Consumers' Costly Responses to Product-Harm Crises*

Rosa Ferrer †　　Helena Perrone ‡

February 2022

Abstract

This paper exploits a major food safety crisis to estimate a full demand model for the unsafe product and its substitutes, recovering consumers' preference parameters for different product characteristics. Counterfactual exercises quantify the relevance of different mechanisms—changes in safety perceptions, idiosyncratic tastes, product characteristics, and prices—driving consumers' responses. We find that consumers' reaction is limited by their preferences for the product's observable and unobservable characteristics. Due to the costs associated with switching from the affected product, the decline in demand following a product-harm crisis tends to understate the true weight of such events in consumers' utility. We find that unobservable taste is a crucial driver of consumers' responses. Our counterfactual exercises illustrate that the demand would have declined further if consumers had had access to a closer substitute. For an accurate assessment of product-harm crises, managerial strategies should therefore account for how different demand drivers bind consumers' substitution patterns.

Keywords: Food safety, demand estimation, scanner data, idiosyncratic utility parameters, nutritional preferences

JEL Classification: L51, L66, K13, M3

*The authors acknowledge research support from INRA, the Government of Catalonia, the Spanish Ministry of Economy and Competitiveness (ECO2010-15052, ECO2008-01116, ECO2013-43011-P, and ECO2016-76998-P), and the Severo Ochoa Programme for Centers of Excellence in R&D (SEV-2015-0563). Perrone gratefully acknowledges financial support by the Deutsche Forschungsgemeinschaft (DFG) through CRC TR 224 (project B04).

†Universitat Pompeu Fabra and Barcelona School of Economics, rosa.ferrer@upf.edu.

‡University of Mannheim and MaCCI, helenaperrone@uni-mannheim.de

1 Introduction

Product-harm crises are frequent and affect a wide variety of industries, such as automobiles, mobile phones, and food.[1] The consumer backlash that usually follows these crises can have severe consequences for firms' revenues. However, does the drop in sales fully reflect the underlying value loss for firms? Consumer reaction may be sticky in the short and medium run due to switching costs. These costs could be due to higher relative prices of substitutes, tastes, habit formation, or the lack of information about alternative products with similar characteristics.[2] As a result, the demand decrease is likely to understate the negative impact of the crisis on the affected firms' value. For a better assessment and management of product-harm crises, it is therefore fundamental to uncover the different mechanisms constraining consumers' responses.

Previous literature has studied the magnitude of product-harm crises' impact on firms' sales, market shares, and brand equity (Hartman, 1987; Dawar and Pillutla, 2000; Marsh et al., 2004; Ma et al., 2010; Freedman et al., 2012). Our paper advances this literature by providing a framework to decompose and quantify the forces behind the demand drops following product-harm crises, and more generally, the arrival of new information about product characteristics.[3] Specifically, our approach allows measuring how much of the drop is explained by consumers' safety concerns and how much is explained by the substitutability of the affected product. Moreover, it permits identifying the key components that could trigger consumers to switch to alternative products.

Our empirical application focuses on a well-documented food safety event, the mad cow epidemic, which allows us to exploit the timing of an abrupt and unanticipated safety shock in the Fall of 2000 in France. We estimate a full demand model and recover the utility parameters governing the extent to which consumers care about safety, prices, product characteristics, and idiosyncratic unobservable taste (i.e., everything that the consumer derives utility from that cannot be explained by observable characteristics). Counterfactual exercises isolate the roles played by each of these dimensions in consumers' demand reaction to the safety crisis.

Note that although consumers' safety preferences are unobservable, we can partially recover them from the data by combining the exogenous safety shock and our structural demand model. We recover consumers' safety preferences from revealed preference data. Hence, a further contribution of our work is to deepen our knowledge of consumers' utility, in particular, how much

[1]For instance, in the automobile industry, hundreds of deaths were caused by faulty ignition devices in General Motors' cars and unintended acceleration problems in Toyota cars (please see Fortune, August 24, 2015, "Ten times more deaths linked to faulty switch than GM first reported", and The Economist, February 11, 2010 "Accelerating into trouble"). In the mobile phone industry, there was a product recall of nearly 2 million Samsung Galaxy Note 7 smartphones sold before September 2016 due to fire and explosion cases (US Consumer Product Safety Commission, 2016). In the area of food safety, in recent decades, there have been frequent safety crises with diverse origins, such as microorganisms (e.g., E. coli in leafy greens, salmonella in peanut butter), toxic substances (e.g., melamine in pet food, mercury in fish, arsenic in chicken and rice, high lead concentrations in children's toys), and potentially fraudulent practices (e.g., the 2013 horse meat scandal). For further information, see www.fda.gov/food and www.efsa.europa.eu.

[2]See for other examples Dubé et al. (2010), Bronnenberg et al. (2012).

[3]Outside the product-harm crises literature, Hendel et al. (2017) is related to our paper in terms of approach. The authors estimate demand functions to assess the impact of a consumers' boycott.

consumers care about safety relative to other dimensions and how elastic their demand is to changes in their product safety perception. Our findings illustrate the crucial role of substitutability in consumers' responses to product-harm crises. The reaction to the crisis relates not only to consumers' estimated idiosyncratic taste for the affected category but also to the estimated idiosyncratic taste for the affected category relative to those of the substitute categories. Therefore, our results highlight the importance of allowing for consumer heterogeneity in observable but, especially, unobservable tastes.

In addition, we also study how the consumers' reactions to the crisis related to nutritional characteristics and affected the nutritional content of their food baskets. The literature still knows little about the potential effect of safety crisis (or informational shocks, more broadly) on households' diets, an additional effect of such crises that can be critical for policy design. We address this gap by documenting how the nutritional content of households' purchases changed in reaction to the safety event.

The product-harm crisis that we study, the French mad cow crisis, originated domestically when potentially infected beef (of French origin) appeared on the shelves of major national retail chains. Widely publicized in the media, the event cast doubt on the effectiveness of the regulatory policies and monitoring procedures, in particular of grocery stores, implemented as a response to the first mad cow scare that had happened four years earlier in the UK.[4] In the French case, information about the events was transmitted promptly to consumers and policymakers, in part because considerable information about the disease transmission had already been gathered thanks to the UK experience. During the UK crisis, in contrast, there was gradual learning and contradictory information as the crisis unfolded. Also, in our particular setting in France, the empirical evidence indicates that there was no shortage of meat supply following the start of the crisis, implying that observed sales decrease result from demand-side movements.[5]

We combine the exogenous shock to preferences associated with the crisis with a demand model based on Dubois, Griffith, and Nevo (2014). In the model, the consumer's utility depends not only on quantities and nutritional characteristics but also on unobservable tastes and safety perception. We estimate the demand for different fresh meat products, including fish. We aggregate the estimable equation at the meat category level but measure the products' nutritional content at the meat-cut level (for example, the nutritional content of 1 gram of ribeye steak, 1 gram of pork tenderloin, or 1 gram of chicken breast).

Perceived product safety is unobservable. However, we can identify changes in its levels

[4] An initial mad cow scare had occurred four years earlier, in March 1996, triggered by the UK government publicly announcing a likely link between consumption of contaminated beef and several human deaths in that country. Because the first crisis started in the UK and France immediately reacted by banning UK beef imports, it did not initially expand to France. Both crises had large impacts on consumption (Lesdos-Cauhapé and Besson, 2007); however, the second crisis was unanticipated and domestic, making it more suitable for our exercise. Additionally, the first crisis did not have an exact start date. The available information on mad cow disease from various sources was contradictory and denied on several occasions until finally confirmed in March 1996.

[5] Time series data from French slaughterhouses, consumption levels, and net exports in France, show that the crisis increased net stocks of fresh beef meat (Lesdos-Cauhapé and Besson, 2007), implying there was no shortage of beef meat in the first months of the crisis, not quantity rationing.

following the crisis separately from other unobservables by assuming that, before the mad cow shock, safety perceptions were constant. We allow these safety perception changes to vary across observationally heterogeneous consumers, adding another dimension to the rich consumer heterogeneity patterns allowed in our approach. Additionally, the unobserved taste for the category, which consists of the utility that consumers derive from a product that cannot be explained by the product's nutritional characteristics or by perceived safety, is household-specific.

Note that the demand model that we use is better suited to the empirical exercise at hand than discrete choice models or almost-ideal demand system models (AIDS, Deaton and Muellbauer, 1980). Discrete choice models (e.g., random utility models, Berry, 1994, Berry et al., 2004) are appropriate for studying substitution across differentiated products within a category but less suitable for comparisons across categories. Furthermore, when examining purchase data across categories, we frequently observe multiple purchase choices during the same period, another feature for which the discrete-choice framework is less suitable. AIDS and other models in the product space are not better alternatives because they do not allow for the study of the effects of different product characteristics (other than prices) on consumers' choices. The empirical exercise uses a comprehensive, individual-level scanner data set that includes every food product purchased by a large sample of French households over 5 years, from 1999 to 2003. The data include product, store chain, store region, as well as household demographics. This data set is complemented by information on the nutritional characteristics of highly disaggregated meat products (in general, the data are provided at the level of the meat cut). We consider 6 product categories: beef and veal (hereafter, beef), beef and veal offal (hereafter, offal), poultry, pork, fish, and other meats (e.g., lamb, horse, game).

The estimation results show a considerable and significant decline in the perceived safety of beef and offal in the fourth months after the event. Our approach enables us to test whether product characteristics matter for consumers' choices. In particular, we find that nutritional composition is a significant determinant of consumers' meat choices, therefore affecting consumers' responses due to the absence of a close nutritional alternative to beef.[6] The estimates of the unobserved taste for different categories indicate that poultry and beef are the average consumer's favorite categories, while fish and other meat are the least favorite ones.

We also allow safety perception adjustments to vary according to the education level of the household's main person responsible for shopping and the region of residence. Households in different regions or with different educational background could have interpreted differently the informational shock. However, the main implications of our empirical analysis are robust to allowing for such household heterogeneity in preferences for safety (or in responses to the safety shock). Also in terms of robustness, we show that our results are robust to an alternative

[6] Nutritional composition may capture dimensions not related to health concerns, such as texture and cooking method. Also, even if most consumers do not know products' exact nutritional values, they may know basic nutritional facts (e.g., beef has more iron than chicken) and choose products accordingly. Moreover, there is evidence that hunger and appetite are associated with nutritional needs (Hill and Blundell, 1986; Barkeling et al., 1990).

identification strategies based on Allcott et al. (2019), which we linearize to be able to include household and category-specific intercepts. An advantage of this approach is that it allows for the inclusion of an unobservable product characteristic.

Our results show that consumers' reactions to a safety crisis are heterogeneous and limited by how much they like the affected product and its main alternatives. The counterfactual exercises help isolate and quantify each of the different drivers of consumers' choices. The first counterfactual exercise isolates the effect of changes in consumers' safety perceptions to disentangle it from potential contemporaneous drivers of demand. In this exercise, we find that the purchased quantities of beef would have been 10% higher, on average, if consumers had not changed their beliefs regarding product safety. We show that to produce an equivalent demand drop, the prices of beef would have had to increase by 17%. To further investigate heterogeneity in the response, we study the correlation between household individual responses' and households' estimated idiosyncratic tastes. We find that the response to the shock varies with unobserved taste across heterogeneous households both in terms of absolute and relative taste with respect to the potential substitutes. This correlation remains when controlling for geographical differences and education levels.

