gambler	650	842	1,492
Low Risk	79	104	183
Moderate Risk	29	31	60
Problem Gambler	11	11	22
Total	769	988	1,757

```
         Pearson chi2(3) =   0.9067   Pr = 0.824
 likelihood-ratio chi2(3) =   0.9009   Pr = 0.825
                    gamma =  -0.0303  ASE = 0.065
          Kendall's tau-b =  -0.0110  ASE = 0.024
```

B.3 DSM

We have 1,671 valid survey respondents that completed the DSM-IV survey questions, and of course everyone in that 1,671 also did FLAGS.

One initial question is how we score these responses. Many of the applications of DSM just ask YES or NO questions (apart from a DON'T KNOW). But we asked the extended list:

Have you found yourself thinking about gambling (e.g. reliving past gambling exp	Freq.	Percent	Cum.
Don't know	13	0.78	0.78
Often	20	1.20	1.97
Sometimes	98	5.86	7.84
Once or twice	101	6.04	13.88
No	1,439	86.12	100.00
Total	1,671	100.00	

Have you found yourself thinking about gambling (e.g. reliving past gambling exp	Freq.	Percent	Cum.
-4	13	0.78	0.78
-3	20	1.20	1.97
-2	98	5.86	7.84
-1	101	6.04	13.88
0	1,439	86.12	100.00
Total	1,671	100.00	

This comes from the MR (Multiple Response) version of the DSM screen developed by Susan Fisher, "Measuring the Prevalence of Sector-Specific Problem Gambling: A Study of Casino Patrons," *Journal of Gambling Studies*, 16(1), 2000, 25-51. She argues these are easier for respondents to follow in a non-clinical setting where one is not face-to-face with the subject. She has also used a closely-related MR version in Sue Fisher, "Developing the DSM-IV-DSM-IV Criteria to Identify Adolescent Problem Gambling in Non-Clinical Populations," *Journal of Gambling Studies*, 16(2/3), 2000, 253-273. A MR version was also used in the British Gambling Prevalence Study of 2007 (p. 135) and 2010 (p. 154), who also proposed a "continuous" scoring for each question rather than the mapping from MR categories to a "binary" YES or NO.

We follow the first Fisher paper and code the first 7 DSM question as YES if the respondent responded "Often" and code the last 3 DSM questions as YES if the respondent responded "Once or Twice," "Sometimes" or "Often." Using these binary classifications, she proposed that one define a subclinical Problem Gambler as someone that had between 1 and 4 positive DSM criteria responses, providing at least one of these was for the last 3 DSM questions. Following the DSM-IV, someone is declared to be a Pathological Gambler if they have 5 or more positive DSM responses.

Using these criteria we have the following:

```
  dsm_score |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |      1,612       96.47       96.47
          1 |         44        2.63       99.10
          2 |          6        0.36       99.46
          3 |          5        0.30       99.76
          4 |          2        0.12       99.88
          5 |          2        0.12      100.00
------------+-----------------------------------
      Total |      1,671      100.00
```

```
      DSM Risk Level |      Freq.     Percent        Cum.
---------------------+-----------------------------------
         Non-Gambler |      1,644       98.38       98.38
     Problem Gambler |         25        1.50       99.88
Pathological Gambler |          2        0.12      100.00
---------------------+-----------------------------------
               Total |      1,671      100.00
```

```
                     |  Lifetime prevalence
      DSM Risk Level |         0          1 |     Total
---------------------+----------------------+----------
         Non-Gambler |       733        911 |     1,644
     Problem Gambler |        13         12 |        25
Pathological Gambler |         0          2 |         2
---------------------+----------------------+----------
               Total |       746        925 |     1,671

          Pearson chi2(2) =   2.1626   Pr = 0.339
 likelihood-ratio chi2(2) =   2.9114   Pr = 0.233
                    gamma =  -0.0703  ASE = 0.193
          Kendall's tau-b =  -0.0089  ASE = 0.025
```

B.4 GACS

We have 1,626 valid survey respondents that completed the GACS survey questions, and of course everyone in that 1,626 also did FLAGS.

Here is the Likert scale used for each question, with one (GACS_5) reverse-coded:

```
   If it were possible, I |
    probably would gamble |
            now.          |      Freq.     Percent        Cum.
--------------------------+-----------------------------------
        strongly disagree |      1,152       70.85       70.85
      moderately disagree |        145        8.92       79.77
          mildly disagree |         70        4.31       84.07
neither agree or disagree |        127        7.81       91.88
             mildly agree |         75        4.61       96.49
         moderately agree |         31        1.91       98.40
           strongly agree |         26        1.60      100.00
--------------------------+-----------------------------------
                    Total |      1,626      100.00
```

If it were possible, I probably would gamble now.	Freq.	Percent	Cum.
1	1,152	70.85	70.85
2	145	8.92	79.77
3	70	4.31	84.07
4	127	7.81	91.88
5	75	4.61	96.49
6	31	1.91	98.40
7	26	1.60	100.00
Total	1,626	100.00	

So the usual way one generates a score from such things is just to average. They do discuss 3 subscales from the 18 questions, but we do not want to presume factor loadings from their statistical analysis would apply to our analysis or population.

Here is the raw tabulation of the scale, rounded to the nearest 0.1 and 1 for ease of viewing:

gacs_scoreR	Freq.	Percent	Cum.
1	526	32.35	32.35
1.1	107	6.58	38.93
1.2	133	8.18	47.11
1.3	232	14.27	61.38
1.4	65	4.00	65.38
1.5	60	3.69	69.07
1.6	53	3.26	72.32
1.7	53	3.26	75.58
1.8	49	3.01	78.60
1.9	29	1.78	80.38
2	19	1.17	81.55
2.1	31	1.91	83.46
2.2	35	2.15	85.61
2.3	25	1.54	87.15
2.4	28	1.72	88.87
2.5	11	0.68	89.54
2.6	15	0.92	90.47
2.7	12	0.74	91.21
2.8	15	0.92	92.13
2.9	10	0.62	92.74
3	4	0.25	92.99
3.1	6	0.37	93.36
3.2	10	0.62	93.97
3.3	8	0.49	94.46
3.4	8	0.49	94.96
3.5	5	0.31	95.26
3.6	4	0.25	95.51
3.7	5	0.31	95.82
3.8	3	0.18	96.00
3.9	6	0.37	96.37
4	27	1.66	98.03
4.1	6	0.37	98.40
4.2	2	0.12	98.52
4.3	2	0.12	98.65
4.4	5	0.31	98.95
4.5	2	0.12	99.08
4.8	1	0.06	99.14
5.1	1	0.06	99.20
5.3	1	0.06	99.26
5.4	1	0.06	99.32
5.5	2	0.12	99.45
5.6	1	0.06	99.51
5.8	1	0.06	99.57
6.1	1	0.06	99.63
6.2	1	0.06	99.69
6.3	1	0.06	99.75
6.7	4	0.25	100.00
Total	1,626	100.00	

RR	0	1	Total
1	476	587	1,063
2	179	203	382
3	40	59	99
4	30	35	65
5	4	2	6
6	5	2	7
7	2	2	4
Total	736	890	1,626

```
         Pearson chi2(6) =   4.5373   Pr = 0.604
 likelihood-ratio chi2(6) =   4.5755   Pr = 0.599
                   gamma =  -0.0236  ASE = 0.047
         Kendall's tau-b =  -0.0119  ASE = 0.024
```

B.5 GRCS

We have 1,656 valid survey respondents that completed the GRCS survey questions, and of course everyone in that 1,656 also did FLAGS.

