Food Scares in an Uncertain World

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Introduction

Partly in response to a spate of well-publicized food scares, the last decade has witnessed increased public awareness of food-safety concerns. Particularly well-known food scares include: the outbreak of Bovine Spongiform Encephalopathy (BSE), commonly known as "mad-cow" disease, in the United Kingdom; the contamination of hamburgers and apple juice with the E. coli O157:H7 bacterium; the contamination of frozen, sugared strawberries with the hepatitis A virus in the United States; the recent "mad-cow outbreaks" in Canada and the United States; and avian influenza ("bird flu") incidents in Asia and the United States. Each scare has had significant economic effects. For example, after an isolated case of BSE was detected on a Canadian farm in May 2003, Canadian beef exports plummeted from a monthly average of \$125 million to only \$14 million in August 2003. And subsequent news of discovery of BSE in the United States virtually evaporated its \$3 billion beef export market.

Food scares follow a very common pattern. Before the scare, consumers behave as though they are relatively indifferent to the hazards associated with foodborne pathogens and contaminants. But once a scare occurs, the typical response is a precipitous decline in demand, followed by a slow, and often incomplete recovery. In some instances, certain segments of the population totally shun the commodity as a result of a scare. This tendency has been repeatedly documented. For example, nearly 60% of Japanese consumers stopped eating beef after a case of BSE in Japan was reported in 2001 (USDA, 2002). Similarly, 8% of consumers in a sample of French households reportedly stopped consumption of beef during a BSE scare in Europe (Adda, 2003).

In an uncertain world, there are at least two possible explanations for such behavior. The most commonly offered is that a food scare fundamentally changes individual attitudes towards risk. A less-explored explanation is that food scares change individual beliefs so that the least desirable outcomes now seem much more likely than before.

Regarding the first, notice that in an expected-utility framework, a total avoidance of such hazards is only explainable by arbitrarily high degrees of risk aversion. Hence, a sudden shunning of a product only seems explicable by consumers becoming arbitrarily risk averse.

This, in turn, suggests a fundamental change in individual attitudes towards other risks. If true, then such a change should be associated with similar changes in other risky markets, particularly if those markets are closely related to the market in which the scare occurs. For example, a person who suddenly becomes infinitely risk averse as a result of a food scare should also now avoid other potentially hazardous food products. We are aware of no empirical evidence that documents such behavior. Not only does this not appear to happen, but often some of the same individuals who have shunned the scare-ridden food product resume its purchases after the negative news has passed (Adda, 2003; FPI, 2004; Wall Street Journal, 2004)). This leaves the latter explanation: a negative food incident changes consumers' beliefs, at least temporarily, about the risks associated with consumption of a food product.

This paper builds an economic model of consumer choice over food products of uncertain quality. The goal is to construct a model that explains the stylized facts of food scares: an immediate and sharp decline in consumption of the product followed by a slow and frequently partial recovery of demand after the scare passes. To do this, we use a model where individual tastes (attitudes towards risk) are not affected by a food scare, but where beliefs about the state of the world reflect the presence of potential Knightian uncertainty and can be influenced by the receipt of information about the presence of food scares. Consumer beliefs about uncertain food quality are represented by *sets of prior probability distributions*, and preferences over these sets of prior distributions are modeled using a dynamic version of Gilboa and Schmeidler's (1989) maximin expected utility (MEU) representation. Consumers update their beliefs about uncertain outcomes in response to receipt of market information using a prior-by-prior application of Bayes' Law.

Our model recognizes the potential presence of Knightian uncertainty for at least three reasons. First, unpredictable, unanticipated, and typically unprecedented food scares are, by definition, "...so entirely unique..." that it is not "...possible to tabulate enough like it to form a basis for any inference of value about any real probability..." (Knight, p. 226). In other words, food scares reflect exactly the type of uncertainty with which Knight was concerned. Second, repeated empirical validations of the Ellsberg Paradox have revealed that individuals behave differently in the presence of Knightian uncertainty than in its absence.

Thus, if Knightian uncertainty is present, it should be recognized and properly modeled. And third, we have chosen a model that, under appropriate circumstances, degenerates to expected utility if the degree of imprecision (defined below) is sufficiently small. One of the goals of our empirical modeling effort is to assess that degree of imprecision for the "mad-cow" crisis in the United Kingdom.

In what follows, as a backdrop to our modeling effort, we first present an overview of events associated with a recent food scare, the "mad-cow" crisis in the United Kingdom, and we briefly relate that scare to other well-known food scares. Although specifics differ across food scares, the "mad-cow" scare appropriately illustrates the typical dynamics of a food scare. Then we develop and analyze a theoretical model that is intended to explain these typical dynamics. The model generates short-run and long-run consumption patterns consistent with those often observed following food incidents. We derive a number of comparative statics results, and then we calibrate our model with meat consumption data for the United Kingdom. The calibrated model is used to assess the importance of various factors affecting food consumption behavior and some of the ambiguous comparative-static effects in the theoretical model. The paper then closes.

1 The Dynamics of a Food-Scare: The UK "Mad-Cow" Crisis

BSE was identified as a new disease in cattle in 1986, following the death of a cow in the United Kingdom. Between 1986 and 1995, UK officials assured the consuming public that UK beef was safe to eat. It was not until the new variant Creutzfeldt-Jacob disease (vCJD) claimed its first human victim that the UK government confirmed the link between it and BSE in March of 1996. As of August 2004, there have been 142 deaths due to the vCJD in the UK (Guardian, 2004). Because the disease has a long incubation period, its eventual impacts remain unknown.

Figure 1 illustrates the cataclysmic decline in beef and veal usage that followed the 1996 announcement. It also illustrates the eventual, partial recovery that is characteristic of food scares. Prior to 1996, UK beef consumption exhibited a definite quarterly pattern of fluctuation around a declining trend. However, immediately following the announcement of the previously unknown (and officially denied) link between BSE and its human variant vCJD, beef consumption dropped by 40% (DTZ/PIEDA, 1998).

Following the 1996 announcement, the European Union banned UK exports of beef world-wide. The ban also affected export of live calves from the UK. The combined effect of the fall in demand for UK beef from UK and overseas consumers, was a contraction in final demand for UK produced beef of 36% in real terms between March 1996 and March 1997 (DTZ/PIEDA, 1998).

The decrease in beef consumption was short-lived, however, and by late 1997 per capita consumption of beef had recovered in line with expected trends (MAFF, 2000). During 1998 and 1999 consumption of beef was in fact above expected trends (DTZ/PIEDA, 1998; MAFF, 2000).

Shortly after its UK outbreak, the BSE scare spread to other European countries. And in 2000, another "mad-cow" scare emerged in Europe. This scare was triggered by the discovery of an infected cow in France in November 2000, and it was most pronounced in France and Italy. French beef consumption decreased by more than 35% (Setbon et al., 2005). In the same month, there was a significant increase in the number of BSE cases registered in France. In reaction to these French cases, beef expenditure in Italy decreased by 32.2% while prices decreased by 0.7% (Mazzocchi, 2004). The scare in Italy was exacerbated by the detection of the first BSE case in a native-born cow in January 2001. Beef consumption following this discovery was 49.2% lower than in January 2000 (Mazzocchi, 2004). A slow recovery started in late Spring 2000, but was still far from complete at the end of 2001 (Mazzocchi, 2004).

The first case of BSE outside of Europe occurred in Japan. On September 10, 2001, it was publicly announced that a dairy cow from Chiba Prefecture had tested positive for BSE. Nearly 60% of Japanese consumers stopped eating beef, but by mid-2002, Japan's beef consumption had recovered to within 10-15 percent of its pre-BSE levels (Carter and Huie, 2004).

