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Money can't buy realism:

Incentives do not interfere with the optimistic update bias

Bachelor Thesis

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Declaration of Authorship

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April 30th, 2018, Friedrichshafen

Date, Place

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Abstract

The present study examines whether individuals exhibit selective updating behaviour when estimating (1) their own risk of incurring a negative life event and (2) the risk of that event happening on average to the population. Furthermore, it is investigated whether an incentive can prevent individuals from selective belief updating regarding their estimate of the population risk. For this study, seventy-four university students participated in an experiment in which an altered version of Garret and Sharot's (2014) task paradigm was applied. It was found that participants exhibited selective updating such that they updated their beliefs more after having received desirable information than after having received undesirable information. This is true for their self-risk estimate and partially true for their estimates of the population risk. The incentive treatment did not interfere with the optimistic update bias. However, findings suggest sex differences in processing negative stimulus material. Also, an alternative analysis method is introduced.

Keywords: belief updating, optimism, incentive

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1. Introduction

When making statements about their future, humans have shown to be optimistically biased across several domains. For instance, people underestimate their chances of divorce (Baker & Emery, 1993), expect to live longer than average (Weinstein, 1980), and make optimistic forecasts of financial returns (Calderon, 1993). Why would they often be so unrealistically optimistic? Essentially, this unrealistic optimism reflects a self-serving motivational bias with numerous benefits: optimists are said to be happier and to perceive more control about their environment than pessimists (Taylor & Brown, 1988). The initial positive outlook pays off when it becomes manifest in greater academic success, higher income, and improved physical and psychological health (Carver, Scheier & Segerstrom, 2010). However, optimism has its downsides, too. Relying on unrealistic optimism can bear costs in contexts such as gambling and trading in the stock market (Makridakis & Moleskis, 2015), or lead to risky behaviours such as not engaging in screening activities (cf. Shepperd, Pogge & Howell, 2017).

A recent strand of research focuses on the fact that people exhibit optimistic learning. Sharot, Korn and Dolan’s (2011) seminal study showed that, when confronted with disconfirming information, individuals update their prior beliefs more when they receive desirable information than when they receive undesirable information. In their experiment, participants were asked to give an estimate of their risk to incur different negative life events. The participants were then confronted with an actuarial base rate for these events and later they were asked to give a self-risk estimate a second time. For instance, participants who overestimated their risk of getting cancer during their lifetime relative to the population base rate readily incorporated the new (desirable) information and changed their belief towards the base rate, while participants who underestimated their risk relative to the base rate did not.

In recent years, substantial evidence was gathered for this so-called *optimistic belief updating* (e.g. Moutsiana et al., 2013; Korn, La Rosée, Heekeren & Roepke, 2016) and the effect has been found to be considerably robust. Studies have shown that framing the estimation question either positively or negatively ("What is the likelihood of this event happening to you / not happening to you") has no impact (Sharot et al., 2012). Also, incentivizing participants does not reduce the bias (Thies, 2018). Moreover, optimistic updating also takes place for positive life events (Garret & Sharot, 2017). In line with findings that populations with low mood predict future outcomes more realistically, individuals suffering from major depressive disorder do not exhibit an optimistic update bias (Korn, Sharot, Walter, Heekeren & Dolan, 2013). Previous research linked the optimistic update bias to a failure of the brain to correctly code undesirable information about the future (Sharot et al., 2011). Eil and Rao (2011) found that updating after receiving desirable information mostly follows Bayesian inference, while updating after receiving undesirable information does not.

There also is criticism of the concept of optimistic belief updating. Shah, Harris, Bird, Catmur and Hahn (2016) expressed doubts concerning methodological problems of the update task paradigm and follow Harris and Hahn (2011) in contending that the unrealistically optimistic behaviour of the participants is a statistical artefact stemming from methodological shortfalls. As a direct response to this criticism, Garret and Sharot (2017) conducted various tests of robustness to underpin the relevance of the optimistic update bias.

Several researchers addressed the question whether optimistic updating also occurs for estimates of the risk of others. For example, Kappes, Faber, Kahane, Savulescu, and Crockett (2018) found that participants exhibited *vicarious optimism*. That is, the optimistic update bias was also found for estimates of the likelihood of negative life events occurring to friends, identifiable strangers, and likeable strangers. Similarly, Garret and Sharot (2014) asked participants to not only estimate their self-risk but also the population base rate for a given negative life event. They found that participants show optimistic updating for base rate estimates, too, but only when they received positive or negative information regarding their estimates of incurring the events themselves.

1.1 Research Question and Hypotheses

In a previous study, Thies (2018) observed that participants exhibited optimistic updating even though they had a monetary incentive to avoid such behaviour. Specifically, before the participants estimated their self-risk a second time, incentivized participants were told to estimate the average population risk of incurring the events "as good as possible". The closer their self-risk estimate was to the formerly presented actuarial base rate, the more money they would get. These instructions may not have been suited best for identifying whether an incentive interferes with the bias since participants were told to estimate their personal self-risk but also to adjust their self-risk estimate towards a population base rate. As it cannot be assumed that the population base rate equals the (actuarial or estimated) self-risk, another method to test whether an incentive really has an effect on the bias's magnitude is necessary.

As to our knowledge, there is no other study than Thies (2018) that tested the robustness of the optimistic update bias under different incentive conditions[1]. In light of Thies' findings and the study's limitations, the present study seeks to explore the

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[1] Shah et al (2016, Experiment 3A) used a monetary incentive so that their participants "pay attention" (p.99)

possible effects of an incentive on optimistic updating in further detail. Thus, the research question reads:

Does a monetary incentive influence the optimistic update bias for population base rates?

The question shall be answered by examining whether participants exhibit selective updating behaviour when estimating (1) their own risk to incur a negative life event and (2) the likelihood that a negative life event happens on average to the population. These first two hypothesis are schematically depicted in Figure 1. Furthermore, it shall be investigated whether an incentive prevents participants from selective belief updating regarding their estimate of population risk.

As prior studies consistently found that participants update their beliefs more towards desirable than towards undesirable information (e.g. Sharot et al., 2011), a similar pattern is expected. Also, Garret and Sharot (2014) found that selective updating for self-risk was not contingent on the method by which trials are classified into desirable and undesirable information. Since we are applying their task paradigm, we expect to find this as well:

(H1a) *Absolute belief update for self-risk will be higher for trials in which participants receive desirable information regarding their self-risk than for trials in which participants receive undesirable information regarding their self-risk.*

(H1b) *Absolute belief update for self-risk will be higher for trials in which participants receive desirable information regarding their estimate of population risk than for trials in which participants receive undesirable information regarding their estimate of population risk.*

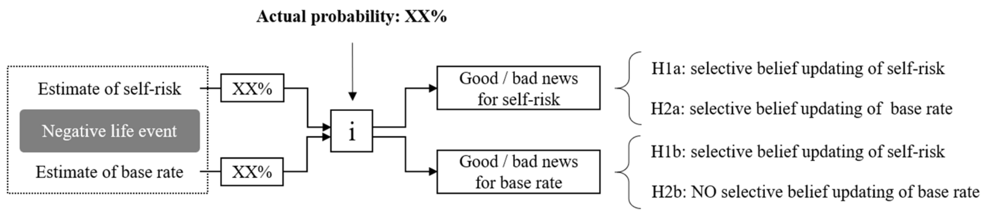

Figure 1 | Schematic representation of H1a, H1b, H2a, and H2b.

We also follow Garret and Sharot (2014) with respect to belief updating for population risk estimates. They found that participants exhibited selective updating behaviour regarding population risk estimates when trials were classified as desirable or undesirable relative to participants' estimates of self-risk, but not when trials were classified relative to their estimates of population risk:

(H2a) *Absolute belief update for population risk will be higher for trials in which participants receive desirable information regarding their self-risk than for trials in which they receive undesirable information regarding their self-risk.*

(H2b) *There will be no difference in absolute belief updates for population risk between trials in which participants receive either desirable or undesirable information for their estimate of population risk.*

As pointed out before, a prior study investigated the effect of a monetary incentive on updating of self-risk estimates. In this study, we want to test whether the optimistic update bias remains robust for population risk estimates if participants have an incentive not to update selectively. If participants are effectively incentivized to suppress biased learning by means of promised monetary benefits, there should be no difference in updates for population risk after receiving either desirable or undesirable information.

(H3) *Incentivized participants exhibit less selective updating behaviour for population risk estimates than non-incentivized participants.*

With the present research question and hypotheses, this study extends the previous study of Thies (2018) to examine incentive effects on optimistic belief updating in further detail. If selective belief updating is observed despite the prospect of a monetary gain even for population risk estimates, further evidence is gathered for the robustness of the bias.

2. Method

2.1 Test Planning

To calculate desired sample sizes, G*Power 3.1.9.2 (Faul, Erdfelder, Lang & Buchner, 2007) was used. The power analysis was based on effect sizes obtained from Thies (2018), in which an effect size (Cohen's *d*, see Cohen, 1988) of information desirability (desirable vs. undesirable) on average absolute belief update of $d = 0.41$ was found. This is a much smaller effect than other studies reported (e.g., Moutsiana et al., 2013). According to Kappes et al. (2018), in these studies, the effect size of information desirability on learning was about $d = 0.9$ on average. To obtain a power of $1\text{-}\beta = .9$ for an effect size of $d = 0.41$, a sample size of 58 was determined. Based on prior studies (e.g., Garret & Sharot, 2014), we expected that about 15% of the participants would exhibit depressive symptoms. These participants are usually excluded from analysis since optimistic updating is not found in depressive populations (Korn et al., 2013). To exclude the possibility that the effective sample size could drop below 58 participants, it was decided to recruit at least 70 participants.