The second counterfactual exercise investigates the importance of idiosyncratic taste which, as defined above, captures everything that gives consumers utility but cannot be explained by observable characteristics or changes in safety perceptions. We analyze the demand for pork because although pork has a similar nutritional profile to beef, the average estimated taste for pork is lower than for beef. Comparing factual pork purchases to the counterfactual pork purchases if the safety shock had affected pork instead of beef, we find that the demand for pork would have dropped on average 19% as a response to the crisis. This drop is almost twice the drop in beef purchases due to the crisis (10%), implying that consumers' response to the product harm crisis would be considerably stronger if they liked the affected product less. In the third counterfactual, we investigate how consumers' reaction relates to the nutritional characteristics of the affected product. We focus on poultry, which has a similar average estimated taste to beef but differs in terms of nutritional characteristics. We find that if the safety shock had affected poultry instead of beef, the demand for poultry would have dropped on average by 11% following the start of the crisis. This is roughly the same reaction for beef (10%) and considerably lower than the counterfactual drop of 19% in the demand for pork. The combination of these two counterfactuals suggests that households' idiosyncratic taste is a key determinant of consumers' responses.[7]

Concerning our study of the product-harm crisis' effect on consumers' nutritional basket, we find that the safety crisis led to an increase in protein –likely due to the substitution towards poultry, which is high on protein– and a decrease in iron and lipids consumed from meat. Iron

[7]In another counterfactual we also quantify the part of the demand reaction due solely to a change in relative prices. Consistent with descriptive statistics showing little variation in relative prices following the crisis, we find that the relative prices were only a minor driver of consumers' reaction. However, changes in relative prices after a product-harm crisis might play a more central role in other settings, adding to the consumers' costs of responding to a product harm crisis.

is an essential nutrient for the general population, and especially for children and pregnant women, and beef is the product in our analysis with the highest iron content.[8] Due to the health relevance of iron and because our utility parameter estimates indicate that consumers value iron, we study the effect of the crisis on the demand for non-meat iron-rich products (lentils, chickpeas, and other beans). This analysis helps us grasp whether consumers are replacing the iron lost from beef. Results show that there is an increase in purchases of non-animal iron-rich foods in the period following the safety event, leading to a significant increase in iron consumed from non-animal sources in that period. However, this increase is not enough to offset the decrease in iron consumed from animal sources.

We also study whether consumers substituted away from meat and fish altogether towards non-meat animal products such as eggs, cheese, and other dairies –i.e., became more vegetarian –or rather replaced beef with other types of meat. The empirical evidence seems to indicate that consumer response to the crisis was predominantly contained within the fresh meat and fish categories. However, we find a significant increase in the purchases of cheese in the first period after the shock, translated into an increase in the relative average household expenditure share on cheese following the crisis.

Overall, our results have at least three potential implications for product-harm crisis management. First, consumers' responses should be interpreted while accounting for how costly it is for them to adjust their consumption. Second, in the medium to long run, the entry of new products with comparable characteristics could revive the demand reaction to the crisis. Finally, and more generally, our analysis points to the relevance for firms of understanding the different components of consumer's preferences to more accurately anticipate and assess consumers' reactions.

The paper is organized as follows. In the rest of this section, we review the empirical literature on product-harm crises, with a particular emphasis on food scares and the mad cow disease crisis. We also discuss our contribution to the existing literature in greater detail. Section 2 describes the specific product-harm crisis that we focus on and compares it to other major product-harm crisis, summarizing the main events that affected public opinion on this matter and comparing it to other relevant product-harm crises. Section 3 describes the data and provides some descriptive statistics. Additionally, it includes the reduced-form analysis of the effects of the crisis on consumers' nutritional baskets, and on quantities and market shares of non-animal iron-rich products and non-meat animal products. Section 4 and section 5 describe the model and the econometric implementation, respectively. Section 6 reports the results of the demand estimation and the counterfactual exercises. Section 7 shows a robustness analysis that estimates utility parameters using an alternative identification strategy based on Allcott et al. (2019). The last section discusses the results and their managerial implications and concludes.

[8] Although iron can be obtained from other types of food or food supplements, iron from animal sources has a substantially higher absorption rate (Alexander et al., 1994). A sudden dietary change is especially relevant because the incidence of iron deficiency in some populations can be large, even in developed countries with low incidences of undernourishment. For example, Black et al. (2013) reports that the incidence of iron-deficiency anemia in Europe is approximately 12% in children and 16% in pregnant women.

Related literature

There is an extensive literature on product-harm crises in both economics and marketing. A large part of this literature relies on reduced-form exercises to study how product safety crises affect sales, firm revenues, and market shares. Examples are Hartman (1987), Marsh et al. (2004), Ma et al. (2010), Freedman et al. (2012), and Borah and Tellis (2016). There is also a branch of the literature that studies how consumers react to product-harm crises through surveys (Morabia et al., 1999; Pennings et al., 2002; Chatard-Pannetier et al., 2004; Setbon et al., 2005) or lab experiments (Siomkos and Kurzbard, 1994; Lei et al., 2012; Ahluwalia et al., 2000).

In contrast to this previous body of literature, we employ a structural demand approach that allows us to recover preference parameters over product characteristics and to conduct counterfactual exercises. We are able not only to quantify the observed demand decrease but also to study the importance of different mechanisms driving consumers' responses (prices and other observable and unobservable product characteristics). In addition, while the previous literature has mostly studied the impact of product-harm crises on brands (e.g., Dawar and Pillutla, 2000; Ma et al., 2010), this paper focuses on crises where consumers' cannot avoid the affected product just by switching to alternative comparable brands.[9] These cases are particularly worth studying because it is especially costly for consumers to react to the crisis, and they might have to switch to a different product category.

Relevant papers that also follow a structural demand approach are Liu and Shankar (2015) and Zhao et al. (2011). Liu and Shankar (2015) examine various product recalls in the US automobile industry. The authors study how the effect of the recalls on brand preference depends on recall characteristics such as media attention, recall severity, and the expected quality of the recalled product. The paper studies both short- and long-run effects by allowing recalls to affect brand preferences over time. Their results show that consumers' negative response to recalls increases with media attention and the severity of the product defect that triggered the recall (for example, whether the defect could be fatal).

Zhao et al. (2011) model consumer choices when there is uncertainty over product quality and consumers learn about mean product quality through their own experience and product recalls. Focusing on a peanut butter safety crisis in Australia, they investigate how the crisis affected consumers' sensitivities to price, quality and risk by allowing demand model coefficients to vary with time-period (before, during, and after the crisis). The authors find that the price coefficient is closer to zero during the crisis than before or after it.

Our paper differs from and complements the two above-mentioned papers by focusing on the analysis of crises with industry-wide effects, instead of brand-specific effects. To do so, we use a continuous choice demand model instead of a discrete choice model. A continuous choice model allows consumers to react both on the intensive and the extensive margins, i.e., by not only

[9]This is likely to be the case in highly differentiated markets or when the crisis affects a large share of firms in an industry. Among several others, see, for example, two recent prominent examples, the 2007 toy-recall crisis and the 2013 horse meat scandal. In the 2007 toy-recall crisis, both investors and consumers seemingly interpreted the toy recalls as resulting from widespread unsafe practices in the sector (Freedman et al., 2012).

switching away from the affected product but also adjusting the quantities purchased conditional on product choice. When the crisis is industry-wide, there is only a fraction of consumers who are willing to incur the costs of completely avoiding the whole product category (instead of just switching brands within a category). Therefore, the continuous choice framework provides a broader picture of consumer responses to industry-wide crises, as it permits us to consider consumers' responses on both margins.

Although our application focuses on a specific product-harm crisis, we believe that our analysis is informative of consumers' responses to product-harm crises in general, as well as to other informational shocks on products' characteristics. The crisis that we examine received substantial media attention, thus making the fraction of uninformed consumers relatively low (see Section 2 for a comparison with other product-harm crises). Therefore, we can study frictions in consumers' responses that are not due to a lack of information.[10] Furthermore, we have an exogenous and unanticipated shock that triggered the crisis, whereas many product-harm crises, when triggered by a decision of the firm as is the case in many product recalls, could arguably be endogenous. Note also that our model includes dynamic effects, allowing for the study of the long-term effects of a product-harm crisis on consumers' preferences and choices. However, we are careful in interpreting these effects because they could be capturing unobserved shocks other than the long-run effect of the crisis (for example, changes in regulation, government announcements, the arrival of new information on the epidemic, etc.)

In our model, crises do not affect price coefficients (or coefficients in general). Instead, we treat product safety as an unobservable characteristic of the product and are able to estimate the change in this characteristic following a major product safety event without having to assume a parametric specification. Note that safety in our model could also be broadly interpreted as product quality, depending on the application.

Prominent papers that also examine the mad cow epidemic are Schlenker and Villas-Boas (2009) and Adda (2007). Schlenker and Villas-Boas (2009) study how sales and future cattle prices respond to two different events related to mad cow. The first event took place in April 1996, when mad cow disease was discussed on a popular American TV talk show (Oprah). The second was in December 2003, when a cow was diagnosed with the mad cow for the first time in the US. They find that the negative effects of the talk show were considerably larger but more short-lived than the effects of the first diagnosis.

Adda (2007) studies how previous exposure to risky products might influence consumption once the risk is made public. Adda (2007)'s results show a nonmonotonic purchase response as a function of previous exposure to the risky product, and consumers with intermediate levels of previous exposure exhibited the strongest reactions. The effect of previous exposure on the consumer response is estimated as an interaction effect between past consumption and the information shock. This dynamic perspective requires one to abstract from the potential role of (static) households' unobserved taste for the product. In particular, Adda (2007) uses a

[10]Therefore, our paper complements the literature on the effects of increased information on consumers' and firms' behavior (e.g., Jin and Leslie, 2003). Our findings show that even when consumers are aware of potential risks, substituting away from their initially optimal purchase choices is costly such that it might not happen.

model in differences that focuses on changes within individual behavior, canceling out individual preference fixed effects. Using a different approach, our analysis recovers household utility parameters and examines their role in explaining consumers' heterogeneous responses. We believe that it is crucial to investigate the role of unobserved preferences because they determine the response to the information shock and past consumption.

Our analysis may be of interest to the literature on consumers' nutritional choices as well to the one on consumers' behavioral biases.[11,12] Product-harm crises could be related to the literature on salience (Bordalo et al., 2012 and Bordalo et al., 2013) due to their potential extreme shocks to health relative to the average health risks that consumers face. Our approach does not rule out subjective risk. We use a model of utility-maximizing consumers conditional on consumers' perceptions. Thus, consumers' perceptions could still be subject to nonrational biases and subjective perceptions.

Our paper also contributes to a law and economics debate about the role of market forces in the production of safe products (in particular, Polinsky and Shavell, 2010; Goldberg and Zipursky, 2010; Ganuza et al., 2016; Daughety and Reinganum, 2012; and Choi and Spier, 2014) by showing empirically that consumers' market's response is constrained in the absence of close substitutes for the affected product.

2 Empirical context and comparable product-harm crises

The empirical application in our analysis focuses on a product-harm crisis that involved the large majority of producers in an industry, as its origin was linked to a widespread industry practice (namely, the type of cattle feed used). Going beyond specific singularities, our application shares features with several other product-harm crises. In particular, it is closely related to other crises that affected a large fraction of producers in a certain industry and also to product-harm crises in markets with highly differentiated products. In both of these cases, switching from the affected product(s) is likely to involve consumers giving up on certain product attributes that they value. Therefore, in these cases, it can be particularly misleading to evaluate the determinants of consumers' responses without accounting for heterogeneous preferences for the affected product and its substitutes.