Each BSE scare was characterized by a sharp initial decline in consumption followed by a gradual recovery to the pre-scare consumption levels (as adjusted for previously existing trends). This type of behavior is routinely manifested after a food scare. For example, immediately following the heptachlor contamination of milk in Oahu, Hawaii in 1982, the estimated loss of projected Class I (fluid) milk sales was 29%, but fifteen months later sales had almost completely recovered (Smith et al., 1988). Other highly-publicized food scares that have followed a similar pattern include: the 1959 cranberry scare in the United States; the salmonella scare of 1988 in the United Kingdom; the alar apple scare of 1989 in the United States; the 1996 E. coli outbreak in Lanarkshire, Scotland; the 1996 outbreaks from the pathogen, Cyclospora, on Guatemalan raspberries exported to the United States and Canada; the 1999 dioxin scare in Belgium; the hepatitis A outbreak in the United States in 2003, associated with consumption of green onions imported from Mexico.

A growing economic literature has documented and analyzed these post-scare consumption dynamics. For example, Pigott and Marsh (2004) note that "the average demand response to food safety concerns is small...This small average effect masks periods of significantly larger responses corresponding with prominent food safety events, but these larger impacts are short-lived with no apparent food safety lagged effects on demand." Sociological studies also recognize that food scares exhibit this specific pattern. Beardsworth and Keil (1996) classify public reaction in five steps with the last two steps being avoidance of the suspect food item and a gradual decrease of public concern as attention switches from the issue, leading to the gradual recovery of consumption.

2 The Model

2.1 Timing and Overview of the Model

We consider a two-period model, $t \in \{1, 2\}$, with a decision-maker choosing a two-good consumption bundle under uncertainty. The timing is as follows. In period t, the decision-maker observes a realization of signal $\lambda \in \Lambda = \{N, S\}$, where N stands for the absence of food scare ("no scare") and S for "food scare". After learning the signal, the decision-maker updates her beliefs about the set $\Theta = \{b, g\}$ which captures all possible events relevant to the decision-maker's *ex post* utility. Upon updating her beliefs, the decision-maker allocates a fixed amount of income, I_t, between goods x and y, with their respective period-t prices given by q_t and 1. The consumption of y involves no uncertainty about the consumer's health, and so we refer to y as 'safe'. x, on the other hand, is of uncertain quality. It can be either 'bad', denoted by b, meaning that the consumer consumes a foodborne disease or contaminant, or it can be 'good', denoted by g, meaning that x does not contain any contaminant. The set of states of Nature in each period, t, is, thus, given by $\Omega \equiv \Lambda \times \Theta$.

The world is uncertain so that the odds of different states of nature Ω are not known with precision. The decision-maker's beliefs in each period are characterized by a *set* Π of probability distributions over Ω. The set of probabilities over $\Omega \times \Omega$ is given by $\Pi \times \Pi$. By assuming that the belief structure Π is the same in both periods, we also assume that the realizations of signal λ and event θ in period 1 are not informative about the likelihood of their realizations in period 2. Hence, updating in response to the receipt of a signal about food quality occurs within periods but not from period to period.

The decision-maker is assumed to have a variation of recursive MEU preferences (Epstein and Schneider (2003)), where conditional preferences have Gilboa and Schmeidler's (1989) maximin expected utility (MEU) form,

$$\min_{(P_1,P_2)\in\Pi\times\Pi} \left[\sum_{t=1}^{2} E_{P_t} u_t \right].$$

Here u_t denotes the decision-maker's period-t ex post utility. Beliefs are updated by a prior-by-prior application of Bayes law.

We specify the decision-maker's preference functional in more detail after we have introduced its different components. However, it is important to notice that the MEU form implies that the decisionmaker is *pessimistic* in the following sense. When evaluating stochastic outcomes, he or she always uses probabilities that yield the lowest possible expected utility over P.

2.2 Beliefs

The prior (in the beginning of each period $t \in \{1, 2\}$) information structure is represented by a convex set Π with its elements being 2×2 probability matrices

$$\Pi = \left\{ \begin{bmatrix} p_b^N & p_b^S + \varepsilon \\ p_g^N & p_g^S - \varepsilon \end{bmatrix} : \varepsilon \in [0, \overline{\varepsilon}] \right\}. \tag{1}$$

Here p_θ^λ ($\theta \in \Theta$, $\lambda \in \Lambda$) and $\overline{\varepsilon}$ are constants that satisfy $0 < p_b^N, p_g^N < 1$, $\min\{p_g^S, 1 - p_b^S\} > \overline{\varepsilon} \geq 0$, and $\sum_{\theta\in\Theta} \sum_{\lambda\in\Lambda} p_\theta^\lambda = 1$.

These conditions ensure that each element P of Π is a proper probability distribution. Notice that in our specification, the decision-maker's beliefs about the simultaneous occurrence of signal N and event $\theta \in \Theta$ are given by a unique probability p_θ^N, which is a fixed number. In contrast, when $\overline{\varepsilon} > 0$, the decision-maker's beliefs about the simultaneous occurrence of signal S and event b (event g) are given by the interval $\left[p_b^S, p_b^S + \overline{\varepsilon}\right]$ $\left(\left[p_g^S - \overline{\varepsilon}, p_g^S\right]\right)$. Hence, the decisionmaker's beliefs about the presence of foodborne pathogens are "imprecise" in the sense of Walley (1991).

The probabilities in Π can be thought of as representing at least two factors: the decision-maker's information on the possible probability distributions and his or her *degree of confidence* in the existing theories surrounding these probability distributions. This interpretation of beliefs can be traced back to Ellsberg (1961). So, for example, if there are several competing hypotheses about the stochastic structure that characterizes the food-borne hazard, but the decisionmaker is convinced that only one is truly valid, then Π would be a singleton. Conversely, if the decisionmaker had no confidence in any of the theories the set Π could be quite large. Parameter $\overline{\varepsilon}$, which measures the length of the interval which the decisionmaker will entertain as possible probabilities of the presence of foodborne contamination, will be referred to as measuring the decision-maker's degree of imprecision in what follows.

Notice that the prior probability of signal realization λ is $\sum_{\theta\in\Theta} p_\theta^\lambda$, which is independent of ε. Hence, our model assumes that there is no prior uncertainty about the signal-generating process. The decision-maker, however, does have uncertain prior beliefs about the possible presence of foodborne hazards (i.e., events in Θ), which in both periods are given by the convex set

$$\left\{ \begin{bmatrix} p_b^N + p_b^S + \varepsilon \\ p_g^N + p_g^S - \varepsilon \end{bmatrix} : \varepsilon \in [0, \overline{\varepsilon}] \right\}.$$

In each period, the realization of signal λ is used by the decision-maker to update her beliefs. In a risky decision environment, Bayes law is almost always used to update beliefs. For uncertain decision environments, however, there is less unanimity about updating, and a number of alternative rules have been considered. We adopt a prior-by-prior Bayesian updating rule, where each prior in Π is updated using Bayes law. Our choice of updating rule is motivated by recent axiomatizations of intertemporal MEU models with prior-by-prior Bayesian updating (Epstein and Schneider (2003), Pires (2002), Siniscalchi (2001), Wakai (2003) and Wang (2003)).[1]

The posterior probability of event θ conditional on signal λ for probability matrix P is

$$\frac{p_\theta^\lambda}{p_b^\lambda + p_g^\lambda}.$$

For Π in (1), the sets of posterior probability distributions over Θ conditional on the realization of signals N and S are given by

$$\begin{bmatrix} \frac{p_b^N}{p_b^N + p_g^N} \\ \frac{p_g^N}{p_b^N + p_g^N} \end{bmatrix} \text{ and } \left\{ \begin{bmatrix} \frac{p_b^S + \varepsilon}{p_b^S + p_g^S} \\ \frac{p_g^S - \varepsilon}{p_b^S + p_g^S} \end{bmatrix} : \ \varepsilon \in [0, \overline{\varepsilon}] \right\},$$

respectively. Thus, following receipt of signal N, the set of posterior probability distributions over Θ is a singleton, so that receiving signal N resolves all uncertainty (but not the risk) in the period it is received. In contrast, uncertainty remains if a food scare occurs.

