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Discussion paper

Mapping risk aversion in Norway using hypothetical income gambles

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Mapping risk aversion in Norway using hypothetical income gambles*

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Abstract

This is the first study that explores the heterogeneity of risk preferences among the Norwegian population. We measure risk aversion as the complement of the maximal relative downside income risk a person is willing to bear with 50 percent chance in return for a doubling of their income with 50 percent chance. The higher this fraction is, the more risk averse is the respondent. Observing for each respondent the range to which their fraction belongs, we use an ordered probit model to estimate the effects of socioeconomic characteristics on risk aversion. We find that women are more risk averse than men, that risk aversion increases with age, and people who are satisfied with their current life situation are significantly more risk averse than very satisfied and dissatisfied people. Under the assumption of constant relative risk-aversion preferences, the sample average for the coefficient of relative risk aversion is 3.9 with a standard deviation of 2.9, reflecting strong heterogeneity of risk preferences. We also impute a cardinal risk measure to every respondent and use this as a regressor in various models that explain risky behavior. We find that the likelihood to smoke, to work in the private sector, to assume the role of a top manager, to work in a small firm, or to take up a loan to finance a risky investment depends negatively on the imputed measure of risk aversion.

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1. Introduction

Many big decisions in life are made behind a veil of uncertainty. Savings decisions, career choices, investments in human and health capital, choices of lifestyle—even the most informed decisions yield payoffs that are contingent on states of the world against which we cannot insure. Among the reasons why some decisions are made rather than others, is people's attitude toward risk, formalized by Arrow (1965) and Pratt (1964) through the concepts of absolute and relative risk aversion. Barsky, Juster, Kimball and Shapiro (1997) (referred to hereafter as BJKS) proposed and explored a methodology to elicit the statistical distribution for relative risk aversion among respondents in the US Health and Retirement Study.[1] In this paper, we use this methodology to measure and explain the distribution of risk aversion for a representative sample of the Norwegian population. By asking respondents to consider hypothetical income gambles, we are able to elicit the range of their degree of relative risk aversion. In a following step, we estimate a cardinal measure for risk aversion for each respondent. The variation in these imputed values are subsequently used to explain the variation in various types of risky behavior, such as smoking, body mass index (BMI), choice of workplace and type, and financial investment strategy. To the best of our knowledge, this is the first study of its kind applied to Norwegian survey data.

The income gamble we use exposes the respondents to a choice between a job with a guaranteed income equal to their current income and a job where there is a 50 percent chance of doubling one's current income against a 50 percent chance of a scaling down of this income with a certain factor. Depending on the respondent's choice, they are presented with a new pair of alternatives where the downscale factor for the risky alternative is adjusted. We specify an ordered probit model with fixed cutoff points that are given by the hypothetical choice question and estimate this on the relevant covariates. By using the information from this model, we then propose and estimate a cardinal risk measure that can be interpreted as the lowest downscale factor of current income the respondent tolerates before rejecting the risky option. The higher this downscale factor, the more risk averse is the respondent.

The data we use stem from three surveys that were conducted within a six-week span during the spring of 2006. The surveys were commissioned by a large Nordic insurer and carried out by Synovate, a major poll institute and market intelligence company in Norway.

The three surveys differ in size and scope. One survey (the main survey) contains a large set of questions regarding state of mind, such as happiness and worries, and on what actions or

[1] See http://hrsonline.isr.umich.edu.

circumstances trigger feelings of trust and safety, in addition to standard questions about socioeconomic characteristics. The questions about safety, worries and trust were presented to the respondent before the income gamble question. The second survey had exactly the same sequence of income gambles as in the main survey, but without the state of mind questions that characterized the main survey. The third survey is similar to the second, except that the formulation of the income gambles now includes a sentence suggesting a lock-in effect. The response pattern reveals significant differences in risk aversion across the three surveys, suggesting that responses to income gambles are affected by the context (precedence/absence of questions related to mood, feelings of safety and security) and the framing of the questions.

Our findings are as follows. Women are significantly more risk averse than men and risk aversion increases with age. Relative risk aversion is insensitive to income level or place of residence. These results are in line with most of the related literature. Inspired by the early experimental findings in psychology by Isen, Nygren and Ashby (1988) and the theoretical discussion concerning utility and happiness by Kimball and Willis (2006), we also ask whether current life satisfaction/happiness is a relevant predictor for risk taking. We find that it is, but not in a monotone way.

In the next step, we estimate a cardinal risk measure conditional on the categorical choice of the respondent and other relevant observable characteristics.[2] This imputed cardinal income risk measure is subsequently used as an explanatory variable in the analysis of different choices that we expect to depend on risk preferences. We find that it negatively affects the likelihood that the respondent smokes, works in the private sector, assumes the role of a top manager, or works in a small firm. It also lowers the likelihood of taking up a loan to finance a risky investment. On the other hand, we do not find evidence that more risk-averse people succeed better to contain their BMI or are less prone to be obese.

The paper is structured as follows. In the next section, we give a short discussion on previous work to measure risk aversion. Thereafter, in section 3, we present the basic income gamble questions and describe theoretically how we recover our measure of relative risk aversion from the answers given to the hypothetical questions. A more detailed description of the data is given in section 4. Section 5 contains descriptive evidence and a comparison of our results with similar data from other countries. In sections 6 and 7, we estimate an ordered probit model for our risk-aversion measure and explain how we impute a cardinal risk-aversion measure for each

[2] In this respect, our approach is different from BJKS and Kimball, Sahm and Shapiro (2008) who estimate an *un*conditional cardinal measure of relative risk tolerance, but closer to Sahm (2007), who estimates a conditional measure of relative risk tolerance measure that she subsequently uses to explain risky holdings of assets.

respondent. Section 8 presents estimates on risky behaviors, using the imputed risk-aversion measure as a regressor. Section 9 concludes.

2. Previous work on measuring risk aversion with survey data

BJKS asked a representative sample of senior US citizens to make choices among four hypothetical lifetime income gambles, allowing them to classify respondents into four mutually exclusive risk-aversion categories. Furthermore, under the assumption of constant relative risk-aversion (CRRA) preferences, the boundaries of these categories precisely determine the interval for each respondent's coefficient of relative risk aversion.

Various authors have subsequently employed this method to elicit a measure for risk aversion. In a survey of Dutch respondents, Kapteyn and Teppa (2002) employed a lifetime income gamble similar to BJKS, but with six rather than four response categories.[3] They subsequently tested whether the risk-aversion category had explanatory power for understanding household asset allocation behavior. Arrondel and Calvo-Pardo (2002) investigated risk aversion among French households and subsequently employed the measure to explain the extent of stockholding.

Several other studies have explored related methods to elicit people's willingness to bear risks. Hanna and Lindamood (2004) compared several variants of the lifetime income gamble questions. In particular, they presented respondents with graphical displays in addition to the standard verbal framing of the income gamble questions. Jonker, Ferrer-I-Carbonell and Hartog (2000) and Guiso and Paiella (2008) proposed a survey measure that can be used to estimate the level of absolute risk aversion. They asked respondents how much they were willing to pay for participating in a lottery where prizes and probabilities are given at the outset. Dohmen *et al.* (2005), using a sample of more than 22,000 Germans, employed both hypothetical questions, as well as more simple risk scales, to explore risk aversion. They found that the simple risk scale question has more predictive power on risky behavior than the answers to the lottery questions.

Asking people to consider hypothetical lotteries or statements that involve risk more generally has both strengths and weaknesses. The main advantage is that the method is inexpensive, in that the researcher does not need to pay out any prizes. At the same time, the way people respond to hypothetical statements seems to be very sensitive to the way these statements are formulated. Slovic (1987) argues that people perceive risks quite differently. He points out that perception of a risky situation is dependent on initial beliefs, former personal

[3] Note, however, that the 1994 version of the US Panel Study on Income Dynamics (PSID) also contained six risk categories (see Sahm (2007)).

experience, knowledge of the field that risk is attributed to, and public attention. If such conditioning factors are independently distributed across respondents, they will be captured by the error term and not cause any bias. Problems, however, arise when they no longer are idiosyncratic, but systematically start to affect responses. Examples of systematic influences are *framing* and *priming*. Kahneman and Tversky (1981), confronting respondents with the same hypothetical risky situation but framed in two different ways (*framing*), obtained preference reversals. *Priming* refers to the incidental activation of knowledge structures, such as trait concepts and stereotypes, by the current situational context (Bargh, Chen and Burrows, 1996, p. 230). Several experimental studies in social psychology have shown that such activation can affect behavioral responses to later stimuli. For example, Bargh, Chen and Burrows (1996) showed that subjects who were primed by showing them words such as *bold*, *rude*, *annoyingly*, *interrupt*, or *disturb*, later in the experiment displayed behavior that is more in line with the suggested traits (*in casu* interrupting two persons having a conversation) than subjects who were shown words like *respect*, *patiently*, *polite*, or *discreetly*. Dijksterhuis and van Knippenberg (1998) found that subjects primed with the stereotype of *professor* or the trait of *intelligent* performed better in a subsequent, ostensibly unrelated, general knowledge task, than subjects in a control group. The opposite was found when priming with the stereotype of *soccer hooligan*.

A concrete example of a systematic influence is when people are asked to compare a new hypothetical (risky) situation with a current one. Many aspects of the latter are well known, while the hypothetical situation is surrounded by uncertainties regarding all aspects that were left unspecified in the questionnaire. Often, a *status quo* bias is the result: people opt for the current situation rather than the hypothetical, because it is relatively free from uncertainty. Kimball, Sahm and Shapiro (2008) argue that the question used by BJKS gives rise to such a bias because it asks the respondent to choose between his/her current job (no change) and a new job with a risky income prospect. A biased answer may then be expected because the respondent is likely to put weight on the known nonmonetary aspects of the current job (the working environment, the nature of the job tasks, and so on). To avoid this possibility of bias, they proposed a question that is not linked to the current situation. In the next section, we follow their advice.

3. The basic income gamble

The gambles that we presented to the respondents follow closely those developed by BJKS, but rather than asking respondents about a choice of their *current* job and a risky alternative, we followed the suggestion of Kimball, Sahm and Shapiro (2008) and asked people to choose between two new jobs, one with a certain and another with a risky income prospect.[4] The exact formulation of the question was as follows.

"Suppose that you are the only income earner in your household. Suppose also that reasons beyond your control force you to change occupation. You can choose between two alternatives. Job 1 guarantees you the same income as your current income. Job 2 gives you a 50% chance of an income twice as high as your current income, but with a 50% chance it results in a reduction of your current income by one third. What is your immediate reaction? Would you choose job 1 or job 2?"

If the respondent selected the safe alternative (job 1), they were presented with a new pair of alternatives, the only difference being that the downside risk of job 2 was one fifth of the current income instead of one third. If, on the other hand, job 2 was selected, a follow-up question presented the respondent with a choice between the safe alternative and a risky job 2 where the downside risk was increased from one third to one half.