2.1 The mad cow epidemic in France

In our application, we exploit an abrupt and unanticipated safety shock in France that affected beef products. As detailed below, its causes are traced to the mad cow disease and the beef industry-wide practice of using meat-and-bone cattle feed. The crisis induced consumers to switch from beef products to alternative fresh meat categories with substantial differences in terms of product characteristics. The start of the crisis was sudden and unexpected, as can

[11] There is a growing literature on the determinants of nutritional choices such as Atkin (2016); Hut and Oster (2018); Allcott et al. (2019)

[12] For instance, Chambers and Melkonyan (2013) provide a behavioral model of uncertainty perception to argue that the sharp drops in consumption following product-harm crises could be due to ambiguous beliefs.

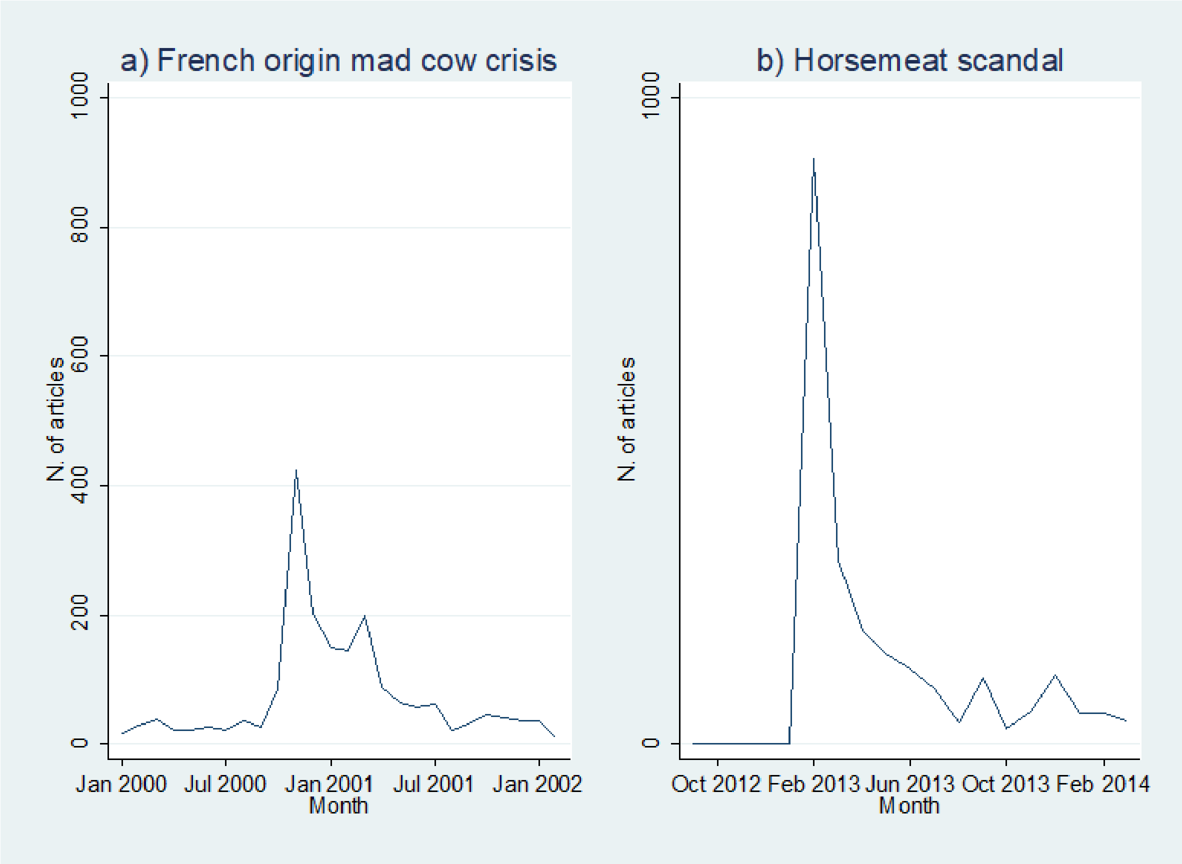

Figure 1: Monthly number of newspaper articles in the French written press mentioning the words (translated to French): a) "mad cow" and "meat", b) "horse meat" and "scandal" or synonyms of "scandal." Source of the data: Lexis-Nexis.

be inferred in Figure 1(a). The figure shows the evolution in the number of French newspaper articles mentioning the words "meat" and "mad cow" from December 1999 to December 2001, with a sharp increase in the number of newspaper articles observed in the figure immediately after the crisis outset in October 2000.

Bovine spongiform encephalopathy (BSE), commonly known as mad cow disease, originated from the use of meat-and-bone cattle feed. The beef industry had widely adopted this form of animal-based feed as an alternative protein source to, for example, soybean feed. UK authorities banned its use in 1988, once the link to the BSE had been established. However, the ban was not perfectly enforced, in part due to the lack of incentives to report and to imperfect surveillance systems. France banned animal-based feed later on, in 1990, and in 1994, reinforced the ban and its control (Al-Zoughool et al., 2010).

Authorities initially excluded the possibility of BSE transmission to humans. In 1993, following the death of a British dairy farmer, researchers found links between the BSE and Creutzfeldt-Jakob disease (vCJD), the human variant of BSE (Sawcer et al., 1993; Smith et al., 1995). However, it was unclear whether the transmission resulted from consumption of infected beef or direct contact with infected animals. In 1994 and 1995, new cases affecting nonfarmers reinforced the hypothesis of transmission via beef consumption. However, it was not until March

20, 1996, that the British Secretary of State for Health, Stephen Dorrell, officially confirmed the likely link between the deaths of several UK citizens and BSE. As a consequence, British beef was banned in France from March 1996 until October 2002 (Borraz et al., 2006).[13]

In this paper, we focus on the second French crisis, which began in October 2000. Unlike the first one, the origin of the second crisis was domestic. Three large supermarket chains (Auchan, Carrefour and Cora) distributed meat that was subsequently found to belong to a herd with a cow infected with BSE. Through a common provider (Soviba, now renamed Elivia), these supermarket chains had purchased the beef from a meat producer in Normandy, Northwestern of France. The infected cow did not enter the food chain; however, these three supermarkets recalled suspect meat from around 10 other cows belonging to the same herd and that had already been commercialized.[14] Also, 30 tons of ground beef were recalled by the most affected supermarket, Carrefour, as it could contain meat from the suspect cows (Wolfer, 2004).[15]

There were three major reasons for consumers' concerns during this second crisis: first, there was evidence that the ban on meat-and-bone meal imposed in 1990 had not been as effective as previously thought; second, unlike in the UK, high-risk cattle (i.e., cattle over the age of 30 months, as the long incubation period of the disease made younger cows less dangerous for human consumption) were not banned for human consumption until January 2001; and third, the number of French cows detected to be infected with BSE had increased from 31 in 1999 to 161 in 2000 (Al-Zoughool et al., 2010).

The 1996 UK original crisis was a major shock to consumers' safety perceptions four years before the episode we focus on. Therefore, french consumers likely had already updated their perception before November 2000. However, there are several reasons to think that the consumers' safety perceptions had stabilized by 1999 when our data begins. First, French beef aggregate consumption appears to be quite flat in the period between January 1998-November 2000 and between January 2002 and December 2003 (Lesdos-Cauhapé and Besson, 2007). Second, as shown in Figure 2(a), the information shock in November 2000 was considerably large. Third, the shock informed about the risks of French beef consumption whereas the 1996 shock affected mostly beef of UK origin, which was banned in France between 1996 and 2002.

Overall, the mad cow disease epidemic caused the deaths of more than 200 people worldwide. After the UK, France was the country with the largest number of human victims (26 deaths).[16] Producers were not held legally liable because their products conformed to the safety regulations in place before the mad cow scare, as European Union legislation excluded the primary sector

[13] In 1999, the European Union lifted the ban on British beef, but France decided to maintain its ban, causing a legal and political dispute between the two countries.

[14] Le Monde, October 24, 2000, "Carrefour décide d'appliquer le principe de précaution extreme" ("Carrefour decides to apply the principle of extreme precaution"); Liberation, October 23, 2000 "Vache folle: un lot suspect se retrouve chez Carrefour" ("Mad cow: a suspect lot found in Carrefour"); La Depeche, October 25, 2000, "Vache folle: Cora et Auchan également concernés et de nouvelles mesures réclamées" ("Mad cow: Cora and Auchan equally concerned and new measures taken"); BBC, October 27, 2000, "More suspect beef sold in France."

[15] The overall amount of meat recalled was less than 0.05% of the meat consumed monthly in France Lesdos-Cauhapé and Besson (2007). We later on also verify that our main results hold when dropping all observations from these 3 supermarkets chains to address potential concerns on supply effects.

[16] UK National CJD Research & Surveillance Unit.

from the strict liability regime that applied to product safety. Thus, vCJD victims were compensated by governments rather than by producers. Due to the mad cow scare, the legislation was revised to include agricultural products in the strict liability regime.[17]

The second French mad cow crisis provides a useful setting to study consumer responses to unanticipated informational shocks. This is because, first, as the shock was unexpected, consumers were unable to anticipate or dissipate their response. Second, given the widespread media coverage, the fraction of uninformed consumers was likely very small. Third, unlike the case of other products analyzed in the literature (e.g., toys and other food products), there is a well-defined set of substitutes for the affected product, namely, other fresh meat, including fish.

2.2 Related product-harm crises

Figure 1(b) shows the media coverage of the 2013 horsemeat scandal, a more recent food-safety crisis in Europe that also received considerable media attention.[18] The cause of this crisis, which affected frozen ground beef, also involved a large number of manufacturers as they shared a common supplier.[19] The affected products represented a large share of the market for frozen cooked dishes and, a priori, it was hard for consumers to identify which brands were or were not involved in the crisis, as many of them shared the same meat suppliers. Hence, consumers willing to react to the crisis likely had to avoid frozen dishes with ground meat as a whole and look for alternative product categories.

Both our application and the horse-meat scandal are product-harm crises in which it can be particularly costly for consumers to react, as it may be difficult to find alternative products with comparable product characteristics as the ones of the affected product. A descriptive study by Yamoah and Yawson (2014) show that consumers' responses to the horse-meat scandal cannot be explained only by risk attitudes, highlighting the relevant role of households' heterogeneous taste for the affected category (frozen ground beef).

Even when product-harm crises are not industry-wide, consumers could still have a hard time finding suitable product alternatives to the affected product. For example, a crisis affecting a product in industries where brands are a crucial component of consumers' preferences (e.g., due to consumer inertia as in Dubé et al., 2010). Figure 2 compares the media coverage of other recent major product-harm crises in France, where the crisis we focus on occurred. Several of the major product-harm crises, in France and elsewhere, have their origins associated with industry-wide practices. For example, Freedman et al. (2012) link the 2007 toy recall to the industry-wide practice of licensing and branding the production of toys, in particular, to Chinese companies, rather than direct manufacturing by the brand owner. In addition, the 2008-2009

[17] Council Directive 85/374/EEC, amended by Directive 1999/34/EC.

[18] When comparing the media coverage between the mad cow crisis at the beginning of the 2000s and the more recent horsemeat scandal it must be taken into account that the Lexis Nexis media coverage database grew considerably between 2000 and 2013. Nevertheless, both scandals stand out compared to the other relevant product harm crises in France, illustrated in Figure 2.

[19] "Horsemeat scandal: Withdrawn products and test results," BBC News, March 22, 2013, http://www.bbc.com/news/world-21412590 and "Horsemeat scandal: Dutch trader found guilty and jailed." BBC News, April 7, 2015, retrieved from: http://www.bbc.com/news/world-europe-32202995.