2.3 Ex post Utility and Habit Formation

Ex post utility in period $t = 1, 2$ depends on the consumption of good x in the current and the previous periods, the consumption of good y in the current period and on the realization

[1] Epstein and Schneider (2003) demonstrate that, when conditional preferences satisfy axioms of the (static) MEU model, dynamic consistency in the sense of Machina (1989) is equivalent to the rectangularity of the set of priors and prior-by-prior Bayesian updating. It is straightforward to verify that belief structure Π is rectangular in the sense of Epstein and Schneider.

of uncertainty $\theta \in \Theta$. Period-1 and period-2 *ex post* utility of the decisionmaker take the following forms:

$$u_1 = y_1 - \exp\left[-\gamma\left(r_\theta x_1 - \beta x_0\right)\right] \tag{2}$$

and

$$u_2 = y_2 - \exp\left[-\gamma\left(r_\theta x_2 - \beta x_1 - \beta^2 x_0\right)\right], \tag{3}$$

where x_0 denotes the initial consumption stock of good x, x_i (y_i) denotes consumption of good x (y) in period $i = 1, 2$, β is a constant in the interval $(0, 1)$, and $\mathbf{r} \equiv (r_b, r_g)$ is a random variable with $r_b = 0$ and $r_g = 1$. Preferences exhibit constant absolute risk aversion in the current period consumption of the uncertain good with γ equalling the (constant) Arrow-Pratt degree of absolute risk aversion.

Preferences depend on the consumption of good x in the current and the previous periods because consumers exhibit *habit formation* in the unsafe good x. Hence, current period utility depends not only on the current consumption of good x but also on the discounted consumption in the previous periods. It is easy to verify that $\frac{\partial^2(-\exp[-\gamma(r_g x_1 - \beta x_0)])}{\partial x_1 \partial x_0} > 0$, $\frac{\partial^2\left(-\exp\left[-\gamma\left(r_g x_2 - \beta x_1 - \beta^2 x_0\right)\right]\right)}{\partial x_2 \partial x_0} > 0$, and $\frac{\partial^2\left(-\exp\left[-\gamma\left(r_g x_2 - \beta x_1 - \beta^2 x_0\right)\right]\right)}{\partial x_2 \partial x_1} > 0$, that is, increases in the past consumption of x increase the marginal utility of the current consumption of x in the event $\theta = g$. We also have that $\frac{\partial^2(-\exp[-\gamma(r_b x_1 - \beta x_0)])}{\partial x_1 \partial x_0} = 0$, $\frac{\partial^2\left(-\exp\left[-\gamma\left(r_b x_2 - \beta x_1 - \beta^2 x_0\right)\right]\right)}{\partial x_2 \partial x_0} = 0$, and $\frac{\partial^2\left(-\exp\left[-\gamma\left(r_b x_2 - \beta x_1 - \beta^2 x_0\right)\right]\right)}{\partial x_2 \partial x_1} = 0$.

2.4 The Decision-maker's Conditional Preference Functional

After observing realization $\lambda \in \{N, S\}$ of the signal in period 1, the decision-maker updates her beliefs about the likelihood of events in $\Theta = \{b, g\}$ and subsequently chooses consumption levels of goods x and y, denoted by x_1^λ and y_1^λ, respectively. (Here, subscripts always refer to time periods, and superscripts always refer to the signal received.) The consumption decision in period 2 depends, among other things, recursively on the consumption of good x in period 1, which, in turn, depends on the realization of the signal in period 1. In period 2, the decision-maker observes realization $\lambda' \in \{N, S\}$ of the signal, then updates her beliefs about the likelihood of events in $\Theta = \{b, g\}$ and subsequently chooses consumption levels of goods x and y, denoted by $x_2^{\lambda'|\lambda}$ and $y_2^{\lambda'|\lambda}$, respectively, where λ stands for the signal received in period 1 and λ' for the signal received in period 2.

In Appendix A it is shown that the decision-maker's preference functional V^S conditional on receiving signal S in the beginning of period 1 can be written as

$$V^S(x_1^S, x_2^{N|S}, x_2^{S|S}) \equiv -\frac{\exp(\gamma\beta x_0)}{p_b^S + p_g^S}\left\{\left(p_b^S + \overline{\varepsilon}\right) + \left(p_g^S - \overline{\varepsilon}\right)\exp\left(-\gamma x_1^S\right)\right\} + I_1 - q_1 x_1^S \tag{4}$$
$$+\delta\left\{\begin{array}{c} -\exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right]\left(\begin{array}{c} p_b^N + (1 - p_b^S - p_g^S - p_b^N)\exp\left(-\gamma x_2^{N|S}\right) \\ +\left(p_b^S + \overline{\varepsilon}\right) + \left(p_g^S - \overline{\varepsilon}\right)\exp\left(-\gamma x_2^{S|S}\right)\end{array}\right) \\ +I_2 - q_2\left(x_2^{N|S} + \left(p_b^S + p_g^S\right)\left(x_2^{S|S} - x_2^{N|S}\right)\right)\end{array}\right\},$$

where $\delta \in (0,1)$ is the discount factor. The objective function conditional on receiving signal N in period 1 has a similar form and is presented in Appendix A. Expression (4) demonstrates an especially important characteristic of our model. By (4), it is apparent that consumers only use the "most pessimistic" probability of the food product being safe in evaluating its consumption. This fact greatly facilitates the analysis that follows.

3 Preliminary Theoretical Analysis

We first analyze the effect of changes in the model parameters on the optimal consumption of the unsafe good conditional on receiving signal $\lambda \in \{N, S\}$ in the first period. We have:

Proposition 1 *The unique optimal consumption pattern* $(x_1^\lambda, x_2^{N|\lambda}, x_2^{S|\lambda})$ *conditional on either realization of the signal* ($\forall\lambda \in \{N,S\}$) *satisfies:*

1. *Period-1 consumption* x_1^λ *conditional on signal* λ *is strictly decreasing in period-1 price* (q_1) *and the discount factor* (δ)*. It is increasing in the initial consumption stock* (x_0)*; and* x_1^λ *does not vary with period-2 price* (q_2)*;*

Period-1 consumption x_1^S *conditional on signal* S *is strictly decreasing in the degree of imprecision* $\overline{\varepsilon}$*; period-1 consumption* x_1^N *conditional on signal* N *does not vary with* $\overline{\varepsilon}$*;*

2i. *Period-2 consumption* $x_2^{N|\lambda}$ *conditional on receiving signal* $\lambda \in \{N,S\}$ *in period 1 and signal* N *in period 2 is strictly decreasing in period-2 price* (q_2) *and the negative of the initial consumption stock* ($-x_0$)*;* $x_2^{N|\lambda}$ *does not vary with the degree of imprecision* $\overline{\varepsilon}$*, period-1 price* (q_1) *and discount factor* (δ)*;*

2ii. *Period-2 consumption* $x_2^{S|\lambda}$ *conditional on receiving signal* $\lambda \in \{N, S\}$ *in period 1 and signal* S *in period 2 is strictly decreasing in the degree of imprecision* $\bar{\varepsilon}$*, period-2 price* (q_2) *and the negative of the initial consumption stock* ($-x_0$)*;* x_1^{λ} *does not vary with period-1 price* (q_1) *and discount factor* (δ)*.*

Proof. (See Appendix B) ■

Price changes in a given period only directly affect consumption in that period. They have no direct effect on consumption in other periods, although the presence of habit formation ensures that indirect effects exist. The presence of habit formation also leads individuals with a relatively large initial consumption of the uncertain food product, x_0, to consume relatively large amounts of that product in future periods.

Increases in $\bar{\varepsilon}$, which reflect an increase in imprecision in beliefs about the presence of foodborne pathogens, lead to an immediate drop in consumption of x in the presence of a food scare (receipt of signal S). An increase in imprecision, when coupled with the consumer's assumed pessimism always leads him or her to attach an effectively lower probability to the absence of food-borne pathogens. Comparative statics for the other parameters remains ambiguous. In a later section, we use a calibrated version of the model to remove some of this ambiguity.