The framing of this question is different from the one used in Kapteyn and Teppa (2002) and Kimball, Sahm and Shapiro (2008). These studies sought to remove the *status quo* bias by suggesting that the cause of job change was rooted in an allergy problem. Instead, we used the phrase *"factors beyond your control"* so not to make the decision to rely on a specific disease/problem that for some respondents might be a remote cause for a job change. We believe that this phrase is more neutral and less prone to cause potential framing or priming problems. Thus, we leave it to the respondent to imagine a reason that would force them to change their job.

Following BJKS, we assume that individuals have a von Neumann–Morgenstern utility function $U(\cdot)$ defined over lifetime income. For an individual who is exactly indifferent between job 1 (with a sure income C) and job 2 with a downside income λC, the scale factor λ is implicitly defined by

$$(1) \qquad \frac{1}{2}U(2C) + \frac{1}{2}U(\lambda C) \equiv U(C).$$

[4] The original question reads: "Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50–50 chance it will double your (family) income, and with a 50–50 chance that it will cut your (family) income by a third. Would you take the new job?" (BJKS, p. 540). Note that the extension "every year for life" was not used in the description of the risky job; only in the secure job description. However, this particular extension was implemented in the later waves. The unconditional responses given in Table 2a in Sahm (2007) tell us, however, that around 60 percent of the US population will choose the highest risk aversion category, irrespective of the wave. Thus, these unconditional averages do not suggest that the exact formulation of the question has a large impact on the results. Our question does not contain the "every year for life" phrase. In reality, few, if any, employers can guarantee an employee a constant lifetime income. Thus, it is likely that respondents interpret the question with different time horizons in mind, even when the phrase "every year for life" is used.

Depending on the way the respondent answers, we can infer to which of the following intervals his/her λ belongs: [0, ½], (½, ⅔], (⅔, 4/5], or (4/5, 1]. Under an assumption of constant relative risk aversion, there is a one-to-one positive relationship between λ and the respondent's coefficient of relative risk aversion, R_r, given by

$$(2) \qquad \lambda = [2 - 2^{1-R_r}]^{\frac{1}{1-R_r}}.$$

Thus, the gamble presented above makes risk aversion independent of the individual's income, owing to the multiplicative description of the risky outcome. The mapping from λ to R_r is shown in the figure below (solid line). The corresponding intervals for R_r are [0, 1], (1, 2], (2, 3.75], and (3.75, ∞). The figure also displays the function $\frac{\lambda}{1-\lambda}$ (dashed line), which turns out to be a good approximation of R_r.

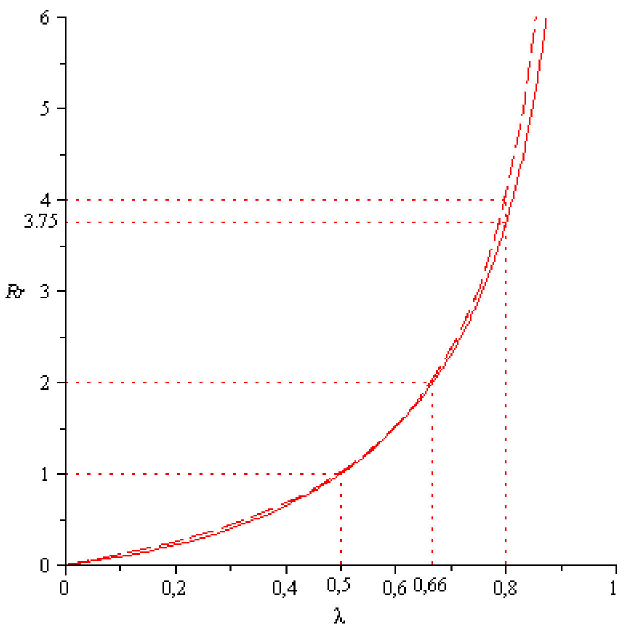

Figure 1. The mapping from λ to R_r (solid line) and to $\frac{\lambda}{1-\lambda}$ (dashed line).

4. A description of the three surveys

The data for our study were gathered through three surveys conducted by a major market intelligence company - Synovate, in the spring of 2006. The main survey (*N*=1554) was commissioned by a large Nordic insurance carrier as part of a study on people's attitudes to issues of safety, security, anxiety, trust, etc. The target group consisted of people in the age group 18–74. For the age group 18–54, the sample was taken from the representative e-base while older respondents were randomly drawn from a representative postal base. The reason for using standard mail for the latter group is that penetration of the Internet declines with age.[5,6] Both the e-base and postal base is built upon the national telephone directory. The response rate for those who answered the questionnaire on the Internet was 51.9 percent. For the postal survey, the response rate was as high as 67.8 percent, implying an overall response rate of 56.6 percent. In the main survey, people were taken first through a list of 28 questions, asking them what makes them feel safe and secure and which situations they fear most, and asking about trust and to which extent they feel satisfied with their current state of life. They were asked then to consider the hypothetical income gambles, previously described. Finally, they were asked about socioeconomic characteristics.

In addition, Synovate conducted two Internet surveys. These were taken from the same e-base as the main survey. They were also targeted to people in the age group 18–79, but for the reason given above, their representativeness is only guaranteed for the age group 18–54. These two Internet surveys only contained the questions on the hypothetical income gambles. The first Internet survey (N=750) used exactly the same wording as the main survey. In the second one (N=1142), the question was reformulated slightly by adding a sentence (underlined):

"Suppose that you are the only income earner in your household. Suppose also that reasons beyond your control force you to change occupation. You can choose between two alternatives. Job 1 guarantees you the same income as your current income. Job 2 gives you a 50% chance of an income twice as high as your current income, but with a 50% chance it results in a reduction of your current income by one third. <u>Shortly after your decision you will know with certainty whether your income increases or decreases for all the coming years</u>. What is your immediate reaction? Would you choose job 1 or job 2?"

We conjecture that this additional sentence would preclude the interpretation of new income draws in future periods, while such an interpretation cannot be ruled out with the former question. How a difference in interpretation affects risk taking is not clear. Suppose that there

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5 According to Eurostat, 69 percent of the households in Norway had Internet access in 2006. (Source: http://epp.eurostat.ec.europa.eu/pls/portal/docs/page/pgp_ds_yearbook/pge_ds_yearbook_01/yearbook/ch12.xls.)

6 The survey methodology is different from BJKS and Guiso and Paiella (2007), who both used data that were collected by personal interviewers. However, Kapteyn and Teppa (2002) and Hartog, Carbonell-I-Ferrer and Jonker (2000) used a combination of Internet and post, while Arrondel and Calvo-Pardo (2002) utilized information from a survey data set that was collected via standard mail.

are just two periods. The risky income lottery without the lock-in effect is represented by gamble A, while in gamble B the lock-in effect is present (see figure 2).

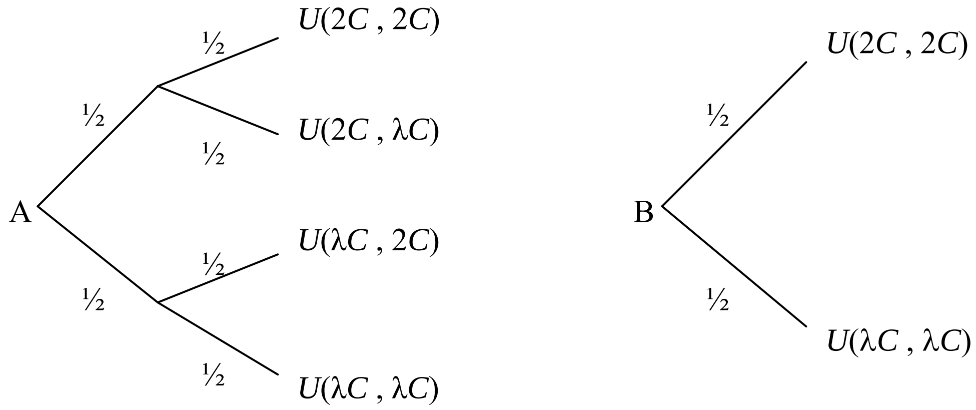

Figure 2. Two-period lifetime income gambles without (A) and with (B) lock-in effect.

A person will regard lottery B better than lottery A if and only if

(3) $$\tfrac{1}{2}U(\lambda C,\lambda C)+\tfrac{1}{2}U(2C,2C)>\tfrac{1}{2}U(\lambda C,2C)+\tfrac{1}{2}U(2C,\lambda C).$$

Richard (1975, Th 1) shows that $U_{12}>0$ is a necessary and sufficient condition for preferring lottery B to lottery A.[7] He calls such a preference "multivariate risk seeking" as opposed to "multivariate risk aversion" which would be characterized by $U_{12}<0$, and which, in the more recent literature, is coined "correlation aversion". Edgeworth complementarity ($U_{12}>0$) is thus one reason for being more prepared to accept income gambles with lock-in effects.

A second reason, proposed by Drèze and Modigliani (1972), is that a rational decision maker prefers an early revelation of relevant information. In the present problem setting, the agent's savings decision will be contingent on the future income (stream) that they expect. In lottery B, this decision can be made after the information is revealed (because current income is fully informative about future income), while this is not the case in lottery A.[8]

To summarize, we have answers on the hypothetical income gambles from 3,466 people. A total of 750 of them (through the first Internet survey) were only asked to answer the

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[7] Using a second-order Taylor approximation around (λC, λC) is equivalent to $\tfrac{1}{2}U_{12}(\lambda C,\lambda C)(2-\lambda)^2>0.$

[8] Lottery B can be considered as a timeless uncertain income prospect, while lottery A is a temporally uncertain prospect. The expected utility value of the former always exceeds that of the latter, because the (savings) decision can be made after the uncertainty is resolved. The difference in value is the expected value of perfect information.

‘standard’ income lottery questions. A total of 1,525 respondents (through the main survey) chose income lotteries after having responded on a battery of questions on safety, security, trust, fears, and worries. We expect that a priming effect makes respondents more likely to select themselves into the higher risk-aversion intervals. Finally, 1,142 respondents (through the second Internet survey) were asked to answer the income lottery question with the additional sentence suggesting a lock-in effect. We expect them to select themselves less frequently into the higher risk-aversion intervals.

5. Descriptive statistics and comparisons with previous work

Table 1 gives information about responses to the two types of risk questions from the three different surveys.

—Table 1 here—

In the main survey, we note that more than 75 percent chose low or just moderate risk, while the comparable number is 62 in the first pure web survey. In the second pure web survey (where the lock-in effect is suggested), the percentage that prefers the two lowest risk categories is around 56 percent. The differences between the main survey and the first pure web survey suggest that the context of the survey has an effect on risk choice. Moreover, the difference between the two web surveys indicates that the suggestion of the lock-in effect increases risk taking—as expected when there is Edgeworth complementarity between consumption in different periods. Because all the web surveys were drawn randomly from the same e-database, and the drawing procedure was similar across surveys, one should expect the differences in responses are mainly connected to either the context or the suggested lock-in effect.

