Food Scares in an Uncertain World

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September 9, 2010

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Introduction

Typically, food scares follow a reverse-J pattern. Before the scare, consumers behave as though they are indifferent to the hazards associated with foodborne pathogens and contaminants. But once a scare occurs, demand declines precipitously only to be followed by a slow, and often incomplete, recovery. In some instances, some segments of the population totally shun the commodity. This tendency has been repeatedly documented. For example, nearly 60% of Japanese consumers stopped eating beef after a case of Bovine Spongiform Encephalopathy (BSE) in Japan was reported in 2001 (USDA, 2002). Similarly, 8% of sampled French consumers stopped consuming beef during a BSE scare in Europe (Adda, 2007).

In an uncertain world, there are at least two possible explanations for such behavior. One such explanation is that a food scare fundamentally changes individual attitudes towards risk (Yeung and Morris, 2001). Another is that food scares change individual risk perceptions so that the least desirable, and oftentimes completely unanticipated, outcomes now seem much more likely than before (Liu et al., 1998).

Regarding the first, notice that a sudden avoidance of a product, which has been previously consumed, only seems explicable by consumers suddenly becoming arbitrarily risk averse. This, in turn, suggests a fundamental change in individual attitudes towards risk. 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 scare in one food market 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 individuals who have shunned the scare-ridden food product resume its purchases once the negative news has passed (Adda, 2007; Food Policy Institute, 2004; Wall Street Journal, 2004)). This suggests that the latter explanation, a negative food incident changes consumers' beliefs, merits further theoretical and empirical consideration.

Turning to the second, note that its fundamental presumption is that one can attach a unique probability to the food hazard and that probability measures the individual's risk perception. We maintain, however, that food scares are, by definition, "...so entirely unique..."

that for them 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 hazard Knight viewed as uncertain and not as risky. Knight (1921) defines risk as randomness with a known probability distribution or one that can be measured precisely and uncertainty as randomness with unknown or unknowable distributions.[1] Because such objective measures of randomness are not available, it thus follows that a change in risk perception represents a change in an individual's subjective beliefs about the hazard associated with the food scare.

As evidenced by repeated empirical validations of the Ellsberg Paradox,[2] there is strong reason to believe, however, that when faced with uncertainty, individuals may not behave as though they possess a unique probability measure over potential uncertain hazards. Thus, if Knightian uncertainty is present in food scares (and we believe that it is), it has empirical implications, and those empirical implications can only be captured by analyzing data from real-world uncertain experiments if one allows for individuals that behave in a fashion that is not consistent with subjective expected utility theory.

[1] In Knight's words; "Uncertainty must be taken in a sense radically distinct from the familiar notion of Risk, from which it has never been properly separated.... The essential fact is that 'risk' means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character; and there are far-reaching and crucial differences in the bearings of the phenomena depending on which of the two is really present and operating.... It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all."

[2] Ellsberg (1961) argued that, when faced with an uncertain decision environment, individuals exhibit behavior sensitive to the weight of evidence about probabilities. In the basic version of the Ellsberg experiment a decision-maker has to bet on the color of a ball drawn from an urn. The decision-maker is presented with two urns containing 100 balls each: urn I, for which the number of balls of each color is known, say, 50 orange and 50 white balls; and urn II, for which the proportions of orange and white balls are not revealed to the decision-maker. Ellsberg has observed that the majority of decision-makers would prefer to bet on urn I (known probability) than on urn II (unknown probability). Such behavior directly contradicts both objective and subjective expected utility theory, and, if descriptive of reality, renders expected-utility theory (more generally probabilistically sophisticated behavior) inappropriate for evaluating situations involving uncertainty. Ellsberg-type behavior has been repeatedly validated in the experimental and empirical literatures.

The specific model that we choose is a variant of the recursive maximin expected utility preference structure where conditional preferences have Gilboa and Schmeidler's (1989) maximin expected utility form. In this framework, individual attitudes towards uncertainty are reflected in the degree of imprecision of individual beliefs, where the degree of imprecision measures the range of probabilistic beliefs that the decision-maker will entertain.

Our paper has two goals. The first 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. The second is to use that model in conjunction with the natural experiment afforded by the "mad-cow" crisis to elicit empirical information on the perception of uncertainty by decision-makers, as reflected in the degree of imprecision associated with their preference structure.

In what follows, as a backdrop to our modeling effort, we first present an overview of events associated with a well-known 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 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. For example, our model explains the sharp drop in consumption characteristic of food scares in terms of the imprecision that is associated with ambiguous beliefs in a world of Knightian uncertainty. We derive a number of comparative statics results, and then we calibrate our model with meat consumption data drawn from the "mad-cow" scare in the United Kingdom. The calibrated model is used to assess the empirical magnitude of the degree of imprecision of the decision-maker's beliefs, 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. Between 1986 and 1995, UK officials assured the consuming public that UK beef was safe to eat. It was not until 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. By August 2004, there were 142 deaths due to vCJD in the United Kingdom (Guardian, 2004).

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). Figure 2 reports the retail price index for the United Kingdom for January 1990-January 1999 period. It reveals that the prices have dropped substantially following the scare. However, the percentage change in beef prices was considerably smaller than the change in consumption.

Following the 1996 announcement, the European Union banned UK exports of beef worldwide. The ban also affected export of live calves from the United Kingdom. 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, 1999, 2000). During 1998 and 1999 consumption of beef was in fact above expected trends (DTZ/PIEDA, 1998; MAFF, 1999, 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 real expenditure in Italy decreased by 32.2% while prices only decreased by 0.7% (Mazzocchi, Monache and Lobb, 2006). 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, Monache and Lobb, 2006). A slow recovery started in late Spring 2000, but was still far from complete at the end of 2001. Mazzocchi, Monache, and Lobb (2006) find that the two BSE scares led to a structural shift in preferences; a decrease of 3.2% in the beef expenditure share.

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 reverse J response: a sharp initial decline in consumption followed by a gradual recovery. 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, van Ravenswaay, and Thompson, 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; and the hepatitis A outbreak in the United States in 2003, associated with consumption of green onions imported from Mexico.

Sociological studies, in particular, 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 Related Studies

A growing literature has documented and analyzed post-scare consumption dynamics. These studies investigate the impact of food safety information (such as information reported by the media and food product recalls) on consumption behavior and the effect of changes in food safety information on consumer welfare.

The existing studies often utilize a media coverage index as a proxy for risk perceptions regarding foodborne hazards. Swartz and Strand (1981) examine the closure of Virginia's James River to the harvest of all seafood that resulted from kepone pollution. The authors find that the intensity of newspaper coverage of the incident had a significant negative effect on consumption of oysters and the Baltimore wholesale market. Smith, van Ravenswaay, and Thompson (1988) extend Swartz and Strand (1981)'s empirical approach by differentiating between negative and positive media coverage and by incorporating other sources of information (such as product recalls and in-store information). They find that negative information had a significant effect on consumption following the 1982 heptachlor contamination of milk in Hawaii. In contrast, positive information had little effect on milk purchases.