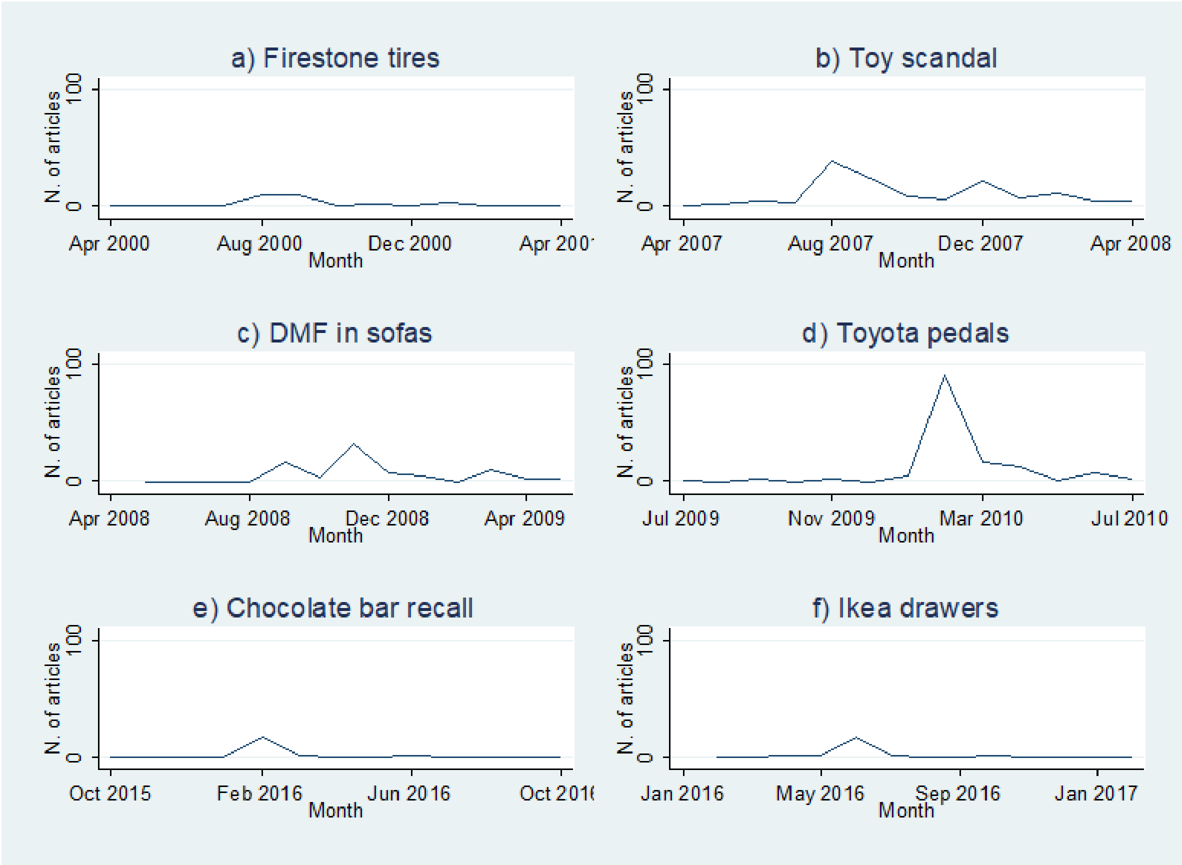

Figure 2: Monthly number of newspaper articles in the French written press mentioning the words (translated to French): (a) "Tires" and "Firestone" or "Bridgestone" or "Ford" (b) "toy" and "plummet" (very similar graph for "toy" and "plummet" and "Mattel" or "Fisher Price") (c) "sofa" and "Conforama" (d) "Toyota" and "brakes" (e) "Snickers" and "bars" and "red plastic" but excluding all Superbowl-related articles mentioning a commercial campaign in this sport's tournament that were not related to the product-harm crisis (f) "Ikea" and "dressers." Source of the data: Lexis-Nexis.

"DMF sofa crisis" in the figure was due to the industry-wide practice in the sofa market of using a toxic antimold chemical (*dimethyl fumarate*) to protect leather sofas. The figure also shows two other product-harm crises, the 2009-2010 Toyota pedal crisis and the 2000 Firestone crisis, that affected the automobile industry, which is characterized by industry-wide practices (e.g., outsourcing the production of distinct automobile parts, Novak and Stern, 2008) and can also be considered a highly branded industry.[20] Over the past decades, the automobile industry has experienced a large number of product recalls also affecting a large fraction of car manufacturers (Liu and Shankar, 2015). Finally, the comparison between Figures 1(b) and 2 shows the relatively high degree of media coverage in our particular application.

[20]The media coverage of the 2000 Firestone crisis is relatively low probably because it mostly affected the American market. Nevertheless, we include it because it occurred in the same year as the crisis we focus on, making it useful as a reference.

3 Data and descriptive statistics

Information on purchase choices and characteristics come from a French nationally representative household-level scanner data set, which covers the period 1999-2003. Households in the sample are given a scanner to record all food purchases during the period. We focus on the subsample of households that buy fresh meat products, including fresh fish. This subsample comprises 3618 households. For each product purchased by the household, there is information on the quantity, price, date of the purchase, and the retailer where it was purchased. There is also comprehensive information on household demographics.

We merge the purchase data with meat-cut-level nutritional information we collected from the French Observatory of Food Nutritional Quality (CIQUAL). In a minority of cases in which nutritional information from CIQUAL was not available for a given meat cut, we used nutritional information from CIV-INRA.[21] The two relevant macronutrients present in meat are proteins (g per 100 g) and lipids (g per 100 g), as fresh meat and fish contain no carbohydrates.[22] We also consider iron (mg per 100 g) because it is a key micronutrient present in meat, as noted in the literature on clinical nutrition (Alexander et al., 1994).[23]

We study purchases of fresh meat and fish, classified into six categories: beef, offal, poultry, pork, other meat, and fish. The category "other meat" includes lamb, rabbit, horse and more rarely consumed meats such as ostrich, wild boar, and roe deer.

Table 1 reports the category average quantity purchased in a month per household, the average category price conditional on purchases, and the average number of households that purchase each category in a given month. It also reports, in the last column, the average monthly volume market share of each product category. Conditional on purchases, poultry is the most consumed category (2.12 kg per month on average), followed by beef, while the least consumed category is offal, followed by other meat. Beef is the most expensive category, followed by other meat and pork. In terms of the number of households that purchase the category, beef is the category with the highest number of households purchasing each month (almost 2000 households on average). A large group of households also purchase poultry (more than 1500 on average each month). The categories consumed by the lowest number of households are offal and other meat. They also have the lowest market shares. In terms of market shares, beef is the most important category, followed closely by poultry.

Table 2 presents the average nutritional composition of each product category and each nutritional component's average price, which is obtained as the ratio between the category average price conditional on purchases and the category average nutritional content. Offal, other meat and beef are the meat categories with the highest iron content. The difference in

[21] Analyses des Compositions Nutritionelles des Viandes, CIV-INRA, 2006-2009, http://www.lessentielesviandes-pro.org.

[22] Calories are generally calculated as a weighted sum of the main nutritional components. The weights used by CIQUAL are 4 kcal/g for proteins and 9 kcal/g for lipids. Other main components of caloric content such as carbohydrates and alcohol are not relevant in our case because they are not present in fresh meat or fish.

[23] Iron in red meat, poultry and fish usually constitutes only approximately 10% of the total iron intake in European omnivore diets, but the absorption of iron from animal proteins is approximately 5 times larger than the absorption of iron from plant sources, (Hercberg et al., 2001; Alexander et al., 1994).

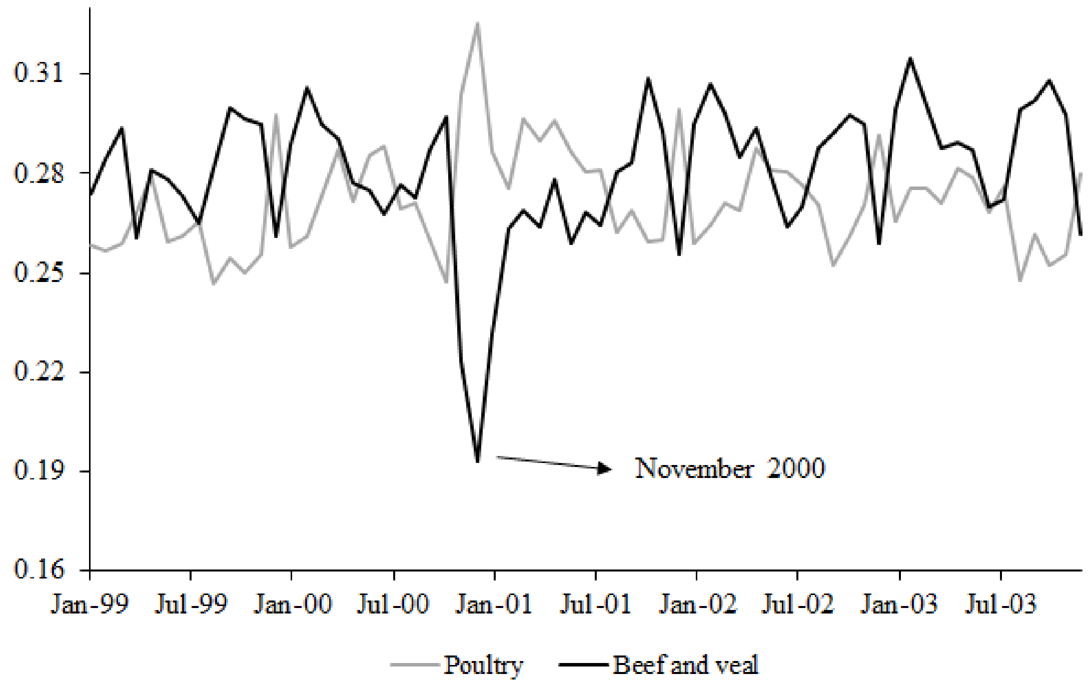

Figure 3: Monthly market shares, 1999-2003

iron content can be quite large: compared to poultry, for example, the iron content in beef and offal is more than twice as large. Although, as shown in Table 1, offal and beef are among the most expensive categories, due to their high iron concentration, they are among the least expensive sources of iron (0.20 euros/mg and 0.38 euros/mg respectively), alongside pork (0.36 euros/mg). Note that pork is also the least expensive source of lipids and proteins.

3.1 Quantities, market shares, and prices of fresh meat

In this section, we show reduced-form evidence on the effect of the safety crisis on meat categories quantities and volume market shares. We also investigate how prices of these categories vary after the safety event. Furthermore, we study the effect of the crisis on total household expenditure, which helps to shed light on how consumers rearranged their purchase baskets after the event.

Table 3 reports the effect of the mad cow event on the average price of beef, poultry, and pork. We investigate the change in prices following the October 2000 event by calculating two different price indexes: a variable-weight price index and a fixed-weight price index. The variable price index weights product (meat cuts) prices by the volume market share of the product in each period. Therefore, this variable index measures changes in transaction prices combined with potential demand shifts toward more or less expensive products within a meat category. In contrast, a fixed price index weights product prices by the average (across all periods) product volume market share, and hence, the weight of each product is the same throughout the period of analysis. Thus, by maintaining fixed the weight of each product, the fixed price index separates transaction prices movements from demand movements. To see more clearly how these indexes differ, suppose for example that the variable price index remains constant. This event could indicate that neither transaction prices nor demand have changed, but it could also be that transaction prices have decreased and demand has shifted to more expensive products (or that transaction prices have increased and demand has shifted to less expensive products) such that the net effect on average prices conditional on purchases is zero. To distinguish between these possible price and demand shifting effects, we should check the fixed price index. If the fixed price index also remains constant, this indicates that transaction prices have not varied. This example describes what we observe in Table 3.

