Dinner with Bayes:

On the Formation of Subjective Risk Beliefs *

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Abstract

We study the formation of subjective beliefs about the risk of contracting a

foodborne illness. A representative sample of French consumers stated their risk

perceptions before and after receiving risk-relevant information about the average

consumer. Regression analyses indicate that prior risk beliefs, education and

understanding of risks as well as self-protective behavior are significant predictors of

subjective, posterior risk estimates. We find that, on average, the revision of beliefs

is consistent with Bayesian updating. However, some subjects responded in a non-

Bayesian manner. In a group-wise analysis, we identify drivers of this seemingly

irrational updating behavior.

Keywords: subjective risk, health-risk information, Bayesian updating, foodborne illness.

JEL: I12, I18, D80

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1. Introduction

People often respond to public-health policies in ways that are inconsistent with economic theory. They overreact to some risks while they ignore others (Slovic et al., 2000); they are reluctant to change unhealthy behavior even though they know it would be better for them (O'Donoghue and Rabin, 2001); and they take healthy behavior as excuse for indulging in unhealthy behavior, e.g. by eating more when foods are low in calories (Downs et al., 2009) or by smoking each cigarette down to the bone when cutting back on cigarettes (Adda and Cornaglia, 2006).

Reasons for such deviations from the rational-consumer model are manifold (McFadden, 2001) and include limited attention, emotional arousal, and difficulties in processing risk-related information (Ruhm and Cawley, 2013). In this paper, we focus on the processing of information and the formation of subjective risk beliefs. In particular, we study how consumers perceive the risk of foodborne illness before and after the provision of risk-related information. As noted by Sloan et al. (2003), risk perception is a critical link in the causal chain between consumer information and behavioral responses.

A better understanding of how consumers form perceptions about food risks and how they adjust such beliefs to new information is of considerable interest. This interest is fueled, in parts, by its implications for the evaluation of existing food safety policies and by regulatory needs to accurately predict behavioral responses to new information campaigns. Accordingly, two relevant questions emerge: Do public information programs affect food risk perceptions? And if so, do they alter consumer behavior?

Answers to these questions require a better understanding of the processing of risk-related information. Both economists and psychologists have long demonstrated that people have

difficulties in understanding and interpreting (changes in) health risks (Arrow, 1982; DellaVigna, 2009; Fischhoff et al., 1993; Frank, 2004; Kahneman, 2003; Loewenstein et al., 2001). They often overestimate small risks and underestimate large ones (Slovic et al., 2004); and while they learn from past experiences and use new information to update their beliefs, they often focus on worst-case scenarios and overreact to warnings (Viscusi, 1997).

A number of studies have addressed the role of information in the formation of subjective risk beliefs. Viscusi and O'Connor (1984) elicited chemical workers' perception of job hazards based on warning labels. Smith and colleagues (1988; 1995) studied the effect of public information programs on homeowners' attitudes toward the risk associated with radon exposure. Dickie and Gerking (1996) explored public perceptions of the risk of skin cancer. More recently, Andersson and Lundborg (2007) and Andersson (2011) examined the perception of road-traffic and overall mortality risks in Sweden, while Viscusi and Hakes (2008) analyzed beliefs about lung cancer risk and smoking behavior in the U.S.

In all of these studies, individuals responded to new information by updating their prior beliefs in the expected direction. However, the studies largely ignored the endogenous nature of health risks (Shogren and Crocker, 1991). That is, they ignored the fact that people often have private information on their health status and, in response, take measures that affect the likelihood or severity of a bad health outcome. These measures are typically unobserved, but may systematically affect risks and decisions. For this reason, it is perfectly rational for consumers to hold beliefs about personal risk that differ from the population-average risk. For example, consumers choose the quality, storage place, and preparation method of their foods and thereby affect their risk of contracting a foodborne illness (Shogren and Stamland, 2007). Obviously, such consumer behavior affects the formation of subjective risk beliefs.

In this paper, we present a novel risk-elicitation protocol that permits capturing the impact of self-protective behavior and other personal characteristics, which may have an effect on the formation of subjective risk beliefs. In what is essentially a panel structure, a representative sample of French consumers stated their perceived chance of contracting foodborne illness from eating fish. We first elicited risk beliefs without any specific information; then with information about the population-average risk, consumption habits, and various risky and risk-averting behaviors. The chained elicitation procedure allows us to explore: (i) the role of personal characteristics in the formation of risk beliefs; (ii) consumers' responses to risk-related information; and (iii) deviations from the Bayesian rationality assumption maintained by standard economic models of consumer choices.