Burton and Young (1996) model consumer reaction to the "mad cow" scare in the United Kingdom as a function of the number of newspaper articles mentioning the BSE crisis. They find a significant effect of media coverage on consumer expenditure on beef. Liu, Huang, and Brown (1998) extend the prospective reference theory of Viscusi (1989) to incorporate a dynamic adjustment process of risk perception. Their model is applied to examine the 1982 heptachlor contamination of milk in Hawaii. The authors find that negative information received from the media has a stronger effect than positive information; negative information affects consumption decisions immediately while positive information is treated as incomplete information by consumers and has a lagged effect on consumption. Pigott and Marsh (2004) examine the effect of food-safety information on demand for beef, pork and poultry in the United States during 1982-1999. Pigott and Marsh (2004) find 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." (p.

154, Pigott and Marsh, 2004) Mazzocchi (2006) demonstrates that a demand model with stochastic parameters may be an attractive alternative to modeling response to food scares via the use of a media coverage index. The methodology is empirically tested using data from four food scares, the 1982 heptachlor milk contamination in Hawaii and the BSE and two E coli scares on U.S. meat demand during 1993–99.

A number of authors have examined the welfare effects of changes in food safety information. Foster and Just (1989) develop a methodology to measure consumer welfare losses due to unawareness about contamination of the consumed product. They demonstrate that when consumers are ignorant about the likelihood of contamination compensating surplus is a proper measure of welfare changes. Mazzocchi, Stefani, and Henson (2004) use the theoretical framework in Foster and Just (2004) and a dynamic Almost Ideal Demand System specification to estimate the cost of ignorance for the 1996 BSE scare in Italy. They estimate considerable losses from being uninformed; per capita cost of ignorance in the early months of the scare reached 50% of the total expenditure on the meat group.

3 The Model

This section develops a model that is intended to capture the dynamics of a typical food scare. Because the model is quite detailed, we break its description into distinct parts. First, we describe the stochastic world in which consumers operate, and how they evaluate those stochastic outcomes. An important component is their belief structure about uncertain outcomes. That belief structure is described in the second subsection. We then describe the consumer's preference (utility) structure, and the last subsection describes the consumer's conditional (on receipt of information) preference functional.

3.1 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 in each period t is as follows. 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. We let Δ denote the probability simplex over Ω. The decision-maker's beliefs in each period are characterized by a *set* Π of probability distributions over Ω. Thus, $\Pi \subseteq \Delta$. The set of probabilities over two-period histories $\Omega \times \Omega$ 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.

Given the story that we are trying to tell, assuming that there is no period-to-period updating of beliefs is quite strong.[3] Moreover, it would be totally unrealistic in a multiple (that is, more than 2) period setting. But in a two-period setting, its main requirement is that by the time decisions for the second period must be taken, the 'panic' or 'hysteria' driven effects that accompany real-world food scares have vanished. Unless the time periods involved are very short (say, days or weeks), this does not seem implausible. Its main role in our work, however, is to provide analytic tractability, and future work should be directed at its relaxation.

The decision-maker is assumed to have a variant of recursive MEU preferences (Epstein and Schneider (2003, 2008)), where conditional preferences have Gilboa and Schmeidler's (1989) maximin expected utility (MEU) form,

$$\min_{(\boldsymbol{\pi}_1,\boldsymbol{\pi}_2)\in\Pi\times\Pi} \left[E_{P_1}u_1 + \delta E_{P_2}u_2\right].$$

[3]This discussion benefits from the insight of an anonymous reviewer.

Here u_t denotes the decision-maker's period-t ex post utility, and E_{P_t} denotes expectation taken with respect to the prior $\boldsymbol{\pi}_t$. 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 an MEU decision-maker reacts to uncertainty *pessimistically* in the following sense. When evaluating stochastic outcomes, he or she always uses probabilities that yield the lowest possible expected utility over P. Although pessimistic behavior may be viewed as restrictive by some, it should be noted that Viscusi (1997) in seeking to explain "alarmist behavior", such as that associated with the "mad-cow" crisis, has reported empirical evidence in a classical Bayesian framework with risk that suggests that individuals routinely place inordinate weight on the highest risk assessments.

3.2 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

$$\Pi = \left\{ \boldsymbol{\pi} \in \Delta : \pi_\theta^N = p_\theta^N \text{ for all } \theta \in \Theta,\ \pi_b^S \in \left[p_b^S, p_b^S + \overline{\varepsilon}\right] \text{ and } \pi_g^S = p_b^S + p_g^S - \pi_b^S \right\}. \quad (1)$$

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 $\boldsymbol{\pi}$ 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 decision-maker'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 decision-maker is convinced that only one is truly valid, then Π would be a singleton. Conversely, if the decision-maker 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 decision-maker will entertain as possible probabilities of the presence of foodborne contamination, will be referred to as measuring the decision-maker's *degree of imprecision* (Walley, 1991) in what follows.[4]

At this point, it may be useful to contrast our model with an expected-utility formulation of the problem. In that setting, because an individual would be probabilistically sophisticated in the sense of Machina and Schmeidler, he or she would always possess a unique prior over the b event occurring. In usual terminology, that would be the individual's risk perception because it would correspond to the "risk" of the hazard occurring. The individuals modeled here are not necessarily probabilistically sophisticated because they have no empirical or objective basis upon which to formulate such a unique prior. Instead their beliefs are characterized by a range of such priors, so that they behave *as though* they have a range of risk perceptions that are characterized by the size (in a set inclusion sense) of the set Π.

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). These beliefs are given, in both periods, by

[4] The size of the set of the decision-maker's beliefs has varying interpretations in the literature on decisionmaking under ambiguity. According to earlier studies (e.g., Dow and Werlang, 1992), the size of the set of the decisionmaker's beliefs, as measured by the degree of imprecision, reflects the decisionmaker's aversion to ambiguity. In contrast, Klibanoff, Marinacci, and Mukerji (2005) point out that the maximin expected utility model "does not, in general, impose a separation of information/beliefs and ambiguity attitudes. In general, the set Π may not be interpreted as being completely characterized by the decision maker's beliefs. It represents beliefs intertwined with ambiguity attitude in an inseparable way." More recent studies have produced and axiomatized models that separate degree of ambiguity perceived by the decision-maker from her attitudes towards that ambiguity. See, for example, Ghirardato and Marinacci (2002), Klibanoff, Marinacci, and Mukerji (2005), and Maccheroni, Marinacci, and Rustichini (2006).

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), Wang (2003), Siniscalchi (2006) and Wakai (2007, 2008)).[5]

Let $\boldsymbol{\pi}(\varepsilon) \equiv \begin{bmatrix} p_b^N & p_b^S + \varepsilon \\ p_g^N & p_g^S - \varepsilon \end{bmatrix}$ for $\varepsilon \in [0, \overline{\varepsilon}]$. The posterior probability of event θ conditional on signal λ for probability distribution $\boldsymbol{\pi}(\varepsilon)$ is denoted by $\pi_{\theta|\lambda}(\varepsilon)$. We have that $\pi_{\theta|N}(\varepsilon) = \frac{p_\theta^N}{p_b^N + p_g^N}$ for all $\varepsilon \in [0, \overline{\varepsilon}]$ and all $\theta \in \Theta$ while $\pi_{b|S}(\varepsilon) = \frac{p_b^S + \varepsilon}{p_b^S + p_g^S}$ and $\pi_{g|S}(\varepsilon) = \frac{p_g^S - \varepsilon}{p_b^S + p_g^S}$ for $\varepsilon \in [0, \overline{\varepsilon}]$. Since $\pi_{\theta|N}(\varepsilon)$ is independent of ε for all $\theta \in \Theta$, in what follows we will use notation $\pi_{\theta|N}$ for the probability of event θ conditional on no scare. 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.