Figure 3 compares the frequency distributions of responses for the web part of the main survey with that for the first pure web survey, ignoring all respondents above age 54.[9] The left histogram illustrates the distribution of responses for the risk question with context and the other histogram illustrates responses for the context-free question. Recall that the income gamble in the main survey was presented after a battery of questions about fears and worries, while the other survey only contained the income gamble. The Kolmogorov–Smirnov test statistic is 1.39 and the p value is 0.042, which indicates a rejection of the null hypothesis of equal empirical distributions at the 5 percent level.

[9] Recall that the main survey was web-based for respondents below age 55, while the pure web surveys also had respondents above age 55.

—Figure 3 here—

Next, we compare the web survey with the context-free question with the web survey that contains the suggested lock-in effect. The frequency distribution is shown in figure 4.

—Figure 4 here—

A Kolmogorov–Smirnov test rejects the null hypothesis of identical distributions at the 1 percent significance level (the test statistic is 2.79 and with the p value less than 0.01). Thus, the suggested lock-in effect seems to have a positive effect on risk taking, as expected.

Before analyzing the response behavior econometrically, we compare our results with other studies. In table 2, we have restricted the sample to those in the same age group as in BJKS and we include results from the Kapteyn and Teppa (2002) and Arrondel and Calvo-Pardo (2002) studies along the with the original BJKS study. [10]

—Table 2 here—

The numbers show considerable variation across countries and, as we suggested above, these may well stem from differences in survey methodology and survey context, in addition to cultural differences. The differences become smaller, however, when one aggregates the two most risk-averse and the two least risk-averse categories. The Norwegian senior population seems to be the most risk averse, followed by the French, while more than 20 percent of the population in The Netherlands and the US choose one of the two most risky options. A pivotal value for R_r, explaining behavioral reactions in savings and portfolio choice, is unity.[11] Less than 6 percent of French senior citizens can then be classified as risk tolerant, while the number for the other three countries lies around 12 percent.

[10] The data set in BJKS consisted of respondents aged from 51 to 61. There are, of course, several methodological problems with such comparisons. Different sampling procedures can entail differences in responses, but the effect of such differences is not observable here. Another problem is that differences in wording of the question or differences ininterpretation of it across populations might exist.

[11] See Eeckhoudt, Etner and Schroyen (2009).

6. Econometric analysis of risk preference

In this section, we explore the effect of socioeconomic characteristics on the elicited attitude toward income risk. Recall that for respondent i, λ_i is the lowest fraction of current income the respondent is willing to accept in order to participate in the income gamble. The higher this fraction, the higher the respondent's risk aversion. Depending on the respondent's acceptance/rejection of income lotteries, we can identify to which of the following four intervals the respondent's λ_i belongs: [0, ½], (½, ⅔], (⅔, 4/5], or (4/5, 1]. These intervals have a natural ordering from "weakly risk averse" to "very risk averse". Because we do not observe λ_i, we regard it as a latent variable depending on the vector of observable covariates x_i (socioeconomic characteristics as well as survey-specific effects) and an unobservable characteristic ε_i that is assumed to be normally distributed with mean 0 and unknown standard deviation, σ

(4) $$\lambda_i = f(x_i, \varepsilon_i), \quad \varepsilon_i \sim N(0, \sigma^2).$$

Assuming that none of the respondents is risk loving, the first interval can be restricted to [0, ½]. We then specify $f(\cdot)$ as

(5) $$\lambda_i = \frac{e^{x_i'\beta + \varepsilon_i}}{1 + e^{x_i'\beta + \varepsilon_i}},$$

so that any combination of individual characteristics is smoothly mapped into the unit interval.[12] The probability of observing respondent i selecting the "lowest" risk-aversion category is then given by

(6a) $$P(\lambda_i \leq \frac{1}{2} \mid x_i) = P(\frac{e^{x'_i\beta + \varepsilon_i}}{1 + e^{x'_i\beta + \varepsilon_i}} \leq \frac{1}{2}) = P(\varepsilon_i \leq -x'_i\beta).$$

Likewise, the probabilities of selecting the intervals (½, ⅔], (⅔, 4/5], or (4/5, 1] are

(6b) $$P(\frac{1}{2} < \lambda_i \leq \frac{2}{3} \mid x_i) = P(\varepsilon_i \leq \log 2 - x'_i\beta) - P(\varepsilon_i > -x'_i\beta),$$

[12] This is equivalent to assuming that the ratio $\lambda/(1\text{-}\lambda)$ is log-normally distributed with mean $x_i'\beta+\varepsilon_i$. If $U(\cdot)$ is CRRA, then for values of R_r below 4, $\lambda/(1\text{-}\lambda)$ is a good approximation for R_r (see figure 1).

(6c) $$P(\frac{2}{3} < \lambda_i \leq \frac{4}{5} \mid x_i) = P(\varepsilon_i \leq \log 4 - x'_i \beta) - P(\varepsilon_i > \log 2 - x'_i \beta), \text{ and}$$

(6d) $$P(\lambda_i > \frac{4}{5} \mid x_i) = 1 - P(\varepsilon_i > \log 4 - x'_i \beta),$$

respectively.

Defining the indicator variable, $I^i_{(a,b]} = 1$ if $\lambda_i \in (a,b]$, and zero otherwise, the likelihood function can be written as

(7) $$L(\beta,\sigma) = \Pi_{i=1}^{N} \Phi(\frac{-x'_i \beta}{\sigma})^{I^i_{(0,1/2]}} [\Phi(\frac{\log 2 - x'_i \beta}{\sigma}) - \Phi(\frac{-x'_i \beta)}{\sigma}]^{I^i_{(1/2,2/3]}}$$
$$[\Phi(\frac{\log 4 - x'_i \beta}{\sigma}) - \Phi(\frac{\log 2 - x'_i \beta}{\sigma})]^{I^i_{(2/3,4/5]}} [1 - \frac{\Phi(\log 4 - x'_i \beta)}{\sigma}]^{I^i_{(4/5,1]}},$$

where $\Phi(\cdot)$ denotes the cumulative standard normal distribution function. Equation (7) can be interpreted as an ordered probit with fixed cutoff points. Because of the fixed cutoffs, we can identify σ.

We estimate equation (7) using a large set of socioeconomic characteristics. We include age, gender, region of residence, educational attainment, income categories, other household characteristics, and characteristics of the respondent's residential location (at a farm, at the countryside, or in a big city). A detailed description of the covariates is given in the heading of table 3 below.

Isen, Nygren and Ashby (1988) (see also Isen (2004), for an overview) argue that positive effects tend to make decision makers less willing to take risks (than those in the control group). The mechanism they advance is that people anticipate that losing may undermine their good mood. The anticipation of these consequences leads to "mood maintenance" and to a decline in the willingness to gamble. On the other hand, Johnson and Tversky (1983) document that those in whom a positive affect is induced discount the likelihood of negative outcomes. These two mechanisms—mood maintenance and optimistic expectations—work in opposite directions and it is an empirical matter which of them dominates. We are in a position to verify these findings because respondents in the main survey were asked to indicate their current level of satisfaction with life on a Likert scale (from 1 = very dissatisfied, to 9 = very satisfied).[13] Table 3 shows the distribution of responses to the life satisfaction question.

[13] Dohmen *et al.* (2005) report that satisfied people are willing to take on more risk. They measured life satisfaction along an 11-point scale and the answer to a general risk question that was phrased as "willingness to take risks, in general" was also measured along an 11-point scale.

—Table 3 here—

Around 25 percent of the sample reported a life satisfaction level less than or equal to 5; about 58 percent indicated that their life satisfaction at indices 6, 7 or 8, and approximately 17 percent of the sample was very satisfied (index level 9). To allow for the possible nonlinear association between risk aversion and life satisfaction, we include two dummies for the satisfaction level: one dummy when the index takes the values 6, 7 or 8, and a second dummy for the satisfaction level 9 (the highest level). The group with a lower level of satisfaction (1–5), thus acts as the reference group.

We have estimated equation (7) using both the pooled set of surveys (N=3446) and the main survey (N=1554). In the first case, we have only information about a restricted set of socio-economic covariates (SES) and no information about current life satisfaction. Specifically, the x_i vector consists of the respondent's age, a gender dummy, region of residence dummies, and dummies for educational attainment. Moreover, we have included survey fixed effects. In the second case, using only the main survey, we apply a full set of SES covariates as well as the two life satisfaction dummies. The covariates are described in detail in the heading of table 4. The descriptive statistics for these covariates and others employed later in the paper are given in Appendix A.

Table 4 gives the maximum likelihood estimates for expression (7).[14] The first column shows the results for the pooled surveys, while the second column shows the results for the main survey.

—Table 4 here—

As in many earlier studies, we find strong evidence for gender differences in risk taking. We note, however, that the gender difference is of lower magnitude in the pooled regression (that includes all surveys), but it is still highly significant. Second, aging has a negative impact on the willingness to take risk.[15] This effect is quite similar across all three surveys (these regressions are not shown in the paper but are available upon request). Third, the negative and highly significant dummies for the pure web surveys confirm that respondents in these surveys were significantly more willing to take risks. Moreover, the significantly lower coefficient attached to the lock-in dummy indicates that this effect contributes to more risk taking. This is an effect we also

[14] We used the NLMIXED procedure in the computer package, SAS, which allows for specifying a general likelihood function.

[15] We also used both age and age squared, but the quadratic effect was insignificant. Whether linear age effect is a pure age effect or a cohort effect cannot be answered, because we only have access to cross-sectional data.

theoretically expected. A standard *t* test of whether risk aversion is equal between the survey with the lock-in effect and the survey without this lock-in is rejected at the 5 percent level.[16]

Most of the results described above are in line with previous research, with some minor adjustments. Strong gender and age effects are found in BJKS, Dohmen *et al.* (2005), in Halek and Eisenhauer (2001) and Sahm (2007). BJKS find nonmonotone age effects (but recall that all their respondents were over 51 years old). Guiso and Paiella (2008) also document age effects and risk aversion depending on birth region. They do not find a strong gender effect. We have no information of birth region, but we note here that the indicator variables for region of residence—which often coincides with birth region—were all insignificant.

We find a significantly positive effect for the dummy indicating a high life satisfaction (viz., 6, 7 or 8 on the 1–9 scale). Thus, people satisfied with their current life situation are significantly less willing to take risks than people who are dissatisfied. We also found a nonsignificant coefficient with the dummy for life satisfaction index 9, indicating that elate people are as risk tolerant as those dissatisfied with life. For them, the optimism about a favorable outcome seems to dominate the need for mood maintenance.