In a nutshell, we find that subjects updated their beliefs in a coherent way. Consumers with higher (lower) prior risk beliefs stated higher (lower) posterior risk beliefs. This finding holds, whether or not we control for risk-relevant or socioeconomic factors. Self-protective behavior had the expected effect on the formation of risk beliefs: consumers who handle food more (less) carefully perceive the risk of contracting a foodborne illness from fish to be smaller (higher). The results underline the importance of controlling for endogenous factors in the formation of risk beliefs, which has direct implications for predicting the outreach of existing health and consumption advisories.

The remainder of the paper is organized as follows. Section 2 outlines and operationalizes the Bayesian learning model proposed by Viscusi (1989). Section 3 describes the elicitation protocol, the survey implementation, and the sample. Section 4 presents descriptive and analytical results. Section 5 summarizes our results.

2. The Bayesian Learning Model

It is widely accepted that people have biased beliefs about the likelihood of rare events (Barberis, 2013). Viscusi (1989) developed a variant of expected-utility theory in which individuals use probabilistic information in a Bayesian fashion to update their prior beliefs. He argued that the Bayesian updating process is consistent with two possible interpretations. First, individuals do not have full confidence in the source of information; second, they treat any risk-related information as imperfect information.

Both interpretations let people discount new information within the decision-making process. This can be formalized in the most basic Bayesian learning model:

$$p_i = \frac{\phi \, q_i + \xi \, r}{\phi + \xi} = (1 - \lambda) q_i + \lambda \, r \,, \tag{1}$$

where p_i denotes individual i's posterior risk belief (i.e., probability of an adverse event); ϕ and ξ are the information contents associated with the prior risk belief q_i and the risk-related information r, respectively; $\lambda = \xi / (\phi + \xi)$ is the relative weight given to new information in the updating of the risk belief.²

The model in Eq. (1) assumes that individuals form their posterior belief as a weighted average of the belief they held prior to receiving the risk-related information and their inferences from the new information. The drawback of this model is that it treats the interpretation of new information as a black box. Smith and Johnson (1988) derived a generalized form of Eq. (1) in which factors that might influence people's perception of the relative precision of either their prior beliefs or the information content will affect the relative weight attributed to the information. As Smith and Johnson note, it is likely that some of these factors will also affect the

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² Andersson and Lundborg (2007) explain how the effect of changes in the information content on the individual's risk belief can be predicted.

formation of prior beliefs. Based on these insights, the Bayesian learning model can be extended to explore heterogeneity in the response to risk-related information.

We assume that people form their posterior risk belief by processing new pieces of information and combining them with knowledge of personal exposure and averting behavior. This leads to the behavioral model:

$$p_{i} = \varphi_{a}(\mathbf{A}_{i}, \alpha) \, q(\mathbf{B}_{i}, \beta) + \varphi_{r}(\mathbf{C}_{i}, \gamma) \, r(\overline{r}, \Delta \mathbf{D}_{i}, \delta), \tag{2}$$

with $\alpha, \beta, \gamma, \delta$ parameter vectors; $\mathbf{q}(\mathbf{B}_i, \beta)$ is a function of personal factors (age, education, gender, experience, etc.) collected in the vector \mathbf{B}_i that determine prior risk beliefs; similarly, $r(\overline{r}, \Delta \mathbf{D}_i, \delta)$ is a function linking personal inferences from the risk-related information to behavioral factors (exposure, self-protection behavior, health status, etc.). Instead of directly including these factors, we measure individual i's behavioral deviation from the average consumer summarized in the vector $\Delta \mathbf{D}_i$. We reason that the deviation is crucial for i's interpretation of the population average risk \overline{r} ; the information contents $\varphi_q(\mathbf{A}_i, \alpha)$ and $\varphi_r(\mathbf{C}_i, \gamma)$ are contingent upon factors (summarized in the vectors \mathbf{A}_i and \mathbf{C}_i) that influence individual perception of the relative precision of prior and new information.

In practice, we do not have sufficient information about the detailed behavioral processes described by Eq. (2) to estimate the parameters in these functions. Yet, under some assumptions, we can still obtain an empirically testable version of the extended Bayesian learning model (Smith and Johnson, 1988). First, we assume there is substantial overlap between \mathbf{A}_i , \mathbf{B}_i , and \mathbf{C}_i . We collapse them into a single vector \mathbf{X}_i . Second, we impose a linearly additive form for each of

³ In the empirical application, we use sample means of behavioral factors as proxies for the behavior of the average consumer. Thus, $\Delta \mathbf{D}_i$ is a vector of mean-centered variables.