3.3 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, on the consumption of good y in the current period and on the realization of uncertainty $\theta \in \Theta$. Period-1 and period-2 *ex post* utility functions of the decision-maker

[5]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.

take the following forms:

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

and

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

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 current period consumption of the uncertain good with γ equalling the (constant) Arrow-Pratt degree of absolute risk aversion. α is a constant that measures *ex post* utility in the absence of consumption of the unsafe food good, x. For example, if $x_0 = x_1 = 0$, then $u_1 = y_1 - \alpha$.

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, captured by the parameter β. 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 $\frac{\partial^2(-\alpha\exp[-\gamma(r_g x_1 - \beta x_0)])}{\partial x_1 \partial x_0} > 0$, $\frac{\partial^2\left(-\alpha\exp\left[-\gamma\left(r_g x_2 - \beta x_1 - \beta^2 x_0\right)\right]\right)}{\partial x_2 \partial x_0} > 0$, and $\frac{\partial^2\left(-\alpha\exp\left[-\gamma\left(r_g x_2 - \beta x_1 - \beta^2 x_0\right)\right]\right)}{\partial x_2 \partial x_1} > 0$, 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 $\frac{\partial^2(-\alpha\exp[-\gamma(r_b x_1 - \beta x_0)])}{\partial x_1 \partial x_0} = 0$, $\frac{\partial^2\left(-\alpha\exp\left[-\gamma\left(r_b x_2 - \beta x_1 - \beta^2 x_0\right)\right]\right)}{\partial x_2 \partial x_0} = 0$, and $\frac{\partial^2\left(-\alpha\exp\left[-\gamma\left(r_b x_2 - \beta x_1 - \beta^2 x_0\right)\right]\right)}{\partial x_2 \partial x_1} = 0$. Substituting for y_1 and y_2 from budget constraints $I_1 = q_1 x_1 + y_1$ and $I_2 = q_2 x_2 + y_2$, respectively, (2) and (3) can be written as $u_1 = I_1 - q_1 x_1 - \alpha \exp\left[-\gamma\left(r_\theta x_1 - \beta x_0\right)\right]$ and $u_2 = I_2 - q_1 x_2 - \alpha \exp\left[-\gamma\left(r_\theta x_2 - \beta x_1 - \beta^2 x_0\right)\right]$.

A number of empirical studies (e.g., Holt and Goodwin, 1997) have documented, both theoretically and empirically, the role of habit formation in consumer demand for meat products. Ignoring such findings in our specification opens the possibility that the model could be interpreted as specifically designed to overstate the effect of ambiguity aversion on the observed demand drop by ignoring a stylized fact of the existing empirical literature. That the model can explain such a precipitous drop even in the presence of habit formation, whose role is to smooth adjustments to structural changes, demonstrates that ambiguity attitudes are important even in the absence of intra-period updating. However, accommodating both habit formation and intra-period updating greatly decreases the parsimony of the current model, and thus we elected to forego updating in favor of the empirically validated habit formation hypothesis.

The main reason for assuming $r_b = 0$ is to reduce the number of parameters that need be backed out of the calibrated model. It implies that the marginal utility of consuming x in the current period in the event of a scare is independent of past consumption of x. This assumption would be very restrictive in a setting with multiple consumers where some had a strong taste for beef, characterized by a relatively large initial stock of consumption, while others did not. However, because we only model a single representative consumer whose initial consumption stock is calibrated to the average pre-scare level, the assumption does not have the same implications as in a framework that differentiates between consumers with different tastes for beef.[6]

3.4 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

[6] This discussion benefits from the insight of an anonymous reviewer.

on receiving signal S in the beginning of period 1 can be written as

$$V^S(x_1^S, x_2^{N|S}, x_2^{S|S}) \equiv -\alpha \exp(\gamma\beta x_0)\left\{\pi_{b|S}(\bar{\varepsilon}) + \pi_{g|S}(\bar{\varepsilon})\exp\left(-\gamma x_1^S\right)\right\} + I_1 - q_1 x_1^S \qquad (4)$$
$$+\delta\left\{\begin{array}{c} -\alpha\exp\left[\gamma\left(\beta x_1^S + \beta^2 x_0\right)\right]\left(\left(p_b^S + p_b^N + \bar{\varepsilon}\right) + p_g^N \exp\left(-\gamma x_2^{N|S}\right) + \left(p_g^S - \bar{\varepsilon}\right)\exp\left(-\gamma x_2^{S|S}\right)\right) \\ +I_2 - q_2\left(x_2^{N|S} + \left(p_b^S + p_g^S\right)\left(x_2^{S|S} - x_2^{N|S}\right)\right) \end{array}\right\},$$

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.

4 Some Theoretical Results

We first analyze the effect of changes in the model parameters on the optimal consumption of the uncertain good conditional on receiving signal $\lambda \in \{N, S\}$ in the first period.[7] 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 *(food scare) is strictly decreasing in the degree of imprecision* $\bar{\varepsilon}$; *period-1 consumption* x_1^N *conditional on signal* N *(no scare) does not vary with* $\bar{\varepsilon}$;

2i. *Period-2 consumption* $x_2^{N|\lambda}$ *conditional on receiving signal* $\lambda \in \{N, S\}$ *in period 1 and*

[7] The proof Proposition 1 (Appendix B) demonstrates that a number of our findings follow directly from the supermodularity of the preference functional V^λ in $(x_1^\lambda, x_2^{N|\lambda}, x_2^{S|\lambda}, -\bar{\varepsilon}, -q_1, -q_2)$. The latter is an implication of the maximin expected utility form, additive separability of the ex post utility function and habit formation. This, in turn, implies that our results regarding the effects of $\bar{\varepsilon}, q_1, q_2$ on the optimal consumption choices will hold for any preference functional that satisfies these properties.

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 $\overline{\varepsilon}$, period-2 price (q_2) and the negative of the initial consumption stock ($-x_0$); $x_2^{S|\lambda}$ 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[8], 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 $\overline{\varepsilon}$, 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 a lower decision weight to the absence of food-borne pathogens. Hence as imprecision grows, the pessimistic consumers attach a lower probability weight to a good outcome, and, thus, they are naturally less willing to consume the potentially hazardous product.

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 behavior. The following proposition makes precise the intuitive statement "sufficiently imprecise":

Proposition 2 *If*

$$\pi_{g|N} > \pi_{g|S}(\overline{\varepsilon}),$$

[8]This result is due to the additive separability of the ex post utility function in goods x and y.

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 ("good") 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 decision-maker evaluates "post-scare" consumption of the food product in terms of this most pessimistic probability, Proposition 2 requires that the decision-maker evaluates consumption of the hazardous food product as though contamination were more likely in the presence of a scare than in its absence.