7. A cardinal measure of the latent λ

We want to use our risk-aversion measure to explain the engagement in (or absence of) several instances of risky behavior. Ideally, we would like to use the conditional expectation $E(\lambda_i \mid x_i, c_i)$, where $c_i \in \{(0,\frac{1}{2}),[\frac{1}{2},\frac{2}{3}),[\frac{2}{3},\frac{4}{5}),[\frac{4}{5},1)\}$ indicates the interval that respondent *i* has implicitly chosen for λ. Because this is not available, we follow Hsiao and Mountain (1985) to obtain a consistent estimate of this conditional expectation.[17] In this way, we construct a cardinal measure for each respondent's attitude toward risk. This has two advantages. First, we do not lose any cardinal information—as a dummy approach would. Second, if one uses a dummy variable approach, one implicitly assumes that all respondents within a given category possess equal risk aversion. This might lead to attenuation bias.

[16] From the variance-covariance matrix of the estimated parameters we obtain the necessary information for calculating the t-value. The test statistic is calculated as $t = \frac{\beta_{s\tan dard} - \beta_{lockin}}{\sqrt{Var(\beta_{s\tan dard}) + Var(\beta_{lockin}) - 2Cov(\beta_{s\tan dard}, \beta_{lockin})}} = \frac{0.1314}{0.04456} = 2.94.$

[17] Two approaches, which are perhaps more straightforward, are the dummy variable approach and the mid-interval approach. The dummy variable approach involves constructing four dummy variables to indicate in which of the four intervals the respondent's λ_i falls and then regressing risky behavior on these dummies and socioeconomic characteristics. The problem with this approach is that the coefficient of a dummy variable cannot be interpreted as the mean response of risky behavior (or the probability of engaging in such behavior) to a marginal change in the risk aversion measure (λ). A second approach consists of replacing the unobserved λ_i by the midpoint of the interval it belongs to (e.g., 9 if respondent *i* has rejected all gambles such that $\lambda_i \, \varepsilon[4/5, 1)$). However, this would result in inconsistent estimates (see Hsiao and Mountain (1985) for a discussion of the latter issue).

Recall that, by assumption, our latent variable is given by equations (4) and (5). The next step is then to produce an estimate for λ_i by estimating the conditional expectation $E(\lambda_i \mid x_i, c_i, \hat{\beta})$. Thus, to estimate the latent λ_i we use information on both the chosen category and individual characteristics that we believe have an effect of risk taking. The density function for λ_i, given that the individual has characteristics x_i, is given by

$$(9) \qquad g(\lambda; x_i'\hat{\beta}, \hat{\sigma}) =_{def} \frac{1}{\lambda(1-\lambda)}\frac{1}{\hat{\sigma}}\phi\left[\frac{\log\frac{\lambda}{1-\lambda} - x_i'\hat{\beta}}{\hat{\sigma}}\right],$$

where $\phi(\cdot)$ is the pdf of the standard normal distribution. In the derivation of equation (9), we used the change of variable technique (for example, see Greene, 2008, p. 1000). Our estimate for the expected value of λ, given the characteristics x_i and the respondent's choice of risk category c_i, is then

$$(10) \qquad E(\lambda_i \mid x_i'\hat{\beta}_i, \hat{\sigma}, c_i) = \frac{\int_{\lambda \in c_i} \lambda\, g(\lambda; x_i'\hat{\beta}, \hat{\sigma})\, d\lambda}{P(\lambda \in c_i \mid x_i'\hat{\beta})}.$$

The denominator in equation (10) is calculated straightforwardly. For example, the probability for λ_i to fall in the interval $\left[\frac{2}{3}, \frac{4}{5}\right)$ is given by

$$(11) \qquad P(\lambda \in c = \left[\tfrac{2}{3}, \tfrac{4}{5}\right) \mid x_i'\hat{\beta}, \hat{\sigma}) = \Phi(\frac{\log 4 - x_i'\hat{\beta}}{\hat{\sigma}}) - \Phi(\frac{\log 2 - x_i'\hat{\beta}}{\hat{\sigma}}).$$

The numerator in equation (10) has no analytical solution and we compute it numerically.

For each respondent, we estimate equation (10) and denote it as $\hat{\lambda}_i$. Figure 5 shows the mean and standard deviation, along with a histogram of $\hat{\lambda}_i$ (panel A is for the pooled data set, while panel B is for the main survey respondents). The average $\hat{\lambda}_i$ is 0.73 for the pooled sample and, as expected, marginally higher in the main survey. We can interpret this number as the average lowest fraction of current income the respondent is willing to accept in order to participate in the income gamble.

—Figure 5 here—

Given an assumption of CRRA preferences, we can also use the method described above to estimate the relative risk-aversion coefficient.[18] The sample average for R_r is 3.92 with a standard deviation of 2.94.[19] This value is significantly smaller than the estimates by BJKS—approximately 8—or Kimball, Sahm and Shapiro (2008)—8.2.[20] The expected R_r conditional on the characteristics of the individual and the chosen risk category is given in table 5 below, while figure 6 shows the sample distribution.

—Table 5 here—

—Figure 6 here—

8. Choices and risk preference

Having established the cardinal risk measure, we now seek its validation. In the main survey, we have information about behavioral traits such as smoking and BMI. Moreover, we observe inherently risky occupational choices, such as working in the private sector, taking a managerial position, or working in a small-sized firm. Additionally, some indicators of intended behavior are observed, such as the willingness to take up a loan to buy risky stocks. Below we estimate several models where we use the observations on the cardinal measure $\hat{\lambda}_i$ to explain variation in risk behavior.

Because $\hat{\lambda}_i$ is a generated regressor, the standard asymptotic properties of test statistics might not hold (Wooldridge, 2002, p. 378; Pagan, 1984). Therefore, we employ a bootstrap methodology that allows us to circumvent some of the parametric problems that might appear in the context of generated regressors. First, we use the original sample to create a new sample by drawing (with replacement) N new observations. Next, for this newly generated sample, we reestimate the vector β and compute the N corresponding values for $\hat{\lambda}_i$. Finally, we estimate the coefficients of our risk-behavior equation. This procedure is then repeated 200 times, yielding 200 estimates for the coefficient vector. The sample covariance matrix then provides us with consistent estimates for the standard errors. This methodology is called "point-based bootstrap"

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[18] As shown in figure 1, $\frac{\lambda}{1-\lambda}$ is a good approximation for R_r. Using equation (5), we arrive at $R_{r_i} \approx e^{x_i'\beta+\varepsilon_i}$. Thus, R_{r_i} is log-normally distributed with parameters $x'_i\beta$ and σ. We then estimate the conditional expectation for R_{r_i}, as in equation (10), using the density and cumulative distribution function for the log-normal distribution.

[19] Restricting ourselves to the main survey data and corresponding parameter estimates, the sample average and standard deviation are 4.59 and 3.18, respectively.

[20] Note, however, that the estimates by BJKS and Kimball *et al.* are based on a sample of respondents aged over 51 years.

(Fox, 2002) or "pairs bootstrap" (MacKinnon, 2006).[21] Moreover, it does not require that the functional form of the model specified is correct, while, for example, the residual bootstrap (that treats the covariates as fixed) relies on the assumption of a correctly specified model (Fox, 2002).[22]

Behavioral risk factors: smoking and BMI

The medical risks connected with smoking and obesity or high BMI are well documented. A high BMI is associated with increased mortality and increased risk of coronary heart disease, diabetes, and some types of cancer. Moreover, research suggests that even small BMI reductions could lead to large health gains (Sturm, 2002). The detrimental effects of tobacco use are even more documented. According to a report on the global tobacco epidemic (World Health Organization, 2008), approximately 5.4 million people die yearly from tobacco-caused illnesses. Tobacco consumption is a leading risk factor for diseases such as stroke, cancer, coronary heart disease, and many others.

Intuitively, one would expect that people with high aversion with respect to income gambles would also avoid behaviors that cause a high BMI or increases the risk for being addicted to tobacco, even when the associated health risk would only result in financial consequences of falling ill (i.e., loss of earnings, medical expenses, etc.).[23] The literature on self-prevention in risky situations shows, however, that such a conclusion may be taken too hastily. Self-prevention is a label for activities that reduce the probability for adverse future events. Eeckhoudt, Gollier and Schlesinger (2005, p. 143) show that an increase in risk aversion does not necessarily lead to an increase in self-prevention. Figure 7 illustrates why.

The solid lines in figure 7 indicate the probabilities for two wealth levels when the decision maker makes an (optimal) self-prevention effort e_0: with probability $p(e_0)$, a loss L happens, while with probability $1\text{-}p(e_0)$ this loss does not happen. With an increased effort level e_1, the new final wealth distribution is given by the dashed vertical probability lines. The variance of final wealth is $p_i(1\text{-}p_i)L^2$. It is easy to check that the variance under effort level e_0 exceeds that under effort level e_1 if $1\text{-}p_1<p_0$, as is the case in the figure. If a moderately risk-averse agent exerts effort level e_1, then a more risk-averse agent will attach greater weight to final wealth variance and, hence, might prefer to exert the lower effort level e_0 even though this effort leads to a

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21 MacKinnon (2006) reports that this bootstrap is valid under heteroskedasticity and that it can be applied to a wide range of models. A potential problem with this methodology is that it does not work well if restrictions on the parameters are imposed.

22 One important requirement, however, is that our original sample is representative for the population of interest.

23 Very likely, such a respondent would also be risk averse with respect to shocks in the health status *per se*. This second kind of risk aversion need not be related to the one with respect to income risk (e.g., when the utility function is additively separable in final consumption and health).

slightly lower expected final wealth. In more general terms, self-prevention does not lead to a second-order dominant shift in the wealth distribution, and whether people that pursue risky behaviors have lower risk aversions is therefore an empirical question.

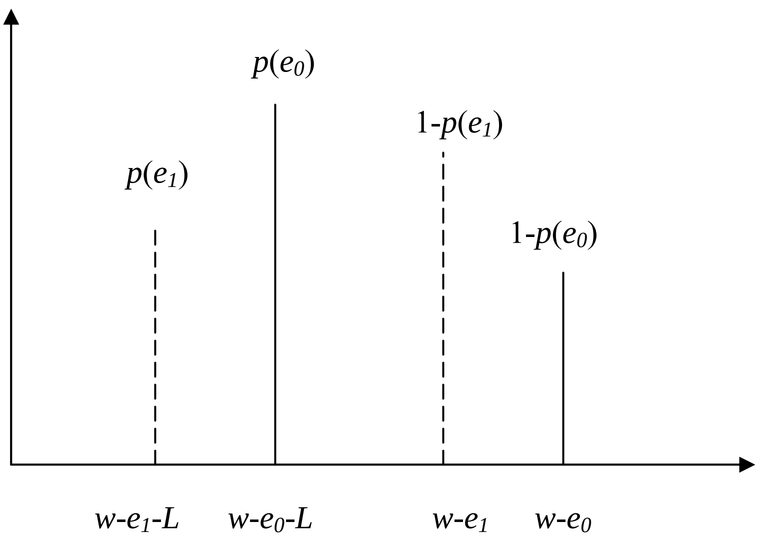

Figure 7. The effect of self-preventive effort on the outcome distribution.