⁴ If individual *i* believes herself to be more (less) exposed to a specific food risk than the average consumer, she will use \overline{r} as a reference risk upon which to adjust her beliefs (Viscusi, 1989).

the behavioral functions in Eq. (2). Upon appending a stochastic error term, we obtain the following empirical model:

$$p_{i} = \theta_{0} \overline{r} + \theta_{1} q_{i} + \theta_{2}' \Delta \mathbf{D}_{i} + \theta_{3}' \mathbf{X}_{i} + \theta_{4}' q_{i} \Delta \mathbf{D}_{i} + \theta_{5}' q_{i} \mathbf{X}_{i} + \theta_{6}' \Delta \mathbf{D}_{i} \mathbf{X}_{i} + \theta_{7}' q_{i} \mathbf{X}_{i} \Delta \mathbf{D}_{i} + \varepsilon_{i}$$

$$\tag{3}$$

In the empirical application presented below, we will use Eq. (3) as our workhorse model.

3. Elicitation protocol

Two premises guided the development of our risk-elicitation protocol. People are not very good in making sense of small probabilities (Kunreuther et al., 2001). Yet they do reasonably well in reporting expectations for specific states of the world as a percent chance (Manski, 2004).

The elicitation proceeded as follows. First, we informed subjects about the population-average risk of contracting a foodborne illness. With this information at hand, they stated on a semi-quantitative scale how frequently they expected to suffer a foodborne illness (from any food). Next, we instructed subjects to assume they will be suffering a foodborne illness sometime next year, and inquired how likely they thought it was (in terms of a percent chance) that the cause for the illness was bad fish. The task was computer-based and subjects indicated their risk estimates using the slider depicted in Fig. 1A.

<INSERT FIGURE 1>

Subjects were then provided with information about the expected fraction of cases of foodborne illness in France that are attributable to fish ($\bar{r} = 16\%$; Vaillant et al., 2005), the consumption habits of French consumers, and behaviors that reduce or increase the risk of contracting a foodborne illness, respectively. We asked them to consider this information when

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⁵ We work with conditional probabilities, as they are more tractable. In the empirical analysis, we control for the conditioning by including the perceived risk of a foodborne illness, i.e., the state we are conditioning on.

revising their previous risk estimate. This time, the percent slider had additional marks indicating the subject's prior risk estimate and the population average risk (Fig. 1B).

4. Data and Results

The risk-elicitation task was included in a large online survey and administered to a French consumer panel during July and September 2012. We obtained answers from 1,009 panel members who eat fish more than three times a month. As the sample matches quotas for age, gender, region, and employment status, we take it to be representative of the population of French fish consumers.⁶ Apart from the usual socioeconomic indicators, we inquired about the quantity and quality of consumed fish; subjects' preferred purchase, storage and preparation methods; the importance of various averting behaviors and various other attributes that may determine food consumption choices (Shogren and Stamland, 2007). Sample statistics are summarized in Table 1.

<INSERT TABLE 1>

The histogram displayed in Fig. 2A illustrates that, before receiving the information about the population average risk, subjects were relatively uncertain about their personal risk (mean = 32%, median = 25%, min = 0%, max = 99%). Moreover, we found a significant spike at 50%, suggesting that some subjects had "no idea as to the answer" (Fischhoff and Bruine De Bruin, 1999). Receiving risk-related information significantly reduced the perceived risk (mean = 23%, median = 16%, min = 0%, max = 93%) and caused the spike at 50% to vanish (Fig. 2B). In fact, most of the respondents did update their prior beliefs (Fig. 2C).

<INSERT FIGURE 2>

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⁶ Quotas were set based on 2009 census data, see http://www.insee.fr/fr/recensement-2009.htm.

The dotted black line represents full ignorance ($\lambda = 0$); the solid green line represents perfect updating ($\lambda = 1$); the dashed red line represents the best fit ($\hat{\lambda} = 0.45$) obtained from regressing p_i on q_i . Note that as \bar{r} is constant across subjects, its effect cannot be separated from the regression intercept. The fitted line implies that subjects typically adjusted upward (downward) if their prior risk belief was smaller (larger) than \bar{r} .

<INSERT FIGURE 3>

Table 2 presents logistic regression estimates of three model specifications broadly consistent with Eq. (3). Model I is a naïve model, which does not take into account that factors affecting the perception of information might also affect the formation of the prior risk belief and the self-protection efforts of the individual (i.e., it assumes $\theta'_4 = \theta'_5 = \theta'_6 = \theta'_7 = 0$); model II includes interaction terms between the prior and the self-protective behavior and between the socioeconomic characteristics and the formation of priors (i.e., it assumes $\theta'_6 = \theta'_7 = 0$); model III contains all two- and three-way interactions included in Eq. (3), although we report only the main effects. Below, we summarize the major findings of the regression analysis.