Our main objective is a model that explains the stylized facts of a food scare. A robust empirical observation is that food scares (here receipt of signal S) decrease consumption of x. If consumer beliefs are "sufficiently imprecise", our model predicts just such a decrease. The following proposition makes precise the intuitive statement "sufficiently imprecise":

Proposition 2 *If*
$$\left(\frac{p_g^N}{p_b^N + p_g^N} > \frac{p_g^S - \bar{\varepsilon}}{p_b^S + p_g^S}\right),$$
consumption following a food scare in period 1 *is strictly lower than in the absence of a food scare* ($x_1^N > x_1^S$; $x_2^{N|N} > x_2^{N|S}$; $x_2^{S|N} > x_2^{S|S}$)*.*

Proof. (see Appendix C) ■

The condition in Proposition 2 requires that the posterior probability of the food product being uncontaminated in the absence of a food scare be greater than the most "pessimistic" posterior probability of it being uncontaminated in the presence of a scare. Because our decisionmaker evaluates "post-scare" consumption of the food product in terms of this most pessimistic probability, the condition requires that the decisionmaker effectively believes that food contamination is more likely in the presence of a scare than in its absence. Intuitively, receiving a "scare" signal process must be truly informative about the possible presence of foodborne contamination if consumers are to react to it by decreasing consumption of the hazardous food product.

It is of particular interest to note that even if there is no food scare in period 2, period-2 consumption conditional on the occurrence of food scare in period 1 is strictly smaller than period-2 consumption conditional on the absence of food scare in the previous period ($x_2^{N|N} > x_2^{N|S}$). Even though updating occurs only within time periods, food consumption is persistently affected by the occurrence of a food scare in period 1. The consumption process has memory because of the assumed presence of habit formation in food consumption. Moreover, a sequence of two food scares results in a larger decline in consumption compared to a single food scare ($x_2^{S|N} > x_2^{S|S}$). Thus, the model predicts that if a scare signal is followed by receipt of a "no-scare" signal the process of recovering from the scare, which is manifested in real-world experience, commences.

Another stylized fact of food scares is that following a scare, some segments of the population completely shun the potentially hazardous food product. Proposition 1, where it was shown that x_1^S and $x_2^{S|\lambda}$ are strictly decreasing in $\bar{\varepsilon}$, suggests (but does not imply) that refusal to consume the food product may occur if there is sufficient imprecision. In fact, it can be shown that when an individual's beliefs are extremely imprecise (as seems natural for most unprecedented food scares), he or she will not consume the hazardous food following a food incident. In Appendix D, we show that there exists a threshold level of $\bar{\varepsilon}$, $\bar{\varepsilon}^t < p_g^S$, such that for all $\bar{\varepsilon} \in [\bar{\varepsilon}^t, p_g^S]$, $x_1^S = 0$, $x_2^{S|S} = 0$, and

$$x_2^{N|S} = \frac{1}{\gamma} \ln \left[\frac{\gamma(1 - p_b^S - p_g^S - p_b^N)}{q_2 \left(1 - p_b^S - p_g^S\right)} \right] + \beta^2 x_0.$$

Intuitively, extreme imprecision is associated with the case where the receipt of a scare signal convinces the decisionmaker that the posterior probability of eating contaminated food approaches zero. Or put another way, the decisionmaker effectively treats receipt of a scare signal as confirming the presence of foodborne contamination.

The prior probability of receiving signal S (the prior probability of a food scare) also plays an important role in determining whether an individual will completely shun the food product of uncertain quality following a food scare. In particular, in our model, consumers are more likely to shun the product if a food scare is a low probability event. We have:

Proposition 3 *When the probability of food scare is sufficiently small, the decision-maker does not consume the hazardous food following a food scare. Specifically, there exists a threshold level* $\pi^t \in [\bar{\varepsilon}, 1]$ *of the probability of signal* S *such that* $x_1^S = 0$ *and* $x_2^{S|S} = 0$ *for all* $\left(p_b^S + p_g^S\right) \in [\bar{\varepsilon}, \pi^t]$.

Proof. (see Appendix E) ■

Appendix E shows that low-probability food scares result in almost complete posterior uncertainty so that following a food scare the range of posterior probabilities of a bad food outcome covers almost the whole probability interval $[0, 1]$. The pessimistic MEU maximizer acts as though the bad health outcome were almost certain. As a consequence, he or she refuses to consume the food product of uncertain quality. Thus, scares are more likely to have drastic consequences for consumption of the hazardous food product if prior to the receipt of the signal the decisionmaker was effectively anticipating receiving a signal that the food product would be fit for human consumption. Scares have bigger consequences for consumption patterns when they are unanticipated probabilistically than when they are perceived as relatively frequent occurrences.

4 Quantitative Analysis

In this section, we calibrate our model using data on beef and veal consumption in the United Kingdom that covers the "Mad-Cow" crisis of the 1990s, and use the calibrated model to investigate quantitatively the degree of imprecision that is consistent with the calibrated model, and how that measured degree of imprecision responds to different assumptions on model parameters.

The period in the model is half a year. Period 1 is the first half of 1996 while period 2 is its second half. The discount factor for half a year is set to $\delta = 0.99$, which is in line with the estimates for the United Kingdom during the time period considered in our simulation (Evans and Sezer, 2002). Consumption is measured by the total UK usage of beef and veal (DEFRA, 2006). Prices are measured by the average retail price index for the United Kingdom (Lloyd et al., 2001).[2] Initially, we parametrize the information structure as:

$$\Pi = \left\{ \begin{bmatrix} 0.001 & 0.007+\varepsilon \\ 0.989 & 0.003-\varepsilon \end{bmatrix} : \varepsilon \in [0, \overline{\varepsilon}] \right\},$$

so that our quantitative analysis takes the prior probability of a "scare" signal emerging as .01, and the prior probability of no-scare as .99. Given that many, if not most consumers, were likely unaware of the potential link between BSE and vCJD prior to its report and the relatively advanced stage of meat processing technology in the United Kingdom, we actually believe that this prior probability of a scare is, in fact, quite high. One of the goals of the quantitative analysis is to determine how altering the prior probability of a scare affects our quantitative results. Notice, in particular, that we have explicitly assumed that posterior probability of the food item being dangerous to health given the presence of a food scare, $\frac{0.007+\varepsilon}{.01}$ is greater than the posterior probability of it not being hazardous. In this sense, we are assuming that the scare signal in question is informative.

The values of the remaining parameter values are summarized in Table 1. Apart from the discount factor, the degree of habit persistence, and the degree of absolute risk aversion, these values reflect the situation in the UK immediately prior and immediately after the revelation of the BSE-vCJD link.

[2] We would like to thank the authors for giving access to their paper.

Table 1: Parameter Values

Price in period 1 (q_1)	250.9
Price in period 2 (q_2)	251.2
Initial consumption stock (x_0)	220.1
Consumption in period 1 following scare in period 1 (x_1^S)	158.3
Consumption in period 2 following scare in period 1 and no scare in period 2 ($x_2^{N\|S}$)	190.0
Discount factor (δ)	0.99
Degree of habit persistence (β)	$\beta \in [0.05, 0.15]$
Degree of absolute risk aversion (γ)	$\gamma \in [0.015, 0.035]$

As we said, a primary goal of this exercise is to determine a quantitative magnitude for the prior and the posterior degree of imprecision given the presence of a scare signal. In what follows, for the sake of economy, we shall only focus on the degree of posterior imprecision for two reasons. The prior degree of imprecision, $\bar{\varepsilon}$, can be obtained from the measured posterior degree of imprecision by simply multiplying the posterior by the prior probability of the scare signal. We also seek to determine how that degree of imprecision responds to differing assumptions on parameters of our model whose magnitudes are not set by the situation in the UK beef and veal market at the time that the link was revealed.

Our baseline model sets the degree of habit persistence, $\beta = 0.1$, and the coefficient of absolute risk aversion, $\gamma = 0.02$. To interpret this coefficient of absolute risk aversion, notice that decision-maker with constant absolute risk aversion and $\gamma = 0.02$ is indifferent between a sure income of 100 and a lottery that pays 0 with probability 0.125 and 250 with probability 0.875. For a realized consumption level, $r_\theta x_1 - \beta x_0$, of 220.1, which is equal to the observed initial consumption stock, a coefficient of absolute risk aversion of .02 implies a coefficient of relative risk aversion of roughly 4.4 while $\gamma = .035$ works out to a coefficient of relative risk aversion of roughly 7.7, and .015 yields a coefficient of relative risk aversion of about 3.3. On the basis of existing empirical work, it is generally felt that the coefficient of relative risk aversion is not much greater than 4. For example, Gollier (2001, p.69) refers to the acceptable range of relative risk aversion as being between [1,4]. Thus, we are intentionally allowing for moderate to very high degrees of risk aversion on the part of consumers because a high degree of risk aversion has been frequently offered as the primary explanation for consumption responses in the aftermath of a food scare.