Here is the Likert scale used for each question:

Gambling makes me happier.	Freq.	Percent	Cum.
strongly disagree	797	48.13	48.13
moderately disagree	162	9.78	57.91
mildly disagree	65	3.93	61.84
neither agree or disagree	364	21.98	83.82
mildly agree	190	11.47	95.29
moderately agree	55	3.32	98.61
strongly agree	23	1.39	100.00
Total	1,656	100.00	

Gambling makes me happier.	Freq.	Percent	Cum.
1	797	48.13	48.13
2	162	9.78	57.91
3	65	3.93	61.84
4	364	21.98	83.82
5	190	11.47	95.29
6	55	3.32	98.61
7	23	1.39	100.00
Total	1,656	100.00	

Raylu & Oei (2004b) document clearly how to score this instrument. We generate the simple average subscale score and then the simple average of those for an overall score.

Here is the raw tabulation of the scale, rounded to the nearest 0.1 and 1 for ease of viewing:

```
grcs_scoreR |      Freq.     Percent        Cum.
------------+-----------------------------------
          1 |        482       29.11       29.11
        1.1 |        195       11.78       40.88
        1.2 |         98        5.92       46.80
        1.3 |        132        7.97       54.77
        1.4 |         86        5.19       59.96
        1.5 |         86        5.19       65.16
        1.6 |         80        4.83       69.99
        1.7 |         44        2.66       72.64
        1.8 |         51        3.08       75.72
        1.9 |         30        1.81       77.54
          2 |         30        1.81       79.35
        2.1 |         32        1.93       81.28
        2.2 |         36        2.17       83.45
        2.3 |         32        1.93       85.39
        2.4 |         20        1.21       86.59
        2.5 |         28        1.69       88.29
        2.6 |         14        0.85       89.13
        2.7 |         16        0.97       90.10
        2.8 |         16        0.97       91.06
        2.9 |          9        0.54       91.61
          3 |          9        0.54       92.15
        3.1 |          8        0.48       92.63
        3.2 |         16        0.97       93.60
        3.3 |          5        0.30       93.90
        3.4 |         15        0.91       94.81
        3.5 |          7        0.42       95.23
        3.6 |          3        0.18       95.41
        3.7 |         10        0.60       96.01
        3.8 |          5        0.30       96.32
        3.9 |          4        0.24       96.56
          4 |         35        2.11       98.67
        4.1 |          5        0.30       98.97
        4.2 |          2        0.12       99.09
        4.3 |          2        0.12       99.21
        4.6 |          1        0.06       99.28
        4.7 |          3        0.18       99.46
        4.8 |          1        0.06       99.52
        4.9 |          1        0.06       99.58
        5.2 |          1        0.06       99.64
        5.5 |          1        0.06       99.70
          6 |          1        0.06       99.76
        6.3 |          1        0.06       99.82
        6.7 |          1        0.06       99.88
        6.9 |          2        0.12      100.00
------------+-----------------------------------
      Total |      1,656      100.00
```

```
grcs_score |  Lifetime prevalence
        RR |         0          1 |     Total
-----------+----------------------+----------
         1 |       472        562 |     1,034
         2 |       179        239 |       418
         3 |        56         64 |       120
         4 |        34         37 |        71
         5 |         6          1 |         7
         6 |         3          0 |         3
         7 |         1          2 |         3
-----------+----------------------+----------
     Total |       751        905 |     1,656

          Pearson chi2(6) =   9.7742   Pr = 0.134
 likelihood-ratio chi2(6) =  11.2655   Pr = 0.081
                    gamma =  -0.0028  ASE = 0.046
          Kendall's tau-b =  -0.0014  ASE = 0.024
```

B.6 GUS

We have 1,695 valid survey respondents that completed the GUS survey questions, and of course everyone in that 1,695 also did FLAGS.

Here is the Likert scale used for each question:

All I want to do now is to gamble.	Freq.	Percent	Cum.
strongly disagree	1,432	84.48	84.48
moderately disagree	89	5.25	89.73
mildly disagree	31	1.83	91.56
neither agree or disagree	86	5.07	96.64
mildly agree	27	1.59	98.23
moderately agree	16	0.94	99.17
strongly agree	14	0.83	100.00
Total	1,695	100.00	

All I want to do now is to gamble.	Freq.	Percent	Cum.
1	1,432	84.48	84.48
2	89	5.25	89.73
3	31	1.83	91.56
4	86	5.07	96.64
5	27	1.59	98.23
6	16	0.94	99.17
7	14	0.83	100.00
Total	1,695	100.00	

Raylu & Oei (2004a) document clearly how to score this: they suggest the total score, since this is viewed as one factor, but the average score would do the same. They drop 2 of the 8 questions (the reverse-coded ones, GUS_7 and GUS_8).

Here is the raw tabulation of the scale, rounded to the nearest 0.1 and 1 for ease of viewing:

gus_scoreR	Freq.	Percent	Cum.
1	996	58.76	58.76
1.1	70	4.13	62.89
1.3	50	2.95	65.84
1.4	66	3.89	69.73
1.5	42	2.48	72.21
1.6	40	2.36	74.57
1.8	126	7.43	82.01
1.9	30	1.77	83.78
2	23	1.36	85.13
2.1	16	0.94	86.08
2.3	18	1.06	87.14
2.4	12	0.71	87.85
2.5	63	3.72	91.56
2.6	15	0.88	92.45
2.8	6	0.35	92.80
2.9	7	0.41	93.22
3	6	0.35	93.57
3.1	10	0.59	94.16
3.3	10	0.59	94.75
3.4	5	0.29	95.04
3.5	3	0.18	95.22
3.6	8	0.47	95.69
3.8	9	0.53	96.22
3.9	6	0.35	96.58
4	23	1.36	97.94
4.1	3	0.18	98.11

4.3	3	0.18	98.29
4.5	1	0.06	98.35
4.6	4	0.24	98.58
4.8	3	0.18	98.76
4.9	3	0.18	98.94
5	2	0.12	99.06
5.1	1	0.06	99.12
5.3	2	0.12	99.23
5.4	1	0.06	99.29
5.5	2	0.12	99.41
5.6	1	0.06	99.47
5.9	1	0.06	99.53
6	1	0.06	99.59
6.3	2	0.12	99.71
6.5	1	0.06	99.76
6.8	1	0.06	99.82
7	3	0.18	100.00
Total	1,695	100.00	

gus_scoreRR	Freq.	Percent	Cum.
1	1,182	69.73	69.73
2	307	18.11	87.85
3	122	7.20	95.04
4	55	3.24	98.29
5	17	1.00	99.29
6	7	0.41	99.71
7	5	0.29	100.00
Total	1,695	100.00	

gus_scoreR R	Lifetime prevalence 0	1	Total
1	505	677	1,182
2	136	171	307
3	59	63	122
4	30	25	55
5	9	8	17
6	5	2	7
7	5	0	5
Total	749	946	1,695

```
          Pearson chi2(6) =  13.2318   Pr = 0.039
 likelihood-ratio chi2(6) =  15.0737   Pr = 0.020
                    gamma =  -0.1055  ASE = 0.047
          Kendall's tau-b =  -0.0514  ASE = 0.023
```

B.7 AUDIT

We have 6,661 valid survey respondents that completed the AUDIT survey questions, and of course everyone in that 6,661 also did FLAGS.