<INSERT TABLE 2>

Subjects updated their risk beliefs in a coherent way, i.e. those with higher (lower) prior risk beliefs stated higher (lower) posterior risk beliefs. This finding holds no matter whether or not we control for interactions between the priors and risk-relevant and/or socio-economic factors. Subjects who were pregnant (or whose partner was pregnant) perceived the risk to be higher – even after receiving information about the average consumer. This suggests that they

⁷ The regression model is: p = 5.878 (0.606) + 0.551 (0.024) * q; brackets contain robust standard errors. Based on the fitted regressors we cannot reject the hypothesis that the regression line passes through [p = 16%, q = 16%].

⁸ The logit transformation is warranted because p_i and q_i are bounded on [0,1]. As the logit is not defined for 0 and 1, we remapped all stated p_i and q_i values to the interval [0.025, 0.975] prior to the transformation.

considered their personal health status when updating their risk beliefs. (Contracting a foodborne illness during pregnancy can cause serious complications including fetal death.) The same was observed for subjects who expressed concern over the safety of seafood because of environmental contaminants.

Subjects with university degree tended to hold lower posterior risk beliefs, as did those who passed a simple test of probabilistic understanding. There are two interpretations of this result. First, it could be that these subjects had a better understanding of the probabilistic nature of risk and therefore formed smaller priors. Second, it could be that subjects with less education also have less trust in the information we provided and therefore updated their beliefs less strongly than more-sophisticated subjects. A negative and significant interaction term between the prior risk belief and a dummy for university attainment favors the former interpretation.

In the naïve model I, self-protective behavior affected the posterior risk assessment in the expected way. Those who eat more raw fish than the sample mean and those who stored fresh fish more often for periods longer than 3 days perceived their risk to be significantly higher; those who wash hands before preparing meals more often than the sample mean perceived their risk to be significantly smaller. However, these self-protection effects are not very stable. Once we insert interaction terms to control for the fact that prior risk beliefs affect self-protective behavior (models II and III), we no longer observe these effects. We even find that those who handle food more carefully (wash hands and food items more often than the sample means) have higher posterior risk beliefs. Here, the causal effect may be reversed, with subjects who are more worried about foodborne illness engaging in more self-protective behavior.

In addition, we ran three probit regressions to identify characteristics of non-Bayesians (those 33.6% of the subjects for whom $\lambda \notin [0,1]$), non-updaters (those 18.3% of the subjects for

whom $\lambda = 0$), and full-updaters (those 8.4% of the subjects for whom $\lambda = 1$). We included interaction terms between regressors and the log-odds ratio of the prior. In Table 3 we report the main effects only. Below, we highlight the most important findings from the probit analysis.

<TABLE 3>

The absolute deviation between the own prior and the average consumer's risk exhibited large explanatory power in predicting whether subjects fully updated their beliefs or whether they updated their beliefs in a non-Bayesian fashion. In particular, subjects were more likely to engage in non-Bayesian or full updating, the smaller the absolute deviation $|q_i - \overline{r}|$ was. Consumers in some geographic regions were more likely to not update at all, while others were more likely to fully update (interpretation of these differences is beyond the scope of this paper).

Subjects who failed the simple risk test were somewhat more likely to update in a non-Bayesian fashion. Older subjects and subjects who judged their lifetime risk of a foodborne illness to be higher than the sample mean were more likely to ignore the information about the average consumer's risk, while subjects who judged their health to be better were less likely to do so. A pregnancy within the household significantly decreased the likelihood of a subject to fully update their risk beliefs.

5. Summary

The results obtained from the extended Bayesian learning model suggest that, on average, subjects behave in line with Bayesian reasoning when evaluating subjective risks. That is, they combine information about the average consumer's risk with their own consumption behavior, their vulnerability toward foodborne illness, and their self-protective behaviors, to refine the assessment of their own risk.

We also note that, while it goes against the theoretical assumptions of the Bayesian learning model, non-Bayesian updating may make perfect sense. If a subject over- or underestimated their risk compared to the average consumer, they could correct this by stating a posterior risk belief that was lower or higher than the average consumer's risk, respectively. For example, a consumer whose prior estimate exceeds the population-average risk but who eats less fish and take more self-protective measures than average should logically report a posterior estimate smaller than the population mean risk. In the Bayesian learning model, this implies an information weight outside the [0,1] interval.

Our results indicate that people's perceptions of the risk of foodborne illness are not random, but systematically related to risk-relevant factors. This is good news for health and safety regulators because it suggests that awareness campaigns might be more effective if people are given not only information about the population-average risk but also about the factors that affect the average consumer's risk. Risk beliefs are also related to other consumer characteristics. Particularly, education appears to affect the way in which risk-relevant information is processed. This is largely in line with results from psychology and suggests that it might be most effective to tailor warnings to the specific needs and characteristics of different target groups.