Given our parameters, the models solves for the factor w by which we normalize prices, the prior and posterior degrees of imprecision $\bar{\varepsilon}$ and consumption in period 2 following scares in periods 1 and 2 ($x_2^{S|S}$). We take $x_2^{S|S}$ to be counterfactual to our data

In Figure 2 we depict the posterior degree of imprecision given by

$$\max_{\varepsilon\in[0,\bar{\varepsilon}]}\frac{p_\theta^S+\varepsilon}{p_b^S+p_g^S}-\min_{\varepsilon\in[0,\bar{\varepsilon}]}\frac{p_\theta^S+\varepsilon}{p_b^S+p_g^S}=\frac{\bar{\varepsilon}}{p_b^S+p_g^S},$$

and how that measured degree of imprecision responds to changes in the degree of absolute risk aversion. The first thing that we note is that the posterior degree of imprecision is quite large, and that it tends to grow as the postulated level of risk aversion increases in what can be thought of as plausible ranges for risk aversion, but that once assumed risk aversion reaches implausibly high levels of risk aversion the degree of imprecision starts to decline.

This pattern of behavior is explained as follows. It is quite well known that it is generally impossible to disentangle uncertainty aversion (here referred to in terms of imprecision) from risk aversion without very specific assumptions on models. More generally, the same model can be interpreted as either perfectly uncertainty averse or perfectly risk averse. When consumers become very excessively risk averse, their behavior becomes extremely conservative and manifests a "safety-first" type of decision process. They will not expose themselves to any perceived risk even if the prior probability of that risk is arbitrarily low. Hence, one expects that effects that might otherwise be attributed to imprecision would in the limit be captured by the extreme risk aversion, and measured precision would decline as we observe here. We emphasize, however, that our quantitative results suggests that this only occurs at levels of risk aversion that are well above commonly accepted values.

We have also solved for $x_2^{S|S}$ in our model which corresponds to what optimal consumption would be if two scare signals were received in a row. We have taken this as being counterfactual to what the market actually experienced. Our analysis suggests that, holding the degree of habit persistence at the baseline number of .1, consumption would be significantly below what it was in the period immediately following the scare (about 158) and is relatively invariant to changes in the degree of risk aversion so long as the degree of risk aversion remains in what are perceived as relatively usual levels (Figure **3**).

We have also investigated the impact on the posterior degree of imprecision and $x_2^{S|S}$ as the probability of the food scare tends to zero. The limiting behavior of the posterior degree of imprecision as a function of the probability of food scare when the latter tends to zero was identified in Proposition 3 (see Appendix E for the formal analysis). The quantitative results suggests that similar behavior is exhibited even in nonlimiting cases. Table 2 reports the results for the posterior degree of imprecision and $x_2^{S|S}$ of allowing the prior probability of a food scare to decline from 1% (baseline case) to 0.001%, where we have varied p_b^S and p_g^S keeping p_b^N and other parameters fixed at their baseline values. These results show that the posterior degree of imprecision uniformly increases and $x_2^{S|S}$ uniformly decreases as the prior probability of a food scare declines.

Table 2: Varying Parameters of the Probability Matrix

	Posterior degree of imprecision	$x_2^{S\|S}$
$p_b^S = 0.007$, $p_g^S = 0.003$ (baseline)	0.14321	97.693
$p_b^S = 0.0007$, $p_g^S = 0.0003$	0.15871	92.204
$p_b^S = 0.00007$, $p_g^S = 0.00003$	0.16038	91.608
$p_b^S = 0.000007$, $p_b^S = 0.000007$	0.16055	91.548

Although we have no firm evidence upon which to base it, our strong conjecture is that *a priori* most food scares are extremely low probability events. We base this conjecture on the fact that the risks involved in many of the most famous food scares were simply not anticipated by the consuming population before the food-scares occured. Therefore, if individuals would have been asked to attach a prior probability to such an event occuring, it seems plausible that that probability would have been extremely low. Table 2 shows that when the prior probability of a scare is quite low, our data suggests that consumers exhibit a high degree of imprecision *a posteriori.* Because a high degree of posterior imprecision implies very conservative behavior on the part of consumers in response to the food scare, their natural reaction to a food scare is to avoid the commodity in question, just as happened in the UK beef and veal markets as well as in other markets where there have been serious food scares.

5 Concluding Remarks

We have built an economic model of consumer choice over food products of uncertain quality. Our model uses a multiple-priors framework to accommodate the presence of Knightian uncertainty as opposed to Knightian risk. The constructed model generates a number of testable prediction and explains the stylized facts of food scares: an immediate and sharp decline in consumption of the product followed by a slow and frequently partial recovery of demand after the scare passes. The calibration of our model with the data on the "mad-cow" crisis in the United Kingdom also offers some insights into factors that account for consumer behavior in response to that scare. The quantitative results from the calibrated model suggest that observed behavior is consistent with sharp changes in beliefs and the presence of Knightian uncertainty, as measured by the degree of imprecision in our model. Specifically, our results suggest that consumers perceive a substantial degree of post-scare uncertainty (posterior degree of imprecision exceeding 14% in the baseline case), and that that degree of imprecision uniformly increases as the prior probability of a food scare declines. Because we conjecture that the prior probability of a food scare was likely quite low, we also conjecture that our results may understate the true degree of posterior imprecision that consumers faced.

6 Appendix A

Conditional Preference Functionals:

Let the posterior probability of event θ conditional on the observation of signal λ for probability matrix P be denoted by $\pi_{\theta|\lambda}$. Denote the sets of posterior probability distributions over Θ conditional on the realization of signals N and S by

$$\begin{aligned}
\Delta^N &\equiv \begin{bmatrix} \pi_{b|N} \\ \pi_{g|N} \end{bmatrix} = \begin{bmatrix} \frac{p_b^N}{p_b^N+p_g^N} \\ \frac{p_g^N}{p_b^N+p_g^N} \end{bmatrix} \text{ and} \\
\Delta^S &\equiv \left\{ \begin{bmatrix} \pi_{b|S} \\ \pi_{g|S} \end{bmatrix} : \begin{bmatrix} \pi_{b|S} \\ \pi_{g|S} \end{bmatrix} = \begin{bmatrix} \frac{p_b^S+\varepsilon}{p_b^S+p_g^S} \\ \frac{p_g^S-\varepsilon}{p_b^S+p_g^S} \end{bmatrix} \text{ for some } \varepsilon \in [0, \overline{\varepsilon}] \right\},
\end{aligned}$$

respectively.

The decision-maker's preference functional conditional on receiving signal λ in the beginning of period 1 can be written as

$$\begin{aligned}
& V^\lambda(x_1^\lambda, y_1^\lambda, x_2^{N|\lambda}, y_2^{N|\lambda}, x_2^{S|\lambda}, y_2^{S|\lambda}; x_0) \\
\equiv & \min_{\substack{\left(\widetilde{\pi}_{b|\lambda}, 1-\widetilde{\pi}_{b|\lambda}\right) \in \Delta^\lambda \\ \left(\pi_{b|N}, 1-\pi_{b|N}\right) \in \Delta^N \\ \left(\pi_{b|S}, 1-\pi_{b|S}\right) \in \Delta^S}} \left[\begin{array}{c} \left(-\widetilde{\pi}_{b|\lambda} \exp\left[\gamma\beta x_0\right] - \left(1-\widetilde{\pi}_{b|\lambda}\right) \exp\left[-\gamma\left(x_1^\lambda - \beta x_0\right)\right] + y_1^\lambda\right) \\ +\delta \left(\begin{array}{c} \pi^N \left[\begin{array}{c} -\pi_{b|N} \exp\left[\gamma\left(\beta x_1^\lambda + \beta^2 x_0\right)\right] \\ -\left(1-\pi_{b|N}\right) \exp\left[-\gamma\left(x_2^{N|\lambda} - \beta x_1^\lambda - \beta^2 x_0\right)\right] \\ +y_2^{N|\lambda} \end{array} \right] \\ +\left(1-\pi^N\right) \left[\begin{array}{c} -\pi_{b|S} \exp\left[\gamma\left(\beta x_1^\lambda + \beta^2 x_0\right)\right] \\ -\left(1-\pi_{b|S}\right) \exp\left[-\gamma\left(x_2^{S|\lambda} - \beta x_1^\lambda - \beta^2 x_0\right)\right] \\ +y_2^{S|\lambda} \end{array} \right] \end{array} \right) \end{array} \right]
\end{aligned}$$

where $\delta \in (0,1)$ denotes the discount factor.