2.2 Participants

Seventy-four students (45% female, $M_{\text{Age}} = 21.97$, $sd = 2.03$) from Zeppelin Universität, located in Friedrichshafen, Germany, participated in the experiment. It took place on five days in March 2018, divided into a total of 22 sessions with between one and six participants each. The participants received a show-up fee of 5€ for contributing 30 minutes of their time. Additionally, they received 3.20€ in case they were assigned to the non-incentivized group or a variable amount between 0€ and 6€ if they were in the incentivized group (see section 2.6). The participants were invited to the experiment if they had not taken part in a preceding experiment using the same materials.

2.3 Stimuli

The stimuli included 40 descriptions of negative life events that were taken from Korn et al. (2013), where items were selected such that their probabilities approximately match a normal distribution (M = 28.9%, sd = 17.1%, W = 0.96617, p > 0.27). The probabilities of these events occurring at least once to a person in the same sociocultural environment as the participant were determined by Sharot et al. (2011) based on online resources (such as Eurostat) and were made available to the author by Christoph Korn. It was assumed that even though the original probabilities applied to the United Kingdom, similar percentage values apply to other Western European countries such as Germany. Participants were told that the likelihoods represent the base rate for an average person of their age and sociocultural environment. All event probabilities laid between 10% and 70%. To ensure that the range of possible overestimation equals the range of possible underestimation, participants were told that the range of percentages laid between 3% and 77%. Furthermore, to control for possible doubt regarding the base rates, participants were asked to what degree (between 0% and 100%) they believed the presented information was accurate. A full table of stimuli is provided in the appendix (Table 2).

2.4 Measures

Two measures were used to control for possible factors influencing biased updating. First, the Life Orientation Test-Revised (LOT-R, Scheier, Carver & Bridges, 1994; Glaesmer, Hoyer, Klotsche & Herzberg, 2008) was included to control for trait optimism. Since less optimistic updating is linked to depression (Korn et al., 2013), participants also had to fill out a German version of the 9-item depression inventory from the Patient Health Questionnaire (PHQ-9, see Spitzer, Kroenke & Williams, 1999, and Kroenke, Spitzer & Williams, 2001).

2.5 Procedure

We apply a variant of the experimental paradigm used in previous studies (e.g. Sharot et al., 2011). This variant follows Garret and Sharot (2014), who did not only ask the participants for an estimate of their self-risk but also an estimate of the population base rate. The paradigm will be described below. The experiment file was created using the OpenSesame Experiment Builder (v3.1.9, Mathôt, Schreij, & Theeuwes, 2012).

2.5.1 Behavioural Task. At the beginning of each trial, participants were shown a brief description of an adverse life event for four seconds (e.g., “Heart failure”) and were instructed to imagine the event happening to themselves in the future. On the next two screens, participants were asked to give an estimate of how likely they deem the event occurring (1) to themselves in the future and (2) on average to the population (“to a person of your age and sociocultural environment”). On the next screen, they were presented the base rate probabilities from Table 2 in the appendix for two seconds. After each of their estimates, participants saw a fixation cross for one second. Additionally, participants were shown another fixation cross for two seconds in between trials. After half of the trials in each set, the order of the two estimation questions (self-risk / population risk) was reversed to avoid sequence effects. We also randomized which of the two estimation questions came first. If participants already

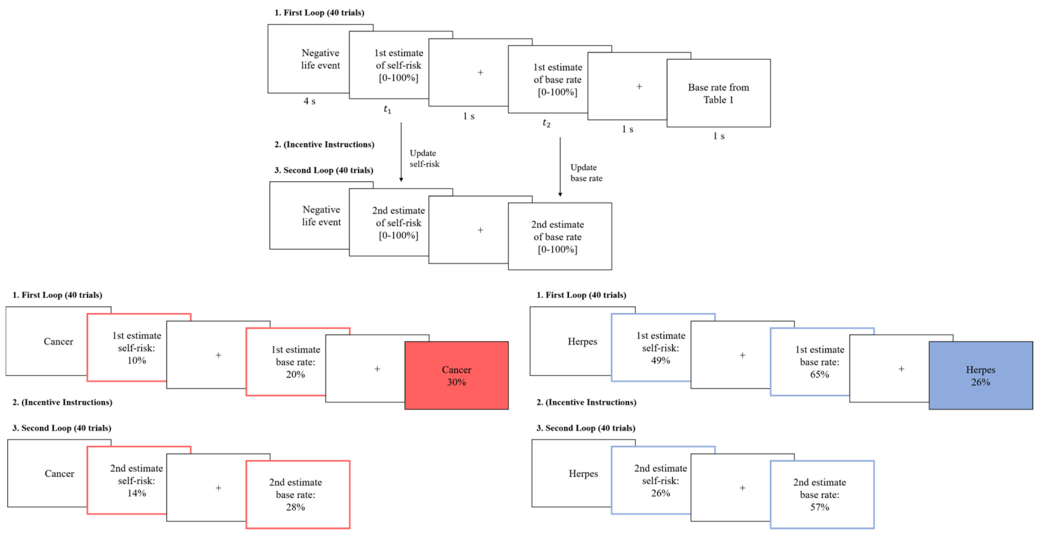

Figure 2 | Task paradigm. Own representation based on Garret and Sharot, 2014. Participants estimated their risk of incurring a given adverse life event and the respective population base rate. In the red illustration, the participant received undesirable information ("bad news") for their self-risk and base rate estimates and therefore updates (2^{nd} estimate - 1^{st} estimate) were rather small. In the blue illustration, the participant received desirable information ("good news") for their self-risk and base rate estimates and therefore updates were higher. In between sets, the two incentive groups received different instructions.

experienced one of the events, they were instructed to give an estimate of how likely they deemed the event occurring to them again.

To see how participants change their beliefs about incurring adverse life events (or about the population base rates, respectively) after having received either desirable or undesirable new information, participants were asked to estimate their self-risk and the base rate again. In the second set of trials, actual event probabilities were not presented again. In both sets of trials, the order of the events was randomized. Figure 2 illustrates the behavioural task.

2.5.2 The Experimental Session. Participants were randomly assigned to incentive conditions (n_{inc} = 35, $n_{non\text{-}inc}$ = 39). After they gave informed consent and read the instructions, participants completed two training trials. Then followed the two sets of 40 trials each, that for each event, two estimates were given. After the behavioural task, participants were asked to give an estimate about how accurate they deemed the presented base rates. Then, participants filled out the LOT-R and PHQ-9 scales, gave demographic information, including age, sex, field of study, number of university semesters, math grade in high school, and continent on which they spent most of their childhood. The latter was asked to control for potential culture-specific differences. Lastly, participants indicated whether they had participated in an experiment using the same materials before. After the experiment, participants were thanked, debriefed, and paid.

2.6 Incentive

In the present study, we were interested in whether participants exhibit biased learning even when they have an incentive not to. Therefore, after the first set of trials, participants in the incentivized group were told that "with a little bit of luck" they could win a "considerable" amount of money[2]. To do so, they were asked to estimate the average population risk of incurring the events as precisely as possible in the second set of trials. We hypothesized that this would lead to non-biased learning for the population risk estimates. The incentive was calculated by drawing a random event at the end of the experiments and comparing the participants' second estimate of the population risk with the provided base rate. The smaller the absolute difference between these two numbers, the higher the paid amount. If the difference was greater than 30 percentage points, participants did not receive any additional pay. If the difference equalled zero, participants gained the maximum extra amount of 6€. Thus, participants received 0.2€ for each percentage point their estimate was closer to the provided base rate than 30 percentage points. To pay participants in the non-incentivized group approximately equally, they received an additional flat-rate bonus

[2] These instructions were taken from Thies (2018) and used in accordance with personal communication with Anja Achtziger (2017), who argued that giving concise information about the incentive mechanism and especially about incentive rate may lead to unwanted interferences with the participants' thought processes.

of 3.20€ which equals an average divergence of 14 percentage points from the base rate. This average divergence was taken from a previous pilot study (Ludwig, 2017).

To avoid confounding effects of the instructions between the first and second set of trials, the instructions of the non-incentivized group and the incentivized group were aligned such that participants in both groups were told that they should try to estimate the base rates as good as possible, but the non-incentivized group was not informed about an extra payment. Another crucial issue is the placement of the incentive instructions. If participants were informed about the incentive at the beginning of the experiment, they might have tried to memorize the event probabilities, potentially distorting the results. For this reason, it was decided to inform the participants about the incentive after they already had completed the first set of trials, so they would have no motivation to remember the event probabilities. Memory effects may still occur, but they are expected to be negligible over the 40 randomized events.

3. Results

For the analysis, IBM SPSS Statistics 25 and R (R Core Team, 2017) in conjunction with the RStudio Software (RStudio Team, 2016) were used. Figures 4 and 5 were created using the R package ggplot2 (Wickham, 2009), Tables were created with the stargazer R package (Hlavac, 2018).

For each negative life event, two absolute belief update terms and two estimation error terms (henceforth EE) were computed as follows:

$$\text{Update}_{\text{Self-Risk}} = |\ \text{Second\_Estimate}_{\text{Self-Risk}} - \text{First Estimate}_{\text{Self-Risk}}\ |$$

$$\text{Update}_{\text{Base\_Rate}} = |\ \text{Second\_Estimate}_{\text{Base\_Rate}} - \text{First Estimate}_{\text{Base\_Rate}}\ |$$

$$\text{Estimation\_Error}_{\text{Self-Risk}} = |\ \text{First\_Estimate}_{\text{Self-Risk}} - \text{Provided\_Base\_Rate}\ |$$

$$\text{Estimation\_Error}_{\text{Base\_Rate}} = |\ \text{First\_Estimate}_{\text{Base\_Rate}} - \text{Provided\_Base\_Rate}\ |$$

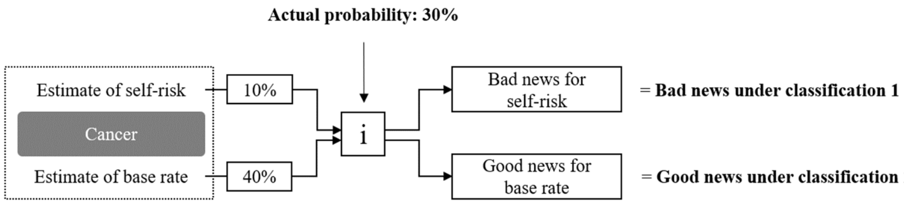

Figure 3 | Schematic representation of the classification procedure.