From Propositions 1 and 2, it follows that in our model the fundamental economic explanation of the initial sharp drop in consumption characteristic of food scares is the ambiguous nature of the consumer's beliefs about Θ. When consumers receive an N signal, they are able to accurately (and uniquely) assess the posterior probability of the unsafe commodity being bad, b. However, when the consumers receive an S signal, their beliefs about the posterior probability of the unsafe commodity being bad are fuzzy and range over the interval $\left[\pi_{b|S}(0), \pi_{b|S}(\bar{\varepsilon})\right]$. Reacting pessimistically to this ambiguity or uncertainty about the likelihood of b occurring, they evaluate the uncertain product in its most unfavorable (probabilistic) light, and thus curtail its consumption.

It is of particular interest to note in Proposition 2 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 commences. Hence, our model can explain the stylized reverse-J shape that consumption follows after the scare.

Another stylized fact is that, following a scare, some segments of the population 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 $\overline{\varepsilon}$, 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 establish:

Proposition 3 *There exists a threshold level of* $\bar{\varepsilon}$, $\overline{\varepsilon}^t < p_g^S$, *such that for all* $\overline{\varepsilon} \in [\overline{\varepsilon}^t, p_g^S]$, $x_1^S = 0$, $x_2^{S|S} = 0$, *and*

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

Extreme imprecision can convince the decision-maker that the "most pessimistic" posterior probability of eating contaminated food approaches one. In such cases, the decision-maker evaluates receipt of a scare signal as confirming the presence of foodborne contamination, and he or she rationally responds by completely avoiding the product.

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, consumers are more likely to shun the product when food scares are, *a priori,* low probability events. We have:

Proposition 4 *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* $\pi^t \in [\overline{\varepsilon}, 1]$ *of the probability of signal* S *such that* $x_1^S = 0$ *and* $x_2^{S|S} = 0$ *for all* $\left(p_b^S + p_g^S\right) \in [\overline{\varepsilon}, \pi^t]$.

Proof. (see Appendix E) ■

The economic explanation is as follows. Appendix E shows that low-probability food scares result in almost complete posterior uncertainty. Hence, in this case, after 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 now evaluates acts as though the bad health outcome were almost certain. As a consequence, he or she rationally refuses to consume the food product of uncertain quality. Thus, our model predicts that food scares evoke the most drastic responses precisely when *a priori,* consumers do not consider them likely to occur. On the other hand, our model suggests that consumer behavior is less drastic when food scares are viewed as relatively frequent occurrences in a probabilistic sense.

5 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 for a "representative UK consumer" that is consistent with the calibrated model, and how that measured degree of imprecision responds to different assumptions on model parameters. Our specification assumes that the consumption good whose product quality is uncertain can be represented by beef and veal consumption.

The period in the model is half a year. Period 1 is taken to be 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).[9] 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 initial 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 in 1996, our judgment is that this prior likely overstates the representative UK consumer's prior

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

beliefs of a food scare.

One of the goals of the quantitative analysis is to determine how altering the prior probability of a scare affects our quantitative results. Notice that, consistent with Proposition 2, the initial quantitative analysis assumes that the 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. Although values of parameters p_b^S, p_g^S, and p_b^N in the baseline and other cases have a relative ranking that in all likelihood reflects actual beliefs, there is no a priori evidence that the average consumer in the UK had beliefs characterized by these values.

However, some insight into the role that posterior imprecision plays in the behavior of our representative individual can be gleaned from considering a simple insurance problem. Suppose for the moment, contrary to our maintained assumptions, that the individual is risk-neutral so that his or her attitudes over ex post consumption of x are linear. Also suppose that his or her valuation of the food item is 100 when g occurs and 0 when b occurs.

If his or her posterior probability of the hazard belongs to the interval

$$[\frac{.007}{.01}, \frac{.007+\bar{\varepsilon}}{.01}],$$

then, given the maximin preference structure, his or her posterior valuation of x is $100\left(.3 - \frac{\bar{\varepsilon}}{.01}\right)$. If this individual were presented with the opportunity to buy insurance in the form of a put option that yielded 50 if b occurs and nothing otherwise, he or she would strictly prefer to purchase the insurance product at any price v satisfying

$$\min\left\{50\left(\frac{.007+\varepsilon}{.01}\right) + 100\left(.3 - \frac{\varepsilon}{.01}\right) : \varepsilon \in [0, \bar{\varepsilon}]\right\} - v > 100\left(.3 - \frac{\bar{\varepsilon}}{.01}\right),$$

or

$$50\left(\frac{.007+\bar{\varepsilon}}{.01}\right) > v.$$

Hence, as the degree if imprecision (as measured by $\bar{\varepsilon}$) grows so too does the individual's willingness to pay for the insurance product. And in the limit as $\frac{.007+\bar{\varepsilon}}{.01} \to 1$, it converges to 50.

The values of the remaining parameters 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 to the revelation of the BSE-vCJD link, immediately after the revelation and half a year after that.

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)	$\gamma \in [0.015, 0.035]$

Note: q_1 and q_2 are the average retail price indexes for the United Kingdom (*Source:* Lloyd et al., 2001); consumption data for x_0, x_1^S, and $x_2^{N|S}$ is based on the total UK consumption measured in thousand tonnes (*Source:* DEFRA, 2006)

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 because the prior degree of imprecision, $\bar{\varepsilon}$, can be obtained from the measured posterior degree of imprecision by simple multiplication. We also seek to determine how that degree of imprecision responds to differing assumptions on the parameters of our model.

Our baseline model sets the degree of habit persistence, $\beta = 0.1$, which is in line with the estimates for habit formation with respect to beef (Holt and Goodwin, 1997), and the coefficient of absolute risk aversion, $\gamma = 0.02$. To interpret this coefficient of absolute risk aversion, notice that a CARA decision-maker with $\gamma = 0.02$ 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 the 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 in the interval [1,4]. Thus, we allow for quite high to very high degrees of risk aversion on the part of consumers.

Given our parameters, the model also solves for the parameter α of the utility function, the prior and posterior degrees of imprecision $\bar{\varepsilon}$ and consumption in period 2 following scares in periods 1 and 2 ($x_2^{S|S}$). In other words, *our interpretation of the data from the UK "mad-cow" crisis is that only one scare occurred in the UK beef market, and, therefore, that $x_2^{S|S}$ is counterfactual to our data.* This assumption is based on the fact that our time periods (one half year) actually correspond to relatively long periods in the consumer cycle during which many other intervening factors likely affected the consumption patterns of beef and closely related products.

In Figure 3 we depict the posterior degree of imprecision given by

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

and how that measured degree of imprecision responds to different assumptions about the degree of absolute risk aversion and the degree of habit formation. Note that the posterior degree of imprecision is quite large, and that, for a fixed level of degree of habit persistence, the posterior degree of imprecision increases as risk aversion increases over what is thought of as plausible ranges. However, once risk aversion reaches very high levels, the degree of imprecision starts to decline although it still remains relatively high.

This pattern of behavior is explained as follows. It is generally impossible to disentangle uncertainty aversion from risk aversion without specific assumptions on the reference model that is used to characterize "uncertainty neutrality" (Epstein, 1999, Ghirardato and Marinacci, 2002). More generally, the same model can be interpreted as either perfectly uncertainty averse or perfectly risk averse. When economic agents become extremely risk averse, their behavior becomes extremely conservative and manifests a "safety-first" type of decision process that is also characteristic of very uncertainty averse consumers. They do not expose themselves to any perceived hazard even if the prior probability of that hazard is arbitrarily low. Hence, in our model if consumers are treated as though they are extremely risk averse, economic effects that could reasonably be attributed to imprecision in an uncertain world are confounded with those emerging from extreme risk aversion. Consequently, the imprecision that could be inferred from a given data set would decline, as we observe here. We emphasize, however, that our quantitative results suggest that this only occurs at very high levels of risk aversion, which, as we discuss below, has very problematic empirical implications for $x_2^{S|S}$ and the rest of our model.