Using (1), (2), (3) and condition $\sum_{\theta\in\Theta}\sum_{\lambda\in\Lambda} p_\theta^\lambda = 1$, the objective function conditional on receiving signal S in period 1 can be written as (4). Similarly, the objective function conditional on receiving signal N in period 1 can be written as

$$V^N(x_1^N, x_2^{N|N}, x_2^{S|N}) = -\frac{\exp(\gamma\beta x_0)}{p_b^N + p_g^N}\left\{p_b^N + p_g^N \exp\left(-\gamma x_1^N\right)\right\} + I_1 - q_1 x_1^N$$

$$+\delta\left\{\begin{array}{c} -\exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right]\left(\begin{array}{c} p_b^N + (1-p_b^S-p_g^S-p_b^N)\exp\left(-\gamma x_2^{N|N}\right) \\ +\left(p_b^S+\overline{\varepsilon}\right) + \left(p_g^S - \overline{\varepsilon}\right)\exp\left(-\gamma x_2^{S|N}\right)\end{array}\right) \\ +I_2 - q_2\left(x_2^{N|N} + \left(p_b^S + p_g^S\right)\left(x_2^{S|N} - x_2^{N|N}\right)\right)\end{array}\right\}.$$

7 Appendix B

Proof of Proposition 1: The proof relies on the curvature properties of the conditional preference functional which are stated and proved in the following two lemmas:

Lemma 4 *V^λ is strictly concave in $(x_1^\lambda, x_2^{N|\lambda}, x_2^{S|\lambda})$ for all $\lambda \in \{N, S\}$.*

Proof. The first-order derivatives of V^S with respect to the choice variables are given by

$$\frac{dV^S}{dx_1^S} = \frac{\gamma\left(p_g^S - \overline{\varepsilon}\right)\exp(-\gamma(x_1^S - \beta x_0))}{p_b^S + p_g^S} - q_1 \tag{5}$$

$$-\delta\gamma\beta\exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right]\left(\begin{array}{c}\left(p_b^N + p_b^S + \overline{\varepsilon}\right) + (1-p_b^S-p_g^S-p_b^N)\exp\left(-\gamma x_2^{N|S}\right) \\ +\left(p_g^S - \overline{\varepsilon}\right)\exp\left(-\gamma x_2^{S|S}\right)\end{array}\right),$$

$$\frac{dV^S}{dx_2^{N|S}} = \delta\left\{\gamma(1-p_b^S-p_g^S-p_b^N)\exp\left[-\gamma\left(x_2^{N|S} - \beta x_1^S - \beta^2 x_0\right)\right] - q_2\left(1-p_b^S-p_g^S\right)\right\}, \tag{6}$$

$$\frac{dV^S}{dx_2^{S|S}} = \delta\left\{\gamma\left(p_g^S - \overline{\varepsilon}\right)\exp\left[-\gamma\left(x_2^{S|S} - \beta x_1^S - \beta^2 x_0\right)\right] - q_2\left(p_b^S + p_g^S\right)\right\}. \tag{7}$$

The second-order derivatives of V^S with respect to the choice variables are given by:

$$\frac{\partial^2 V^S}{\partial\left(x_1^S\right)^2} = -\frac{\gamma^2\left(p_g^S - \overline{\varepsilon}\right)\exp(-\gamma(x_1^S - \beta x_0))}{p_b^S + p_g^S} \tag{8}$$

$$-\delta\left(\gamma\beta\right)^2\exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right]\left(\begin{array}{c} p_b^N + p_b^S + \overline{\varepsilon} + (1-p_b^S-p_g^S-p_b^N)\exp\left(-\gamma x_2^{N|S}\right) \\ +\left(p_g^S - \overline{\varepsilon}\right)\exp\left(-\gamma x_2^{S|S}\right)\end{array}\right) < 0,$$

$$\frac{\partial^2 V^S}{\partial\left(x_2^{N|S}\right)^2} = -\delta\gamma^2(1-p_b^S-p_g^S-p_b^N)\exp\left[-\gamma\left(x_2^{N|S} - \beta x_1^S - \beta^2 x_0\right)\right] < 0, \tag{9}$$

$$\frac{\partial^2 V^S}{\partial\left(x_2^{S|S}\right)^2} = -\delta\gamma^2\left(p_g^S - \overline{\varepsilon}\right)\exp\left[-\gamma\left(x_2^{S|S} - \beta x_1^S - \beta^2 x_0\right)\right] < 0. \tag{10}$$

$$\frac{\partial^2 V^S}{\partial x_1^S \partial x_2^{N|S}} = \delta\beta\gamma^2(1 - p_b^S - p_g^S - p_b^N)\exp\left(-\gamma\left(x_2^{N|S} - \beta x_1^S - \beta^2 x_0\right)\right) > 0, \tag{11}$$

$$\frac{\partial^2 V^S}{\partial x_1^S \partial x_2^{S|S}} = \delta\beta\gamma^2\left(p_g^S - \overline{\varepsilon}\right)\exp\left(-\gamma\left(x_2^{S|S} - \beta x_1^S - \beta^2 x_0\right)\right) > 0, \tag{12}$$

$$\frac{\partial^2 V^S}{\partial x_2^{S|S}\partial x_2^{N|S}} = 0, \tag{13}$$

The Hessian matrix is given by $H \equiv \begin{bmatrix} \frac{\partial^2 V^S}{\partial\left(x_1^S\right)^2} & \frac{\partial^2 V^S}{\partial x_1^S \partial x_2^{N|S}} & \frac{\partial^2 V^S}{\partial x_1^S \partial x_2^{S|S}} \\ \frac{\partial^2 V^S}{\partial x_1^S \partial x_2^{N|S}} & \frac{\partial^2 V^S}{\partial\left(x_2^{N|S}\right)^2} & \frac{\partial^2 V^S}{\partial x_2^{N|S}\partial x_2^{S|S}} \\ \frac{\partial^2 V^S}{\partial x_1^S \partial x_2^{S|S}} & \frac{\partial^2 V^S}{\partial x_2^{N|S}\partial x_2^{S|S}} & \frac{\partial^2 V^S}{\partial\left(x_2^{S|S}\right)^2} \end{bmatrix}$. One can verify that

$$\begin{aligned} \det H = {} & -\delta^2\gamma^6\left(p_g^S - \overline{\varepsilon}\right)(1 - p_b^S - p_g^S - p_b^N)\times \\ & \times \exp\left(-\gamma(x_2^{N|S} + x_2^{S|S}) + 2\gamma(\beta x_1^S + \beta^2 x_0)\right)\times \\ & \times \begin{bmatrix} \frac{\left(p_g^S - \overline{\varepsilon}\right)\exp(-\gamma(x_1^S - \beta x_0))}{p_b^S + p_g^S} \\ +\delta\beta^2\exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right]\left(p_b^N + p_b^S + \overline{\varepsilon}\right) \end{bmatrix} < 0 \end{aligned} \tag{14}$$

and

$$\det\begin{bmatrix} \frac{\partial^2 V^S}{\partial\left(x_2^{N|S}\right)^2} & \frac{\partial^2 V^S}{\partial x_2^{N|S}\partial x_2^{S|S}} \\ \frac{\partial^2 V^S}{\partial x_2^{N|S}\partial x_2^{S|S}} & \frac{\partial^2 V^S}{\partial\left(x_2^{S|S}\right)^2} \end{bmatrix} = \det\begin{bmatrix} \frac{\partial^2 V^S}{\partial\left(x_2^{N|S}\right)^2} & 0 \\ 0 & \frac{\partial^2 V^S}{\partial\left(x_2^{S|S}\right)^2} \end{bmatrix} > 0. \tag{15}$$