Note that all the terms are unsigned. The update terms express how much a participant changed his belief from the first estimate after having received new information; the EE expresses by how much the participant initially over- or underestimated the risk of incurring a given event. Based on the EEs, trials were classified as either desirable or undesirable information trials, using two criteria. For the first classification ("classification one"), trials were classified as desirable ("good news") when the participant initially overestimated their self-risk to incur the event relative to the provided base rate (i.e., trials with a signed EE for self-risk greater than zero). Trials were classified as undesirable ("bad news") when the participant initially underestimated their self-risk to incur the event relative to the provided base rate (i.e., trials with a signed EE for self-risk smaller than zero). For the second classification ("classification two"), trials were classified as desirable or undesirable depending on whether the participant initially overestimated or underestimated the *population risk* relative to the provided base rate (i.e., trials with a signed EE for population risk greater or smaller than zero). This classification procedure is exemplified in Figure 3.

3.1 Data Exclusion

Twenty-five participants indicated that they had participated in a preceding experiment using the same materials (Thies, 2018), and thus, were excluded from all further analyses. If not indicated differently, data of six additional participants were not used for analysis due to PHQ-9 scores of ten or higher, indication a (mild) major depression. This was done since depressed individuals were found not to exhibit biased learning (Korn et al., 2013). Moreover, one participant was excluded because he gave self-risk estimates of 0% for 73 out of 80 trials. As a result of data exclusion, all analyses reported here are based on a sample size of $N = 43$. Note that the substantial reduction of the sample lead to a substantial reduction of observed power (see section 4.3).

Of the remaining data points, trials were excluded from the analysis if participants needed more than ten seconds for an estimate. Also, trials in which the EE was zero, i.e., trials in which the participants' first estimates of self-risk or population risk equalled the base rate, were excluded. Lastly, trials in which the estimate was either 0% or 100% were not analysed. Since participants were told that all probabilities laid between 3% and 77%, excluding these trials was deemed appropriate. Note that if one information (e.g. the self-risk estimate) was excluded for one of the reasons mentioned above, the other one (e.g. the population risk estimate) was still included in the analysis, if it does not meet any of the exclusion criteria. After the data was excluded, 2953 (86%) self-risk estimations and 3211 (93%) base rate estimations were left from a total of 3440 estimations each.

3.2 Measures

Cronbach's alphas were calculated for the LOT-R ($\alpha = .54$) and PHQ ($\alpha = .77$). Overall, participants scored relatively high on the LOT-R ($M = 17.36$, $sd = 2.55$) and relatively low on the PHQ ($M = 5.17$, $sd = 2.39$, not including participants with a PHQ score of ten or higher). Furthermore, the participants deemed the presented base rates to be reasonably accurate ($M = 51.34\%$, $sd = 21.04\%$). Participants across incentive conditions did not differ in these measures (see Table 3 in the appendix for an overview).

3.3 Covariates

Most studies using similar task paradigms as Sharot et al. (2011) include the EE as a covariate to rule out the possibility that the initial error is solely responsible for the observed differential updating, as suggested by formal learning theories (Sharot et al., 2011). Thus, in the subject-based analyses, we control for the average difference between average EEs for good and bad news, while in the trial-based analyses, we control for the EE for each trial. We perform the analyses on both a by-trial level and a by-subject level since covariates vary from trial to trial and subjects' average EEs may be misleading (Garret & Sharot, 2017).

3.4 Trial-based Analyses

First, we conducted independent-samples t-tests to compare absolute updates after receiving either desirable or undesirable information. Under classification one, the difference between self-risk updates for undesirable and desirable information was statistically significant: participants updated their self-risk estimates more after they received desirable information (good news) than after they received undesirable information (bad news), M_{Bad} = 11.22, sd = 11.25, M_{Good} = 16.25, sd = 14.36, $t(1510) = -7.61$, $p < .001$, $d = 0.40$. A similar but less pronounced pattern was observed for updates of population risk estimates, M_{Bad} = 15.14, sd = 13.24, M_{Good} = 16.73, sd = 14.68, $t(1510) = -2.19$, $p < .05$, $d = 0.11$. Under classification two, updates for undesirable and desirable information differed significantly for self-risk, M_{Bad} = 11.59, sd = 11.64, M_{Good} = 14.53, sd = 14.27, $t(1547) = -4.44$, $p < .001$, $d = 0.23$, and for population risk, M_{Bad} = 15.17, sd = 13.36, M_{Good} = 16.58, sd = 14.54, $t(1547) = -1.98$, $p < .05$, $d = 0.1$.

We then entered absolute updates for self-risk and population risk estimates into a 2 (information desirability: good news vs. bad news, between) x 2 (incentive condition: incentivized vs. not incentivized, between) analysis of covariance (ANCOVA) with the EEs as covariate. This was done for both classifications. Note that under classification one, self-risk EEs were used as covariate, while under classification two, we controlled for population risk EEs. Under classification one, there was a significant main effect of information desirability on update of self-risk estimates, $F(1, 1507) = 58.63$, $p < .001$, $\eta_p^2 = .04$, and a marginally significant main effect of information desirability on update of population risk estimates, $F(1, 1507) = 3.24$, $p < .1$, $\eta_p^2 = .002$, such that updates towards desirable information were greater than updates towards undesirable information. Under classification two, the main effect of information desirability was statistically significant for update of self-risk, $F(1, 1544) = 9.04$, $p < .01$, $\eta p^2 = .01$, but not for population risk, $F(1, 1544) = 1.2$, $p > .25$. No statistically significant main effect nor interaction with information desirability was observed for incentive condition (all *F*s < 1). Tables 22-25 summarise these findings.

To extend this traditional approach to analysing self-risk and population updates, we computed three linear regression models for each classification and type of estimate (self-risk, population risk). In the first model, absolute updates were regressed on information desirability (bad news vs. good news), condition (incentivized vs. not incentivized) and EEs. The second model added PHQ scores and sex as additional predictors. Note that we also included subjects with a PHQ score higher than or equal to ten. Lastly, the third model added three interaction terms: incentive condition by information desirability, PHQ score by information desirability, and EE by information desirability. For self-risk update under classification one, the three models are summarized in Table 1. The hierarchical regression models for population risk

	Dependent variable:		
	Absolute Update of self-risk estimates		
	(1)	(2)	(3)
type of news	4.478***	4.335***	3.405*
	(0.589)	(0.588)	(1.502)
EE self-risk	0.293***	0.294***	0.181***
	(0.021)	(0.021)	(0.030)
PHQ score		−0.035	0.149
		(0.084)	(0.111)
sex		2.467***	2.655***
		(0.580)	(0.618)
condition			0.894
			(0.801)
type of news*condition			−0.261
			(1.185)
type of news*PHQ score			−0.510**
			(0.169)
type of news*EE self-risk			0.220***
			(0.041)
constant	5.681***	4.680***	5.207***
	(0.548)	(0.822)	(1.096)
Observations	1,711	1,711	1,711
R^2	0.135	0.144	0.164
ΔR^2		0.009***	0.020***
Adjusted R^2	0.134	0.142	0.160
Residual Std. Error	12.013 (df = 1708)	11.955 (df = 1706)	11.828 (df = 1702)
F Statistic	132.742*** (df = 2; 1708)	71.636*** (df = 4; 1706)	41.685*** (df = 8; 1702)
Note:			*p<0.05; **p<0.01; ***p<0.001

Table 1 | Results of hierarchical regression analyses for update of self-risk (trial level, classification 1). Information desirability (type of news), sex, and condition are dummy variables with the value 0 representing bad news, female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

under classification one and for self-risk and population risk under classification two are found in the appendix.

For self-risk under classification one, information desirability is a significant predictor for subsequent update in all three models, such that the update is greater for good news than for bad news. The same is true for the EE: for every percentage point of divergence, the subsequent estimation update will increase by a fraction of a percentage point. Interestingly, we also found sex to be a significant predictor: ceteris paribus, updates from male participants were greater than updates from females. As expected, we also found two of the interactions to be statistically significant. The information desirability by PHQ score interaction can be interpreted such that more depressive participants (those with higher PHQ scores) updated less after receiving good news than participants who are less or not at all depressive. Finally, the information desirability by EE of self-risk interaction shows that the magnitude of EE predicted greater updates only after participants received desirable information. In other words, participants "learned" more from desirable than from undesirable information. This confirms the hypothesis that selective updating is not contingent on the EE and updating for good news is greater than updating for bad news. Note that the difference in R^2 (denoted by ΔR^2) is statistically significant for models two and three, i.e., both models explain significantly more variation of the dependent variable than the respective previous models.[3] For population risk under classification one (see Table 4 in the appendix), information desirability was a significant predictor only in the first two models, while the EE, again, was a significant predictor in all three models. However, models two and three did not explain significantly more variation of the dependent variable than does model one. Incentive condition was not a significant predictor in any of the models.