Here is the Likert scale used for each of the first 8 questions:

How often during the last year have you found that you were not able to stop dri	Freq.	Percent	Cum.
Never	5,707	85.85	85.85
Less than monthly	695	10.45	96.30
Monthly	154	2.32	98.62
Weekly	65	0.98	99.59
Daily or almost daily	27	0.41	100.00
Total	6,648	100.00	

```
  How often |
 during the |
  last year |
   have you |
 found that |
   you were |
not able to |
   stop dri |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |      5,707       85.85       85.85
          1 |        695       10.45       96.30
          2 |        154        2.32       98.62
          3 |         65        0.98       99.59
          4 |         27        0.41      100.00
------------+-----------------------------------
      Total |      6,648      100.00
```

But the last 2 questions have different coding, with the numerical values shown:

```
Have you or someone else been |
      injured because of your |
                 drinking?    |      Freq.     Percent        Cum.
------------------------------+-----------------------------------
                           No |      6,071       91.32       91.32
Yes, but not in the last year |        467        7.02       98.35
    Yes, during the last year |        110        1.65      100.00
------------------------------+-----------------------------------
                        Total |      6,648      100.00
```

```
Have you or |
    someone |
  else been |
    injured |
 because of |
       your |
drinking?   |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |      6,071       91.32       91.32
          2 |        467        7.02       98.35
          4 |        110        1.65      100.00
------------+-----------------------------------
      Total |      6,648      100.00
```

Bablor et al. (2001) document clearly how to score this: they suggest the total score, since this is viewed as one factor. While the average score would do the same, we want comparability to cutoff thresholds stated in terms of the score. For instance, here is the default categories based on the total score:

Box 6		
Risk Level	**Intervention**	**AUDIT score***
Zone I	Alcohol Education	0-7
Zone II	Simple Advice	8-15
Zone III	Simple Advice plus Brief Counseling and Continued Monitoring	16-19
Zone IV	Referral to Specialist for Diagnostic Evaluation and Treatment	20-40

*The AUDIT cut-off score may vary slightly depending on the country's drinking patterns, the alcohol content of standard drinks, and the nature of the screening program. Clinical judgment should be exercised in cases where the patient's score is not consistent with other evidence, or if the patient has a prior history of alcohol dependence. It may also be instructive to review the patient's responses to individual questions dealing with dependence symptoms (Questions 4, 5 and 6) and alcohol-related problems (Questions 9 and 10). Provide the next highest level of intervention to patients who score 2 or more on Questions 4, 5 and 6, or 4 on Questions 9 or 10.

Here is the raw tabulation of the scale, with extra lines between the above "zones":

```
audit_score |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |        406        6.11        6.11
          1 |        575        8.65       14.76
          2 |        712       10.71       25.47
          3 |        928       13.96       39.43
          4 |        998       15.01       54.44
          5 |        711       10.69       65.13
          6 |        556        8.36       73.50
          7 |        386        5.81       79.30
------------+-----------------------------------
          8 |        313        4.71       84.01
          9 |        212        3.19       87.20
         10 |        169        2.54       89.74
         11 |        148        2.23       91.97
         12 |         87        1.31       93.28
         13 |        103        1.55       94.83
         14 |         66        0.99       95.82
         15 |         45        0.68       96.50
------------+-----------------------------------
         16 |         50        0.75       97.25
         17 |         36        0.54       97.79
         18 |         26        0.39       98.18
         19 |         19        0.29       98.47
------------+-----------------------------------
         20 |         21        0.32       98.78
         21 |         14        0.21       98.99
         22 |         19        0.29       99.28
         23 |          8        0.12       99.40
         24 |          7        0.11       99.50
         25 |          9        0.14       99.64
         26 |          3        0.05       99.68
         27 |          4        0.06       99.74
         28 |          2        0.03       99.77
         29 |          3        0.05       99.82
         30 |          1        0.02       99.83
         31 |          1        0.02       99.85
         32 |          3        0.05       99.89
         33 |          2        0.03       99.92
```

```
         34 |          3        0.05       99.97
         35 |          1        0.02       99.98
         40 |          1        0.02      100.00
------------+-----------------------------------
      Total |      6,648      100.00
```

Here are the evaluations of treatments:

```
audit_scor |  Lifetime prevalence
         e |         0          1 |     Total
-----------+----------------------+----------
         0 |       188        218 |       406 
         1 |       263        312 |       575 
         2 |       306        406 |       712 
         3 |       393        535 |       928 
         4 |       431        567 |       998 
         5 |       326        385 |       711 
         6 |       241        315 |       556 
         7 |       177        209 |       386 
         8 |       142        171 |       313 
         9 |       101        111 |       212 
        10 |        77         92 |       169 
        11 |        62         86 |       148 
        12 |        49         38 |        87 
        13 |        50         53 |       103 
        14 |        27         39 |        66 
        15 |        26         19 |        45 
        16 |        24         26 |        50 
        17 |        21         15 |        36 
        18 |        13         13 |        26 
        19 |         9         10 |        19 
        20 |        13          8 |        21 
        21 |        11          3 |        14 
        22 |        13          6 |        19 
        23 |         5          3 |         8 
        24 |         3          4 |         7 
        25 |         4          5 |         9 
        26 |         1          2 |         3 
        27 |         1          3 |         4 
        28 |         0          2 |         2 
        29 |         1          2 |         3 
        30 |         0          1 |         1 
        31 |         0          1 |         1 
        32 |         2          1 |         3 
        33 |         0          2 |         2 
        34 |         2          1 |         3 
        35 |         0          1 |         1 
        40 |         0          1 |         1 
-----------+----------------------+----------
     Total |     2,982      3,666 |     6,648 

          Pearson chi2(36) =  41.8557   Pr = 0.232
 likelihood-ratio chi2(36) =  45.1015   Pr = 0.142
                     gamma =  -0.0288  ASE = 0.016
           Kendall's tau-b =  -0.0193  ASE = 0.010
```

B.8 BAI

We have 1,671 valid survey respondents that completed the BAI survey questions, and of course everyone in that 1,671 also did FLAGS.

Here is the Likert scale used for each question:

Fear of dying	Freq.	Percent	Cum.
Not at all	1,253	74.99	74.99
Mildly but it didn't bother me much.	267	15.98	90.96
Moderately - it wasn't pleasant at time	112	6.70	97.67
Severely - it bothered me a lot.	39	2.33	100.00
Total	1,671	100.00	

Fear of dying	Freq.	Percent	Cum.
1	1,253	74.99	74.99
2	267	15.98	90.96
3	112	6.70	97.67
4	39	2.33	100.00
Total	1,671	100.00	

Beck and Steer (1990) document clearly how to score this: they suggest the total score, since this is viewed as one factor, but the average score would do the same. We have 21 BAI questions. Here is the raw tabulation of the scale, rounded to the nearest 0.1 for ease of viewing:

bai_scoreR	Freq.	Percent	Cum.
1	537	32.14	32.14
1.1	159	9.52	41.65
1.2	139	8.32	49.97
1.3	130	7.78	57.75
1.4	105	6.28	64.03
1.5	90	5.39	69.42
1.6	88	5.27	74.69
1.7	58	3.47	78.16
1.8	50	2.99	81.15
1.9	47	2.81	83.96
2	51	3.05	87.01
2.1	41	2.45	89.47
2.2	40	2.39	91.86
2.3	16	0.96	92.82
2.4	22	1.32	94.14
2.5	12	0.72	94.85
2.6	14	0.84	95.69
2.7	9	0.54	96.23
2.8	10	0.60	96.83
2.9	10	0.60	97.43
3	14	0.84	98.26
3.1	8	0.48	98.74
3.2	2	0.12	98.86
3.3	1	0.06	98.92
3.4	7	0.42	99.34
3.5	4	0.24	99.58
3.6	2	0.12	99.70
3.7	1	0.06	99.76
3.8	1	0.06	99.82
4	3	0.18	100.00
Total	1,671	100.00	