Tables

 Table 1: Sample statistics.

Variable	Observations	Mean	St. Dev.	Min	Max
Prior risk belief (in %)	1,009	31.6	24.56	0	99
Posterior risk belief (in %)	1,009	23.29	19.98	0	93
Male	1,009	0.49	0.5	0	1
Age	1,009	43.56	13.48	18	80
Monthly household income	951	2,845	1,190	250	5,000
Educational attainment: primary school	1,005	0.03	0.16	0	1
Educational attainment: secondary school	1,005	0.11	0.31	0	1
Educational attainment: high school	1,005	0.31	0.46	0	1
Educational attainment: university	1,005	0.55	0.50	0	1
Region: Greater Paris	1,009	0.20	0.40	0	1
Region: North	1,009	0.06	0.24	0	1
Region: East	1,009	0.09	0.29	0	1
Region: Central East	1,009	0.08	0.27	0	1
Region: Central West	1,009	0.09	0.29	0	1
Region: West	1,009	0.13	0.34	0	1
Region: South-West	1,009	0.11	0.31	0	1
Region: South-East	1,009	0.12	0.32	0	1
Region: Mediterranean	1,009	0.12	0.33	0	1
Kids < 10yrs in household	1,009	0.28	0.45	0	1
Number of household members	1,009	2.75	1.34	1	9
Body mass index	1,006	25.25	4.93	13.59	48.01
Pregnancy in household	1,009	0.10	0.31	0	1
Private health insurance	999	0.96	0.2	0	1
Smoked cigarettes per day	1,009	3.57	7.75	0	40
Health assessment (on a scale from 0-10)	1,009	7.36	1.71	0	10
Food risk perception: important risk	1,009	0.06	0.02	0	1
Food risk perception: somewhat important risk	1,009	0.17	0.38	0	1
Food risk perception: intermediate risk	1,009	0.33	0.47	0	1
Food risk perception: less important risk	1,009	0.38	0.49	0	1
Food risk perception: unimportant risk	1,009	0.05	0.22	0	1
Seafood poses health risks	1,009	0.48	0.5	0	1
Subject passes risk test	1,009	0.93	0.25	0	1
Annual foodborne illness risk	1,009	2.41E-3	5.80E-3	1.00E-5	3.29E-2
Times fish eaten raw	1,009	0.95	1.73	0	10
Times fish eaten canned	1,009	2.08	1.71	0	10
Times hands washed before preparation	1,009	7.21	3.87	0	10
Times fish washed before preparation	1,009	5.75	4.31	0	10
Times fish refrozen after defrosting	1,009	5.26	4.43	0	10
Times fish stored unfrozen for > 3 days	1,009	0.83	2.14	0	10
Re-use of plates that contained raw fish	1,009	0.65	1.92	0	10
Fish prepared well done	1,009	5.96	4.07	0	10
Annual fish consumption (in kg)	989	12.42	8.93	1.04	49.92

Table 2: Logistic regression estimates (§ Mean-centered parameters; *p<0.10; **p<0.05; ***p<0.01.)