(8), (9), (10), (14) and (15) imply that V^S is strictly concave in $(x_1^S, x_2^{N|S}, x_2^{S|S})$. Thus, when $p_g^S > \overline{\varepsilon}$, V^S is strictly concave in $(x_1^S, x_2^{N|S}, x_2^{S|S})$. Finally, we have omitted the proof of strict concavity of V^N since the derivations are almost identical. ■

Lemma 5 *For all $\lambda \in \{N, S\}$, V^λ is supermodular in $(x_1^\lambda, x_2^{N|\lambda}, x_2^{S|\lambda}, -\overline{\varepsilon}, -q_1, -q_2)$.*

Proof. Differentiating (5), (6) and (7) with respect to $\overline{\varepsilon}$ we obtain

$$\frac{\partial^2 V^S}{\partial x_1^S \partial\overline{\varepsilon}} = -\frac{\gamma\exp\left[-\gamma\left(x_1^S - \beta x_0\right)\right]}{p_b^S + p_g^S} - \delta\gamma\beta\exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right]\left(1 - \exp\left(-\gamma x_2^{S|S}\right)\right) < 0, \tag{16}$$

$$\frac{\partial^2 V^S}{\partial x_2^{N|S} \partial \overline{\varepsilon}} = 0. \tag{17}$$

$$\frac{\partial^2 V^S}{\partial x_2^{S|S} \partial \overline{\varepsilon}} = -\delta\gamma \exp\left[-\gamma\left(x_2^{S|S} - \beta x_1^S - \beta^2 x_0\right)\right] < 0, \tag{18}$$

Differentiating (5), (6) and (7) with respect to q_1 and q_2 we obtain

$$\frac{\partial^2 V^S}{\partial x_1^S \partial q_1} = -1 \text{ and } \frac{\partial^2 V^S}{\partial x_2^{N|S} \partial q_1} = \frac{\partial^2 V^S}{\partial x_2^{S|S} \partial q_1} = 0 \tag{19}$$

and

$$\frac{\partial^2 V^S}{\partial x_1^S \partial q_2} = 0, \ \frac{\partial^2 V^S}{\partial x_2^{N|S} \partial q_2} = -\delta\left(1 - p_b^S - p_g^S\right) < 0, \text{ and } \frac{dV^S}{dx_2^{S|S}} = -\delta\left(p_b^S + p_g^S\right) < 0. \tag{20}$$

From (11), (12), (13), (16), (17), (18), (19) and (20) it follows that V^S is supermodular in $(x_1^S, x_2^{N|S}, x_2^{S|S}, -\overline{\varepsilon}, -q_1, -q_2)$. ■

From Theorem 2.8.4 in Topkis (1998) and Lemma (5) it follows immediately that the unique optimum $(x_1^\lambda, x_2^{N|\lambda}, x_2^{S|\lambda})$ is strictly decreasing in $\overline{\varepsilon}, q_1$ and q_2. To prove monotonicity of the conditional preference functional with respect to parameters x_0 and δ, we will invoke the Implicit Function Theorem. Differentiating (5), (6) and (7) with respect to x_0 and evaluating the derivative at the optimal $(x_1^S, x_2^{N|S}, x_2^{S|S})$ we obtain

$$\frac{\partial^2 V^S}{\partial x_2^{N|S} \partial x_0} = \delta\gamma^2\beta^2(1 - p_b^S - p_g^S - p_b^N) \exp\left(-\gamma\left(x_2^{N|S} - \beta x_1^S - \beta^2 x_0\right)\right) > 0, \tag{21}$$

$$\frac{\partial^2 V^S}{\partial x_2^{S|S} \partial x_0} = \delta\gamma^2\beta^2\left(p_g^S - \overline{\varepsilon}\right) \exp\left(-\gamma\left(x_2^{S|S} - \beta x_1^S - \beta^2 x_0\right)\right) > 0. \tag{22}$$

$$\frac{\partial^2 V^S}{\partial x_1^S \partial x_0} = \frac{\gamma^2\beta(1-\beta)\left(p_g^S - \overline{\varepsilon}\right)\exp(-\gamma(x_1^S - \beta x_0))}{p_b^S + p_g^S} + q_1 > 0, \tag{23}$$

Differentiating (5), (6) and (7) with respect to δ and evaluating the derivative at the optimal $(x_1^S, x_2^{N|S}, x_2^{S|S})$ we obtain

$$\frac{\partial^2 V^S}{\partial x_1^S \partial \delta} = -\gamma\beta \exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right] \begin{pmatrix} \left(p_b^N + p_b^S + \overline{\varepsilon}\right) + (1 - p_b^S - p_g^S - p_b^N)\exp\left(-\gamma x_2^{N|S}\right) \\ + \left(p_g^S - \overline{\varepsilon}\right)\exp\left(-\gamma x_2^{S|S}\right) \end{pmatrix} < 0, \tag{24}$$

$$\frac{\partial^2 V^S}{\partial x_2^{N|S}\partial\delta}=\frac{\partial^2 V^S}{\partial x_2^{S|S}\partial\delta}=0, \tag{25}$$

From the implicit function theorem we have

$$\begin{bmatrix} \frac{dx_1^S}{dx_0} & \frac{dx_1^S}{d\delta} \\ \frac{dx_2^{N|S}}{dx_0} & \frac{dx_2^{N|S}}{d\delta} \\ \frac{dx_2^{S|S}}{dx_0} & \frac{dx_2^{S|S}}{d\delta} \end{bmatrix} =$$

$$-\frac{1}{\det H}\begin{bmatrix} \frac{\partial^2 V^S}{\partial\left(x_2^{N|S}\right)^2}\frac{\partial^2 V^S}{\partial\left(x_2^{S|S}\right)^2} & -\frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{N|S}}\frac{\partial^2 V^S}{\partial\left(x_2^{S|S}\right)^2} & -\frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{S|S}}\frac{\partial^2 V^S}{\partial\left(x_2^{N|S}\right)^2} \\ -\frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{N|S}}\frac{\partial^2 V^S}{\partial\left(x_2^{S|S}\right)^2} & \frac{\partial^2 V^S}{\partial\left(x_1^{S}\right)^2}\frac{\partial^2 V^S}{\partial\left(x_2^{S|S}\right)^2}-\left(\frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{S|S}}\right)^2 & \frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{N|S}}\frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{S|S}} \\ -\frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{S|S}}\frac{\partial^2 V^S}{\partial\left(x_2^{N|S}\right)^2} & \frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{N|S}}\frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{S|S}} & \frac{\partial^2 V^S}{\partial\left(x_1^{S}\right)^2}\frac{\partial^2 V^S}{\partial\left(x_2^{N|S}\right)^2}-\left(\frac{\partial^2 V^S}{\partial x_1^S\partial x_2^{N|S}}\right)^2 \end{bmatrix}\times$$

$$\times\begin{bmatrix} \frac{\partial^2 V^S}{\partial x_1^S\partial x_0} & \frac{\partial^2 V^S}{\partial x_1^S\partial\delta} \\ \frac{\partial^2 V^S}{\partial x_2^{N|S}\partial x_0} & \frac{\partial^2 V^S}{\partial x_2^{N|S}\partial\delta} \\ \frac{\partial^2 V^S}{\partial x_2^{S|S}\partial x_0} & \frac{\partial^2 V^S}{\partial x_2^{S|S}\partial\delta} \end{bmatrix},$$

where $\det H$ is given by (14), the second-order derivatives with respect to choice variables are given by (8), (9), (10), (11), (12), and (13), and $\frac{\partial^2 V^S}{\partial x_2^{N|S}\partial x_0}$, $\frac{\partial^2 V^S}{\partial x_2^{S|S}\partial x_0}$ and $\frac{\partial^2 V^S}{\partial x_1^S\partial x_0}$are given by (21), (22) and (23), respectively; $\frac{\partial^2 V^S}{\partial x_1^S\partial\delta}$ is given by (24) while $\frac{\partial^2 V^S}{\partial x_2^{S|S}\partial\delta}$ and $\frac{\partial^2 V^S}{\partial x_2^{N|S}\partial\delta}$ are given by (25). Given the sign conditions that these second-order derivatives satisfy, it is straightforward to verify that $\frac{dx_1^S}{dx_0}, \frac{dx_2^{N|S}}{dx_0}, \frac{dx_2^{S|S}}{dx_0} > 0$ and $\frac{dx_1^S}{d\delta}, \frac{dx_2^{N|S}}{d\delta}, \frac{dx_2^{S|S}}{d\delta} < 0.$■