Under classification two, for self-risk, information desirability is a significant predictor of update in the first two models, while the EE significantly predicted self-risk update in all three models (see Table 5 in the appendix). As in classification one, male participants updated more than their female counterparts. The interaction between information desirability and EE of population risk reached statistical significance as well, indicating that participants learned more from EEs they have made when they received good news than when they received bad news. Note that the

[3] To identify whether differences in R^2s were significant, ANOVAs comparing the residual sums of squares of the three models were conducted (cf. University of Virginia Library, 2016).

third model did not explain significantly more variation than the second model. For population risk updates under classification two, information desirability was not a significant predictor in any of the models (see Table 6 in the appendix). Again, the EE (for population risk) was a strong predictor for subsequent updates. Additionally, the PHQ score negatively predicted updates for population risk: higher values on the PHQ were associated with lower updates in general. Model three did not add any explained variation to model two. Again, incentive condition and the incentive condition by information desirability interaction were not significant predictors.

Comparing all models, it stands out that the information desirability by EE interaction was significant for self-risk under both classifications but not for population risk. Furthermore, sex was a significant predictor for self-risk under both classifications but not for population risk under either classification.

3.5 Subject-based Analyses

On a by-subject level, paired-samples t-tests revealed that, under classification one, the differences in updates for both self-risk and population risk estimates were statistically significant: participants updated their self-risk and population estimates more after having received desirable information than after having received undesirable information, $M_{\text{Self\_Bad\_C1}} = 11.61$, $sd = 4.08$, $M_{\text{Self\_Good\_C1}} = 16.41$, $sd = 5.73$, $t(40) = -5.00$, $p < .001$, $d = 0.95$, $M_{\text{Pop\_Bad\_C1}} = 14.83$, $sd = 5.95$, $M_{\text{SPop\_Good\_C1}} = 16{,}80$, $sd = 4.89$, $t(40) = -2.08$, $p < .05$, $d = 0.37$. Under classification two, only updates for self-risk differed significantly, $M = 11.57$, $sd = 14.08$, $t(42) = -3.14$, $p < .01$, $d = 0.57$.

To control for the possibility that differences in update are due to differences in the magnitude of EEs, for each classification, average updates were entered into a 2 (information desirability: good news vs. bad news, within) x 2 (type of estimate: self-risk vs. population risk, within) x 2 (incentive condition: incentivized vs. not incentivized, between) repeated-measures analyses of covariance (ANCOVA) with the differences in EEs as covariates. Under classification one, the model did not reveal any significant main effects or interactions. However, there was a marginally significant main effect for the type of estimate, such that updates were smaller for self-risk estimates than for estimates of population risk, $F(1, 38) = 3.35$, $p < .1$, $\eta_p{}^2 = .08$.

Under classification two, a similar but more obvious pattern was observed. There was a significant main effect of type of estimate, $F(1, 39) = 15.46$, $p < .001$, $\eta_p{}^2 = 0.28$, and a marginally significant information desirability by type of estimate interaction, $F(1,39) = 3.76$, $p < .1$, $\eta_p{}^2 = .09$, such that for self-risk, the difference between updates for undesirable and desirable information was greater than for population risk. Tables 20-21 summarise these findings.

On the by-subject level, we computed similar regression models as for the by-trial level analysis. Since we deal with information desirability as a within-factor, we were not able to include the interactions of model three in these regressions. None of the models' effect sizes was significantly greater than zero (Tables 7 - 14).

3.6 Explorative Analysis

When comparing self-risk estimates and population risk estimates on a subject level, we found that, on average, participants initially estimated their self-risk to incur the negative life events lower than they estimated the population risk ($M_{\text{First\_Estimate\_Self}} = 32.12$, $sd = 7.89$, $M_{\text{First\_Estimate\_Pop}} = 37.10$, $sd = 4.99$, $t(42) = -4.10$, $p < .001$, $d = 0.54$). This is also true for the participants' second estimates ($M_{\text{Second\_Estimate\_Self}} = 30.12$, $sd = 8.16$, $M_{\text{Second\_Estimate\_Pop}} = 36.67$, $sd = 4.21$, $t(42) = -5.23$, $p < .001$, $d = 0.69$). This supports prior research regarding unrealistic optimism (e.g. Weinstein, 1980).

We also checked for sex differences by including the sex variable as a factor in a 2 (information desirability: good news vs. bad news, between) x 2 (incentive condition: incentivized vs. not incentivized, between) x 2 (sex: female vs. male, between) ANCOVA and we found a significant interaction of information desirability, incentive condition and sex on the by-trial level, $F(1, 1503) = 8.60$, $p < .01$, $\eta_p^2 = .01$. The same effect was revealed using a 2 (information desirability: good news vs. bad news, within) x 2 (incentive condition: incentivized vs. not incentivized, between) x 2 (sex: female vs. male, between) repeated measures ANCOVA on the by-subject level, $F(1, 36) = 5.07$, $p < .05$, $\eta_p^2 = 0.12$. This effect was only observed for population risk updates under classification one, i.e. when classifying news based on the participants' self-risk estimates. Female participants in the incentivized condition exhibited less selective updating behaviour for population risk than female participants in the non-incentivized condition, while males across conditions did not differ. In other words, for females, the incentive treatment had the hypothesized effect and did contribute to less selective updating behaviour.

We also analysed estimation times. Paired samples t-tests revealed that participants were slower in giving their first estimates than in giving their second estimates for self-risk, $t(41) = 5.60$, $p < .001$, $d = -0.83$, and population risk, $t(41) = 5.12$, $p < .001$, $d = -0.73$. Additionally, participants took significantly longer for their estimate of population risk than for their estimate of self-risk. This was true for both first, $t(41) = -5.38$, $p < .001$, $d = 0.86$, and second estimates, $t(41) = -5.50$, $p < .001$, $d = 0.84$. Furthermore, participants needed more time estimating their self-risk when they were about to receive bad news for their self-risk than when they were about to receive good news. This effect only reached marginal significance, $t(41) = 1.865$, $p < .1$, $d = -0.21$. Table 19 in the appendix summarises these findings.

Regarding belief updating, formal learning models suggest that learning is mediated by an error signal (Sharot, 2011). In the present case, the error signal is given by the EE, which exerts great influence on subsequent update. To test whether selective updating is not just an artefact due to the initial error, several methods have been proposed other than using the EE as a covariate. One of these methods is to calculate a learning rate (Kappes et al., 2018), i.e. the unstandardized regression coefficient of the EE regressed on update. For our data, paired samples t-tests showed that learning rates for good and bad news differed significantly only for self-risk estimates under classification one ($M_{\text{LR\_Bad}}$ = 0.23, sd = 0.32, $M_{\text{LR\_Good}}$ = 0.48, sd = 0.45, $t(39)$ = -3.39, p < .01, d = 0.66). A second method that has been suggested by Ludwig (2017) is to calculate the update as percentage of the EE. For our sample, comparing these percentages for good versus bad news did reveal significant differences for self-risk under classification one, $M_{\text{Self\_Bad}}$ = 0.65, sd = 0.24, $M_{\text{Self\_Good}}$ = 0.88, sd = 0.36, $t(40)$ = -3.35, d = 0.66 and two, $M_{\text{Self\_Bad}}$ = 0.61, sd = 0.26, $M_{\text{Self\_Good}}$ = 0.75, sd = 0.25, $t(41)$ = -3.78, d = 0.57, but not for population risk under either classification (ts < 1.5).

4. Discussion

In the present study, we were able to replicate prior findings on a by-trial level (see Figure 4). Our results provide evidence for a selective belief updating for self-risk under classification one and two, confirming H1a and H1b. In other words, the optimistic update bias remains robust even under classification two, i.e., when classifying news in a way that is unrelated to the initial estimate of self-risk. Furthermore, on a by-trial level, a marginally significant selective updating effect was found for population risk estimates under classification one, but not two. Thereby, our data supports H2b, but only partially H2a. When analysing data on a by-subject level,

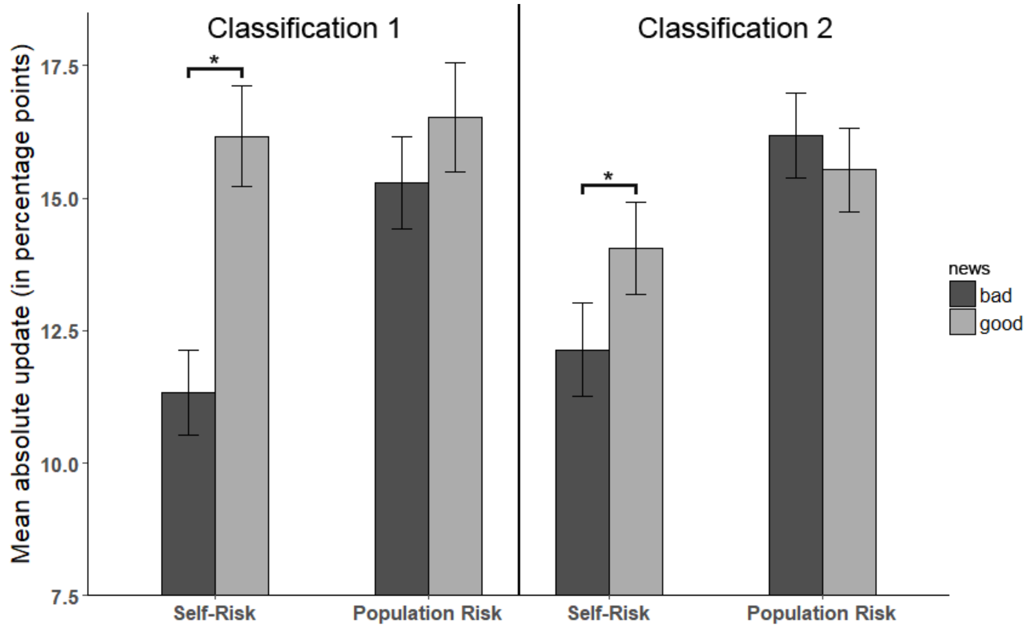

Figure 4 | Updating behaviour for self-risk and population risk under both classifications (trial level). Error bars represent standard errors, asterisks indicate a statistically significant difference ($p < .05$). $N_{\text{class1}} = 1512$, $N_{\text{class2}} = 1549$.

no evidence supporting our first and second hypotheses was found when explicitly controlling for the difference in EEs. However, when comparing updates for good and bad news as function of the estimation error, differences between updates for undesirable and desirable information were found, but only for self-risk.