Smoking

Table 6 shows a probit model where the dependent variable takes the value of 1 if the respondent smokes and 0 otherwise. The unconditional probability of smoking is estimated to be 25.5 percent in the sample. The official figure from Statistics Norway for 2005 is 24 percent. Moreover, our sample shows that the fraction of smokers declines quite drastically from 66 years of age and above. This pattern is confirmed by the figures given by Statistics Norway where the fraction of smokers is independent of age in the range from 25 to 66 years, but falls from 27 percent to 14 percent for ages above 66 years.[24] For that reason, we include age squared in the regression, as well as a dummy variable for respondents over 66 years of age.

—Table 6 here—

[24] The Norwegian Institute of Public Health (www.fhi.no/dav/F96A862E2C.pdf) reports that the probability for dying between 40 and 70 years of age is, on average, 9 percent and 14 percent for nonsmoking women and men, respectively. For persons that smoke more than 20 cigarettes per day, these numbers are 26 percent for women and 41 percent for men.

We model the probability of smoking as a function of age, gender, education, personal income, and the cardinal measure of $\hat{\lambda}$. Income is represented by dummy variables, where the reference category is personal income less than 100,000 NOK. We also include dummy variables for working sector, educational attainment, and whether the respondent is a student. The effect of the cardinal risk-aversion measure is statistically significant at the 5 percent level and the estimate can be translated into a marginal effect of –0.15. Thus, if $\hat{\lambda}$ increases by 0.5 (a difference of this magnitude is like comparing a person with $\hat{\lambda}<1/2$ with a person with a $\hat{\lambda}>4/5$) then this reduces the probability of smoking by 7.5 percent, an economically significant effect.[25]

The income dummies suggest an inverse U-shaped relationship between the probability of smoking and income.[26]

Body mass index

Our main survey data show an average BMI of 26.5 for men and 25.3 for women. These numbers are quite similar with those of other public sources. The Norwegian Institute for Public Health reports 26.4 for men and 25.2 for women in Oslo in 2001. Other regional health surveys indicate that the average male BMI typically ranges from 26 to 27 and the average female BMI from 25 to 26. Restricting us to obesity (a BMI>30), 16 percent of men and 15 percent of women in our sample satisfy that criterion.

—Table 7 here—

The first column in table 7 shows results from a regression where the dependent variable is BMI. Because smoking may cause a higher metabolism (cf. Flegal *et al.*, 1998), and because this is endogenous, we control for this through a two-stage least squares procedure. First, we use a linear probability model to regress smoking on all the relevant covariates plus dummies for educational attainment and whether the respondent is a student. Highly educated people and

[25] The marginal effect is first estimated for each individual in the sample. The mean marginal effect is the mean of the individual effects. An alternative is to calculate the marginal effect as a function of the mean of the regressors. Wooldridge (2002, p. 466) discusses the pros and cons connected with these alternatives.

[26] As an alternative to using income dummies, we estimated a cardinal income measure for each respondent based on their reported income interval and the underlying assumption that income is log-normally distributed in the population (i.e., the Hsiao-Mountain (1985) method explained earlier). The estimated log of income, as well as its square, were then used in the probit regression (regression is not reported but available upon request). The corresponding estimated coefficients were significant at the 10 percent level, as expected, and confirm the inverse U shape.

students are expected to be better informed about the adverse consequences of smoking than people with little or no education, and this expectation is confirmed in the data. We argue that the association between BMI and education is less clear. A student or a highly educated person may be more informed about negative consequences of high BMI, but on the other hand, this group is more likely to work in occupations that require less physical work. Moreover, the data confirms that the association between BMI and education is zero. Thus, we believe that using instruments for education in the first step can be justified both theoretically and empirically. Therefore, we use educational attainment and a student dummy as an instrument in the first stage. In the second stage, we regress BMI on the predicted probability of smoking and the other above-mentioned covariates. As in the other regressions, we control for region of residence, income, employment sector, and type of residential location (see the heading of table 7 for details).

We find that BMI is negatively correlated with $\hat{\lambda}$, thus indicating that those who are more risk averse tend to have a lower BMI. However, even though the point estimate is of economic significance, the effect is statistically weak and we cannot reject the null hypothesis of zero association.[27] The effect of smoking on BMI is positive, although not statistically significant at the conventional levels.[28] The effect of age is significantly positive, but it tapers off as people age. As expected, the conditional mean estimates confirm that men have a higher BMI than women.

Borghans and Golsteyn (2006) advance the hypothesis that high individual discount rates lead to high values for the BMI. The reasoning is that persons with a high discount rate put less weight on future adverse outcomes, implying excessive consumption today. Thus, differences in the individual discount rate can very well lead to mirroring differences in the body mass index.[29] They test this hypothesis using different proxies for the discount rate and find that some support their hypothesis. One proxy they use is an indicator whether respondents often have problems to pay their bills in due time. Borghans and Golsteyn (2006) find that people with this problem indeed tend to have higher BMI. We have access to a similar variable in our main survey. Specifically, respondents were asked to indicate their concern about "not having enough money to pay an unexpected bill" by an integer between 1 (severely worried) and 5 (not worried at all). We reduced this indicator to a dummy variable (one for index 1, zero for index 2–5). The

[27] Whether BMI is a high-quality measure of obesity is somewhat disputed. For example, it does not distinguish between fat mass from lean mass (Sturm, 2002).
[28] One interpretation of the positive association is that people who have a potential for high BMI use cigarettes as a weight control instrument.
[29] Moreover, one can extend this model to also include a probabilistic discount rate where people with some probability place weight on future consequences (the future self) and with some probability focus on the current pleasure of food (the current self); see Cutler, Glaesar and Shapiro (2003).

column labeled 'Model 2' in table 7 gives the results. The "liquidity-fear" dummy has the expected sign but it is not statistically significant. In addition, it does not alter the coefficient with $\hat{\lambda}$, nor the other parameter estimates.

We also estimated a linear probability model for obesity (BMI>30). The results (not reported) show a negative but insignificant coefficient of $\hat{\lambda}$. Again, the coefficient with the "liquidity-fear" dummy, a proxy for a low individual discount rate, is positive but now significant at the 10 percent level.

To summarize, we find that risk aversion has a significant negative effect on the decision to smoke, but not on the effort to reduce BMI. We do not find any strong empirical support for the high discount rate hypothesis of Borghans and Golsteyn (2006).

Labor market choices I

Several studies have explored the connection between self-employment and risk preferences. BJKS found that the probability of self-employment increases in risk tolerance. More recently, Cramer *et al.* (2002) found that risk aversion has a clear negative effect on entrepreneurship. Moreover, Ekelund *et al.* (2005) confirm a positive relationship between risk tolerance and self-employment in Finland using psychometric survey questions. Lastly, in a recent study by Brown *et al.* (2008) using the US Panel Study on Income Dynamics (PSID), a positive relationship between self-employment and risk tolerance is confirmed.

The main survey contains information on whether a person works in the private sector, whether the respondent holds a management position, as well as the number of employees in the firm in which they are working. We now explore whether our cardinal risk-aversion measure can explain variations in these characteristics of the working place.

The first column of table 8 shows a binary probit model for the decision to work in the private sector or not. The dependent variable takes the value of one if the person works in the private sector and zero if they work in the public sector. Approximately 56 percent of the working sample is connected to the private sector. A small number of respondents work in the NGO sector, but these are not included. Likewise, persons not working are also excluded.

The second column models the probability for having a Top Manager role. Middle managers, specialists and other employees are the reference group.[30] Approximately 11 percent of the respondents claim that they have a Top Manager role. Top Managers are often paid

[30] The question about managerial role included the following alternatives: Top Leader, Other Leader, Middle Manager, Specialist/Project Leader and Ordinary Employee. Our definition of Top Manager includes the categories Top Leader and Other Leader.

through bonus schemes, introducing a risky component in their salary. On the other hand, Top Managers may be exposed less to an unemployment risk—rather than being the victim of a restructuring, they are the ones who restructure a firm in adverse times.

—Table 8 here—

Our empirical results show that the degree of risk tolerance increases the likelihood of being employed in the private sector, as well as the likelihood of ending up in a top position. Both effects are (highly) significant, both in the economic and statistical sense. Interestingly, the male gender effect remains strongly positively significant for both employment decisions. As we have controlled for risk aversion, the argument that women are less likely to take up a leader role cannot be attributed to them being more risk averse. Having a university degree, while increasing the likelihood of ending up as a Top Manager, lowers the probability of working in the private sector— the Norwegian public sector is indeed a large employer of highly educated civil servants.

Labor market choices II

Mayo and Murray (1991) provide empirical evidence that the likelihood for a firm to exit the market—and therefore the employment risk—negatively depends on its size (and age). The reason could be that smaller firms have a smaller contract base or a more homogenous customer base, making them more vulnerable to product market shocks.

In table 9, we present an ordered probit model for the probability to work in a large firm. Only private sector employees that work in firms with 10 employees or more are retained. This restriction leaves us with 368 respondents.

—Table 9 here—

As expected, we find that $\hat{\lambda}$ is positive, indicating that there is a positive relationship between risk aversion and the probability of working in large firms. Here, the estimate is significant at the 5 percent level. Together with findings of Mayo and Murray (1991), this suggests that more risk-tolerant workers sort into firms with a higher failure risk. The internal mobility that exists in large firms may be an additional reason for attracting more risk-averse workers.

If workers were identical in all respects (including their risk aversion), this would mean that large firms in equilibrium offer a lower risk premium. Empirical studies document, however, a significantly *positive* relationship between wage and firm size (see, e.g., Brown and Medoff, 1989 for the US, Albæk *et al.*, 1998, for the Nordic countries). Because large firms tend to offer higher wages, it means that workers sort into large and small firms according to some unobservable characteristics. One explanation, offered by Mayo and Murray (1991) and Evans and Leighton (1989), is that firms with higher failure risk attract workers with lower endowments of attributes that enhance productivity. Our result does not dismiss such an explanation, but it does suggest that sorting according to some nonobservable productivity characteristic need not be that strong; the fact that workers in a small-sized firm are more risk tolerant means that the risk premium offered by a such a firm need not be that high.

Borrowing for stock investment

The main survey contained the question: "How likely is it that you would borrow money to invest in stocks?" Respondents were given four answer alternatives (answer percentage in brackets): "very likely" (2 percent), "likely" (3 percent), "somewhat likely" (21 percent), and "not likely at all" (74 percent). Our hypothesis is that the more risk-averse people are, the less likely they will invest borrowed money in risky assets.

Because of the natural ordering of the responses to this question, we use an ordered probit regression to investigate the relationship. Moreover, we include all relevant covariates that might have an impact on the choice. The details are given in the heading of table 10.

—Table 10 here—

The association between the loan for stock investment and our cardinal measure of risk preference is strong—both economically and statistically significant. If $\hat{\lambda}$ were to increase by 0.5, the probability for answering either "very likely" or "likely" is reduced by approximately 3.6 percentage points and the probability for "somewhat likely" by almost 9.5 percentage points.[31] We have also run this regression with income dummies and a dummy for whether the person is a student, without altering the results.