As can be seen in Table 3, the coefficient of the interaction of the category dummies with the dummies indicating 1 to 10 months after October 2000 are nonsignificant for all products and for neither of the two price indexes, suggesting that the event had minimal impact on prices. This result is consistent with the agricultural statistical reports at the time (Lesdos-Cauhapé and Besson, 2007), which say that although intermediate prices varied during the crisis, the same was not true for consumer prices.

Table 4 shows the effect of the safety event on quantities and volume market shares of beef (Columns 1 and 2), poultry (Columns 3 and 4), and pork (Columns 5 and 6). In the 3 months following safety event, there is a significant drop in the quantities purchased and the market share of beef as indicated by the coefficients of the interaction of 1 to 3 months after the event and beef. The estimated coefficient of the beef category indicator measures the average quantity purchased of beef in a month (controlling for time period fixed effects), i.e., 3276.35. With respect to this average quantity, beef quantities drop by about 19%, 26%, and 22% in the first, second and third months following the event, respectively, taking into account not only the beef specific drop (-833.50, -1256.47, and -714.33, respectively) but also the common effect of the crisis across categories (217.06, 389.28, and 0, respectively). Quantities and market share of poultry, on the other hand, significantly increased in the two first months following the event. Quantities of poultry increased by around 2% in the first month and 32% in the second month. In contrast to what happens to poultry, we find no significant effect of the event on the monthly purchased quantities or market share of pork, which is the third most purchased category (see Table 1). Additionally, as shown in the last column of Table 4, it appears that consumers' responses were predominantly contained within the fresh meat and fish categories as the event has no significant effect on monthly purchased quantities of overall fresh meat and fish. As detailed in the next subsection, where we further investigate the demand for the outside good, we find evidence of an increase in the expenditure share of cheese; however, the main sales effects of the crisis seem to have happened within the fresh meat and fish product categories.

The above evidence is consistent with a shift in demand from beef to poultry in the initial period of the crisis and with the market share movements depicted in Figure 3. It is likely that households' unobservable taste for each category play a determinant role in explaining the substitution from beef to poultry considering that the nutritional characteristics of these two meat categories differ considerably.

3.2 Impact on basket of characteristics and non-meat products

In this subsection, we investigate the effects of the mad cow event on consumers' nutritional baskets. We also study whether there is evidence that consumers substituted meat for other non-meat products with similar observable characteristics (i.e., rich in protein such as dairy products and in iron such as beans). In Appendix A.1 we complement this analysis by studying the crisis' effect on the expenditure of non-meat products more generally.

Table 5 shows the estimates of the event's effects on the mean nutritional content of households' meat purchases. In the table, the dependent variables are the mean content of protein, lipids, and iron, respectively, per 100 g of fresh meat and fish (all categories taken together) purchased per household each month. We observe that the nutritional content of purchased baskets changes after the event. Consistent with the observed decline in beef purchases, the mean iron content in the baskets decreases significantly in the first months following the event. Hence, under the new nutritional basket composition, households would have to increase meat and fish consumption to reach the iron intake from before the crisis. But as can be seen in Table 6, this does not seem to happen as there is also a drop in the total amount of iron consumed from meat and fish (i.e., the iron amount per gram of each fish and meat product purchased times the quantity purchased of the product, summed over all purchases in these categories). In contrast, the mean protein content of households' meat purchases increased in the first months following the event. This was likely due to an increase in the consumption of poultry, which is high on protein. Note, however, that the increase in protein is not necessarily health beneficial because nutritional research shows that the typical diet in developed countries already includes too much protein.[24]

The above results show that the consumer reaction to the safety shock affected not only meat purchased quantities but also the nutritional composition of the food basket. The significant decline in mean iron content per household is noteworthy because, as discussed earlier in this paper, iron is a crucial nutrient in consumers' diets and female iron deficiency anemia is frequently observed even in developed countries. Thus, we examine iron consumption in more detail by looking at the total amount of iron purchased via both meat and non-meat products.[25] That is, the amount of iron per gram in each product times the total quantity each household purchased of that product summed over the animal and non-animal foods considered. All regressions include household-category fixed effects and standard errors are clustered by household level.

As further discussed below, we find that the total overall amount of iron consumed from meat and fish decreases significantly after the event and the effect seems to last several periods, as shown in Table 6 (Column 4). To investigate the degree to which consumers replaced animal

[24]Excessive protein intake can have negative health consequences, including reduced energy, kidney disease, and osteoporosis, and can even cause some cancers ("Nutrition for Everyone: Protein." United States Center for Disease Control and Prevention, October 4, 2012, www.cdc.gov/nutrition/everyone/basics/protein.html). For example, on average, Americans eat twice the recommended daily amount of protein (National Center for Health Statistics, http://nchstats.com).

[25]A further reason to study iron consumption in more detail is that our demand estimates show that consumers obtain positive utility from iron (see preference parameter estimates in Table 8 below).

with non-animal iron sources after the crisis, we first focus on purchases of the main non-animal iron sources, i.e., lentils, chickpeas, spinach, and other high-iron beans. Columns 1 and 2 of Table 6 show the results of a regression in which the dependent variable is the households' monthly quantity purchased (in kg) and expenditure share of lentils, chickpeas, and other beans. We find that on average purchased quantities of these iron-rich products significantly increase by 60 grams during the first 4-weeks period after the shock; however, we do not find an effect on the expenditure share.

The results in the table are consistent with households increasing their purchases of iron-rich non-animal foods in the period following the product safety event to compensate for the drop in iron from meat purchases. Column 3 of Table 6 shows regression results of the household monthly amount of non-animal iron-rich products (lentils, chickpeas, and other beans).

We find a significant increase of approximately 1 mg of iron amount from non-meat products purchased during the first period after the shock (Column 3 of Table 6), in line with the significant increase in quantities of non-animal iron-rich food. Nevertheless, the significant increase in iron from non-animal sources does not offset the significant drop in the iron amount from animal sources (all fresh meat-and-fish categories). As shown in Column 4, we find that households' overall purchased amount of iron from meat sources during the first period after the shock significantly declines by around 8 mg (approximately 60% of the daily iron recommended value). Interestingly, in our sample, we also observe that approximately one-half of households below the median level of iron consumption from animal sources are also below the median level of consumption from plant sources (results not shown in the paper).

We next investigate the effect of the safety crisis on households' monthly expenditure and purchased quantities of food products of animal origin other than meat, i.e., dairy products and eggs.[26] We focus on expenditure and expenditure shares because quantity comparisons across dairy and eggs are not straightforward to interpret due to differences in form and format of products in these categories.[27] We compute expenditure shares as expenditure relative to the overall expenditure on fresh meat and fish, dairy, and eggs.

Results of this analysis are in Table 7. We find a relevant significant effect for cheese (Columns 1 and 2). The expenditure share of cheese increases significantly by approximately 1% relative to the other categories in the first period following the shock. As several popular French cheeses are made of goat and sheep milk, the increase in cheese expenditures could be consistent with consumers avoiding cow-origin products in general due to the crisis. Note also that Dubois, Griffith, and Nevo (2014) find empirical evidence indicating that the typical French household has a relatively high idiosyncratic taste for dairy products compared to other countries. This also seems to be the case in our sample where the average expenditure on cheese corresponds to 50% of the expenditure on eggs and overall dairy products. Substitution from

[26]We focus on the years 1999, 2000, and 2001 as the definition of some product categories changed for 2002 and 2003 creating noise. Notice that despite dropping these two years, there are still more than 12 periods before and after the safety shock.

[27]We also did the analysis for quantities of dairy and eggs. Estimated effects of the crisis are very similar to the ones obtained with expenditures.

beef towards cheese is consistent not only with nutritional preferences but also with idiosyncratic tastes being key determinants of substitution patterns across food categories.

With respect to other dairy products and eggs, we find a significant increase of around 6 euros in the second period after the event (Column 3 of Table 7). However, we do not find any significant effect on the corresponding expenditure share (Column 4 of Table 7). Hence, the increase in expenditure could be a nominal effect, which would be consistent with the significant increase in overall food expenditure shown in Appendix A.1.

4 The model

Our demand model is based on Dubois et al. (2014). Consumers' utility depends both on product characteristics as in discrete-choice models and hedonic price models, and on quantity consumed of each product, as in demand models such as AIDS.[28] As a result of the preferences being defined both over the characteristics and the product space, the estimable equations include not only product observable characteristics (nutrients) but also household and product-specific intercepts which capture household unobserved taste. Therefore, with this model specification, we can test whether observed product characteristics affect consumers choices and, moreover, measure the relevance of product observed characteristics relative to product-specific intercepts in determining products' purchases. Furthermore, the model generalizes the weak separability assumption common in traditional demand models by allowing for interactions between different products through their characteristics.

4.1 The setup

We consider $\mathcal{N}$ food products which are divided into J product categories, each category j having K_j subcategories. Household i has the following utility function:

$$U(x_i, z_i, y_i; \eta_i) = \prod_{j=1}^{J} \left(\sum_{k=1}^{K_j} f_{ikj}(y_{ikj}) \right)^{\mu_{ij}} \prod_{c=1}^{C} h_{ic}(z_{ic}) \exp(\gamma_i x_i) \tag{1}$$

where z_i is the vector of product characteristics' consumption of household i, y_{ikj} is the vector of quantities of food consumed letting each product n be labeled kj if it is the kth food item of food group j, x_i is the quantity of the numeraire, and η_i are socio-demographic characteristics of household i. Each product n has C characteristics $\{a_{n1,...,} a_{nC}\}$. Let $(C \times 1)$ be the dimension of the vector of product characteristics, z_i. Then, $z_i = A'y_i$, where the matrix $A \equiv \{a_{nc}\}_{n=1,...,\mathcal{N};c=1,...,C}$ measures product characteristics per unit of consumption for each of the $\mathcal{N}$ products.

Note that absent product characteristics z_i in the above utility function, the utility function would be weakly separable across categories, as is traditional in the demand literature. However, preferences over characteristics break this weak separability by creating interaction

[28] For discrete choice models see McFadden et al. (1973) and Berry et al. (2004); for hedonic price models, see for example Griliches (1961), Rosen (1974), Epple (1987); and for AIDS, see Deaton and Muellbauer (1980).

between categories of products through their nutritional content. That is, as consumers obtain utility directly from characteristics regardless of their source, the marginal utility of consuming each product is affected by other products' consumption through the amount of a certain characteristic already present in these other products.[29]

The utility obtained from products within the same category and from product characteristics are given by the individual-specific utility functions f_{ikj} and h_{ic}, respectively. As in Dubois et al. (2014), we assume that the utility for products within a given category is described by a Constant Elasticity of Substitution (CES) utility function $f_{ikj}(y_{ikj}) = \lambda_{ikj} y_{ikj}^{\theta_{ij}}$. With respect to product characteristics, we assume that $h_{ic} = e^{\beta_c z_{ic}}$.

Note that the model is very flexible with respect to consumer and product heterogeneity. The specific functional forms we use, however, impose some constraints on how income and prices affect demand. In particular, expenditures in each food category will depend on individual consumer characteristics, but quantity will not vary with changes in consumer income though in the estimation we can control for income variation across consumers. Additionally, the model limits non-linear price effects.

4.2 Household behavior

The problem of household i is to choose quantities of the $\mathcal{N}$ food products (plus the numeraire) to maximize utility subject to the budget constraint:

$$\max_{x_i, y_i} \prod_{j=1}^{J} \left(\sum_{k=1}^{K_j} \lambda_{ikj} y_{ikj}^{\theta_{ij}} \right)^{\mu_{ij}} \exp\left(\sum_{c=1}^{C} \beta_c z_{ic} + \gamma_i x_i \right)$$

$$s.t. \sum_{j=1}^{J} \sum_{k=1}^{K_j} y_{ikj} p_{kj} + p_0 x_i \leqslant I_i$$

$$z_i = A' y_i$$

$$x_i, y_i \geqslant 0$$

where p_{kj} is the unit price of food, p_0 is the price of the numeraire, and I_i is household i's income. Recall that a product is labelled kj if it is the kth item of category j.