Why would participants update their estimate of population risk selectively when trials were classified based on the initial over- or underestimation of self-risk (i.e. under classification one) but not under classification two? This somewhat stands in contrast to Kappes et al. (2018) who argued that individuals do not exhibit vicarious optimism for unidentified strangers[4]. At a glance, this behaviour suggests "spill-over" effects. Undesirable information for the self (i.e. bad news under classification one) might lead to less processing of the presented base rate information in general, thereby not only affecting subsequent estimates of self-risk but also estimates of population

[4] Although it is questionable whether a "person in the same sociocultural environment" meets the criteria of an unidentified stranger.

risk. Still, selective updating under classification one is much less pronounced for population risk estimates than for self-risk estimates. This might well be due to unrealistic optimism at the outset: the difference between individuals' estimates for their self-risk and the population risk will not cross a certain threshold because humans tend to think that bad things are more likely to happen to others (Weinstein, 1980). In fact, it was observed that the participants' second self-risk estimates were still more optimistic than their second population risk estimates.

Likewise, selective updating was less obvious for self-risk when classifying news relative to population risk estimates (classification two) and did not occur at all for population risk estimates. Summing up these findings, it may be suggested that individuals are affected by information that concerns themselves directly, while information regarding others is given less attention. According to Harris (2017), a motivated attention account would predict that in the update task paradigm, participants' attention would be drawn more towards emotionally relevant events, such as negative life events. Harris further cites Taylor's (1991, as cited in Harris, 2017) mobilization-minimization hypothesis which proposes that negative information is selectively attended to but in the following cognitive processes, their impact is decreased. Given our findings, one could assume that desirable or undesirable information regarding the risk of negative life events occurring to the population is of little (personal) emotional relevancy. Thus, under classification two selective updating is less pronounced for self-risk estimates and is de facto not existent for population risk estimates. This also implies that selective updating for self-risk under classification two may only occur because of the optimistic update bias's strength for self-risk estimates and coincidental parity of information (desirable or undesirable) for classification one and two (i.e., in many instances, information desirability is classified equally under both classification schemes).

Finally, our third hypothesis could not be confirmed by our planned analyses. Overall, even a relatively strong incentive did not lead to less selective updating for population risk estimates under any classification.

4.1 Discussion of the Regression Analyses

In this study, we added another element to our strategy of analysis. Instead of focussing on ANCOVAs only, we also conducted regression analyses which provided us with some additional interesting findings. While we were not able to deduct anything from the regression analyses on a by-subject level due to the sample reduction, the regression analyses on the trial level were more informative. For self-risk under classification one, we saw that the EE significantly predicts subsequent update but we could also clearly identify the effect of selective updating which is most apparent in the positive regression coefficient of the interaction between information desirability and EE. Furthermore, we saw that PHQ score has a negative influence on subsequent update after receiving good news only. This confirms prior findings that depressive populations display less belief updating after receiving desirable information (Korn et al., 2013). Similar results were obtained for self-risk under classification two, except that the PHQ score did not interact with information desirability. Under both classifications, male sex significantly predicted greater update for any type of news. This finding is somewhat puzzling, as the effect can hardly be attributed to male overconfidence (Lundeberg, Fox & Punćochaŕ, 1994) because it would imply more selective updating overall, but not a generally increased update for news of any type. For this reason, we exploratively added an EE by sex interaction term to our hierarchical regression models of update of self-risk and population risk.

We found that for self-risk under classification one, the new (fourth) model explained significantly more variation than the third model. Moreover, male sex did not significantly predict update anymore, but the EE by sex interaction did (see Table 15 in the appendix). For population risk, adding the EE by sex interaction term leads to a significant increase of R^2 relative to the other models (Table 16 in the appendix). Apparently, male participants are "learning" more from their EE. One possible explanation is given by the negativity bias. The negativity bias states that information with a negative valence has a more severe impact on subsequent psychological processes than information with a neutral or positive valence (Kanouse & Hanson, 1972). Findings of Grabe and Kamhawi (2006) indicate that there may be sex differences for the negativity bias. They observed that, for negative information, men had a better recognition memory than women. This explanation remains speculative, but we encourage to check for sex differences when assessing the strength of the EE as a predictor for following updates. Moreover, under classification two, the EE by sex interaction as predictor did not become significant for either self-risk or population risk (see Tables 17-18).

For population risk, the regression analyses revealed similar effects as the ANCOVA. Under classification one, the second and third regression models did not explain more than the first. So, information desirability and EE are significant predictors for subsequent update of population risk estimates. Interestingly, under classification two, while information desirability ceases to be a significant predictor for update of population risk (as in the ANCOVAs), the PHQ score exerts a statistically significant negative influence on update after either type of news. In other words, participants with higher PHQ scores generally updated less for news of either type under classification two. Even though there is evidence that depressive individuals display different belief updating patterns regarding their self-risk than healthy ones (e.g. Korn et al., 2013), there is not yet a clear image of how depressive individuals update their population risk estimates. With this finding, a first hint in that regard is given; but a closer and more specific investigation is needed to validate it.

Since the effect sizes of the regression analyses on the by-subject level are negligible, we refrain from further interpreting those. We would assume the EE to have a significant effect on subsequent update in all of the models. That this is not the case can probably be attributed to the restricted sample size.

4.2 Discussion of the Explorative Analysis

4.2.1 News, Incentive, and Sex. When controlling for sex in the explorative analysis on both a by-trial level and a by-subject level, we found a significant three-way interaction between incentive, information desirability, and sex under classification one. As indicated in Figure 5, it is characterized by the fact that incentivized female participants did not display selective updating while female participants who were not incentivized did. Men, on the other hand, did not display selective updating across conditions. This might also well be due to sex differences in the negativity bias as discussed above. Due to the negativity bias, men may be more affected by imagining negative events in

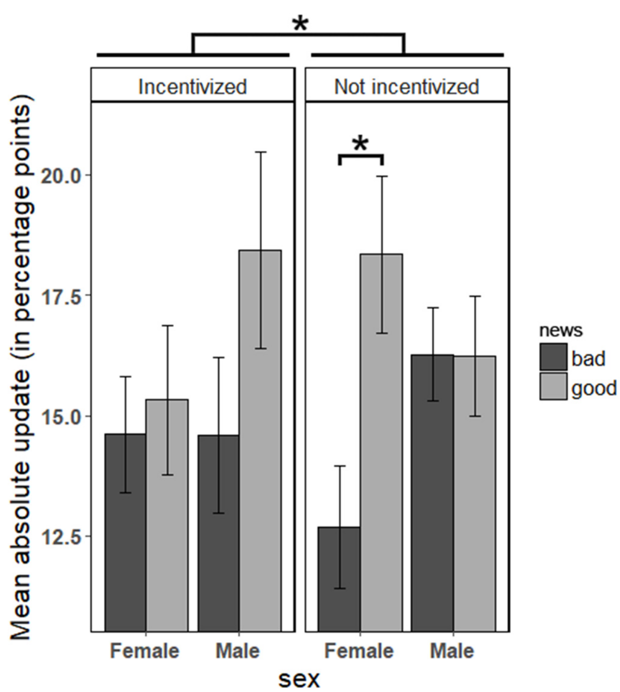

Figure 5 | Interaction of information desirability (news), incentive condition, and sex (subject level). Error bars represent standard errors, asterisks indicate a statistically significant difference ($p < .05$). $N_{inc} = 34$, $N_{non\text{-}inc} = 38$.

the first place and can remember them better later on (Grabe & Kamhawi, 2006). This may be an explanation why they do not exhibit selective updating behaviour for their population risk estimates. Women may be less affected by imagining negative events (Grabe and Kamhawi, 2006), which may be an explanation for their selective updating behaviour in the non-incentivized condition. However, when given an incentive, women may have enough motivation to overcome their selective updating behaviour.

4.2.2 Estimation Times. Participants were faster in giving estimates for self-risk than for population risk. The intuitive interpretation is that participants do have a clear picture of their own (low) risk, while they need to deliberate about the population base rate. Moreover, there was a tendency that participants gave their self-risk estimates faster when they were about to receive desirable information than when they were about to receive undesirable information. This somewhat strengthens similar findings of Thies (2018), who argued that this might be related to the availability heuristic (Tversky & Kahnemann, 1976). It states that individuals assess the probability of an event by the ease with which occurrences of that event come to mind. If certain negative life events are perceived as very common, participants may initially overestimate their risk of incurring them and then give their estimate very quickly due to the high cognitive availability. On the other hand, if an event is uncommon and less cognitively available, participants may tend to deliberate longer and then underestimate their risk, which eventually leads to bad news.

4.3 Limitations

Although we were able to find evidence supporting our hypothesis on a by-trial basis, this study suffered from the exclusion of 31 participants. The resulting sample size did not allow us to find any statistically significant effects on the by-subject basis after controlling for covariates. To solve this issue, supplementary experimental sessions with new subjects would be necessary, but could not be conducted within the scope of this work.

Another notable limitation is that the design of the present study differs from that of previous studies. In order to implement an incentive mechanism, the instructions had to be altered. The instructions for participants in the incentive group had to involve a description of the behaviour that was incentivized. In this case, unbiased belief updating for population risk estimates was incentivized. Hence, instructions were to estimate the population risk “as precisely as possible”, based on the base rate that participants were presented before. To isolate a possible incentive effect, the instructions across incentive conditions had to be aligned such that the non-incentivized group, too, received the instruction to estimate the population risk as precisely as possible, but not the information that there was an extra payment. This already constitutes a change to the usual instructions, which just read: “Please estimate your personal risk and the average risk, again”. Lacking studies which examine the unique effect of extending the instructions in such fashion, we cannot know whether this change already affects the outcome.