9. Summary and conclusion

This is the first study that explores the heterogeneity of risk preferences among the Norwegian population. In order to disclose preferences, we made use of hypothetical income gambles

[31] Recall that in an ordered probit/logit model, the marginal effects sum to zero (see Greene, 2008, p. 833).

similar to the ones proposed by Barsky *et al.* (1997). We proposed and estimated a cardinal risk measure of risk aversion that can be interpreted as the lowest fraction of current income the respondent is willing to keep (with 50 percent probability) to accept a gamble where the upside is a doubling of income (with 50 percent probability). The higher this fraction, the more risk averse the respondent is. The cardinal risk measure was estimated conditional on the categorical choice of the respondent and other relevant observable characteristics. Our cardinal measure differs from both Kimball, Sahm and Shapiro (2008) who use an unconditional method for estimating risk tolerance and Sahm (2007) who extends the Kimball, Sahm and Shapiro approach by estimating conditional risk tolerance. Our estimates show that Norwegians are pretty risk averse (the sample average for R_r is 3.92) but also that there is a strong heterogeneity in risk preferences (the sample standard deviation for R_r is 2.94).

Our imputed risk-aversion measure was then used to explain variation in different risk behaviors. We found that our measure has a significant negative effect on the decision to smoke; that it negatively affects the likelihood of working in the private sector, taking a role as a top manager, or working in a small private firm; and lastly, it negatively affects the likelihood of taking up a loan to invest in risky assets. On the other hand, we did not find evidence for risk aversion affecting the BMI-level.

Moreover, we also found that people who reported to be quite satisfied with their current life situation display a higher risk aversion. Their avoidance of income gambles can be understood as "mood maintenance" (Isen, Nygren and Ashby, 1988). The higher risk tolerance of elate people may be explained by their optimistic belief that the gamble will result in a positive outcome (Johnson and Tversky, 1983). These findings point to a possible noise factor in studies that aim to measure risk aversion through survey techniques. If the "current mood" of the respondent is an important influencing factor, then one can expect considerable variation in the responses over time. This fact is also documented in Sahm (2007) who reports that unexplained transitory variation in relative risk tolerance is ten times larger than the systematic variation. One possible research path to reduce the unexplained variation in responses might therefore be to include questions that can map the "mood" of the respondent under the interview situation.

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TABLES AND DIAGRAMS

Table 1. Responses to income gamble: results from three surveys[a]

	Survey type					
	Main survey		web survey: standard question no context		web survey: suggested lock-in effect	
	Percent	Count	Percent	Count	Percent	Count
Relative risk-aversion category						
$4/5=\lambda^*<1$ *($R_r>3.76$)*	36.79	561	29.73	223	23.20	265
$2/3=\lambda^*<4/5$ *($2<R_r<3.76$)*	41.31	630	33.07	248	33.45	382
$1/2/=\lambda^*<2/3$ *($1<R_r<2$)*	8.59	131	20.00	150	23.47	268
$\lambda^*<1/2$ *($R_r<1$)*	13.31	203	17.20	129	19.88	227
All	100.00	1525	100.00	750	100.00	1142

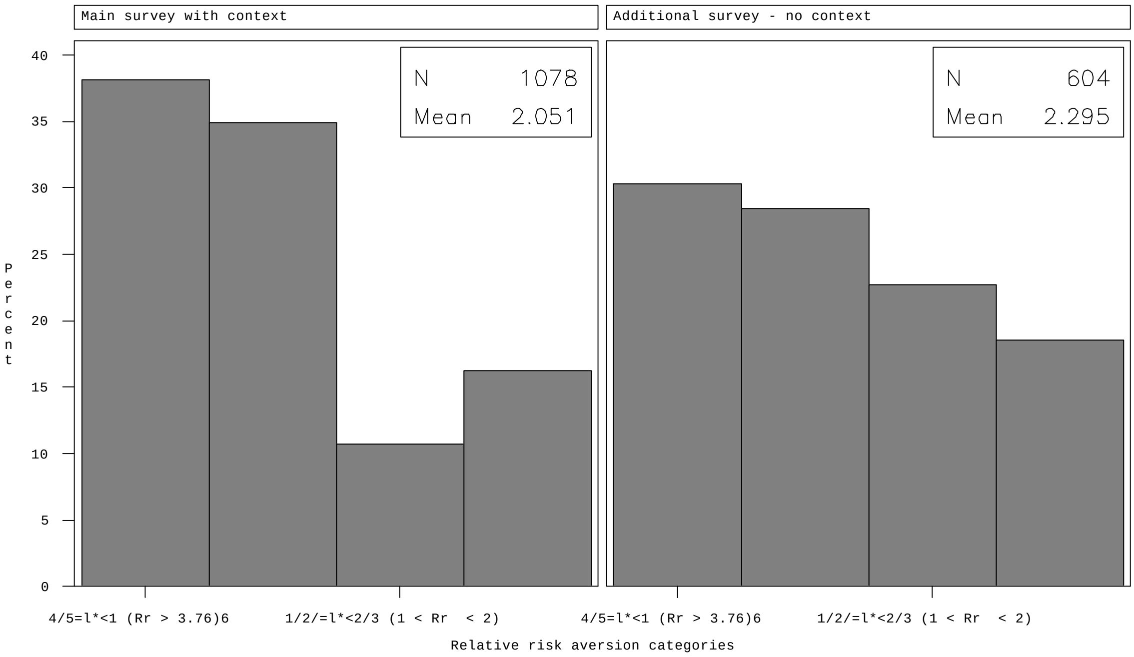
Table 2. Cross-country comparisons of responses to the income gamble (respondents aged 51 to 61)

Risk-aversion category	Main survey, Norway	Barsky *et al.,* USA	Arrondel and Calvo-Pardo, France*	Kapteyn and Teppa, The Netherlands*	Web surveys with no context and suggested lock-in effect, Norway
$4/5 \leq \lambda^* < 1$ ($R_r > 3.76$)	32.66	64.6	48.6	66.3	26.97
	} 86.4	} 76.2	} 85.4	} 79.8	} 70.2
$2/3 \leq \lambda^* < 4/5$ ($2 < R_r < 3.76$)	53.54	11.6	36.8	13.5	43.3
$1/2 \leq \lambda^* < 2/3$ ($1 < R_r < 2$)	5.39	10.9	8.7	9.0	16.4
	} 13.8	} 23.7	} 14.6	} 20.2	} 29.8
$\lambda^* < 1/2$ ($R_r < 1$)	8.42	12.8	5.9	11.2	13.4
All	100.00	100.00	100.00	100.00	100.00
N	297	11 707	2954	178	134

*In Arrondel and Calvo-Pardo (2002) and Kapteyn and Teppa (2002), all respondents over 50 are included.

Figure 3. Histogram over responses to the income gamble. With and without context.

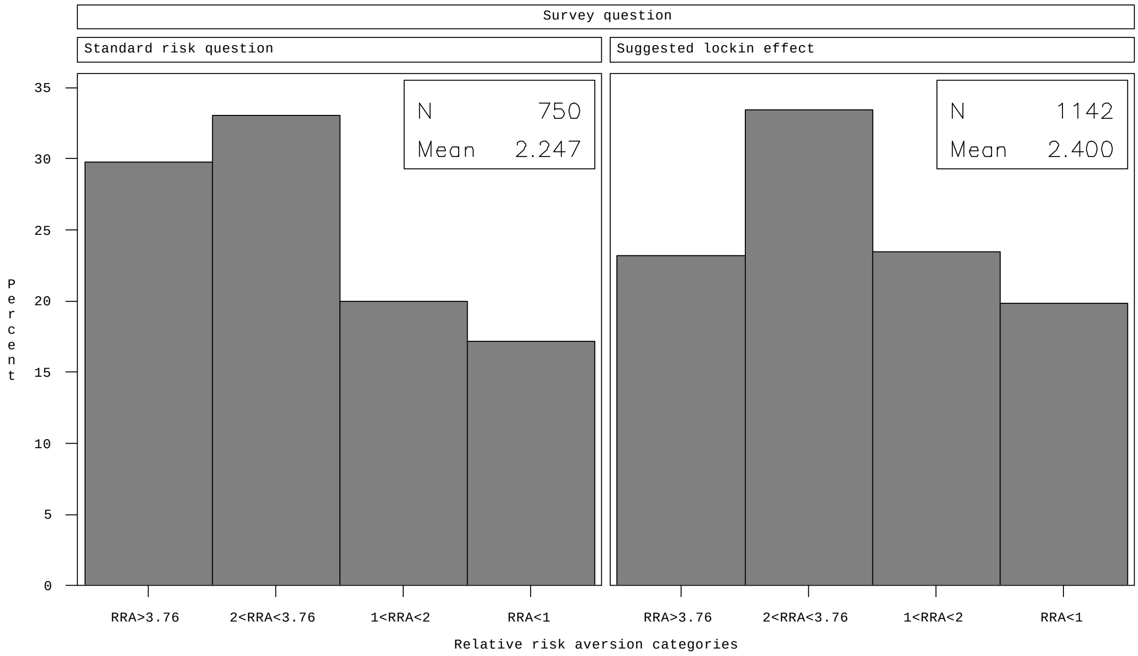
Left: Standard risk question with context. Right: Standard risk question without context. Note that we have only included those who answered from the main web survey; this implies that respondents are 18 to 54 years of age.



*The highest risk-aversion category is coded 1 and the lowest category is coded 4.

Figure 4. Histogram over responses to the income gamble. Standard risk question compared with lock-in question.

Left: Standard risk question. Right: Income gamble with suggested lock-in effect.



*The highest risk-aversion category is coded 1 and the lowest category is coded 4.

Table 3. Frequency table: index for life satisfaction—main survey

Frequency table of life satisfaction				
Satisfaction index	Frequency	Percent	Cumulative frequency	Cumulative percent
1=Lowest	29	1.87	29	1.87
2	70	4.52	99	6.39
3	67	4.32	166	10.71
4	98	6.32	264	17.03
5	130	8.39	394	25.42
6	159	10.26	553	35.68
7	365	23.55	918	59.23
8	368	23.74	1286	82.97
9=Highest	263	16.97	1549	99.94
10=Do not know	1	0.06	1550	100.00

Table 4. Ordered probit estimation of equation (7)

Cutoff thresholds in the regression are given by the design of the experiment. These are 0, log2 and log4. In addition to the parameters given in the table, we have controlled for marital status in the main survey that includes the categories: married, cohabiting, single, divorced, and widow/widower. Married is the reference category. Moreover, we have also controlled for type of residential location: living at a farm, living in the countryside, small community in the countryside, small town less than 5,000 inhabitants, medium town 5,000–20,000 inhabitants, smaller city 20,000 to 100,000 inhabitants, and large city >100,000 inhabitants. Living in the countryside/farm is the reference group. Primary school is the reference category for education. We also control for whether the respondent is working, retired, or on a disability pension. Finally, we control for income using eight income categories and five geographical regions. Oslo is the reference category for region. The main survey is the reference category for the survey and women are the reference category for gender. Statistical significance at the 10 percent level is denoted with *, significance at the 5 percent level with **, significance at the 1 percent level with ***. These are based upon a two-sided *t* test. We find that respondents living in towns with 5,000 to 20,000 inhabitants are significantly more risk averse, otherwise none of the SES control variables are significant at the 5 percent level.