Here are the evaluations of treatments:

bai_scoreR	Lifetime prevalence 0	1	Total
1	245	292	537
1.1	72	87	159
1.2	60	79	139
1.3	53	77	130
1.4	58	47	105
1.5	33	57	90
1.6	45	43	88
1.7	28	30	58
1.8	18	32	50
1.9	22	25	47
2	22	29	51
2.1	17	24	41
2.2	16	24	40
2.3	6	10	16
2.4	11	11	22
2.5	5	7	12
2.6	5	9	14
2.7	4	5	9
2.8	3	7	10
2.9	5	5	10
3	7	7	14
3.1	5	3	8
3.2	1	1	2
3.3	0	1	1
3.4	2	5	7
3.5	2	2	4
3.6	0	2	2
3.7	0	1	1
3.8	0	1	1
4	1	2	3
Total	746	925	1,671

```
          Pearson chi2(29) =  20.4571   Pr = 0.878
 likelihood-ratio chi2(29) =  22.4397   Pr = 0.802
                     gamma =   0.0250  ASE = 0.032
           Kendall's tau-b =   0.0163  ASE = 0.021
```

B.9 BDI

We have 1,695 valid survey respondents that completed the BDI survey questions, and of course everyone in that 1,695 also did FLAGS.

Here is the Likert scale used for each question:

Loss of Interest in Sex	Freq.	Percent	Cum.
I have not noticed any recent ch	1,159	68.38	68.38
I am less interested in sex than	316	18.64	87.02
I am much less interested in sex	117	6.90	93.92
I have lost interest in sex comp	103	6.08	100.00
Total	1,695	100.00	

Loss of Interest in Sex	Freq.	Percent	Cum.
0	1,159	68.38	68.38
1	316	18.64	87.02
2	117	6.90	93.92
3	103	6.08	100.00
Total	1,695	100.00	

Beck et al. (1961) document clearly how to score this: they suggest the total score, since this is viewed as one factor, but the average score would do the same.

Here is the raw tabulation of the scale, rounded to the nearest 0.1 for ease of viewing:

bdi_scoreR	Freq.	Percent	Cum.
0	631	37.23	37.23
.1	167	9.85	47.08
.2	110	6.49	53.57
.3	67	3.95	57.52
.4	52	3.07	60.59
.5	35	2.06	62.65
.6	44	2.60	65.25
.7	63	3.72	68.97
.8	51	3.01	71.98
.9	50	2.95	74.93
1	50	2.95	77.88
1.1	34	2.01	79.88
1.2	27	1.59	81.47
1.3	33	1.95	83.42
1.4	26	1.53	84.96
1.5	18	1.06	86.02
1.6	19	1.12	87.14
1.7	23	1.36	88.50
1.8	25	1.47	89.97
1.9	15	0.88	90.86
2	16	0.94	91.80
2.1	13	0.77	92.57
2.2	16	0.94	93.51
2.3	10	0.59	94.10
2.4	13	0.77	94.87
2.5	8	0.47	95.34
2.6	7	0.41	95.75
2.7	10	0.59	96.34
2.8	7	0.41	96.76
2.9	7	0.41	97.17
3	9	0.53	97.70
3.1	6	0.35	98.05
3.2	6	0.35	98.41
3.3	4	0.24	98.64
3.4	5	0.29	98.94
3.5	3	0.18	99.12
3.6	3	0.18	99.29
3.7	1	0.06	99.35
3.8	4	0.24	99.59
3.9	2	0.12	99.71
4	4	0.24	99.94
4.2	1	0.06	100.00
Total	1,695	100.00	

B.10 BIS

We have 1,761 valid survey respondents that completed the BIS survey questions, and of course everyone in that 1,761 also did FLAGS.

Here is the Likert scale used for each question:

I plan tasks carefully.	Freq.	Percent	Cum.
Never	74	4.21	4.21
Occasionally	494	28.12	32.33
Often	786	44.74	77.06
Almost always / Always	403	22.94	100.00
Total	1,757	100.00	

I plan tasks carefully.	Freq.	Percent	Cum.
1	74	4.21	4.21
2	494	28.12	32.33
3	786	44.74	77.06
4	403	22.94	100.00
Total	1,757	100.00	

Patton, Stanford and Barratt (1995) document clearly how to score this: they suggest the total score, since this is viewed as one factor, but the average score would do the same. We have 30 BIS questions.

Here is the raw tabulation of the scale, rounded to the nearest 0.1 for ease of viewing:

bis_scoreR	Freq.	Percent	Cum.
1	3	0.17	0.17
1.1	2	0.11	0.28
1.2	3	0.17	0.46
1.3	1	0.06	0.51
1.4	3	0.17	0.68
1.5	3	0.17	0.85
1.6	6	0.34	1.20
1.7	52	2.96	4.15
1.8	116	6.60	10.76
1.9	214	12.18	22.94
2	291	16.56	39.50
2.1	366	20.83	60.33
2.2	309	17.59	77.92
2.3	209	11.90	89.81
2.4	102	5.81	95.62
2.5	53	3.02	98.63
2.6	17	0.97	99.60
2.7	3	0.17	99.77
2.8	3	0.17	99.94
2.9	1	0.06	100.00
Total	1,757	100.00	

Appendix C
Summary Statistics

Of the 65,592 Danes that were invited to participate in the survey, only 8,405 completed the entire survey, while 3,331 started but did not complete the survey. We here present the background information that is available for participants and non-participants.

We have background information for all participants and non-participants on gender, age, and region, but we have missing values for the other variables for several non-participants. We received background information on non-participants from the companies that administered the survey, and they could not provide complete information for all invited people.