The second observation stemming from examination of Figure 3 is that for a fixed level of absolute risk aversion the posterior degree of imprecision is a decreasing function of the degree of habit persistence. *A priori,* one cannot determine the relationship between the degree of imprecision and the degree of habit persistence that would explain arbitrary consumption patterns. This is not surprising. Our analytical model yields ambiguous comparative statics results for the effect of habit persistence on the optimal consumption pattern. One reason for this ambiguity is that it is not possible to determine the effect of habit persistence on the marginal utility of period-1 consumption following a scare (x_1^S).

This effect consists of two parts of different signs, the effect of changes in habit persistence on period-1 marginal utility and the effect on period-2 marginal utility. The first is positive, while the second is negative. For the calibrated model, the second effect dominates the first. As a result, holding other parameters fixed, increases in habit persistence result in a decrease in period-1 consumption following a scare (x_1^S). Thus, the negative relationship between the degree of imprecision and the degree of habit persistence emerges in our empirical analysis because our numerical exercise holds x_1^S fixed at the actual consumption level following the "mad cow" scare (about 158). Hence, increases in degree of habit persistence, which push for a smaller x_1^S are balanced by decreases in degree of imprecision, which result in larger x_1^S.

We have also solved for $x_2^{S|S}$. In our model, this corresponds to what optimal consumption of the hazardous product would be if two scare signals were received in a row. As noted, we have taken this as counterfactual to what the market experienced during the UK "mad-cow" crisis. Figure 4 depicts consumption following two scares as a function of the degree of absolute risk aversion and the degree of habit persistence. The analysis suggests that, holding the degree of habit persistence at the baseline level 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. However, as the degree of risk aversion is allowed to rise to extreme levels, the simulated value of $x_2^{S|S}$ gradually rises towards the level that beef consumption reached immediately after the scare (about 158). As noted above, as risk aversion becomes quite large, measured imprecision tends towards zero, and in the limit the expected-utility model applies. Because updating in response to the second scare signal can only occur within the second period, then apart from effects due to habit formation consumer response to the second scare signal should be exactly the same as the first. Because the model is calibrated to set hazardous consumption at roughly 158, as risk aversion becomes extreme second period consumption should climb towards that level. Our view is that such behavior is implausible, and we would expect two scares in a row to be reinforcing. However, our specification does not allow period 2 beliefs to depend upon period 1 outcomes, and therefore, this reinforcement effect cannot be captured by our model.[10] Hence, we view this result as evidence against the presence of extreme risk aversion on the part of consumers.

Our numerical exercise also demonstrates that consumption following two food scares is an increasing function of habit persistence (see Figure 4). That is, repeat bad news has a relatively small effect on consumers with a relatively large degree of habit persistence.

We have also investigated the changes in 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 4 (see Appendix E for the formal analysis). The quantitative results suggest that similar behavior is exhibited even in nonlimiting cases. Table 2 reports the results for the posterior degree of imprecision and $x_2^{S|S}$ by allowing the prior probability of a food scare to decline from 5% 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.

[10] We would like to thank an anonymous reviewer for this observation.

Table 2: Varying Parameters of the Probability Matrix

	Posterior degree of imprecision	$x_2^{S\|S}$
$p_b^S = 0.035$ $p_g^S = 0.015$	0.076	115.15
$p_b^S = 0.007$ $p_g^S = 0.003$ (baseline)	0.143	97.69
$p_b^S = 0.0007$ $p_g^S = 0.0003$	0.159	92.20
$p_b^S = 0.00007$ $p_g^S = 0.00003$	0.160	91.61
$p_b^S = 0.000007$ $p_g^S = 0.000003$	0.161	91.55

Note: The variable $x_2^{S|S}$ is measured in thousand tonnes, the same units as the variables x_0, x_1^S, and $x_2^{N|S}$.

Although we have no firm evidence, our conjecture is that *a priori* most food scares are extremely low probability events. The hazards involved in many of the most famous food scares were simply not anticipated by the consuming population before the food-scares occurred. Therefore, if one had been able to elicit a prior probability for such an event occurring, it seems plausible that that probability would have been extremely low. Table 2 shows that when the prior probability of a scare is set at such a low level, our data suggests that consumers would exhibit a very high degree of posterior imprecision. 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. Table 2 also demonstrates that even when the probability of the scare is set at the very large level of 0.05 (the first row in Table 2) the corresponding posterior degree of imprecision is still substantial (7.6%) even though it is lower than under the baseline scenario.

As stressed throughout the paper, a stylized fact of food scares is that some segments of the population stop consuming the potentially hazardous food product following a scare. Proposition 3 addresses this issue theoretically. We have demonstrated in the previous section that product shunning occurs when the consumer's beliefs are *sufficiently* imprecise. Thus, it is natural to attempt to measure belief imprecision for such consumers and to contrast it with the degree of imprecision of the representative UK consumer. To solve the calibrated model for the degree of imprecision associated with completely shunning of beef consumption, we need to exchange some of the factuals and counterfactuals in the simulation analysis. Specifically, the levels of consumption following one and two scares, x_1^S and $x_2^{S|S}$, are both set to zero while consumption following a scare in period 1 but no scare in period 2, $x_2^{N|S}$, is now treated as counterfactual. The initial consumption stock x_0 is left at its baseline value, and all parameters of the model are set at their baseline levels.

The results show that the prior degree of imprecision $\overline{\varepsilon}$ that would be associated with consumers shunning beef consumption is arbitrarily close to p_g^S, which is its largest feasible value.[11] The posterior degree of imprecision is thus also arbitrarily close to its largest feasible value $\frac{p_g^S}{p_b^S+p_g^S}$. This empirical finding was robust to varying the parameters of the model. Hence, our empirical analysis suggest that consumers who shunned the food product immediately after the scare were consumers who had maximally imprecise beliefs.

5.1 Expected-Utility and the Mad-Cow Scare

Finally, we solve the calibrated model under the assumption that the decision-maker has expected utility preferences. The purpose of this exercise is to compare the beliefs and counterfactual consumption patterns under the MEU model with the standard expected utility model.[12]

We have run the following "expected utility simulation". All of the parameters of the model were set at their baseline values with the exception of p_b^S. Instead of setting p_b^S equal

[11] Recall that we have imposed restriction $\overline{\varepsilon} < p_g^S$ on the parameters of the model, an assumption also maintained in the calibration exercise. We have stated that degree of imprecision is "arbitrarily close" to p_g^S because the calibration exercise always yields a difference between p_g^S and $\overline{\varepsilon}$ which is equal to the maximal degree of accuracy of the computer program.