Variables	Model I		Model II		Model III				
	Coef.		Std. Error	Coef.		Std. Error	Coef.		Std. Error
(Intercept)	-2.011	***	0.338	-2.429	***	0.594	-2.827	***	0.596
Prior risk estimate	0.029	***	0.001	0.043	***	0.014	0.041	**	0.017
Liftetime risk of foodborne illness	0.020		0.075	0.069		0.115	0.086		0.192
Male	-0.151	**	0.064	-0.031		0.113	-0.074		0.131
Age	0.006	*	0.003	0.004		0.005	0.004		0.005
BMI	-0.002		0.007	0.008		0.012	0.001		0.014
Pregnant	0.158	*	0.095	0.181		0.194	0.829	***	0.218
Private health insurance	0.104		0.161	-0.512	**	0.239	-0.084		0.314
Number of cigarettes per day	-0.001		0.004	0.006		0.006	0.007		0.008
Health score	-0.026		0.020	0.041		0.030	0.061	*	0.034
University degree	-0.160	**	0.064	-0.198	*	0.108	-0.166		0.127
Household income (in k€)	-0.049		0.031	-0.033		0.047	-0.053		0.054
Passed risk test	-0.238	**	0.113	-0.077		0.230	-0.606	**	0.279
Kids < 10 live in household	0.034		0.091	-0.132		0.148	-0.273	*	0.140
Household size	0.011		0.031	0.060		0.047	0.130	***	0.046
Foods present an important health risk	-0.019		0.163	-0.201		0.292	-0.500		0.304
Seafood is risky	0.078		0.060	0.275	***	0.103	0.266	**	0.110
Annual fish consumption (in log of kg)	0.029		0.047	-0.004		0.086	0.077		0.085
Region: North	0.043		0.128	-0.139		0.240	0.272		0.347
Region: East	-0.185	*	0.108	-0.210		0.163	0.177		0.221
Region: Central East	0.100		0.143	-0.412		0.275	-0.558	**	0.271
Region: Central West	0.093		0.105	-0.149		0.166	-0.145		0.215
Region: West	-0.065		0.106	-0.044		0.166	0.082		0.188
Region: South-West	-0.168		0.123	-0.041		0.206	0.304		0.246
Region: South-East	0.026		0.112	0.213		0.190	0.097		0.179
Region: Mediterranean	-0.043		0.105	-0.264		0.161	-0.213		0.191
Intake of fresh fish §	0.000		0.001	0.001		0.001	0.003		0.011
Intake of canned fish §	0.000		0.001	0.001		0.001	0.015		0.023
Intake of fish sticks §	0.001	*	0.000	0.000		0.001	-0.002		0.008
Amount of fish eaten raw (on 0-10 scale) §	0.049	**	0.019	-0.031		0.037	0.130		0.546
Hands washed before preparation (on 0-10 scale) §	-0.017	**	0.008	0.001		0.014	0.462	***	0.162
Fish washed before preparation (on 0-10 scale) §	-0.003		0.008	-0.007		0.013	0.534	***	0.161
Fish refrozen after defrosting (on 0-10 scale) §	0.001		0.007	-0.000		0.012	0.011		0.141
Fish stored > 3 days in the fridge (on 0-10 scale) §	0.021	*	0.013	-0.002		0.020	-0.475		0.477
Re-use of plates that contained raw fish (on 0-10 scale) §	-0.001		0.014	-0.000		0.023	-0.548		0.555
Fish prepared well done (on 0-10 scale) §	-0.011		0.008	-0.029	**	0.013	-0.658	***	0.150
Interactions: prior risk belief x self-protection behavior	NO			YES			YES		
Interactions: prior risk belief x socioeconomics	NO			YES			YES		
Interactions: socioeconomics x self-protection behavior	NO			NO			YES		
Interactions: socioeconomics x prior risk belief x socioeconomics	NO			NO			YES		
McFadden R ²	0.468			0.489			0.736		
Adj. McFadden R ²	0.465			0.483			0.694		
Observations	932			932			932		

Table 3: Probit estimates of non-Bayesian, non, and full updating (§ Mean-centered parameters; *p<0.10; **p<0.05; ***p<0.01.)

Variables	Non-Bayesians		Non-updaters		Full-updaters	
	Coef.	z-value	Coef.	z-value	Coef.	z-value
Logit of prior risk belief	0.122	0.166	-1.090	1.139	0.815	0.641
Absolute deviation between q and r	-0.035 ***	8.750	-0.002	0.400	-0.028 ***	4.000
Male	-0.115	0.878	-0.033	0.177	0.134	0.766
Age	0.007	1.167	0.014 **	2.000	-0.004	0.500
Monthly household income	-0.137	0.576	-0.250	0.794	0.356	1.020
Squared monthly household income	0.024	0.615	0.036	0.679	-0.105 *	1.842
University degree	0.045	0.333	0.249	1.407	0.593 ***	3.408
Region: North	-0.108	0.444	-0.739	0.859	-0.509	1.365
Region: East	-0.296	1.179	0.099	0.294	0.692 **	2.149
Region: Central-East	-0.002	0.008	0.599	1.589	0.624 *	1.788
Region: Central-West	-0.095	0.337	0.823 ***	2.918	-0.642	1.558
Region: West	-0.059	0.284	0.330	1.071	0.114	0.344
Region: South-West	0.178	0.832	0.087	0.207	0.541 *	1.815
Region: South-East	-0.263	1.190	0.651 **	2.342	-0.141	0.478
Region: Mediterranean	-0.130	0.578	0.362	1.346	-0.006	0.020
Kids < 10yrs in household	0.090	0.520	-0.110	0.400	-0.261	1.111
Number of household members	0.076	1.134	-0.047	0.470	0.039	0.402
Body mass index	-0.084	0.884	0.059	0.536	0.016	0.086
Squared body mass index	0.002	1.000	-0.001	0.500	0.000	0.100
Smoked cigarettes per day	-0.009	1.125	0.010	1.000	-0.008	0.667
Pregnancy in household	-0.034	0.169	0.081	0.316	-0.891 ***	2.733
Private health insurance	-0.090	0.327	0.195	0.513	0.454	1.170
Own health (on 0-10 scale)	0.016	0.410	-0.106 **	2.208	0.006	0.118
Seafood poses health risks	0.178	1.391	-0.170	1.018	-0.111	0.634
Subject passes risk test	-0.375 *	1.820	0.357	1.266	0.282	0.870
Foodborne illness risk §	3.170	0.355	23.724 **	2.395	6.899	0.486
Annual fish consumption (in kg) §	-0.004	0.500	0.003	0.333	-0.011	1.100
Amount of fish eaten raw (on 0-10 scale) §	0.023	0.676	-0.034	0.723	-0.070	1.591
Amount of fish eaten canned (on 0-10 scale) §	-0.019	0.559	0.081	1.473	0.017	0.347
Hands washed before preparation (on 0-10 scale) §	0.013	0.765	-0.029	1.115	-0.009	0.391
Fish washed before preparation (on 0-10 scale) §	-0.022	1.375	-0.003	0.130	0.021	1.050
Fish refrozen after defrosting (on 0-10 scale)§	-0.007	0.467	0.028	1.400	-0.003	0.143
Fish stored >3 days in the fridge (on 0-10 scale) §	0.013	0.406	0.005	0.135	0.000	0.005
Use of plates that contained raw fish (on 0-10 scale) §	-0.023	0.605	-0.081 *	1.723	0.013	0.255
Fish prepared well done (on 0-10 scale) §	0.024	1.500	-0.005	0.217	-0.016	0.762
Observations	925		925		925	
Akaike Inf. Crit.	1,175.847		858.5		587.1	