	Completed					Partially Completed					Non-Participants				
	N	*Mean*	*Std. Dev.*	*Min*	*Max*	*N*	*Mean*	*Std. Dev.*	*Min*	*Max*	*N*	*Mean*	*Std. Dev.*	*Min*	*Max*
Female	8405	0.54	0.50	0	1	3331	0.58	0.49	0	1	53856	0.62	0.49	0	1
Age	8405	49.19	14.82	18	75	3331	48.15	15.23	18	75	53856	41.32	14.07	18	75
Young (18-29)	8405	0.13	0.33	0	1	3331	0.16	0.36	0	1	53856	0.24	0.42	0	1
Middle (30-39)	8405	0.15	0.36	0	1	3331	0.15	0.35	0	1	53856	0.23	0.42	0	1
Ripe Aged (40-49)	8405	0.20	0.40	0	1	3331	0.20	0.40	0	1	53856	0.25	0.43	0	1
Older (50+)	8405	0.52	0.50	0	1	3331	0.49	0.50	0	1	53856	0.29	0.45	0	1
Capital Region	8405	0.49	0.50	0	1	3331	0.55	0.50	0	1	53856	0.44	0.50	0	1
Central Denmark	8405	0.17	0.37	0	1	3331	0.15	0.36	0	1	53856	0.18	0.39	0	1
North Denmark	8405	0.06	0.25	0	1	3331	0.06	0.23	0	1	53856	0.07	0.26	0	1
Zealand	8405	0.12	0.33	0	1	3331	0.11	0.31	0	1	53856	0.13	0.34	0	1
Southern Denmark	8405	0.16	0.37	0	1	3331	0.13	0.33	0	1	53856	0.17	0.38	0	1
Lives in a House	8405	0.56	0.50	0	1	3000	0.55	0.50	0	1	42699	0.55	0.50	0	1
Owns a House	8405	0.55	0.50	0	1	3030	0.56	0.50	0	1	43046	0.53	0.50	0	1
Lives with a Partner	8405	0.64	0.48	0	1	2991	0.64	0.48	0	1	38373	0.63	0.48	0	1
Children in Household	8405	0.26	0.44	0	1	944	0.25	0.43	0	1	9177	0.43	0.50	0	1
Civil Servant	8405	0.39	0.49	0	1	3094	0.44	0.50	0	1	44428	0.43	0.49	0	1
Retired	8405	0.23	0.42	0	1	3094	0.17	0.38	0	1	44428	0.08	0.27	0	1
Unskilled	8405	0.05	0.22	0	1	3094	0.04	0.20	0	1	44428	0.06	0.24	0	1
Skilled	8405	0.10	0.30	0	1	3094	0.08	0.28	0	1	44428	0.12	0.33	0	1
Self Employed	8405	0.05	0.21	0	1	3094	0.04	0.20	0	1	44428	0.04	0.20	0	1
Vocational Training	8405	0.23	0.42	0	1	2993	0.19	0.39	0	1	37716	0.19	0.39	0	1
Low Formal Education	8405	0.21	0.41	0	1	2993	0.21	0.41	0	1	37716	0.26	0.44	0	1
Short Education (<3 Y. College)	8405	0.10	0.31	0	1	2993	0.09	0.29	0	1	37716	0.09	0.28	0	1
Med. Education (3-4 Y. College)	8405	0.29	0.45	0	1	2993	0.31	0.46	0	1	37716	0.30	0.46	0	1
High Education (5+ Y. College)	8405	0.17	0.38	0	1	2993	0.18	0.38	0	1	37716	0.15	0.36	0	1
Low Income (<300,000)	8405	0.37	0.48	0	1	3033	0.36	0.48	0	1	43021	0.42	0.49	0	1
Med. Income (300,000-500,000)	8405	0.34	0.47	0	1	3033	0.33	0.47	0	1	43021	0.32	0.47	0	1
High Income (500,000-800,000)	8405	0.12	0.33	0	1	3033	0.12	0.32	0	1	43021	0.10	0.30	0	1
Very High Income (>800,000)	8405	0.02	0.15	0	1	3033	0.03	0.16	0	1	43021	0.02	0.15	0	1
Silent about Income	8405	0.14	0.35	0	1	3033	0.16	0.37	0	1	43021	0.14	0.34	0	1
Q: Experienced Death	8405	0.12	0.33	0	1	33	0.12	0.33	0	1	0				
Q: Has been Hospitalized	8405	0.10	0.30	0	1	33	0.06	0.24	0	1	0				
Q: Trigger 40 DKK	8405	0.38	0.49	0	1	33	0.24	0.44	0	1	0				
Q: Trigger 500 DKK	8405	0.05	0.22	0	1	33	0.03	0.17	0	1	0				
Q: Currently Smoker	8405	0.20	0.40	0	1	32	0.34	0.48	0	1	0				

Note: The last 5 variables are based on additional questions asked in the surveys (see Appendix A).

Appendix D
The Ordered Probit Statistical Model

We document here the statistical model developed for the primary analyses. The outcome of interest is the FLAGS risk level, which can take on any of the ordinal values h={1, 2, 3, 4, 5} corresponding to the five FLAGS risk categories, (1) no detectable risk; (2) early risk; (3) intermediate risk; (4) advanced risk; and (5) problem gambler. The statistical tool to analyze the ordinal outcome is the Ordered Probit model. The probability that outcome y_j=h for a given individual j is defined by

$$\Pr(y_j = h) = \Pr(\kappa_{h-1} < x_j\beta + u_j \le \kappa_h) = \Phi(\kappa_h - x_j\beta) - \Phi(\kappa_{h-1} - x_j\beta)$$

where x_j is a vector of k independent variables and β are the k corresponding coefficients. κ_i are the cut points between the various outcome possibilities, where $\kappa_0 = -\infty$ and $\kappa_5 = +\infty$. The error term u_j is assumed to be normally distributed and $\Phi(\cdot)$ is the cumulative standard normal distribution function. The probability of observing outcome h for individual j is then defined by the probability that $x_j\beta + u_j$ falls between the cut points κ_{h-1} and κ_h.

We estimate the cut points κ_1 to κ_4 and the vector of coefficients β using maximum likelihood. The log likelihood function is

$$\ln L(\beta, \kappa_h) = \sum_{j=1}^{n} \sum_{h=1}^{H} I_h(y_j = h) \ln\left(\Phi(\kappa_h - x_j\beta) - \Phi(\kappa_{h-1} - x_j\beta)\right)$$

where $I_h(y_j = h) = 1$ if $y_j = h$, and 0 otherwise. H is the highest outcome: in the case of a FLAGS risk level H=5. *n* is the number of respondents for whom we can calculate a valid FLAGS risk level.

As independent variables, we include treatments (FLAGS first, randomized questions, lifetime frame), demographic characteristics (sex, age, and income), as well as an indicator for smoking and an indicator for subcontractor. To analyze the effects of scores in other gambling screens on FLAGS levels, we expand the model by adding the score in the other instrument as an independent variable. When other gambling screens are analyzed we simply replace the ordered outcome variable y_j with the risk category from the other gambling screen.

We make two extensions to the Ordered Probit model. First, we control for sample weights, and second, we correct for sample selection. Sample weights are constructed from administrative data at Statistics Denmark on the population size of men and women in various age groups and regions in Denmark, and we specify in the estimation that each observation in the data is weighted by the corresponding sample weight.

To correct for sample selection, we model the decision to participate in the survey as

$$s_j = 1(z_j\gamma + v_j > 0)$$

where $s_j = 1$ if an invited participant completes the survey, z_j is a vector of independent variables that affect participation in the survey, γ is vector of coefficients, and v_j is a random error. We assume that v_j from the selection equation and u_j from the ordered probit equation have a bivariate normal distribution with mean zero and covariance matrix

$$\begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$$

We jointly estimate the cut points κ_1 to κ_4, the vector of coefficients β from the ordered probit equation, the vector of coefficients γ from the selection equation, and the correlation coefficient ρ using maximum likelihood. The log likelihood is

$$\ln L(\beta, \kappa_h, \gamma, \rho) = \sum_{\substack{j=1 \\ i \notin S}}^{N} \ln\left(\Phi(-z_j\gamma)\right)$$

$$+ \sum_{\substack{j=1 \\ i \in S}}^{N} \sum_{h=1}^{H} I_h(y_j = h) \ln\left(\Phi_2(z_j\gamma, \kappa_h - x_j\,\beta\,, -\rho) - \Phi_2(z_j\gamma, \kappa_{h-1} - x_j\,\beta\,, -\rho)\right)$$

where S is the set of participants for whom the outcome y_j is observed. $\Phi_2(\cdot)$ is the cumulative bivariate normal distribution function, and $\Phi(\cdot)$ is the standard normal distribution.

When the correlation coefficient ρ of the bivariate normal distribution is equal to 0, the log likelihood becomes

$$\ln L(\beta, \kappa_h, \gamma) = \sum_{j=1}^{N} \omega_j \ln\left(\Phi(-z_j\gamma)\right)$$

$$+ \sum_{\substack{j=1 \\ i \in S}}^{N} \sum_{h=1}^{H} \omega_j I_h(y_j = h) \ln\left(\Phi(\kappa_h - x_j\beta) - \Phi(\kappa_{h-1} - x_j\beta)\right)$$

which is simply the sum of two likelihood functions: the probit model on selection and the ordered probit model on FLAGS levels.

Appendix E
Predicted FLAGS Levels

We present predicted FLAGS levels for the sample and the population. We start with the Ordered Probit model and report the predicted prevalence rates for the sample below. The point estimates of each FLAGS level are presented in Table 3.