[12] We are indebted to the editor and an anonymous reviewer for suggesting this quantitative exercise.

to 0.007 we solve the calibrated model for p_b^S. On the other hand, the degree of imprecision, $\overline{\varepsilon}$, is set to zero which amounts to the decision-maker having expected utility preferences. We also solve the calibrated model for the counterfactual consumption $x_2^{S|S}$.

The "expected utility simulation" yields $p_b^S = 0.206$. Thus, for the expected utility model to explain the observed consumption pattern the prior probability of a scare has to be equal to 20.6% + 0.3% = 20.9%. Although some may certainly disagree, 20.9 strikes us as an implausibly high prior for a food scare in the United Kingdom at the time of the "mad-cow" crisis. Our quantitative results also indicate that unless further constrained, $x_2^{S|S}$ would have become negative indicating, of course, that consumers would have shunned beef entirely. While beef consumption did decline markedly, it never approached zero. Thus, we conclude that the expected-utility specification yields a less plausible description of what occurred than the MEU specification.

6 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. The constructed model generates a number of testable predictions 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 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. Our theoretical and quantitative results 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 baseline results may understate the true degree of posterior imprecision that consumers faced in the UK "mad-cow" crisis.

Our analysis has focused on the role that Knightian uncertainty can play in generating and explaining a food-scare. We have chosen this particular focus because food scares appear to be events for which 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). The natural experiment associated with the "mad-cow" crisis affords us an opportunity to elicit some empirical information on decision-maker attitudes towards ambiguity in the context of our chosen model.

While ambiguity is the focus of our analysis, we should also note that one can always choose a parametrized expected utility model that is consistent with the observed equilibrium behavior for our maximin expected utility model. Specifically, for any parameterization of our model that is characterized by the presence of ambiguity (non-singleton Π) and fits the *observed consumption pattern* there exists a parameterization of an expected utility model that also fits the *observed consumption pattern.* This parameterization of an expected utility model will differ from the corresponding parameterization of the maximin expected utility model by the choice of beliefs. In such a context, a decision-maker's beliefs about the likelihood of the hazard occurring might be thought of as his or her risk perception, and the receipt of a signal about the true state of the world would be interpreted as leading to an updating or a change in the individual's risk perception.

Some readers of our paper have argued on this basis that, by the principle of Occam's razor, the current model should be replaced by a subjective expected-utility model because the latter is simpler. Logically, however, Occam's razor slices the other way. The current model is actually simpler than an expected-utility model because it invokes strictly weaker, and not stronger, assumptions on individual behavior than an expected-utility model. Thus, Occam's razor dictates the choice of the current model over an expected-utility model in such situations.

Moreover, it is quite easy to show that even if our maintained model of preferences were more general than the maximin expected utility (for example, nondecreasing and quasi-concave preferences) there would still exist a similar relationship between this more general preference structure and the expected utility model; if a parameterization of the more general model could explain the observed behavior then there would exist a parameterization of an expected utility model that would also fit the observed data (Machina, 1982).

The current model, therefore, has the advantage over a more general model of offering some rather clear predictions about behavior and within its parametrization an ability to approximate the roles that ambiguity aversion and risk aversion play in individual decisions. At the same time, it invokes fewer assumptions than the expected-utility model, and the only additional difficulty that it carries is the potential nondifferentiability of the objective function. But, as we have shown, that is easily handled.

Finally, we would like to note that the model and its theoretical predictions should generalize in a number of directions. First, one could consider a more general preference functional. A natural generalization is an $\alpha-$maximin expected utility, which is a weighted functional of the most pessimistic and the most optimistic scenarios with the weight α measuring the degree of pessimism. One can demonstrate that as long as the decision-maker is sufficiently pessimistic, our theoretical results remain intact. Another potential extension is a more general information structure. Recall that we have assumed that the realizations of signals and events in the first period are not informative about the likelihood of their realizations in the second period, i.e., updating occurs within periods but not from period to period. It is quite plausible that scares spill over to the subsequent periods even when no scares occur after the initial period. That consumption does not recover to the pre-scare levels when the period of bad news has passed may be due not only to the habit formation modeled in this paper but also due to this informational spillover. We have chosen not to extend the present paper in these directions mainly because of the inadequacy of the existing data to accommodate these more general structures in the calibration exercise.

7 Appendix A

Conditional Preference Functionals:

Denote the sets of posterior probability distributions over Θ conditional on the realization of signals N and S by

$$\Delta^N \equiv \begin{bmatrix} \pi_{b|N} \\ \pi_{g|N} \end{bmatrix} \text{ and}$$

$$\Delta^S \equiv \left\{ \begin{bmatrix} \pi_{b|S}(\varepsilon) \\ \pi_{g|S}(\varepsilon) \end{bmatrix} : \varepsilon \in [0, \overline{\varepsilon}] \right\},$$

respectively.

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

$$V^\lambda(x_1^\lambda, y_1^\lambda, x_2^{N|\lambda}, y_2^{N|\lambda}, x_2^{S|\lambda}, y_2^{S|\lambda}; x_0)$$

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

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

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

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

8 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 5 *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

$$\begin{aligned}\frac{dV^S}{dx_1^S} &= \alpha\gamma\pi_{g|S}\left(\bar{\varepsilon}\right)\exp(-\gamma(x_1^S-\beta x_0)) - q_1 \\ &-\delta\gamma\beta\alpha\exp\left[\gamma\left(\beta x_1^S+\beta^2 x_0\right)\right]\left(\left(p_b^N+p_b^S+\bar{\varepsilon}\right)+p_g^N\exp\left(-\gamma x_2^{N|S}\right)+\left(p_g^S-\bar{\varepsilon}\right)\exp\left(-\gamma x_2^{S|S}\right)\right),\end{aligned} \tag{5}$$

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

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

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

$$\frac{\partial^2 V^S}{\partial\left(x_1^S\right)^2} = -\alpha\gamma^2\pi_{g|S}\left(\bar{\varepsilon}\right)\exp(-\gamma(x_1^S-\beta x_0)) \tag{8}$$

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

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

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

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

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

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

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

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

and

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

The expressions (8), (9), (10), (14) and (15) imply that 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 6 *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

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

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

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

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

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

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 (6) 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

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

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

$$\frac{\partial^2 V^S}{\partial x_1^S \partial x_0} = \gamma^2 \beta (1-\beta) \pi_{g|S} \left(\overline{\varepsilon}\right) \alpha \exp(-\gamma (x_1^S - \beta x_0)) + q_1 > 0, \quad (23)$$

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

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

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

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 $\frac{dx_1^S}{d\delta}, \frac{dx_2^{N|S}}{d\delta}, \frac{dx_2^{S|S}}{d\delta} < 0$.■

9 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

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

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

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

10 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

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

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

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

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 $x_2^{N|S}$.■

11 Appendix E

Proof of Proposition 4: Consider the difference between the largest and the smallest probability of event $\theta \in \{b, g\}$ conditional on S