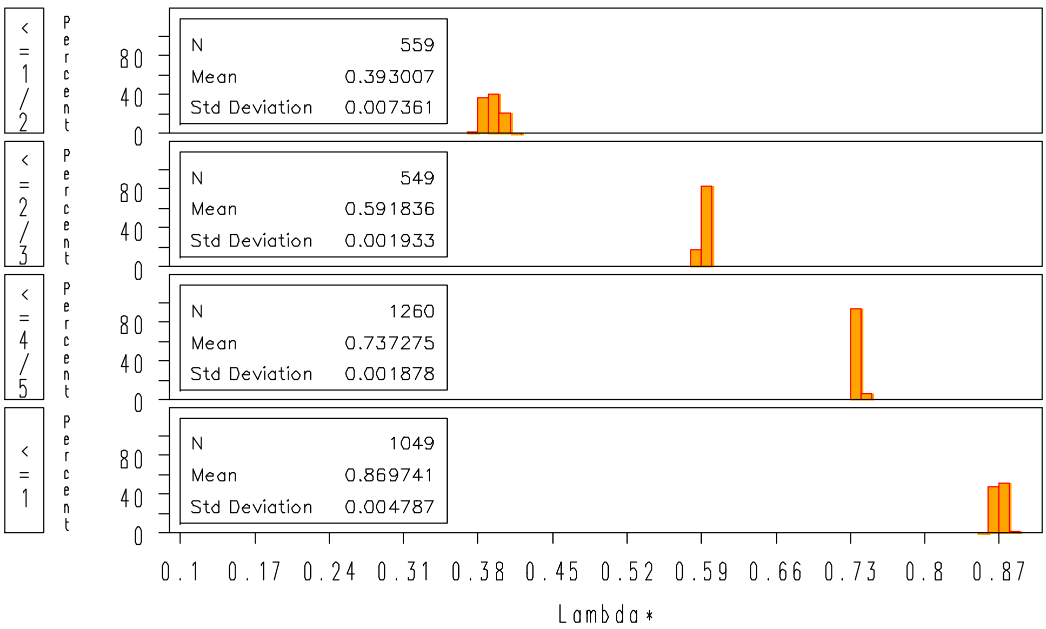
	Estimate (Std err)	Estimate (Std err)
Parameter	All surveys with limited set of SES covariates	Main survey with full set of SES covariates
Intercept	1.0064*** (0.0742)	0.769*** (0.192)
Age	0.0051*** (0.0011)	0.007*** (.002)
Gender (male=1)	–0.1032*** (0.0327)	–0.255*** (.052)
East region	0.0375 (0.0514)	0.0086 (0.109)
Southwest region	0.0428 (0.0660)	0.0407 (0.123)
West region	0.0108 (0.0596)	–0.0565 (0.105)
Middle region	0.0214 (0.0663)	–0.0542 (0.108)
North region	–0.0805 (0.0707)	–0.0296 (0.133)
High school	–0.0233 (0.0464)	0.0039 (0.087)
University/college degree	–0.0813* (0.0442)	–0.0850 (.085)
Dummy for context-free question	–0.2201*** (0.0427)	–
Dummy for suggested lock-in effect	–0.3515*** (0.0377)	–
High life satisfaction (index from 6 to 8)	–	0.118** (0.059)

	Estimate (Std err)	Estimate (Std err)
Parameter	All surveys with limited set of SES covariates	Main survey with full set of SES covariates
Very high current life satisfaction (index=9)	–	–0.001 (.078)
Standard deviation (sigma)	0.8804*** (0.0169)	0.869*** (0.026)
N	3446	1554
Log-likelihood	–4555.90	–1897.31

Figure 5. Histogram of $\hat{\lambda}$.

The histogram shows the distribution of $\hat{\lambda}$ given that the respondent chose risk category c, c =1,2,3,4 and conditional on his/her characteristics.
Panel a) depicts the distribution for the full sample. Panel b) shows a similar histogram for the main survey.

Panel a): All surveys



Panel b): Main survey

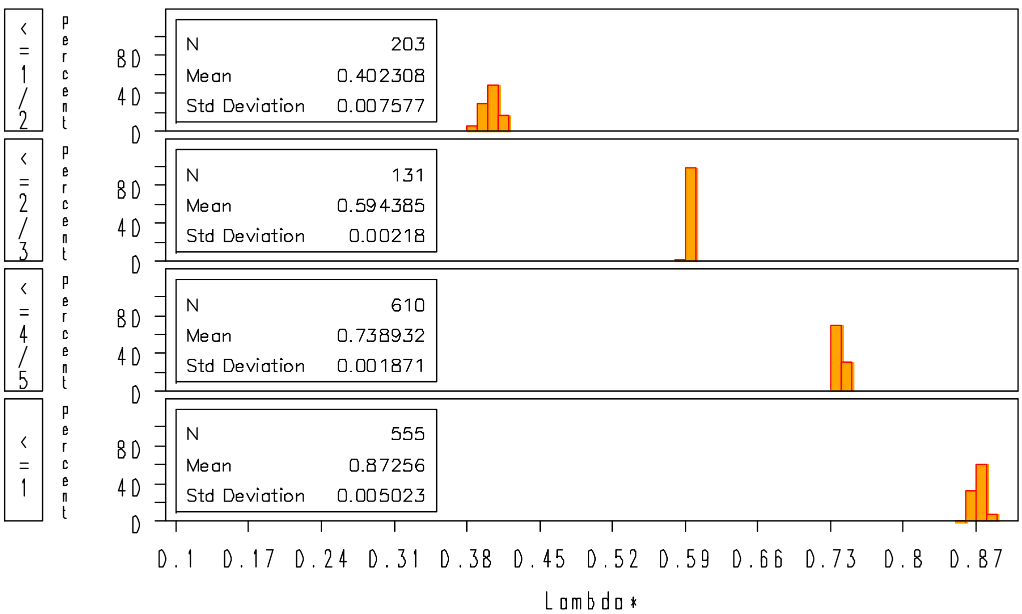


Table 5. Expected R_r conditional on individual characteristics and chosen risk category: all surveys

Risk Category	N	$E(R\_r \mid x_i, c_i, \hat{\beta})$	Std Dev	Minimum	Maximum
0<*R_r*<1	559	0.673	0.011	0.647	0.707
1<*R_r*<2	549	1.484	0.007	1.466	1.507
2<*R_r*<3.75	1260	2.881	0.016	2.834	2.925
R_r>3.75	1049	8.179	0.332	7.430	9.390

Figure 6. Histogram of $E(R_{ri} \mid x_i, c_i, \hat{\beta})$: all surveys.

Solid curve depicts the log-normal distribution estimated on the sample.

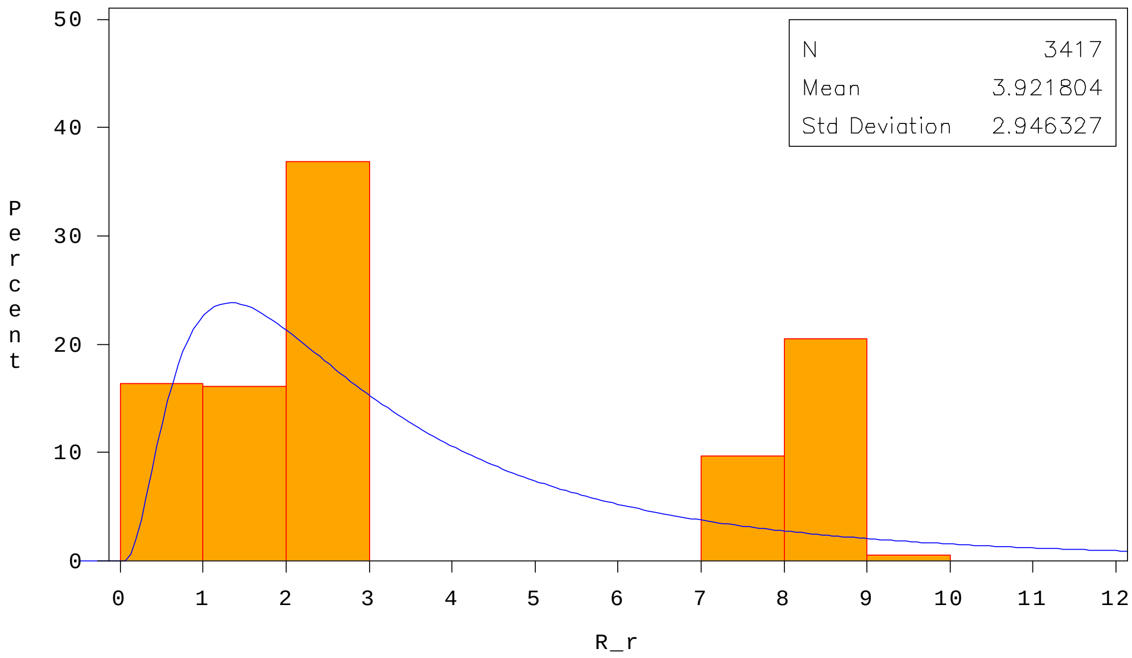


Table 6. Risk preferences and the probability of smoking

The dependent variable is incidence of smoking, coded as 1 for a smoker and 0 otherwise. Of the 1,445 observations for which we observe this decision, 369 respondents are smokers. This number constitutes 25.5 percent of the sample. The regression includes income dummies and a full set of dummies for the working sector. The reference groups are income less than 100,000 NOK and industry sector, respectively. Dummies for high school, university education, current student, male, five geographical regions and a dummy for age over 66 years are also included. The estimates for region and working sector are not reported. Bootstrapped standard errors are based on 200 random samples from the original data set with replacement. Statistical significance at the 10 percent level is denoted with *, significance at the 5 percent level with **, significance at the 1 percent level with ***. These are based upon a two-sided *t* test. The *t* value is calculated as the original estimate divided by the bootstrapped standard error.[32]

	Model with income dummies and cardinal risk proxy
Parameter	Estimate Standard error
Intercept	–0.7990* 0.4758
Age	0.0481** 0.0242
Age squared	–0.0006** 0.0003
$\hat{\lambda}$	–0.4976** 0.2501
Eighth highest income	0.3440* 0.1817
Seventh highest income	0.3153* 0.1869
Sixth highest income	0.2718 0.1950
Fifth highest income	0.2481 0.2168
Fourth highest income	0.2274 0.2346
Third highest income	–0.0534 0.2562
Second highest income	–0.1082 0.4467
Highest income	–0.2058 1.2123
Male	–0.0890 0.0846
Current student	–0.7882*** 0.2434

[32] Given asymptotic normality of the bootstrap sampling distribution estimator, this procedure to calculate the *t* values can be justified (see Fox, 2002).