Variable	Obs	Mean	Std. Dev.	Min	Max
no_risk	8405	.7969066	0	.7969066	.7969066
early_ris	8405	.1201666	0	.1201666	.1201666
int_risk	8405	.0390244	0	.0390244	.0390244
adv_risk	8405	.0325996	0	.0325996	.0325996
pg	8405	.0113028	0	.0113028	.0113028

We now add sample weights in the Ordered Probit model and generate predicted prevalence rates for the adult Danish population. The results are presented below, and are also reported in Table 3.

	Mean	Linearized Std. Err.	[95% Conf.	Interval]
no_risk	.7596452	1.57e-16	.7596452	.7596452
early_risk	.1327652	8.23e-19	.1327652	.1327652
int_risk	.0423434	1.44e-18	.0423434	.0423434
adv_risk	.0470056	4.73e-18	.0470056	.0470056
pg	.0182405	7.55e-19	.0182405	.0182405

Finally, we estimate the Ordered Probit model with controls for sample selection and sample weights calculated for the sample frame. We can only predict the FLAGS level for the respondents because we do not observe some of the demographic variables or treatment variables for non-participants. We therefore weight the predictions by the sample weights for the participants.

	Mean	Linearized Std. Err.	[95% Conf.	Interval]
no_risk	.9539403	.0009286	.9521201	.9557605
early_risk	.0287174	.0004591	.0278175	.0296174
int_risk	.0082087	.0001816	.0078528	.0085647
adv_risk	.0070422	.0002048	.0066407	.0074437
pg	.0020914	.0000913	.0019124	.0022704

Appendix F
Additional Figures on Marginal Effects of Demographic Characteristics

We present additional figures that illustrate the marginal effects of demographic characteristics on FLAGS levels. The estimations are based on the Ordered Probit model with controls for sample selection and sample weights.

Figure F1: Marginal Effect of Being Young
on Probability of *FLAGS* Gambling Risk Level
Young defined as aged between 18 and 29

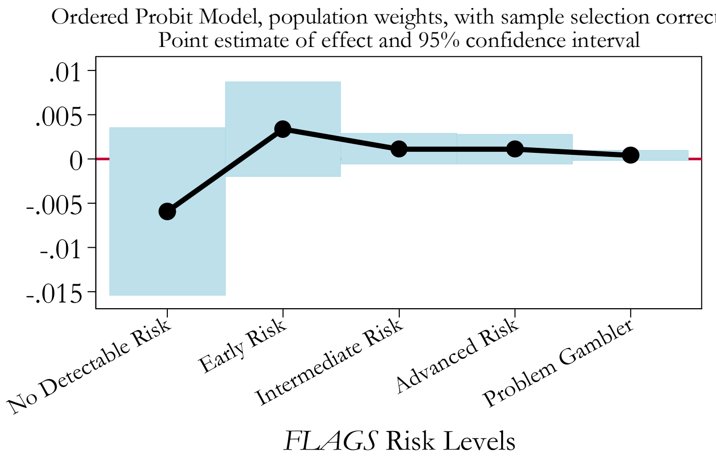


Figure F2: Marginal Effect of Being Ripe_Aged
on Probability of *FLAGS* Gambling Risk Level
Ripe-Aged defined as aged between 40 and 49

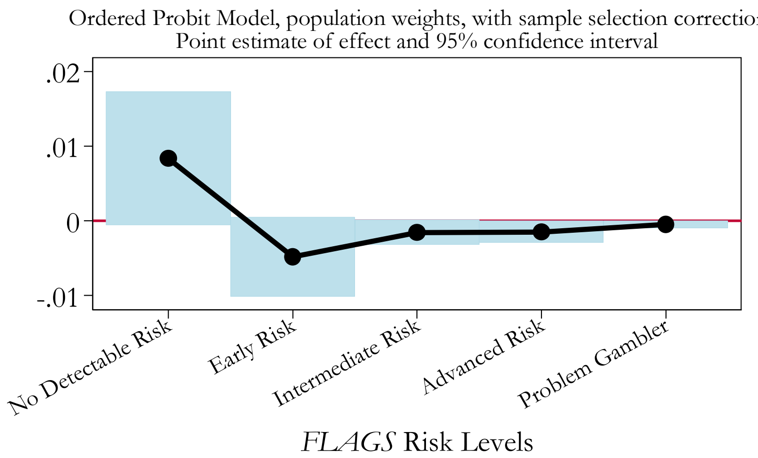


Figure F3: Marginal Effect of Being Older
on Probability of *FLAGS* Gambling Risk Level

Older defined as aged 50 and over

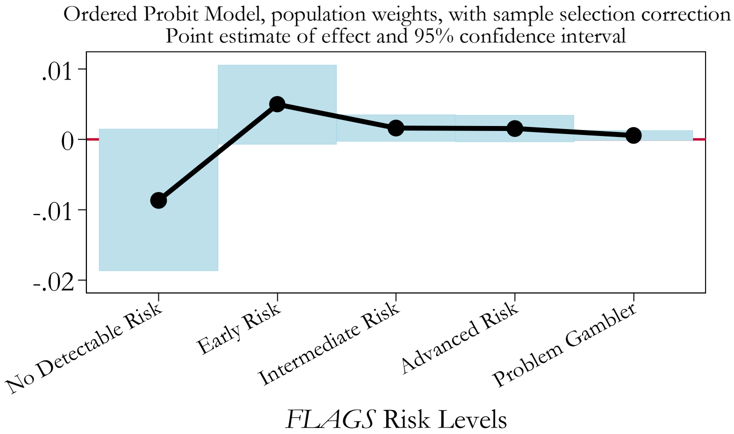


Figure F4: Marginal Effect of Having Medium Income
on Probability of *FLAGS* Gambling Risk Level

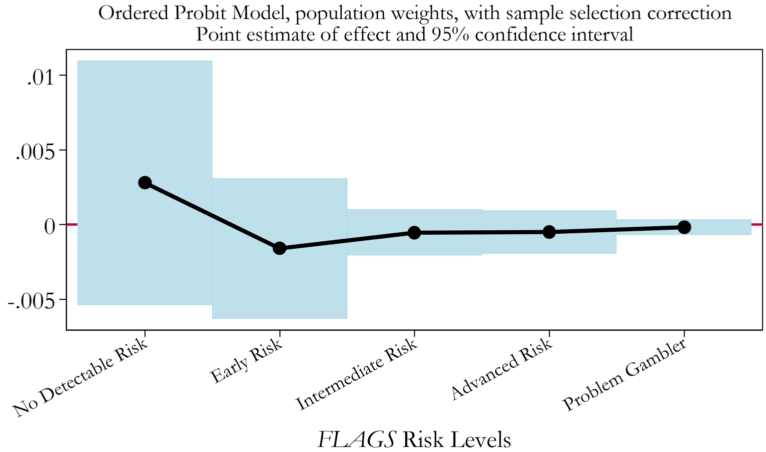


Figure F5: Marginal Effect of Having High Income
on Probability of *FLAGS* Gambling Risk Level