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

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 $\lim_{\left(p_b^S + p_g^S\right)\downarrow\bar{\varepsilon}} \frac{\bar{\varepsilon}}{p_b^S + p_g^S} = 1$. That is, as probability of S gets arbitrarily close from above to $\bar{\varepsilon}$, 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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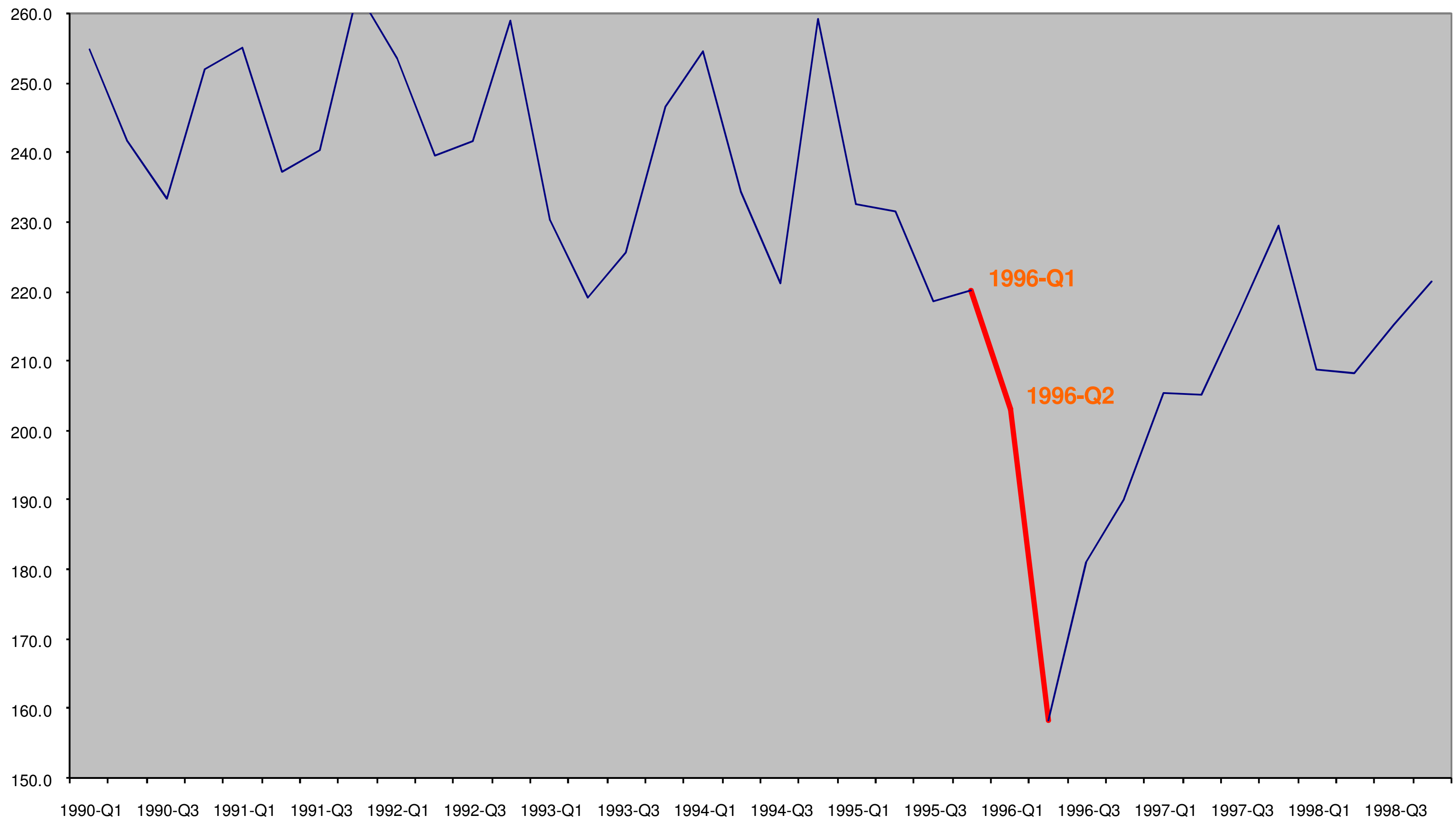
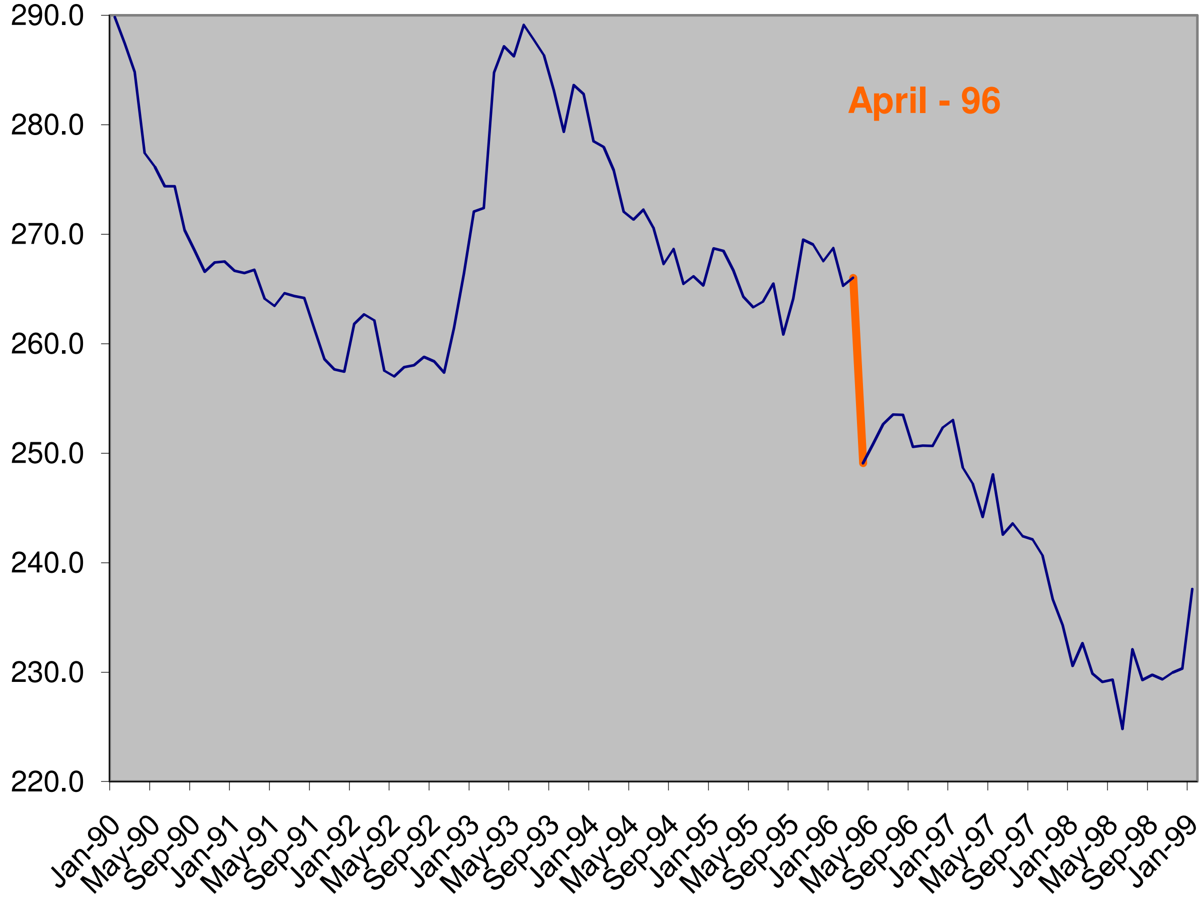
Figure 1: UK Total Domestic Usage of Beef and Veal (01/1990 - 12/1999)
Units: 1,000 Tonnes Dressed Carcase Weight