Hence, for each product y_{ikj} the first-order condition of the household's maximization problem is given by:

$$\mu_{ij} \frac{\theta_{ij} \lambda_{ikj} y_{ikj}^{\theta_{ij}}}{\sum_l \lambda_{ilj} y_{ilj}^{\theta_{ij}}} + \sum_c \beta_c a_{kjc} y_{ikj} = \gamma_i \frac{p_{kj}}{p_0} y_{ikj}$$

Then, summing the above first-order conditions over k for each given j yields:

[29] For example, the marginal utility of beef can be affected by the purchased amount of poultry due to the iron content present in poultry.

$$\sum_k p_{kj} y_{ikj} = p_0 \frac{\mu_{ij}\theta_{ij}}{\gamma_i} + \sum_c p_0 \frac{\beta_c}{\gamma_i} \sum_k a_{kjc} y_{ikj} \tag{2}$$

The equation above has been aggregated at the product-category level and the left-hand side variable is the household's expenditure on food category j. There is conceptually no reason for working with a lower or higher level of aggregation. The level of aggregation chosen should be the most meaningful for the application at hand (Dubois et al., 2014).[30] The household's estimable purchase decision equation derives directly from this aggregated first-order condition, which allows us to directly introduce household heterogeneity in preferences.

5 Econometric Implementation

5.1 The estimable equation

The estimable equation comes from the first-order condition of the consumer problem, Equation (2). We add time subscripts t to quantities and prices as they may vary over time and across consumers and markets. We also add individual household subscripts i to prices, p_{ikjt}, because in our data prices are observed conditional on household purchases. Additionally, we normalize the price of the outside good such that $p_0/\gamma_i = 1$. The term $\mu_{ij}\theta_{ij}$ measures the intensity of household i's preferences for product category j that cannot be explained by its characteristics. We assume it is unobservable and we allow it to be affected by period-specific shocks. We decompose it into a combination of terms, $\Psi_{ijt} + \delta_{ij} + \xi_t + \epsilon_{ijt}$, which capture elements of preferences and the environment as detailed below.

Hence, the estimable equation is:[31]

$$\omega_{ijt} = \sum_{c=1}^{C} \beta_c z_{ijct} + \Psi_{ijt} + \delta_{ij} + \xi_t + \epsilon_{ijt}, \tag{3}$$

where $\omega_{ijt} \equiv \sum\limits_k p_{ikjt} y_{ijt}$ is the expenditure on meat category j by household i in period t and $z_{ijct} \equiv \sum_k a_{kjc} y_{ikjt}$ is the amount of nutrient c household i obtains from category j in period t. As discussed in the previous section, Equation (2) and, hence, also Equation (3), are aggregated at the category level, which we consider to be the different meat groups (beef, offal, poultry, pork, fish, and other meat). This is the most meaningful level of aggregation in our setting because the safety shock affected entire categories of products rather than individual products separately. We can therefore introduce the shock to safety directly into the estimable equation as a shock affecting $\mu_{ij}\theta_{ij}$. The term Ψ_{ijt} captures this safety shock. This term measures the per period variation in the preferences for category j that is due to the change in the safety perception following the product-harm crisis. Letting $t = \tau$ be the time period right after the

[30] In the Implementation section below, we define what a product category is in our context and why we chose this level of aggregation.

[31] We also consider in the robustness section an alternative approach which follows Allcott et al. (2019) and implies a different estimable equation and identification strategy. Using the empirical strategy based on Allcott et al., we obtain empirical results consistent with the ones in our main specification.

event that triggers the safety crisis, we specify the effect of the shock as:

$$\Psi_{ijt} = \begin{cases} \psi_{it} + \phi_{it} & \text{if } j \in \{\text{beef products}\} \text{ and } t \in \{\tau, ..., \tau + 17\} \\ \phi_{it} & \text{if } j \notin \{\text{beef products}\} \text{ and } t \in \{\tau, ..., \tau + 17\} \\ 0 & \text{if } t \notin \{\tau, ..., \tau + 17\}. \end{cases}$$

This component of the estimable equation is a novelty of our work with respect to Dubois et al. (2014). We decompose Ψ_{ijt} into two effects. First, ψ_{it} measures the effect of the crisis on the preferences for the directly affected product category. The effect is allowed to vary over time during the 18 time periods following the crisis. In addition, the effect of safety shock on preferences is allowed to vary across households as different households may have different preferences with respect to safety or they may update their safety perceptions differently. Second, ϕ_{it} captures the effect of the product-harm crisis on other product categories not directly involved in the product-harm crisis.[32] Hence, our model is sufficiently flexible to allow for spillover effects of product-harm crises on purchases of nonaffected product categories relative to the outside good. Finally, the overall effect is restricted to being equal to zero before the crisis and 18 time periods after the beginning of the crisis, that is, we assume there is no safety perception updating outside the 18 months following the crisis.

Preferences over meat categories are likely to vary across households. For example, some households might derive more utility from beef than do other households. The household-category effect δ_{ij} is meant to capture this. We call this term the idiosyncratic taste of the household for each meat category: it comprises all that gives consumer i utility from consuming category j that cannot be explained by nutritional characteristics or safety perception. The term ξ_t of the estimable equation captures common factors affecting the preferences for all meat and fish categories in each period. For example, fresh meat and fish could taste better during winter months.

The last term, ϵ_{ijt}, which is left as the econometric error term, includes preference shocks at the household-category-period level. These shocks might be correlated with nutrients in consumers' baskets as periods of higher expenditures on a certain category could be correlated with choice of meats cuts within that category which are richer or poorer in certain nutrients. As discussed in the next subsection, we address the potential endogeneity of nutrients using instrumental variables correlated with nutritional choices a_{kjc} and therefore nutrient demands but not with these preference shocks.

[32]An alternative interpretation of Ψ_{ijt} would be that it picks up changes in supply associated with the crisis, for example, meat shortage or changes in product display. Under this interpretation, variation in meat sales would be mainly driven by supply-side effects rather than demand. However, we believe this supply-side story to be unlikely because, first, as discussed in Footnote 5, there is no evidence that there was a shortage of meat during the crisis. We observe that even the three directly affected supermarkets continued selling beef right after the crisis started. Second, although we do not directly observe supermarket display choices, major changes in store meat space allocation at short notice are likely limited as fresh meat and fish need refrigeration (e.g., reducing the possibility of major end-of-the-aisle effects in the short term).

5.2 Instruments for nutritional content

As mentioned above, Equation (3) has a potential endogeneity problem. The econometric error term ϵ_{ijt} consists of period-specific random preference shocks affecting the strength of consumers' preferences for a certain meat category. These random shocks may be correlated with contemporaneous nutritional choices, in which case z_{ijct} would be endogenous.

We address the potential endogeneity of z_{ijct} using instrumental variables. Valid instrumental variables in this context are variables that vary by household and period and are correlated with the nutritional content of consumers' choices, but uncorrelated with purchase quantity decisions. Therefore, changes in product availability due to exogenous reasons are valid instruments, as they have an impact on nutritional availability. Exogenous changes in the menu of products available affect the menu of nutrients that consumers encounter in the market each period. In particular, it affects the available nutritional content per kg in the market, which is correlated with the nutritional content of consumers' per period choices but uncorrelated with their willingness to pay for the different products (conditional on household preference heterogeneity).

Because availability is not directly observable in the data, we use a proxy for product availability that captures market-level variation in available products that could be due to entry or exit of products as well as changes in market structure. Note that which products are available in each market are typically correlated with consumers' preferences. Therefore, our proxy for product availability is a valid instrument for households' nutritional choices conditional on our rich set of controls for household preference heterogeneity (household-category specific intercepts and heterogeneous responses to the shock). Furthermore, the safety shock potentially affects consumers' preferences through its effect on consumers' product safety perception. Product availability could also change due to seasonal shocks to consumers' preferences. Hence, when we refer to exogenous changes in product availability, we mean exogenous also conditional on the safety shock and the different seasons, which we explicitly control for in the estimated equations.

We construct the instruments in the following way. Although we do not directly observe product or nutrient availability at the store level, we can approximate it by listing all the products purchased per period in a given store chain in the region of residence of the household. In this way, we obtain the menu of nutritional attributes available per period, store, and region conditional on overall households' purchases. To create the menu of nutrients available for each household each period, we assign each household to a reference group, depending on its geographical area of residence and favorite retailer chain, defined as the retailer chain most visited by the household each year (so household reference groups are year-specific). The geographical areas are the 21 administrative regions of metropolitan France at that time. We then list all meat products purchased by at least one household from the reference group in a certain period. We interpret this list as an approximation of the set of available meat products for households in that reference group during that period. For each list (i.e., reference group) and product category, we compute the average nutritional content (unweighted by quantities or frequency of purchase) across sub-products. Our instrumental variables are these averages per nutrient, meat category and reference group. Note that the averages vary per household, category, and period and are correlated with purchases' nutritional content. Our identifying assumption is that the variation in these unweighted averages of nutritional content, Ω_{ijct}, are uncorrelated with the econometric error term, conditional on the household-category fixed effects, δ_{ij}, the household-period-category fixed effects, Ψ_{ijt}, and the common factors, ξ_t.[33]

Figure 4 illustrates how the instruments for the different nutrients vary across periods and reference groups. We observe that the instrumental variables for beef vary considerably across periods, regions and stores. Similar variation exists for other categories. Note also that the safety shock in October 2000 does not appear to have affected the variability of the instruments, implying there is no evidence that the shock affected nutritional availability in a systematic way.

We did a number of robustness exercises considering alternative definitions of the reference groups. Furthermore, we estimated the demand model in subsamples that excluded reference groups with less than 3 households, reference groups in which households made few purchases a year, etc., to check whether our results were being driven by just a few households or outlier purchase behavior. The main estimation results are robust to these changes.

6 Results

In this section, we first present the demand parameter estimates. We then describe the counterfactual exercises and present their results.

In the demand model and consistent with previous analysis in this paper, we consider 6 separate product categories: beef, offal, poultry, pork, fish, and other meat. We show demand parameter estimation results for our preferred specification, in which the per-period safety shock is allowed to affect all product categories. We constrain the per-period safety shock to be the same across the categories not directly implicated in the safety crisis, that is, poultry, pork, fish, and other meat. However, we allow the safety shock to differ between beef and beef offal, accommodating the possibility that consumers see offal as riskier than other beef cuts, for example. Furthermore, we also allow the changes in the categories' safety perception following the crisis to vary across observably heterogeneous households. In the regression results, we also allow households' safety perceptions to differ in terms of region of residence and education level of the main person responsible for shopping. Our main results also hold when we estimate alternative specifications that consider other dimensions of household observable heterogeneity, such as the presence of children in the household and the gender of the main person responsible for shopping. Note that consumer observable heterogeneity in responses to the safety crisis

[33] Explicit controls for unobserved household heterogeneity avoid correlation between our instruments (proxies for nutrients' per period and per market availability) and the error term in the estimable equation. But one could still worry about the instruments being potentially correlated to period-specific idiosyncratic unobserved shocks to household preferences, especially in smaller reference groups where individual households' choices have a higher weight. To address this concern, we test the robustness of our results by re-estimating our model using (i) considerably larger reference groups based on a more aggregated geographical dimension, (ii) using a subsample that excludes the 10% smallest reference groups, and (iii) doing both jointly. As shown in Appendix A.2, we find that our point estimates remain mainly unchanged.