Furthermore, the observed power for some of our observations was very low. This especially concerns the effect of information desirability on updates of population risk estimates ($1\text{-}\beta \leq .5$, see Table 23). This could be due to the limited sample size, but this might also indicate that the effect is either very small or just a coincidental observation.

Lastly, the sample might not be representative, as it was drawn at a private university. It may be that the participants in the incentivized group were not any more motivated than those in the non-incentivized group because the promised incentive (“a considerable amount of money”) was not strong enough. Participants across conditions may also already have had a strong intrinsic base-line motivation to perform well (disregarding of whether they would receive additional pay or not) which would make it difficult to find differences between incentive conditions.

5. Conclusion

The present study asked the question:

Does a monetary incentive influence the optimistic update bias for population base rates?

Although we addressed the shortcomings of Thies (2018) regarding their incentive treatment, we did not find any evidence for our hypothesis that participants with a monetary incentive displayed less selective updating for population risk than those without. We conclude that the optimistic update bias is robust and not affected by monetary incentives. However, our exploratory analyses revealed sex differences in responding to the incentive treatment. Yet, the question also remains open whether individuals actually update their population risk estimate because the evidence we found was lacking statistical power.

With the present study, we also propose an alternative method of analysing data on a trial-level. With hierarchical regression models, it is possible to obtain an estimate by how much the single predictor variables actually influence the subsequent update. Lastly, we encourage optimistic update researchers to examine sex effects on updating in general, given our observations that initial error signals affect men and women differently, as becomes apparent in the interactions between sex and EE.

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7. Appendix

7.1 Stimuli

Table 2 | List of stimuli.

English original	German translation
Abnormal heart rhythm	Herzrhythmusstörungen
Alzheimer's disease	Alzheimer-Erkrankung
Arteries hardening (narrowing of blood vessels)	Arteriosklerose (Verkalkung der Blutgefäße)
Autoimmune disease	Autoimmunerkrankung
Being cheated by husband/wife	Ehemann/Ehefrau geht fremd
Bicycle theft	Fahrraddiebstahl
Bone Fracture	Knochenbruch
Cancer (of digestive system/lung/prostate/breast/skin)	Krebserkrankung (Magen/Darm/Lunge/Prostata/Brust/Haut)
Card fraud	Bank-/Kreditkartenbetrug
Chronic high blood pressure	Chronischer Bluthochdruck
Chronic ringing sound in ear (tinnitus)	Tinnitus (Ohrgeräusche)
Death before age 80	Tod vor dem 80. Lebensjahr
Dementia	Demenz
Diabetes (type 2)	Diabetes
Divorce	Scheidung
Domestic Burglary	Einbruch in Haus/Wohnung
Fraud when buying something on the internet	Betrug bei Internetkauf
Having a stroke	Schlaganfall
Having fleas/lice	Läuse haben
Heart failure	Herzversagen
Hepatitis A or B	Hepatitis A oder B
Herpes	Herpes
Household accident	Haushaltsunfall
Irritable bowel syndrome (disorder of the gut)	Reizdarm
Knee osteoarthritis (causing knee pain and swelling)	Kniearthrose
Liver disease	Lebererkrankung
Migraine	Migräne
More than £30000 of debts	Schulden über 50.000 Euro
Obesity	Fettleibigkeit
Osteoporosis (reduced bone density)	Osteoporose (Knochenschwund)
Severe hearing problems	Schwere Hörprobleme
Severe teeth problems when old	Schwere Zahnprobleme im Alter
Skin burn	Verbrennung (1. / 2. / 3. Grades)
Sport-related accident	Sportunfall
Theft from person	Opfer von Taschendiebenstahl
Victim of violence at home	Opfer von häuslicher Gewalt
Victim of violence by acquaintance	Opfer von Gewalt durch einen Bekannten
Victim of violence by stranger	Opfer von Gewalt durch einen Fremden
Victim of violence with need to go to A&E	Gewaltopfer mit Notaufnahmenaufenthalt
Witness of a traumatizing accident	Zeuge eines traumatisierenden Unfalls

7.2 Sample Descriptive Statistics

Table 3 | Sample descriptive statistics.

Characteristic	Incentivized	Not incentivized	Total
n	35	39	74
Female sex	60%	31%	45%
Age (years)	21.83	22.1	22
Field of study	CCM (7) CME (9) PAIR (6) SPE (13)	CCM (3) CME (14) PAIR (5) SPE (17)	CCM (10) CME (23) PAIR (11) SPE (30)
Continent of origin	97% Europe	97% Europe	97% Europe
Math grade in high school	2.45	2.05	2.24
LOT-R	16.71	17.15	16.95
PHQ	7.29	5.92	6.57

Notes:

Math grade in high school follows the German grading system from 1 (excellent) to 6 (insufficient).

Possible minimum / maximum of LOT-R: 0 / 24 (high values indicate high trait optimism).

Possible minimum / maximum of PHQ: 0 / 27 (high values indicate depression).

Fields of Study at Zeppelin University: CCM (Communication, Culture & Management), CME (Corporate Management & Economics), PAIR (Politics, Administration, and International Relations, SPE (Sociology, Politics & Economics).

7.3 Hierarchical Regression Models

Table 4 | Results of hierarchical regression analyses for update of population risk (trial level, classification 1). Information desirability (type of news), sex, and condition are dummy variables with the value 0 representing bad news, female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of population risk estimates		
	(1)	(2)	(3)
type of news	1.438*	1.419*	2.115
	(0.624)	(0.626)	(1.617)
EE self-risk	0.357***	0.357***	0.366***
	(0.022)	(0.022)	(0.032)
PHQ score		−0.103	−0.115
		(0.089)	(0.120)
sex		0.750	1.034
		(0.617)	(0.665)
condition			1.078
			(0.863)
type of news*condition			−0.759
			(1.276)
type of news*PHQ score			−0.005
			(0.182)
type of news*EE self-risk			−0.018
			(0.044)
constant	8.155***	8.439***	7.730***
	(0.580)	(0.876)	(1.180)
Observations	1,711	1,711	1,711
R^2	0.137	0.139	0.140
ΔR^2		0.002	0.001
Adjusted R^2	0.136	0.137	0.136
Residual Std. Error	12.731 (df = 1708)	12.728 (df = 1706)	12.736 (df = 1702)
F Statistic	135.934*** (df = 2; 1708)	68.747*** (df = 4; 1706)	34.553*** (df = 8; 1702)
Note:			*p<0.05; **p<0.01; ***p<0.001

Table 5 | Results of hierarchical regression analyses for update of self-risk (trial level, classification 2). Information desirability (type of news), sex, and condition are dummy variables with the value 0 representing bad news, female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of self-risk estimates		
	(1)	(2)	(3)
type of news	1.674**	1.655**	1.887
	(0.590)	(0.589)	(1.464)
EE population risk	0.340***	0.339***	0.283***
	(0.022)	(0.022)	(0.036)
PHQ score		−0.043	0.091
		(0.084)	(0.128)
sex		2.244***	2.452***
		(0.584)	(0.628)
condition			0.808
			(0.891)
type of news*condition			−0.431
			(1.198)
type of news*PHQ score			−0.265
			(0.172)
type of news*EE population risk			0.094*
			(0.046)
constant	6.252***	5.439***	5.067***
	(0.548)	(0.804)	(1.147)
Observations	1,758	1,758	1,758
R^2	0.127	0.134	0.138
ΔR^2		0.007***	0.004
Adjusted R^2	0.126	0.132	0.134
Residual Std. Error	12.260 (df = 1755)	12.214 (df = 1753)	12.201 (df = 1749)
F Statistic	127.348*** (df = 2; 1755)	67.996*** (df = 4; 1753)	35.028*** (df = 8; 1749)

Note: *p<0.05; **p<0.01; ***p<0.001

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Table 6 | Results of hierarchical regression analyses for update of population risk (trial level, classification 2). Information desirability (type of news), sex, and condition are dummy variables with the value 0 representing bad news, female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of population risk estimates		
	(1)	(2)	(3)
type of news	−0.505	−0.425	−0.437
	(0.529)	(0.530)	(1.320)
EE population risk	0.645***	0.646***	0.641***
	(0.020)	(0.020)	(0.032)
PHQ score		−0.205**	−0.228*
		(0.075)	(0.116)
sex		−0.072	−0.021
		(0.526)	(0.566)
condition			0.625
			(0.803)
type of news*condition			−0.998
			(1.080)
type of news*PHQ score			0.044
			(0.155)
type of news*EE population risk			0.009
			(0.041)
constant	4.844***	6.102***	6.049***
	(0.492)	(0.723)	(1.034)
Observations	1,758	1,758	1,758
R^2	0.372	0.375	0.375
ΔR^2		0.003*	0
Adjusted R^2	0.372	0.374	0.373
Residual Std. Error	11.005 (df = 1755)	10.988 (df = 1753)	10.998 (df = 1749)
F Statistic	520.784*** (df = 2; 1755)	263.034*** (df = 4; 1753)	131.409*** (df = 8; 1749)
Note:			*p<0.05; **p<0.01; ***p<0.001

Table 7 | Results of hierarchical regression analyses for update of self-risk after participants received bad news (subject level, classification 1). Sex and condition are dummy variables with the value 0 representing female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of self-risk estimates for bad news		
	(1)	(2)	(3)
EE self-risk	−0.002	0.005	0.020
	(0.138)	(0.142)	(0.143)
PHQ score		0.063	0.032
		(0.173)	(0.175)
sex		1.137	1.636
		(1.213)	(1.294)
condition			−1.458
			(1.337)
constant	11.663***	10.639***	11.332***
	(0.993)	(1.764)	(1.871)
Observations	47	47	47
R^2	0	0.022	0.049
ΔR^2		0.022	0.027
Adjusted R^2	0	0	0
Residual Std. Error	4.092 (df = 45)	4.140 (df = 43)	4.131 (df = 42)
F Statistic	0.0002 (df = 1; 45)	0.320 (df = 3; 43)	0.538 (df = 4; 42)
Note:			*p<0.05; **p<0.01; ***p<0.001