Source: Department of Environment, Food and Rural Affairs (DEFRA), United Kingdom (available at www.defra.gov.uk)

Figure 2. Retail Price Index of Beef, the United Kingdom (01/1990 - 01/1999)



Source: Lloyd, McCorriston, Morgan and Rayner (2004)

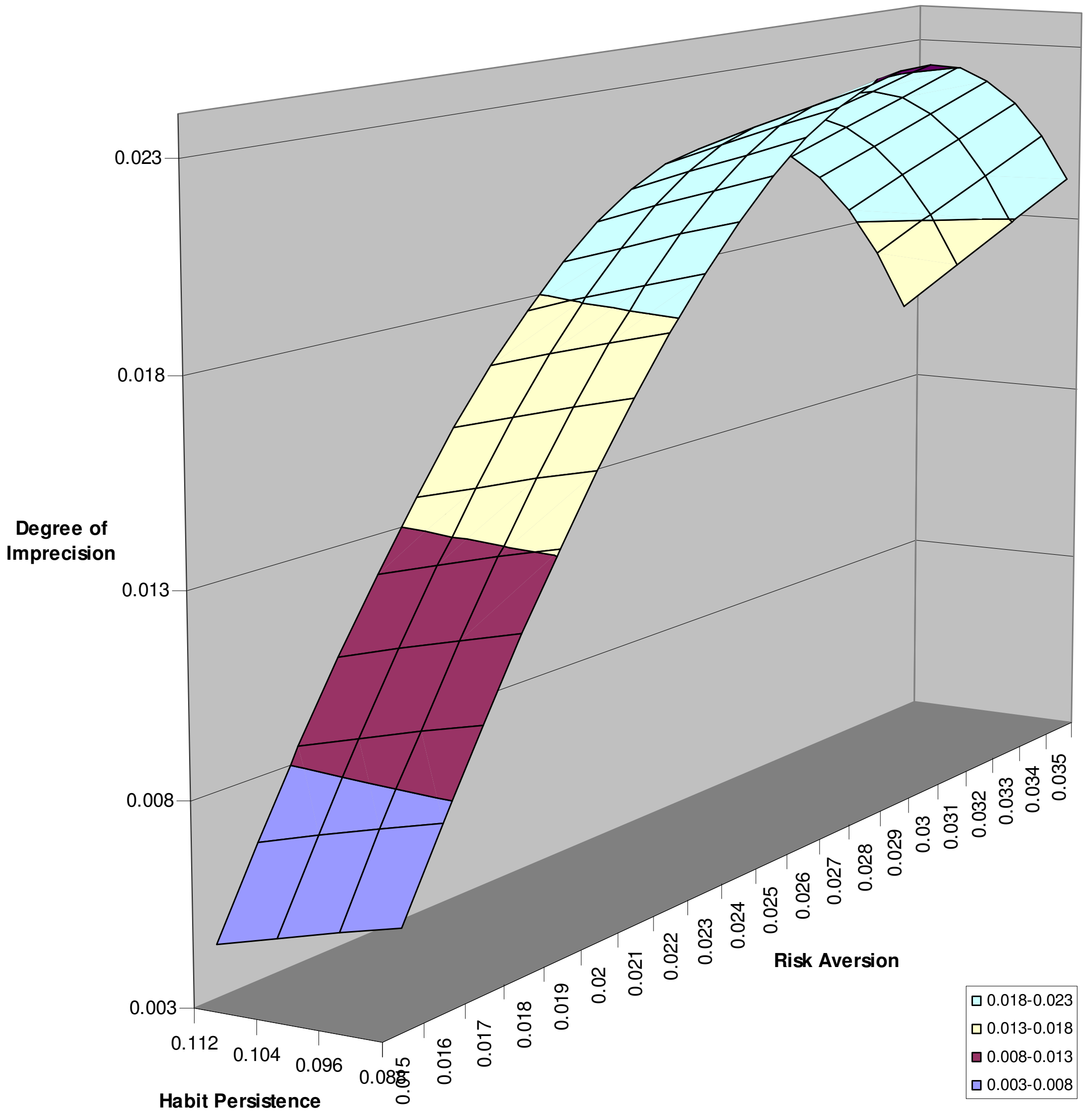


Figure 3: Posterior Degree of Imprecision as a Function of Degree of Absolute Risk Aversion and Degree of Habit Persistence

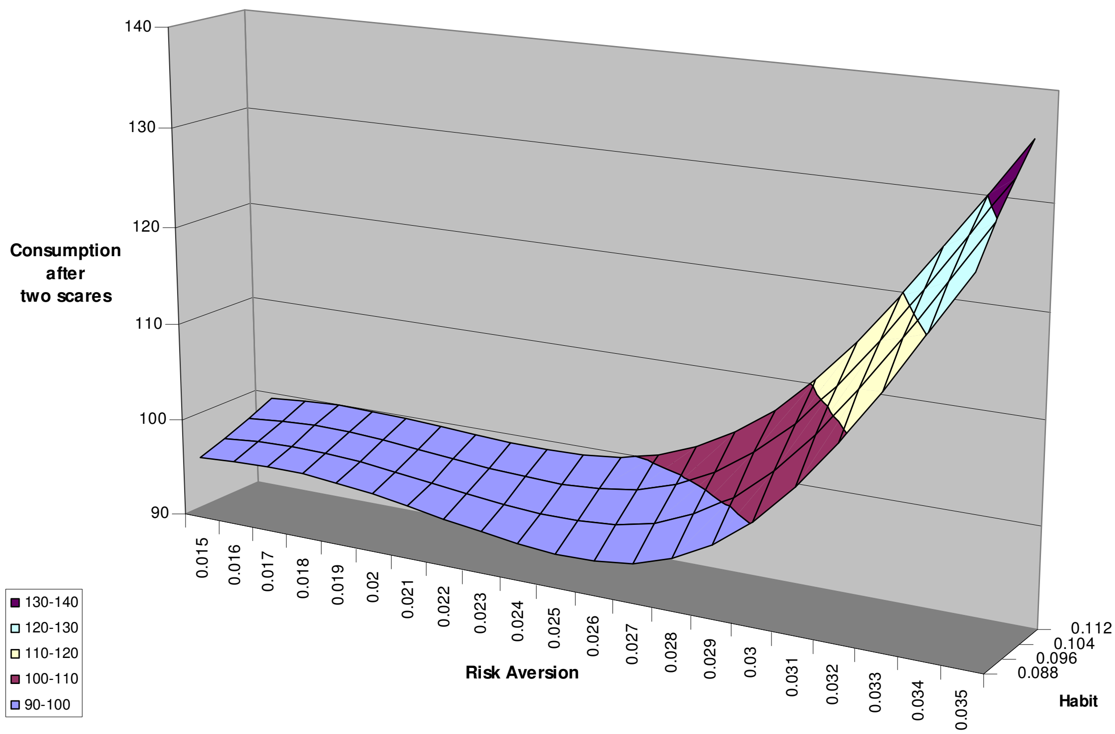


Figure 4: Consumption Following Two Scares as a Function of Degree of Absolute Risk Aversion and Degree of Habit Persistence