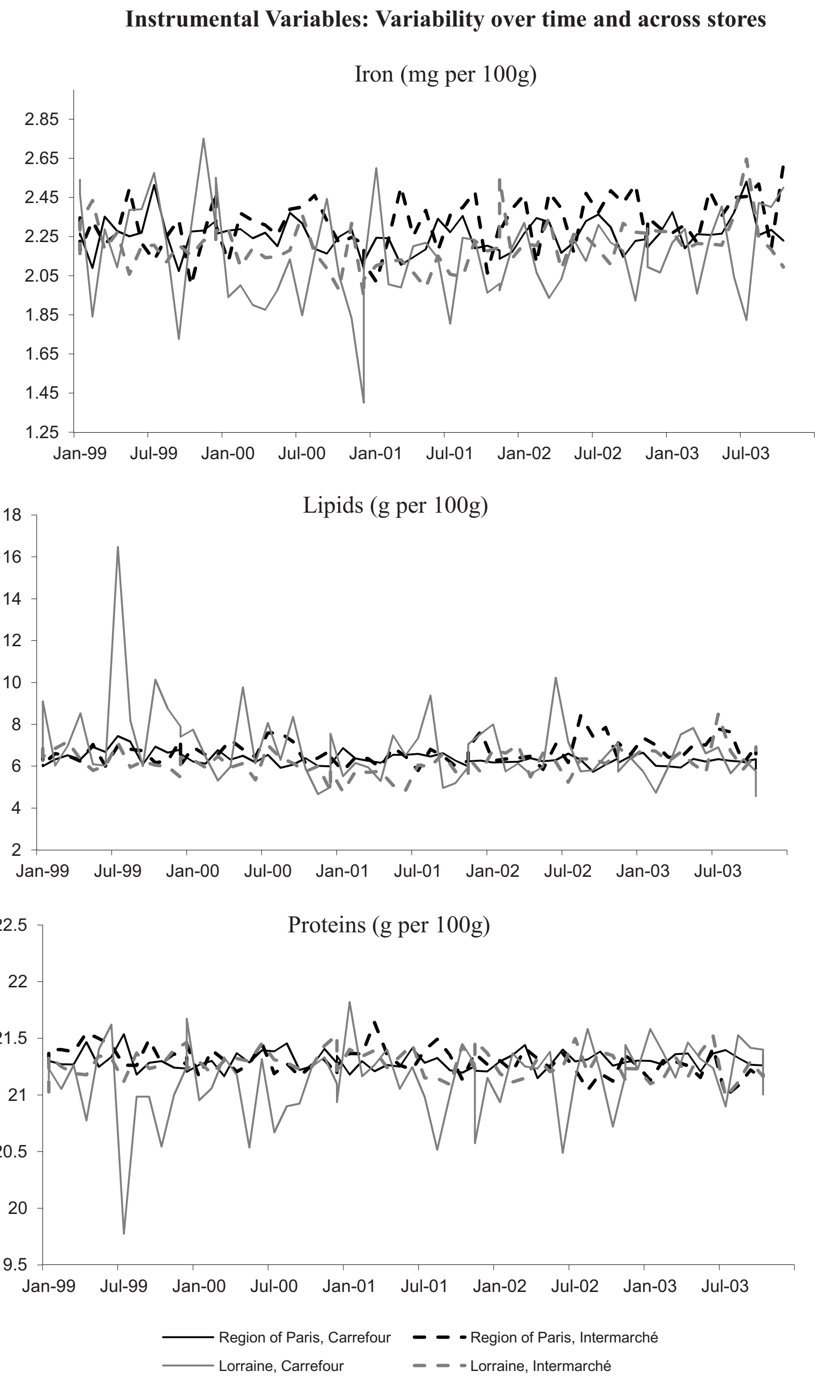

Figure 4: Monthly average nutrient content of beef products available in the corresponding favorite store. The units of iron are in mg per 100 grams, and the units of lipids and proteins are in grams per 100 grams of meat, 1999-2003.

adds yet another source of preference heterogeneity in our approach. The primary source is the household-category-specific intercepts, which capture the household-specific utility from consuming each category that cannot be explained by nutritional characteristics nor safety.

6.1 Utility parameter estimates

Table 8 presents our utility parameter estimates. The first column reports OLS estimates and the second and third columns report estimates using instrumental variables. Column 2 shows parameter estimates for a specification in which the shocks to safety perception are the same across all households. Column 3 shows estimates for a specification that allows safety perception adjustments to vary according to the region and education level of the household's main person responsible for shopping and the region of residence. This serves as a robustness exercise as households in different regions or with different educational background could have updated their safety perception differently following the informational shock.[34]. All equations include household-category fixed effects that measure the household-specific taste for each category.[35] In all regressions standard errors are clustered by household.

In all specifications, we observe a significant decline in the safety perception of beef during the months right after the event, as can be inferred by the negative and significant shocks to these categories in the four months right after the event. The estimated common shocks associated with the mad cow crisis and affecting all fresh meat and fish categories ($\hat{\phi}_{it}$) are estimated to be positive and significant in the first four periods following the event, and then negative and significant in the two following periods. The sign and magnitude of these common shocks estimates do not have a straightforward interpretation. They may pick up spillover effects from the safety crisis on other meat categories but also any other common unobserved shock affecting meat purchases in each period. In the specification with heterogeneous shocks across regions and education levels (Column 3), we obtain very similar estimates. French regions updated safety perceptions very similarly. We also do not find substantial differences in how households with different education levels updated their safety perceptions after the shock.

We also find negative and significant shocks to beef in some later months. These could be consistent with a revival of the crisis associate with related events several months after the original shock. The timing of these shocks (specifically, periods 7 and 8) coincide with peaks in the number of newspaper articles observed in Figure 1.[36] Our main analysis in the remaining

[34]Some previous literature such as Anderberg et al. (2011) has found larger responses to safety scares in regions with higher education levels. Also, regional differences could arise due to differences in information transmission by local media.

[35]Although not presented in the paper, we obtain very similar results when also including interactions between seasons and household-category fixed effects. We also obtain similar results when we allow the adjustment in safety perceptions to vary according to the presence of children in the households and household income level. In addition, we obtain also very similar results when dropping all the observations in the sample corresponding to purchases at the three supermarkets that recalled meat during the event. Dropping these observations (approximately 20% of the sample) permits to rule out that our results are driven by potential supply effects at these specific supermarkets.

[36]In particular, the large significant coefficients for months 7 to 10 after the event observed in Table 8 coincide with the increase in media coverage after the death of French teenager Arnaud Eboli. The media had reported in the past about him having been diagnosed with a variant of Creutzfeldt-Jakob Disease, but his death, on

of the paper focuses on the estimated coefficients for the four months closely following the beginning of the crisis because the arrival of new related information in later months could be associated with potential confounding unobserved events. For instance, the shock after period 7 could be associated to an unobserved shock affecting all fresh meat and fish, as indicated by the significant negative coefficient of the common shock also after period 7.

Concerning nutritional characteristics, we find that they significantly affect consumers' preferences. The estimated coefficient for iron is positive and significant in all specifications, and it is higher in magnitude in the specifications using instrumental variables. The coefficients for proteins and lipids are also significant in all specifications, although their signs change when we correct for the endogeneity of nutritional content. In the instrumental variables regressions, proteins have a negative impact on utility whereas lipids have a positive impact. Note that both the magnitude and the standard errors of the nutritional coefficients are very similar across the specification with homogeneous and heterogeneous responses to the safety shocks.[37] The negative coefficient for proteins may initially appear surprising, but it is likely related to the fact that all meat categories are highly protein-rich relative to daily recommended values (see Table 2). Regarding the coefficients for lipids, note that the nutrient coefficients measure not only health or dietary concerns but also, taste for the flavor of the nutrient, for example. Hence, the estimated lipids coefficient may be capturing households' preference for the taste of fat in meat (for instance, they may prefer more marbled red meat cuts to the leanest cuts).[38]

An advantage of our model is that it allows us to recover each household i's individual unobserved taste for each category j, δ_{ij}. Column 1 of Table 9 reports the estimates of δ_{ij} averaged across households, which we interpret as the estimated unobserved taste of the average household for j. As shown in the table, the average household's favorite category in terms of unobserved taste is poultry, followed closely by beef. The estimated average household's tastes for fish, pork, and other meat are similar and considerably lower than the ones for beef and poultry, and the average household's least preferred category is offal. As we can

April 24, 2001, and the resulting lawsuit and judicial investigation, were widely covered in the French media, e.g., Le Monde, July 28, 2001, "Arnaud Eboli est mort de la variante de la maladie de Creutzfeldt-Jakob. Les conclusions de deux rapports d'expertise." For robustness, we also consider an alternative way to measure the shock to safety perception. Instead of exploiting the before and after variation in safety perception due to the mad cow event in October 2000, we consider the intensity of the media coverage of the mad cow threat in the period between January 2000, and December 2002. The number of news stories in a certain period serves as a proxy for the amount of public safety information on the affected product. Our main results also hold under this alternative approach.

[37]We do not find systematic differences across geographical regions or educational levels. In the Online Appendix we plot the heterogeneous shocks by both the education level of the main person responsible for shopping and the household's geographic region. There is no systematic relevant difference between the different categories. A plausible explanation of the small differences across these groups could be the widespread media coverage of the safety shock across all regions and media outlets.

[38]As mentioned before, we have checked the robustness of our results to our instrumental variables by estimating the model on a subsample that excludes reference groups that have less than 3 households and have less than 3 households who make a purchase each year. Estimation results for the subsample are identical to those of the complete sample concerning the significance and the sign of the estimated coefficients. In terms of absolute values of the point estimates, they are slightly higher once we drop the smaller reference groups, therefore reinforcing our results. Generally, the outcome of this robustness exercise indicates that our estimates are not driven by the behavior of a few individual households or purchases.

also see in Column 2, there is considerable variation with respect to idiosyncratic unobservable tastes. Therefore, in Subsection 6.3, we study the relationship between heterogeneous consumer taste and heterogeneous consumers' responses. Additionally, in the next subsection, we derive counterfactuals based on the average household's preferences to decompose and quantify the possible drivers of consumers' demand responses.

6.2 Counterfactual exercises

We use our model and the parameter estimates to conduct counterfactual exercises that isolate the different drivers of the demand reaction to the product-harm crisis. These counterfactual exercises are not intended as policy counterfactuals, but they permit quantifying the determinants of consumer choices.

The first counterfactual exercise isolates the utility effects of the negative safety shock. The second and the third counterfactual exercises illustrate how costly it is for consumers to switch away from their original choice to products that differ in terms of unobservable and observable product characteristics, respectively. The last counterfactual measures how much of the reaction to the crisis was due to changes in relative prices. Each counterfactual focuses on a different source of potential utility loss associated with reacting to the crisis.

6.2.1 Counterfactual 1: consumer reaction due to the safety shock

This first counterfactual isolates the effect of the change in safety perceptions from changes in prices and product attributes. The exercise simulates average monthly purchased quantities in the four months after the event if there were no shocks to safety perceptions. We first do the exercise for the average household, as defined below, and then also at the individual level (see results section and Appendix A.3) to study how households' responses to the shock relate to their idiosyncratic unobserved taste for beef.