8 Appendix C

Proof of Proposition 2: Evaluating (5), (6) and (7) at the optimal $(x_1^N, x_2^{N|N}, x_2^{S|N})$, i.e. at the solution to $\frac{dV^N}{dx_1^N}=\frac{dV^N}{dx_2^{N|N}}=\frac{dV^N}{dx_2^{S|N}}=0$, we obtain

$$\frac{dV^S}{dx_1^S}|_{(x_1^N,x_2^{N|N},x_2^{S|N})}=\gamma\left(\frac{p_g^S-\bar{\varepsilon}}{p_b^S+p_g^S}-\frac{p_g^N}{p_b^N+p_g^N}\right)\exp\left[-\gamma\left(x_1^N-\beta x_0\right)\right]<0, \tag{26}$$

$$\frac{dV^S}{dx_2^{N|S}}|_{(x_1^N,x_2^{N|N},x_2^{S|N})}=\frac{dV^S}{dx_2^{S|S}}|_{(x_1^N,x_2^{N|N},x_2^{S|N})}=0. \tag{27}$$

Strict concavity of V^S and V^N combined with (26) and (27) imply $(x_1^N, x_2^{N|N}, x_2^{S|N}) > (x_1^S, x_2^{N|S}, x_2^{S|S})$.■

9 Appendix D

Proof for a threshold level of $\bar{\varepsilon}$: Using $\bar{\varepsilon} = p_g^S$, (5), (6) and (7) can be re-written as

$$\frac{dV^S}{dx_1^S} = -q_1 - \delta\gamma\beta \exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right] \begin{pmatrix} \left(p_b^N + p_b^S + \bar{\varepsilon}\right) + (1 - p_b^S - p_g^S - p_b^N)\exp\left(-\gamma x_2^{N|S}\right) \\ + \left(p_g^S - \bar{\varepsilon}\right)\exp\left(-\gamma x_2^{S|S}\right) \end{pmatrix} < 0, \tag{28}$$

$$\frac{dV^S}{dx_2^{N|S}} = \delta\left\{\gamma(1 - p_b^S - p_g^S - p_b^N)\exp\left[-\gamma\left(x_2^{N|S} - \beta x_1^S - \beta^2 x_0\right)\right] - q_2\left(1 - p_b^S - p_g^S\right)\right\}, \tag{29}$$

$$\frac{dV^S}{dx_2^{S|S}} = -\delta q_2\left(p_b^S + p_g^S\right) < 0. \tag{30}$$

Continuity of V^S in $\bar{\varepsilon}$ and (28) and (30) imply existence of a threshold level such that, for all values of $\bar{\varepsilon}$ exceeding the threshold, $x_1^S = 0$ and $x_2^{S|S} = 0$. The expression for $x_2^{N|S}$ in the text is obtained by equalizing (29) to zero and solving for $x_2^{N|S}$.■

10 Appendix E

Proof of Proposition 3: Consider the difference between the largest and the smallest probability of event $\theta \in \{b, g\}$ conditional on S

$$\max_{\varepsilon\in[0,\bar{\varepsilon}]} \frac{p_\theta^S + \varepsilon}{p_b^S + p_g^S} - \min_{\varepsilon\in[0,\bar{\varepsilon}]} \frac{p_\theta^S + \varepsilon}{p_b^S + p_g^S} = \frac{\bar{\varepsilon}}{p_b^S + p_g^S},$$

where the maximum and the minimum are taken with respect to the set of posterior probabilities. According to Dow and Werlang (1992), this expression defines the (posterior) degree of uncertainty associated with event θ.

Note that $\bar{\varepsilon}$ is the smallest permissible (by conditions imposed on Π) value of probability of signal S. We have that $\lim_{\left(p_b^S+p_g^S\right)\downarrow\overline{\varepsilon}} \frac{\overline{\varepsilon}}{p_b^S+p_g^S} = 1$. That is, as probability of S gets arbitrarily close from above to $\overline{\varepsilon}$, the posterior degree of uncertainty associated with both b and g tends to 1. Since the degree of uncertainty is equal to the difference between the upper and the lower probabilities, following a food scare with a sufficiently small probability the range of probabilities of an adverse outcome covers almost the whole probability segment $[0, 1]$. Since the decision-maker's preference functional is continuous in the conditional probabilities, he/she will shun consumption of the hazardous food.■

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Figure 1: UK Total Domestic Usage of Beef and Veal (01/1990 - 12/1989)

Figure 2: Posterior degree of imprecision as a function of degree of absolute risk aversion (γ)

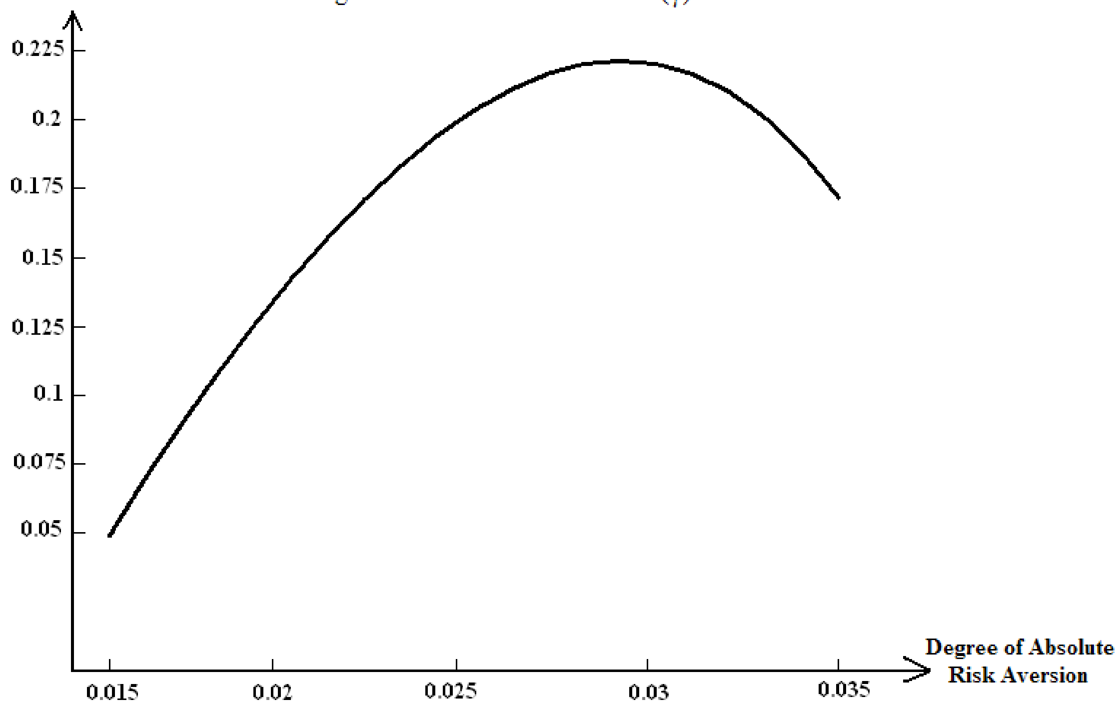

Figure 3: Consumption following scares in both periods as a function of degree of absolute risk aversion (γ)