	Model with income dummies and cardinal risk proxy
Parameter	Estimate Standard error
High school	–0.3161** 0.1298
University education	–0.6498*** 0.1426
N	1421
Log-likelihood	–758.82
Pseudo-R2	0.0590

Table 7. Risk preferences and BMI

The dependent variable is body mass index (BMI). The method is two-stage least squares. The first-stage regression includes the full set of covariates in the BMI-regression plus education attainment and a dummy for current student. The education attainment and the student variable are highly significant for predicting smoking but not associated with BMI. Regressions include income dummies and a full set of dummies for the working sector. Type of residential location is also included. These are: a) living in the countryside, b) small town, c) medium town, d) small city, e) medium city, and f) large city. Living on a farm is the reference group. The estimates for income, geographical region, working sector and type of residential location are not reported. Bootstrapped standard errors are based on 200 random samples from the original data set with replacement. Statistical significance at the 10 percent level is denoted with *, significance at the 5 percent level with **, significance at the 1 percent level with ***. These are based upon a two-sided *t* test. The *t* value is calculated as the original estimate divided by the bootstrapped standard error.

	Model 1	Model 2 Includes proxy for individual discount rate
Parameter	Estimate Standard error	Estimate Standard error
Intercept	20.5129*** 1.4784	20.4591*** 1.7217
Age	0.1966*** 0.0751	0.1958** 0.0785
Age squared	–0.0019** 0.0008	–0.0019** 0.0008
$\hat{\lambda}$	–0.5408 0.9495	–0.5363 1.0323
Male	1.2322*** 0.2885	1.2430*** 0.3039
Smoker	3.0874 2.0801	2.9854 2.0730
Lack of liquidity proxy	—	0.4118 0.5661
N	1419	1419
Adj R-square	0.0424	0.0440

Table 8. Risk preferences and the probability of work in the private sector or having a management role

The dependent variable is 1 if the person works in the private sector (column 1) or if the respondent has a manager role (column 2). Middle managers, specialists, project leaders, and other employment categories constitute the reference group in the manager equation. Only persons active in the labor market are included. Approximately 56 percent of those who are active in the labor market work in the private sector. A little more than 11 percent report having a manager role. The regression in the first column includes age, gender, education, geography, and type of residential location; that is: a) living in the countryside, b) small town, c) medium town, d) small city, e) medium city, and f) large city. Living on a farm is the reference group. The regression in the second column involves all the mentioned covariates plus dummies for the working sector. The industry sector is the reference group. The reported standard errors are based on 200 random samples with replacement from the original data set. Statistical significance at the 10 percent level is denoted with *, significance at the 5 percent level with **, significance at the 1 percent level with ***. These are based upon a two-sided *t* test. The *t* value is calculated as the original estimate divided by the bootstrapped standard error.

	Work in private sector	Having a manager role (not middle manager)
Parameter	Estimate Standard error	Estimate Standard error
Intercept	1.7865*** 0.3793	–2.2518*** 0.7468
Age	–0.0135*** 0.0035	0.0849** 0.0329
Age squared	0.0000 0.0003	–0.0008** 0.0004
$\hat{\lambda}$	–0.5259* 0.2746	–0.9699*** 0.3586
Male	0.4922*** 0.0987	0.4265*** 0.1338
University education	–0.7315*** 0.1400	0.5005** 0.2187
High school	0.0391 0.1425	0.5089** 0.2222
N	1111	1111
Log-likelihood	–650.11	–320.59
(Pseudo-R2)	0.14	0.152

Table 9. Risk preferences and the probability of working in a large firm

Ordered probit regression. Results from a regression where there are four ordered categories: 10–19 employees (82 respondents); 20–99 employees (122 respondents); 100–199 employees (40 respondents); and over 200 employees (124 respondents). The equation includes gender, age, income, region, and type of residential location (living in the countryside, small town, medium town, small city, medium city and large city). Living on a farm is the reference group. Working sector dummies are included to control for systematic variation between working sector and firm size. The industry sector is the reference group. The reported standard errors are based on 200 random samples with replacement from the original data set. Statistical significance at the 10 percent level is denoted with *, significance at the 5 percent level with **, significance at the 1 percent level with ***. These are based upon a two-sided *t* test. The *t* value is calculated as the original estimate divided by the bootstrapped standard error.

	Only private sector respondents.
	Estimate Standard error
Cutoff 1	–1.1498 0.9470
Cutoff 2	–0.8192 0.9470
Cutoff 3	0.1627 0.9470
Age	0.0015 0.0089
$\hat{\lambda}$	0.7466** 0.3488
Male	0.1761 0.1556
High school	–0.2189 0.2722
University education	–0.0300 0.2768
N	368
Log-likelihood	–481.46
(Pseudo-R2)	0.0699

Table 10. Risk preferences and the probability of an intentional loan for stock investment

The dependent variable is whether a person is willing to obtain a loan for stock investment: coded 4 if this option was highly likely; 3 if it was likely; 2 if it was somewhat likely; and 1 if it was not likely at all. Of the 1,472 observations for which we observe this decision, 29 respondents chose option 1, 47 chose option 2, 306 chose option 3, and 1,090 chose option 4. The regression in the first column includes age, gender, education, geography, and type of residential location; that is: a) living in the countryside, b) small town, c) medium town, d) small city, e) medium city, and f) large city. Living on a farm is the reference group. The estimates for income, region and residential location are not reported. Bootstrapped standard errors are based on 200 random samples from the original data set with replacement. Statistical significance at the 10 percent level is denoted with *, significance at the 5 percent level with **, significance at the 1 percent level with ***. These are based upon a two-sided *t* test. The *t* value is calculated as the original estimate divided by the bootstrapped standard error.

	Ordered probit regression
Parameter	Estimate Standard error
Cutoff 1	–1.6743** 0.7767
Cutoff 2	–1.2127 0.7767
Cutoff 3	–0.1610 0.7767
Age	–0.0264 0.0188
Age squared	0.0002 0.0002
$\hat{\lambda}$	–0.8826*** 0.2242
Male	0.3061 0.0790
High school	0.2613** 0.1064
University education	0.1855* 0.1122
N	1472
Log-likelihood	–1026
Pseudo-R2	0.0533

Appendix: Descriptive statistics for the main survey (N=1554)

	Average	Standard deviation	Median	1st percentile	99th percentile	Number of obs.
$2/3<\lambda<4/5$	0.41	0.49	0.00	0.00	1.00	1554
$1/2<\lambda<2/3$	0.08	0.28	0.00	0.00	1.00	1554
$\lambda<1/2$	0.13	0.34	0.00	0.00	1.00	1554
Fraction males, binary	0.49	0.50	0.00	0.00	1.00	1554
Age in years	43.88	15.24	43.00	18.00	73.00	1554
Number of children	1.61	1.36	2.00	0.00	5.00	1525
Fraction of people with middle income, binary	0.46	0.50	0.00	0.00	1.00	1554
Fraction of people with high income, binary	0.25	0.43	0.00	0.00	1.00	1554
Fraction of people with highest incomes, binary	0.04	0.19	0.00	0.00	1.00	1554
Body mass index	25.78	4.44	25.14	17.93	40.39	1550
Fraction studying, binary	0.06	0.24	0.00	0.00	1.00	1554
Fraction unemployed, binary	0.02	0.14	0.00	0.00	1.00	1554
Fraction on disability pension, binary	0.06	0.23	0.00	0.00	1.00	1554
Fraction on old age pension, binary	0.10	0.30	0.00	0.00	1.00	1554
Fraction with college/university degree, binary	0.49	0.50	0.00	0.00	1.00	1554
Fraction that resides on a farm, binary	0.06	0.24	0.00	0.00	1.00	1554
Fraction residing in small city, binary	0.12	0.32	0.00	0.00	1.00	1554
Fraction residing in large city, binary	0.28	0.45	0.00	0.00	1.00	1554
Fraction in east region, binary	0.40	0.49	0.00	0.00	1.00	1554
Fraction in south east region, binary	0.10	0.30	0.00	0.00	1.00	1554
Fraction in western region, binary	0.18	0.38	0.00	0.00	1.00	1554
Fraction in middle region, binary	0.12	0.32	0.00	0.00	1.00	1554
Fraction in north region, binary	0.09	0.29	0.00	0.00	1.00	1554
Fraction smokers	0.25	0.44	0.00	0.00	1.00	1554
Fraction work in private sector	0.42	0.49	0.00	0.00	1.00	1551

Descriptive statistics for the main survey: active in the labor market (N=1089)

	Average	Standard deviation	Median	1st percentile	99th percentile	Number of obs.
2<RRA<3.76	0.35	0.48	0.00	0.00	1.00	1089
1<RRA<2	0.11	0.31	0.00	0.00	1.00	1089
RRA<1	0.16	0.37	0.00	0.00	1.00	1089
Fraction males, binary	0.45	0.50	0.00	0.00	1.00	1089
Age in years	35.47	10.09	35.00	18.00	53.00	1089
Number of children	1.32	1.30	1.00	0.00	4.00	1089
Fraction of people with middle income, binary	0.43	0.50	0.00	0.00	1.00	1089
Fraction of people with high income, binary	0.25	0.43	0.00	0.00	1.00	1089
Fraction of people with highest incomes, binary	0.04	0.20	0.00	0.00	1.00	1089
Body mass index	25.60	4.73	24.78	17.59	40.90	1089
Fraction with primary school only, binary	0.00	0.05	0.00	0.00	0.00	1089
Fraction with college/university degree, binary	0.49	0.50	0.00	0.00	1.00	1089
Fraction working in firms with less than 6 employees, binary	0.09	0.28	0.00	0.00	1.00	1089
Fraction working in firms with more than 199 employees	0.22	0.41	0.00	0.00	1.00	1089
Fraction reporting to be a top leader or other higher ranked leader	0.08	0.28	0.00	0.00	1.00	1089
Fraction that resides on a farm, binary	0.05	0.22	0.00	0.00	1.00	1089
Fraction residing in small city, binary	0.12	0.33	0.00	0.00	1.00	1089
Fraction residing in large city, binary	0.31	0.46	0.00	0.00	1.00	1089
Fraction in east region, binary	0.40	0.49	0.00	0.00	1.00	1089
Fraction in south east region, binary	0.08	0.28	0.00	0.00	1.00	1089
Fraction in western region, binary	0.18	0.39	0.00	0.00	1.00	1089
Fraction in middle region, binary	0.13	0.33	0.00	0.00	1.00	1089
Fraction in north region, binary	0.08	0.28	0.00	0.00	1.00	1089
Fraction smokers	0.26	0.44	0.00	0.00	1.00	1089

	Average	Standard deviation	Median	1st percentile	99th percentile	Number of obs.
Fraction work in private sector	0.49	0.50	0.00	0.00	1.00	1089

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