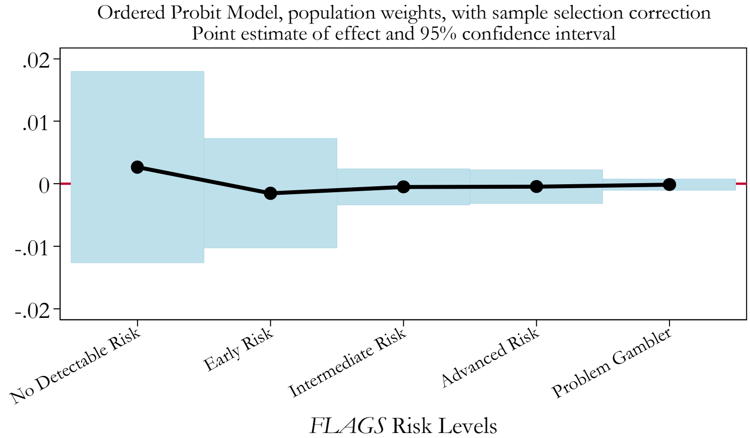


Figure F6: Marginal Effect of Having Very High Income
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model, population weights, with sample selection correction
Point estimate of effect and 95% confidence interval

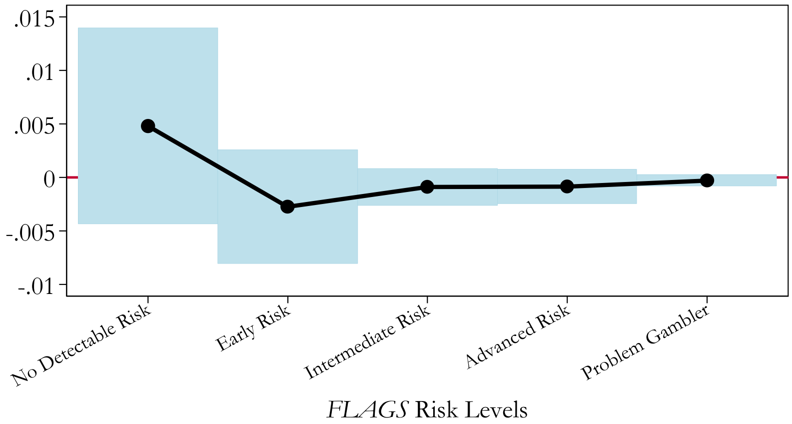
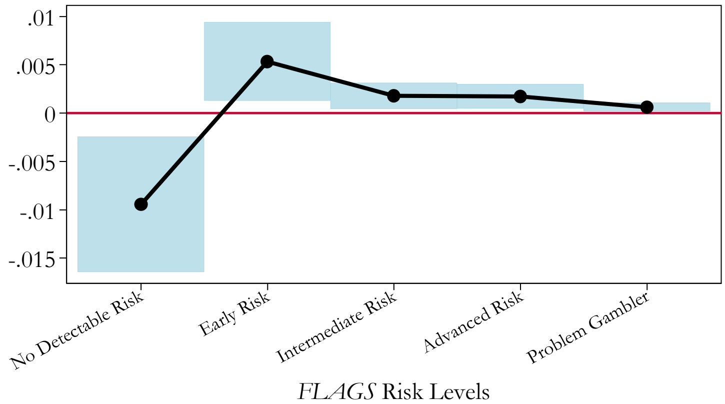


Figure F7: Marginal Effect of Being Smoker
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model, population weights, with sample selection correction
Point estimate of effect and 95% confidence interval



Appendix G
Marginal Effects of other Survey Instruments on FLAGS Level

The figures below show the marginal effects of scores from other gambling screens on predicted FLAGS levels. The estimations are based on the Ordered Probit model with no controls for sample selection or survey weights.

Figure G1: Marginal Effect of DSM Level
on Probability of *FLAGS* Gambling Risk Level

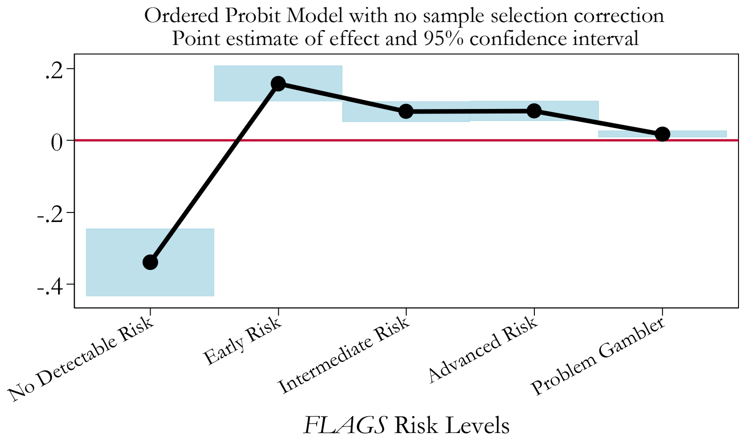


Figure G2: Marginal Effect of PGSI Level
on Probability of *FLAGS* Gambling Risk Level

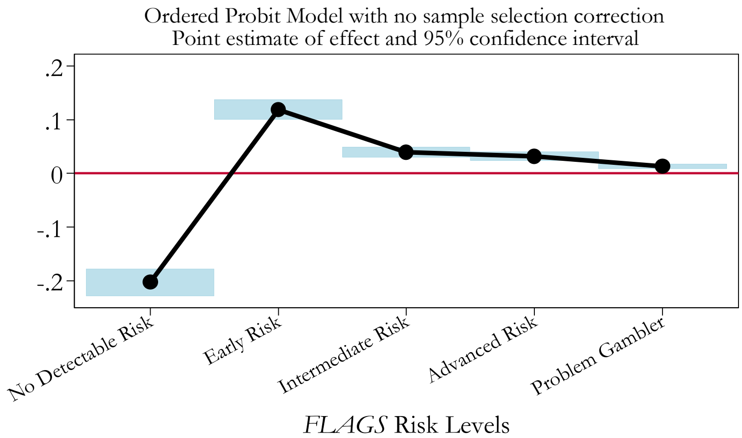


Figure G3: Marginal Effect of GACS Score
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval

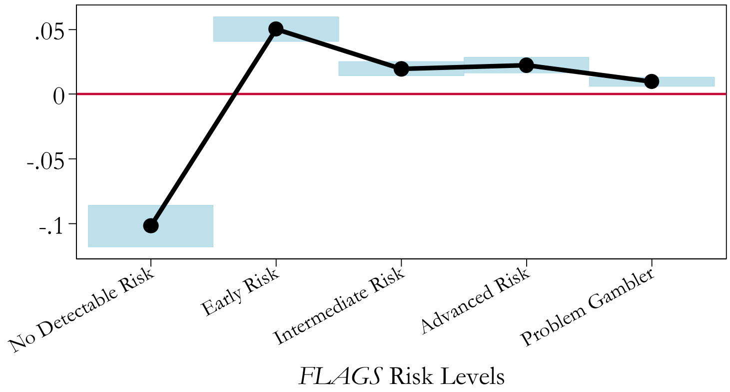


Figure G4: Marginal Effect of GRCS Score
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval

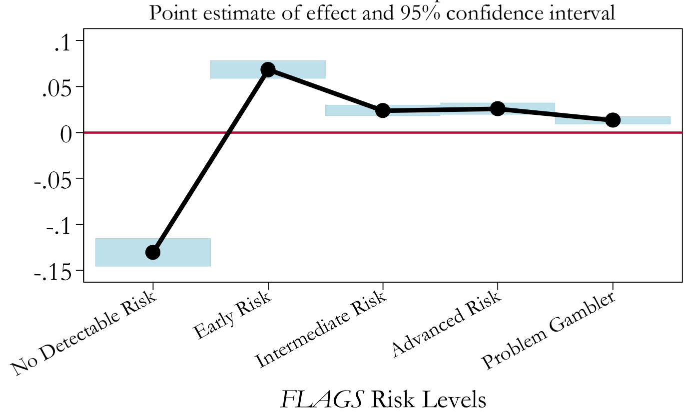


Figure G5: Marginal Effect of GUS Score
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval

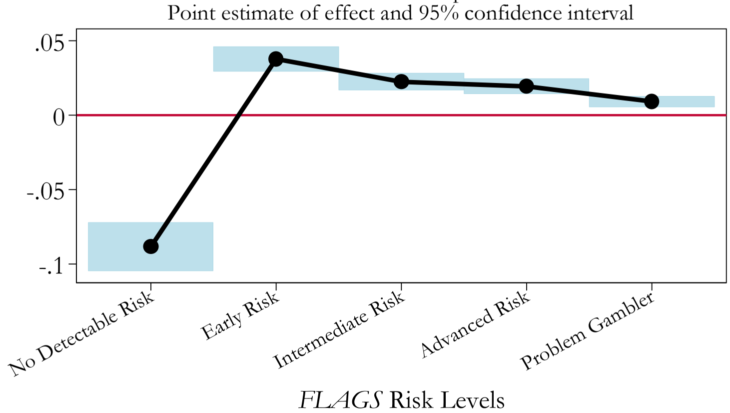


Figure G6: Marginal Effect of AUDIT Score
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval

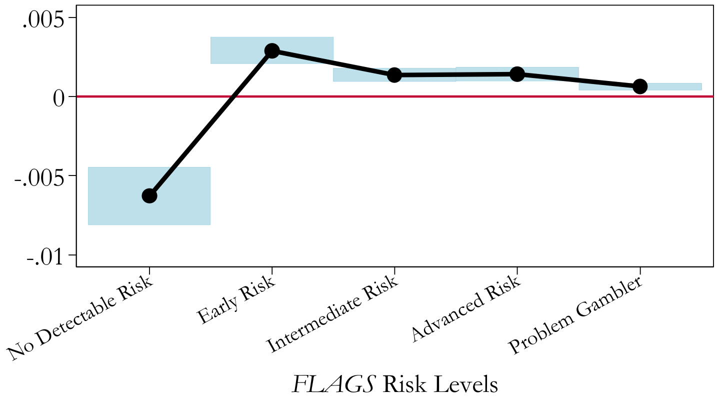


Figure G7: Marginal Effect of BAI Score
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval

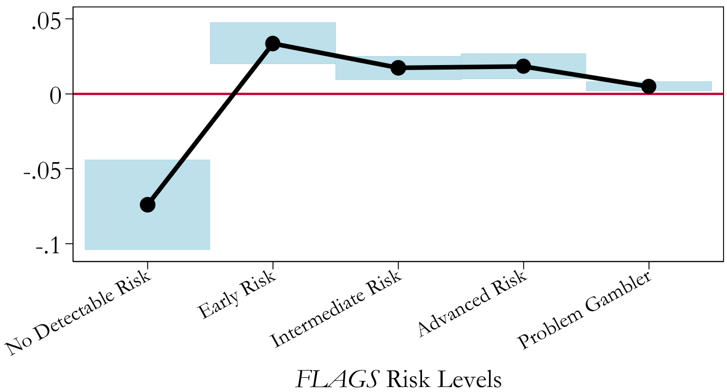


Figure G8: Marginal Effect of BDI Score
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval

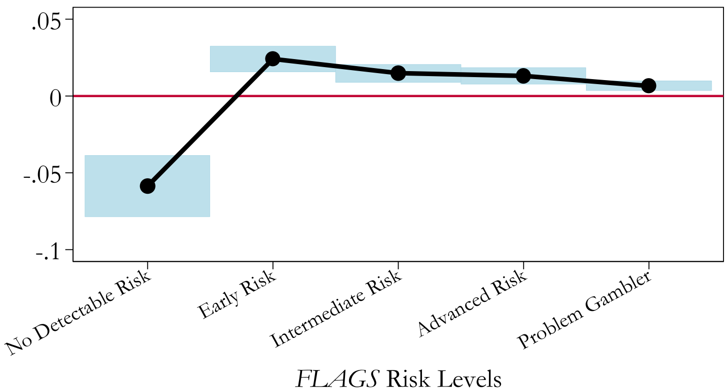
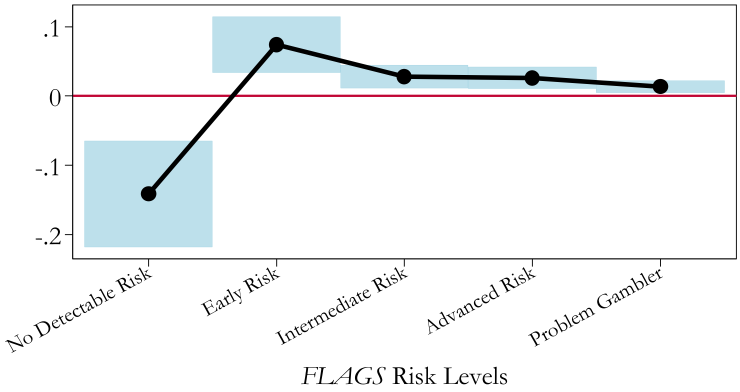


Figure G9: Marginal Effect of BIS Score
on Probability of *FLAGS* Gambling Risk Level

Ordered Probit Model with no sample selection correction
Point estimate of effect and 95% confidence interval



Conclusion

The three chapters in the thesis study the elicitation of individual discount rates and gambling prevalence rates in Denmark. The thesis contributes to our understanding of individual decision making over time, the association between individual discount rates and accumulated private saving, and the identification and measurement of problem gambling.

The first chapter is motivated by mixed results in the literature on the sensitivity of elicited individual discount rates with respect to background consumption and consumption smoothing. I use simulated choice data from standard decision tasks in time preference experiments and show that individual discount rates are robust to time-invariant background consumption and consumption smoothing if the utility function is elicited jointly. The main contribution of the first chapter is the clarification of the mixed conclusions from previous studies on the relevance of background consumption and consumption smoothing for the identification of individual discount rates. The analysis also reveals new research possibilities on time preferences. In particular, individual discount rates are highly sensitive to time-variant background consumption and consumption smoothing. I also find that binary choices over annuities may alleviate the need to control for utility curvature in the elicitation of individual discount rates.

The second chapter contributes to the scarce empirical literature on the association between individual discount rates and private saving behavior. We overcome the challenge of obtaining reliable information on individual discount rates and financial wealth by combining data from a field experiment in Denmark with administrative data from Statistics Denmark. We find significantly lower discount rates for wealthy subjects than for poor subjects, but we do not find any evidence of present bias and no significant association between present bias and financial liquidity. The empirical evidence that we present on individual discount rates and private wealth is consistent with predictions from life cycle models with exponential discounting, but the empirical evidence that we present on present bias and financial liquidity is not consistent with predictions from life cycle models with quasi-hyperbolic discounting. These findings contribute to our understanding of individual saving and investment decisions in Denmark. The availability of unique administrative data and infrastructure to conduct field experiments in Denmark offers many new research possibilities; one can for example study the association between individual risk and time preferences and portfolio choice.

Finally, the third chapter estimates prevalence rates of problem gambling in Denmark. We find that 95% of the population has no detectable risk, 2.9% has an early risk, 0.8% has an intermediate risk, 0.7% has an advanced risk, and 0.2% can be classified as problem gamblers. We identify several methodological issues that have not been addressed in previous studies, such as the use of "trigger" questions and the effect of sample selection on estimated prevalence rates. Our analysis shows significant effects of sample selection, and the results suggest that previous estimates of gambling prevalence in Denmark (and elsewhere) may be significantly upward biased. One can furthermore stratify the sample according to indicators of gambling risk and characterize problem gamblers in terms of their risk and time preferences. Indeed, the survey was designed with this research outlook in mind and the results will contribute further to our understanding of gambling behavior.

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