Figures

Figure 1: Elicitation of prior (Panel A) and posterior (Panel B) risk beliefs.

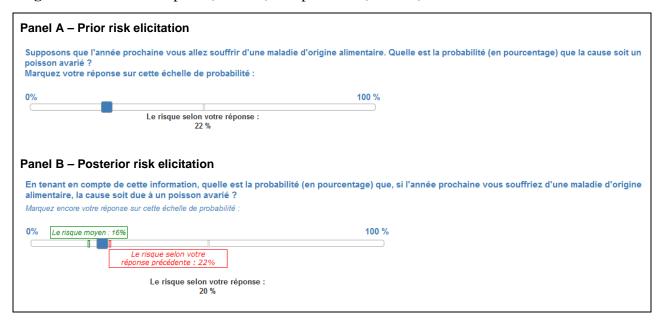
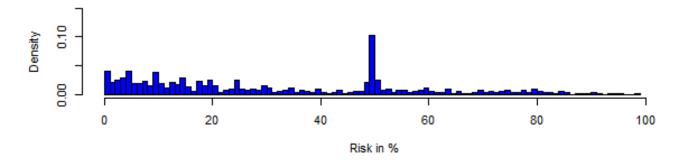
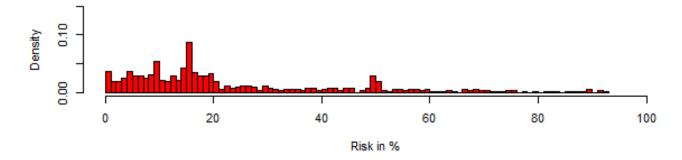


Figure 2: Histograms of elicited prior risk (Panel A), posterior risk (Panel B), and individual updating behavior (Panel C).

Panel A - without information



Panel B - with information



Panel C - updating effect

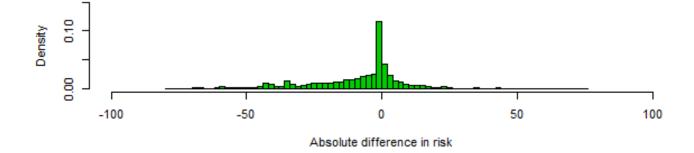
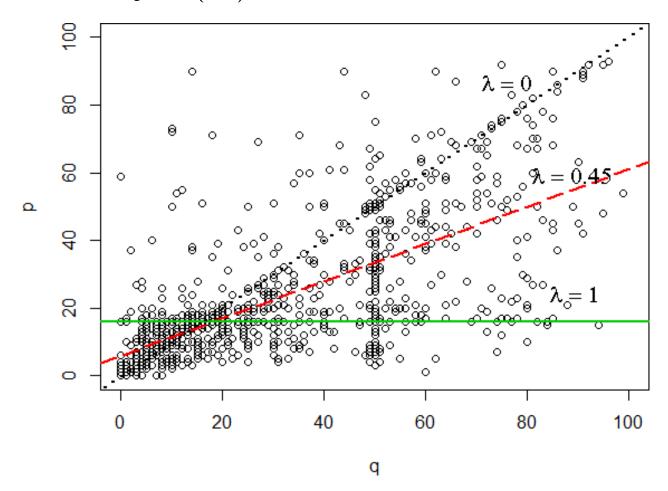


Figure 3: Prior vs. posterior risk beliefs: the solid green line results from perfect updating $(\lambda=1)$; the dashed red line results from regressing p_i on q_i ($\hat{\lambda}=0.45$); the dotted black line results from full ignorance ($\lambda=0$).