Table 8 | Results of hierarchical regression analyses for update of self-risk after participants received good news (subject level, classification 1). Sex and condition are dummy variables with the value 0 representing female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of self-risk estimates for good news		
	(1)	(2)	(3)
EE self-risk	0.240	0.195	0.195
	(0.193)	(0.191)	(0.194)
PHQ score		−0.220	−0.218
		(0.232)	(0.238)
sex		3.109	3.091
		(1.627)	(1.760)
condition			0.051
			(1.818)
constant	14.837***	14.914***	14.890***
	(1.390)	(2.366)	(2.545)
Observations	47	47	47
R^2	0.033	0.132	0.132
ΔR^2		0.099	0
Adjusted R^2	0.012	0.072	0.050
Residual Std. Error	5.730 (df = 45)	5.554 (df = 43)	5.619 (df = 42)
F Statistic	1.548 (df = 1; 45)	2.184 (df = 3; 43)	1.600 (df = 4; 42)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 9 | Results of hierarchical regression analyses for update of population risk after participants received bad news (subject level, classification 1). Sex and condition are dummy variables with the value 0 representing female sex, and non- incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of population risk estimates for bad news		
	(1)	(2)	(3)
EE self-risk	−0.065	−0.094	−0.084
	(0.133)	(0.135)	(0.137)
PHQ score		−0.148	−0.168
		(0.164)	(0.167)
sex		1.370	1.690
		(1.153)	(1.239)
condition			−0.933
			(1.280)
constant	15.047***	15.460***	15.904***
	(0.959)	(1.676)	(1.792)
Observations	47	47	47
R^2	0.005	0.059	0.070
ΔR^2		0.054	0.016
Adjusted R^2	0	0	0
Residual Std. Error	3.953 (df = 45)	3.934 (df = 43)	3.956 (df = 42)
F Statistic	0.240 (df = 1; 45)	0.894 (df = 3; 43)	0.796 (df = 4; 42)
Note:			*p<0.05; **p<0.01; ***p<0.001

Table 10 | Results of hierarchical regression analyses for update of population risk after participants received good news (subject level, classification 1). Sex and condition are dummy variables with the value 0 representing female sex, and non- incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of population risk estimates for good news		
	(1)	(2)	(3)
EE self-risk	0.107	0.098	0.095
	(0.169)	(0.176)	(0.179)
PHQ score		−0.060	−0.053
		(0.213)	(0.219)
sex		−0.286	−0.394
		(1.498)	(1.620)
condition			0.316
			(1.673)
constant	16.267***	16.848***	16.697***
	(1.214)	(2.177)	(2.342)
Observations	47	47	47
R^2	0.009	0.011	0.012
ΔR^2		0.002	0.001
Adjusted R^2	0	0	0
Residual Std. Error	5.003 (df = 45)	5.112 (df = 43)	5.170 (df = 42)
F Statistic	0.403 (df = 1; 45)	0.164 (df = 3; 43)	0.129 (df = 4; 42)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 11 | Results of hierarchical regression analyses for update of self-risk after participants received bad news (subject level, classification 2). Sex and condition are dummy variables with the value 0 representing female sex, and non- incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of self-risk estimates for bad news		
	(1)	(2)	(3)
EE population risk	−0.049	−0.089	−0.085
	(0.143)	(0.149)	(0.151)
PHQ score		0.088	0.080
		(0.182)	(0.187)
sex		1.331	1.450
		(1.306)	(1.412)
condition			−0.340
			(1.431)
constant	11.824***	10.797***	10.965***
	(0.986)	(1.590)	(1.756)
Observations	49	49	49
R^2	0.003	0.028	0.029
ΔR^2		0.025	0.004
Adjusted R^2	0	0	0
Residual Std. Error	4.388 (df = 47)	4.427 (df = 45)	4.474 (df = 44)
F Statistic	0.118 (df = 1; 47)	0.431 (df = 3; 45)	0.331 (df = 4; 44)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 12 | Results of hierarchical regression analyses for update of self-risk after participants received good news (subject level, classification 2). Sex and condition are dummy variables with the value 0 representing female sex, and non- incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of self-risk estimates for good news		
	(1)	(2)	(3)
EE population risk	−0.019	−0.110	−0.098
	(0.192)	(0.194)	(0.196)
PHQ score		0.065	0.036
		(0.237)	(0.243)
sex		3.415	3.837*
		(1.703)	(1.834)
condition			−1.202
			(1.858)
constant	14.206***	12.538***	13.132***
	(1.325)	(2.074)	(2.280)
Observations	49	49	49
R^2	0	0.082	0.091
ΔR^2		0.082	0.009
Adjusted R^2	0	0	0
Residual Std. Error	5.897 (df = 47)	5.774 (df = 45)	5.811 (df = 44)
F Statistic	0.010 (df = 1; 47)	1.345 (df = 3; 45)	1.100 (df = 4; 44)

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 13 | Results of hierarchical regression analyses for update of population risk after participants received bad news (subject level, classification 2). Sex and condition are dummy variables with the value 0 representing female sex, and non- incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of population risk estimates for bad news		
	(1)	(2)	(3)
EE population risk	−0.178	−0.200	−0.192
	(0.142)	(0.145)	(0.147)
PHQ score		−0.196	−0.216
		(0.178)	(0.182)
sex		1.433	1.725
		(1.276)	(1.374)
condition			−0.834
			(1.393)
constant	15.828***	16.463***	16.874***
	(0.980)	(1.554)	(1.709)
Observations	49	49	49
R^2	0.032	0.089	0.096
ΔR^2		0.057	0.007
Adjusted R^2	0.012	0.028	0.014
Residual Std. Error	4.361 (df = 47)	4.325 (df = 45)	4.356 (df = 44)
F Statistic	1.567 (df = 1; 47)	1.462 (df = 3; 45)	1.171 (df = 4; 44)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 14 | Results of hierarchical regression analyses for update of population risk after participants received good news (subject level, classification 2). Sex and condition are dummy variables with the value 0 representing female sex, and non- incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:		
	Absolute Update of self-risk estimates for good news		
	(1)	(2)	(3)
EE population risk	−0.019	−0.110	−0.098
	(0.192)	(0.194)	(0.196)
PHQ score		0.065	0.036
		(0.237)	(0.243)
sex		3.415	3.837*
		(1.703)	(1.834)
condition			−1.202
			(1.858)
constant	14.206***	12.538***	13.132***
	(1.325)	(2.074)	(2.280)
Observations	49	49	49
R^2	0	0.082	0.091
ΔR^2		0.082	0.009
Adjusted R^2	0	0	0
Residual Std. Error	5.897 (df = 47)	5.774 (df = 45)	5.811 (df = 44)
F Statistic	0.010 (df = 1; 47)	1.345 (df = 3; 45)	1.100 (df = 4; 44)