References

- Adda J., Cornaglia F., 2006. Taxes, cigarette consumption, and smoking intensity. *American Economic Review* 96, 1013-1028.
- Andersson H., 2011. Perception of Own Death Risk: An Assessment of Road-Traffic Mortality Risk. *Risk Analysis* 31, 1069-1082.
- Andersson H., Lundborg P., 2007. Perception of own death risk. *Journal of Risk and Uncertainty* 34, 67-84.
- Arrow K.J., 1982. Risk perception in psychology and economics. *Economic Inquiry* 20, 1-9.
- Barberis N., 2013. The psychology of tail events: Progress and challenges. *American Economic Review* 103, 611-616.
- DellaVigna S., 2009. Psychology and Economics: Evidence from the Field. *Journal of Economic Literature* 47, 315-372.
- Dickie M., Gerking S., 1996. Formation of risk beliefs, joint production and willingness to pay to avoid skin cancer. *Review of Economics and Statistics* 78, 451-463.
- Downs J.S., Loewenstein G., Wisdom J., 2009. Strategies for Promoting Healthier Food Choices. *American Economic Review* 99, 159-164.
- Fischhoff B., Bruine De Bruin W., 1999. Fifty-Fifty = 50%? *Journal of Behavioral Decision Making* 12, 149-163.
- Fischhoff B., Bostrom A., Quadrel M.J., 1993. Risk perception and communication. *Annual Review of Public Health* 14, 183-203.
- Frank R.G., 2004. Behavioral economics and health economics. NBER Working Paper No. 10881.
- Kahneman D., 2003. Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review* 93, 1449-1475.
- Kunreuther H., Novemsky N., Kahneman D., 2001. Making low probabilities useful. *Journal of Risk and Uncertainty* 23, 103-120.
- Loewenstein G.F., et al., 2001. Risk as feelings. *Psychological Bulletin* 127, 267-286.
- Manski C.F., 2004. Measuring expectations. *Econometrica* 72, 1329-1376.
- McFadden D., 2001. Economic choices. American Economic Review 91, 351-378.
- O'Donoghue T., Rabin M., 2001. Choice and procrastination. *Quarterly Journal of Economics* 116, 121-160.
- Ruhm C., Cawley J. 2013. The Economics of Risky Behaviors. In: McGuire TG, Pauly MV, Barros PP (Eds), Handbook of Health Economics, vol. 2. Elsevier: New York, NY.

- Shogren J.F., Crocker T.D., 1991. Risk, self-protection, and ex ante economic value. *Journal of Environmental Economics and Management* 20, 1-15.
- Shogren J.F., Stamland T., 2007. Valuing lives saved from safer food a cautionary tale revised. *American Journal of Agricultural Economics* 89, 1176-1182.
- Sloan F.A., Smith V.K., Taylor D.H., 2003. The smoking puzzle: Information, risk perception, and choice. Harvard University Press, Cambridge, MA.
- Slovic P., Fischhoff B., Lichtenstein S. 2000. Facts and Fears: Understanding Perceived Risk. In: Slovic P (Ed), The Perception of Risk. Earthscan, London.
- Slovic P., et al., 2004. Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk Analysis* 24, 311-322.
- Smith V.K., Johnson F.R., 1988. How do risk perceptions respond to information? The case of radon. *Review of Economics and Statistics* 70, 1-8.
- Smith V.K., Desvousges W.H., Payne J.W., 1995. Do risk information programs promote mitigating behavior? *Journal of Risk and Uncertainty* 10, 203-221.
- Vaillant V., et al., 2005. Foodborne infections in France. *Foodborne Pathogens and Disease* 2, 221-232.
- Viscusi W., Hakes J.K., 2008. Risk beliefs and smoking behavior. *Economic Inquiry* 46, 45-59.
- Viscusi W.K., 1989. Prospective Reference Theory: Toward an Explanation of the Paradoxes. *Journal of Risk and Uncertainty* 2, 235-264.
- Viscusi W.K., 1997. Alarmist decisions with divergent risk information. *Economic Journal* 107, 1657-1670.
- Viscusi W.K., O'Connor C.J., 1984. Adaptive responses to chemical labeling: Are workers Bayesian decision makers? *American Economic Review* 74, 942-956.