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 15 | Results of hierarchical regression analyses for update of self-risk (trial level, classification 1), including the EE by sex interaction. Information desirability (type of news), sex, and condition are dummy variables with the value 0 representing bad news, female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:			
	Absolute Update of self-risk estimates			
	(1)	(2)	(3)	(4)
type of news	4.478***	4.335***	3.405*	3.415*
	(0.589)	(0.588)	(1.502)	(1.500)
EE self-risk	0.293***	0.294***	0.181***	0.131***
	(0.021)	(0.021)	(0.030)	(0.035)
PHQ score		−0.035	0.149	0.150
		(0.084)	(0.111)	(0.111)
sex		2.467***	2.655***	0.652
		(0.580)	(0.618)	(0.999)
condition			0.894	0.912
			(0.801)	(0.800)
type of news*condition			−0.261	−0.166
			(1.185)	(1.184)
type of news*PHQ score			−0.510**	−0.498**
			(0.169)	(0.169)
type of news*EE self-risk			0.220***	0.211***
			(0.041)	(0.041)
EE self-risk*sex				0.105*
				(0.041)
constant	5.681***	4.680***	5.207***	6.178***
	(0.548)	(0.822)	(1.096)	(1.159)
Observations	1,711	1,711	1,711	1,711
R^2	0.135	0.144	0.164	0.167
ΔR^2		0.009***	0.020***	0.003*
Adjusted R^2	0.134	0.142	0.160	0.163
Residual Std. Error	12.013 (df = 1708)	11.955 (df = 1706)	11.828 (df = 1702)	11.809 (df = 1701)
F Statistic	132.742*** (df = 2; 1708)	71.636*** (df = 4; 1706)	41.685*** (df = 8; 1702)	37.895*** (df = 9; 1701)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 16 | Results of hierarchical regression analyses for update of population risk (trial level, classification 1), including the EE by sex interaction. Information desirability (type of news), sex, and condition are dummy variables with the value 0 representing bad news, female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:			
	Absolute Update of population risk estimates			
	(1)	(2)	(3)	(4)
type of news	1.438*	1.419*	2.115	2.129
	(0.624)	(0.626)	(1.617)	(1.613)
EE self-risk	0.357***	0.357***	0.366***	0.298***
	(0.022)	(0.022)	(0.032)	(0.038)
PHQ score		−0.103	−0.115	−0.114
		(0.089)	(0.120)	(0.119)
sex		0.750	1.034	−1.737
		(0.617)	(0.665)	(1.074)
condition			1.078	1.103
			(0.863)	(0.860)
type of news*condition			−0.759	−0.628
			(1.276)	(1.273)
type of news*PHQ score			−0.005	0.010
			(0.182)	(0.182)
type of news*EE self-risk			−0.018	−0.031
			(0.044)	(0.044)
EE self-risk*sex				0.145**
				(0.044)
constant	8.155***	8.439***	7.730***	9.074***
	(0.580)	(0.876)	(1.180)	(1.246)
Observations	1,711	1,711	1,711	1,711
R^2	0.137	0.139	0.140	0.145
ΔR^2		0.002	0.001	0.005***
Adjusted R^2	0.136	0.137	0.136	0.141
Residual Std. Error	12.731 (df = 1708)	12.728 (df = 1706)	12.736 (df = 1702)	12.700 (df = 1701)
F Statistic	135.934*** (df = 2; 1708)	68.747*** (df = 4; 1706)	34.553*** (df = 8; 1702)	32.085*** (df = 9; 1701)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 17 | Results of hierarchical regression analyses for update of self-risk (trial level, classification 2), including the EE by sex interaction. Information desirability (type of news), sex, and condition are dummy variables with the value 0 representing bad news, female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:			
	Absolute Update of self-risk estimates			
	(1)	(2)	(3)	(4)
type of news	1.674**	1.655**	1.887	1.875
	(0.590)	(0.589)	(1.464)	(1.464)
EE population risk	0.340***	0.339***	0.283***	0.262***
	(0.022)	(0.022)	(0.036)	(0.042)
PHQ score		−0.043	0.091	0.092
		(0.084)	(0.128)	(0.128)
sex		2.244***	2.452***	1.759
		(0.584)	(0.628)	(0.987)
condition			0.808	0.817
			(0.891)	(0.891)
type of news*condition			−0.431	−0.416
			(1.198)	(1.198)
type of news*PHQ score			−0.265	−0.261
			(0.172)	(0.172)
type of news*EE population risk			0.094*	0.094*
			(0.046)	(0.046)
EE population risk*sex				0.040
				(0.044)
constant	6.252***	5.439***	5.067***	5.398***
	(0.548)	(0.804)	(1.147)	(1.204)
Observations	1,758	1,758	1,758	1,758
R^2	0.127	0.134	0.138	0.139
ΔR^2		0.007***	0.004	0.005
Adjusted R^2	0.126	0.132	0.134	0.134
Residual Std. Error	12.260 (df = 1755)	12.214 (df = 1753)	12.201 (df = 1749)	12.202 (df = 1748)
F Statistic	127.348*** (df = 2; 1755)	67.996*** (df = 4; 1753)	35.028*** (df = 8; 1749)	31.225*** (df = 9; 1748)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 18 | Results of hierarchical regression analyses for update of population risk (trial level, classification 2), including the EE by sex interaction. Information desirability (type of news), sex, and condition are dummy variables with the value 0 representing bad news, female sex, and non-incentivized condition, respectively. Numbers for variables represent unstandardized regression coefficients with standard errors in parentheses.

	Dependent variable:			
	Absolute Update of population risk estimates			
	(1)	(2)	(3)	(4)
type of news	−0.505	−0.425	−0.437	−0.449
	(0.529)	(0.530)	(1.320)	(1.320)
EE population risk	0.645***	0.646***	0.641***	0.620***
	(0.020)	(0.020)	(0.032)	(0.038)
PHQ score		−0.205**	−0.228*	−0.227*
		(0.075)	(0.116)	(0.116)
sex		−0.072	−0.021	−0.709
		(0.526)	(0.566)	(0.890)
condition			0.625	0.634
			(0.803)	(0.803)
type of news*condition			−0.998	−0.983
			(1.080)	(1.080)
type of news*PHQ score			0.044	0.048
			(0.155)	(0.155)
type of news*EE population risk			0.009	0.009
			(0.041)	(0.041)
EE population risk*sex				0.040
				(0.040)
constant	4.844***	6.102***	6.049***	6.378***
	(0.492)	(0.723)	(1.034)	(1.085)
Observations	1,758	1,758	1,758	1,758
R^2	0.372	0.375	0.375	0.376
ΔR^2		0.003*	0	0.001
Adjusted R^2	0.372	0.374	0.373	0.373
Residual Std. Error	11.005 (df = 1755)	10.988 (df = 1753)	10.998 (df = 1749)	10.998 (df = 1748)
F Statistic	520.784*** (df = 2; 1755)	263.034*** (df = 4; 1753)	131.409*** (df = 8; 1749)	116.920*** (df = 9; 1748)

Note: *p<0.05; **p<0.01; ***p<0.001

7.4 T-tests of Estimation Times

Table 19 | Paired samples t-tests of estimation times (subject level). Asterisks indicate a statistically significant (p < .05) correlation.

	Mean (sd) 1	Mean (sd) 2	r	t	df	p	d
1st est. Time Self-Risk, 2nd Est. Time Self-Risk	20.97 (5.75)	18.02 (5.96)	.85*	73	6.080	<.001	-0.830
1st Est. Time Pop. Risk, 2nd Est. Time Pop. Risk	21.38 (13.73)	17.74 (16.54)	.65*	73	5.780	<.001	-0.730
1st Est. Time Self-Risk, 1st Est. Time Pop. Risk	20.97 (5.75)	18.02 (5.96)	.59*	73	-6.920	<.001	0.860
2nd Est. Time Self-Risk, 2nd Est. Time Pop. Risk	21.38 (13.73)	17.74 (16.54)	.65*	73	-7.010	<.001	0.840
1st Est. Self-Risk before bad news, 1st Est. Self-Risk before good news	20.97 (5.75)	18.02 (5.96)	.73*	73	2.460	<.05	-0.210
1st Est. Pop. Risk before bad news, 1st Est. Pop. Risk before good news	21.38 (13.73)	17.74 (16.54)	.81*	73	-0.956	>.3	0.110

7.5 Analyses of Covariance

Table 20 | Repeated measures analysis of covariance with update as dependent variable (subject level, classification 1). Factors are information desirability (type of news: good vs. bad, within), type of estimation (self-risk vs. population risk, within), condition (incentivized vs. not incentivized, between). The difference in EEs between bad and good news was used as covariate.

	df (error)	F	p	η_p^2	Observed power
type of news (within)	1 (38)	1.13	0.30	0.03	0.18
type of estimation (within)	1 (38)	3.35	0.08	0.08	0.43
condition (between)	1 (38)	0	0.96	0	0.01
type of news*condition	1 (38)	0.19	0.67	0.01	0.07
type of estimation*condition	1 (38)	0.33	0.57	0.01	0.09
type of news*type of estimation	1 (38)	2.71	0.11	0.07	0.36
type of news*type of estimation*condition	1 (38)	0.25	0.62	0.01	0.08
Difference in EEs between bad and good news (cov.)	1 (38)	0.67	0.42	0.02	0.13

Table 21 | Repeated measures analysis of covariance with update as dependent variable (subject level, classification 2). Factors are information desirability (type of news: good vs. bad, within), type of estimation (self-risk vs. population risk, within), condition (incentivized vs. not incentivized, between). The difference in EEs between bad and good news was used as covariate.

	ddf (error)	F	p	η_p^2	Observed power
type of news (within)	1 (39)	0.05	0.95	0	0.05
type of estimation (within)	1 (39)	15.46	<.001	0.28	0.97
condition (between)	1 (39)	0.01	0.91	0	0.01
type of news*condition	1 (39)	0.45	0.83	0	0.06
type of estimation*condition	1 (39)	0.22	0.64	0.01	0.07
type of news*type of estimation	1 (39)	3.76	0.06	0.09	0.47
type of news*type of estimation*condition	1 (39)	0.23	0.63	0.01	0.08
Difference in EEs between bad and good news (cov.)	1 (39)	1.22	0.28	0.03	0.19

Table 22 | Analysis of covariance with update of self-risk as dependent variable (trial level, classification 1). Between-factors are information desirability (type of news: good vs. bad), condition (incentivized vs. not incentivized). The EE for each trial was used as covariate.

	df (error)	F	p	η_p^2	Observed power
type of news	1 (1507)	58.63	<.001	0.04	1
condition	1 (1507)	0.33	0.56	0	0.09
type of news*condition	1 (1507)	0.01	0.93	0	0.05
EE (cov.)	1 (1507)	203.83	<.001	0.12	1

Table 23 | Analysis of covariance with update of population risk as dependent variable (trial level, classification 1). Between-factors are information desirability (type of news: good vs. bad), condition (incentivized vs. not incentivized). The EE for each trial was used as covariate.

	df (error)	F	p	η_p^2	Observed power
type of news	1 (1507)	3.24	0.07	0	0.43
condition	1 (1507)	0.31	0.86	0	0.05
type of news*condition	1 (1507)	0.82	0.36	0	0.15
EE (cov.)	1 (1507)	243.58	<.001	0.14	1

Table 24 | Analysis of covariance with update of self-risk as dependent variable (trial level, classification 2). Between-factors are information desirability (type of news: good vs. bad), condition (incentivized vs. not incentivized). The EE for each trial was used as covariate.

	df (error)	F	p	η_p^2	Observed power
type of news	1 (1544)	9.04	$<.01$	0.01	0.85
condition	1 (1544)	0.30	0.58	0	0.09
type of news*condition	1 (1544)	0.07	0.79	0	0.06
EE (cov.)	1 (1544)	222.20	$<.001$	0.13	1

Table 25 | Analysis of covariance with update of population risk as dependent variable (trial level, classification 2). Between-factors are information desirability (type of news: good vs. bad), condition (incentivized vs. not incentivized). The EE for each trial was used as covariate.

	df (error)	F	p	η_p^2	Observed power
type of news	1 (1544)	1.24	0.27	0	0.20
condition	1 (1544)	0.19	0.66	0	0.07
type of news*condition	1 (1544)	0.72	0.40	0	0.14
EE (cov.)	1 (1544)	915.82	$<.001$	0.37	1