In the counterfactual exercises, we focus on the "average" household. The average household is defined as reproducing exactly the average consumption by category observed in the data. Hence, the average household's monthly purchases in category j in the four months after the safety event is:[39]

$$\bar{y}_j \equiv \frac{1}{4N} \sum_{i=1}^{N} \sum_{t=\tau}^{4} y_{ijt}.$$

The average price paid by the average household during this four-month period is the average expenditure in category j during the 4-month period $\bar{w}_j \equiv \frac{1}{4N} \sum_{i=1}^{N} \sum_{t=\tau}^{4} w_{ijt}$ divided by the average consumption in category j, $\bar{y}_j$:

$$\bar{p}_j \equiv \frac{\bar{w}_j}{\bar{y}_j};$$

[39] We obtain similar empirical results when we consider 3 to 6 months after the shock.

Furthermore, the amount of nutrient c in the average household's purchases in category j is given by:

$$\bar{a}_{jc} \equiv \frac{\bar{z}_{cj}}{\bar{y}_j};$$

where $\bar{z}_{cj} \equiv \frac{1}{4N} \sum_{i=1}^{N} \sum_{t=\tau}^{4} z_{ijct}$.

Similarly, the unobserved components of the average household preference for category j are given by:

$$\bar{\Psi}_j \equiv \frac{1}{4N} \sum_{i=1}^{N} \sum_{t=\tau}^{4} \Psi_{ijt};$$

$$\bar{\delta}_j \equiv \frac{1}{N} \sum_{i=1}^{N} \delta_{ij};$$

and

$$\bar{\xi}_j \equiv \frac{1}{4N} \sum_{i=1}^{N} \sum_{t=\tau}^{4} \xi_{ijt}.$$

Then, for the average household during the four months after the crisis, Equation (3) can be written as:

$$\bar{p}_j \bar{y}_j = \sum_{c=1}^{C} \beta_c \bar{a}_{jc} + \bar{\Psi}_j + \bar{\delta}_j + \bar{\xi}_{ij}$$

Isolating $\bar{y}_j$, we obtain the purchases of the average household in category j averaged over the 4-month period following the event, where we replace β_c and the unobserved preference components by their estimated value (indicated by a hat above the respective letter):

$$\bar{y}_j = \left(\hat{\Psi}_j + \hat{\delta}_j + \hat{\xi}_j\right) / \left(\bar{p}_j - \sum_{c=1}^{C} \hat{\beta}_c \bar{a}_{jc}\right) \tag{4}$$

To obtain the counterfactual monthly mean purchases of the average household if there were no shocks to her safety perception, we set $\hat{\Psi}_j$ equal to zero for the four months after the shock:

$$\bar{y}(\text{no shock})_j = \left(\hat{\delta}_j + \hat{\xi}_j\right) / \left(\bar{p}_j - \sum_{c=1}^{C} \hat{\beta}_c \bar{a}_{jc}\right).$$

We compare the counterfactual $\bar{y}(\text{no shock})_j$ and the factual $\bar{y}_j$ from Equation (4). The percentage difference is calculated as:

$$\frac{\bar{y}(\text{no shock})_j - \bar{y}_j}{\bar{y}_j}.$$

To obtain a monetary measure of the impact of the safety information shock, we also calculate the variation in prices that would lead to the same quantity variation as the safety shock.

Hence, we calculate the following counterfactual prices:

$$\bar{p}(\text{no shock})_j = \left(\sum_{c=1}^{C} \hat{\beta}_c \bar{a}_{jc} + \hat{\delta}_j + \hat{\xi}_j \right) / \bar{y}(\text{no shock})_j. \tag{5}$$

Results of Counterfactual 1

Table 10, first line, reports the results for this hypothetical scenario in which there is no shock to consumers' safety perception of beef after the event. The table shows in its first and second columns, respectively, the factual and simulated average monthly quantities purchased of beef after the event by the average household. By factual quantities we mean the model predicted quantities using observed data. Because the average quantities observed in the data may differ from the model predicted one due to the error term, it is best practice to compare model predicted factual and counterfactual quantities. Column 3 shows the percentage difference between the simulated and factual quantities, and the last column shows how much prices would have to vary to lead to the demand variation shown in the third column.

If the average household had not changed its belief about product safety, the average monthly purchase of beef in the four months after the event would have been 10% higher than the factual quantities after the event. Beef prices would have to be 17% higher than factual prices after the crisis to lead to the same quantity drop as the safety shock. This result implies a price elasticity of demand of approximately -0.5.[40]

In addition to the exercise using the average household, we study consumer reaction at the individual household level. We find substantial heterogeneity in consumers' responses to the safety shock. To study this heterogeneity, we follow an exercise similar to that of the average household but focusing on individual household purchases averaged over the four months following the safety crisis. Appendix A3 shows the details on how we calculate average and simulated quantities and prices for each household.

Figure 5 plots the percentage variation between simulated and factual individual quantities averaged over the four months after the event against households' unobserved tastes for beef. Whereas there is a large group of consumers in the upper tail of the taste distribution who do not respond to the safety shock, consumers with lower estimated taste for beef seem to adjust their purchases of beef considerably in response to the safety shock.

Note that our empirical approach allows to separately capture time-variant and time-invariant components of consumers' preferences for the different meat categories, that is, (i) the time-invariant preferences for the different nutrients (i.e., the β_c's), (ii) the time-invariant unobserved taste for the meat category (the δ_{ij}'s), and (iii) the time-variant safety perception of consumers, which is affected by the shock. Hence, to check that the safety shock is not contaminating the estimates of the time-invariant preference parameters (i) and (ii), we re-estimate them on a subsample of the data that excludes the 18 months following the safety event. For this subsam-

[40]This elasticity for beef is in line with other measures in the literature. Okrent and Alston (2012) find that the beef price elasticity in the US is -0.7, and Boizot-Szantai and Sans (2014) find the beef price elasticity between -0.4 and -0.6 for France.

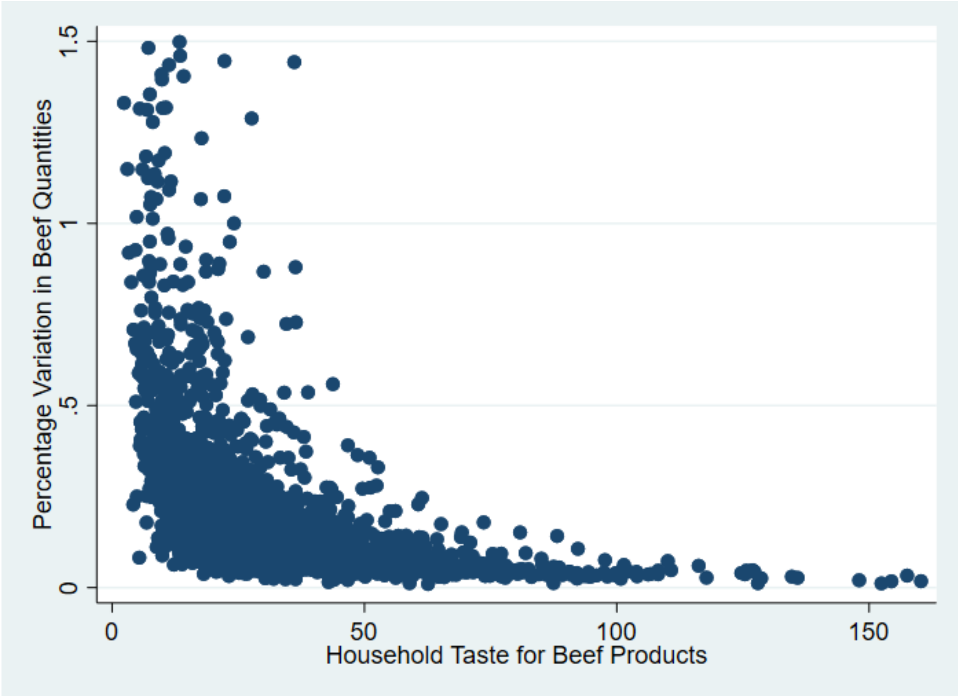

Figure 5: Relationship between households' taste for beef (estimated excluding the 18 months after the product-harm crisis) and their percentage variation in simulated quantities in the countefactual scenario of no safety shock relative to factual quantities purchased

ple, the model parameters should be free of any potential effect of the crisis on consumer or supply behavior. We find estimated nutritional preference parameters and standard errors that are very close in magnitude to those estimated using the whole sample.

6.2.2 Counterfactual 2: consumer reaction due to tastes

Counterfactual 2 studies how the average household might respond differently to the safety crisis depending on how much it likes the affected product irrespective of observable nutritional characteristics. The exercise also provides an idea of the size of the demand effect that we should expect in cases that food safety crises involve meat categories that consumers like less than beef.

This exercise compares beef, the affected category, and pork. Relative to poultry, pork is more similar to beef in terms of iron and protein content and iron and protein price per unit (see Table 2). However, the average consumer's estimated unobservable taste for pork is substantially lower than that for beef (and than that for poultry, see Table 9). We calculate the difference between the factual quantity of pork purchased by the average consumer after the mad cow event (averaged over four months) and the counterfactual quantity the average consumer would have purchased in the same period had pork suffered a safety shock of the size of the estimated beef shock.[41]

[41] An alternative exercise to isolate the effect of idiosyncratic unobservable taste in explaining the demand response to the shock, and that yield equivalent results to the one we do here, is the following. Consider a product

As before, the average household purchased quantity is calculated using Equation (4). The simulated monthly purchased quantities of category j in the four months after the mad cow event if j had suffered the same safety shock as beef is given by

$$\bar{y}(\text{beef shock})_j = \left(\hat{\Psi}_{beef} + \hat{\delta}_j + \hat{\xi}_j\right) / \left(\bar{p}_j - \sum_{c=1}^{C} \hat{\beta}_c \bar{a}_{jc}\right) \tag{6}$$

The difference between the quantities in (4) and (6) is that in the latter we apply the estimated value for the beef safety shock $\hat{\Psi}_{beef}$ to other categories other than beef. Hence we simulate the quantity purchased by the average household had the safety shock affected category j, $j \neq$ beef (we report results for j=pork).

Can we obtain a measure of the importance of tastes in limiting the quantity reaction in monetary terms? We calculate what would be the price associated with purchased quantities $\bar{y}(\text{beef shock})_j$ when the beef safety shock is set to zero:

$$\bar{p}(\text{beef shock})_j = \left(\sum_{c=1}^{C} \hat{\beta}_c z_{ijct} + \hat{\delta}_j + \hat{\xi}_j\right) / \bar{y}(\text{beef shock})_j$$

Results for Counterfactual 2

The second line of Table 10 reports the results for counterfactual exercise 2, in which we obtain simulated quantities by applying the beef safety shock on pork. Comparing factual (Column 1) and simulated (Column 2) quantities averaged over the four months after the crisis, we see that purchases of pork would have been 19% lower (Column 3) if pork had suffered the same safety shock as beef. That is more almost double the effect that we get for beef: counterfactual 1 quantifies the safety shock effect on beef to be a reduction of around 10% in purchased quantities (see the first line of Table 10).

The last column of Table 10, second line, shows the importance of taste in limiting demand in monetary terms. It shows the price variation yielding the same demand decrease as the safety shock on pork. In the absence of a shock, pork prices should change by 37% for demand to vary by 19%.

6.2.3 Counterfactual 3: consumer reaction due to nutritional characteristics

In this counterfactual exercise, we study the role of nutritional characteristics in conditioning households' responses to the safety threat. Alike what we do in counterfactual 2, we simulate purchased quantities after the mad cow event if the safety shock had happened to poultry and quantify the drop in poultry purchases in this case. Here, we focus on poultry because it is a product category that the average consumer likes for its unobservable characteristics as much or even more than beef, but that differs from beef considerably in terms of nutrients. Hence this

that has the same observable characteristics as beef (nutritional characteristics and prices) but the unobservable taste of pork. Then let the safety shock affect pork and calculate the difference in simulated purchases with and without the shock.

counterfactual exercise helps to understand the relevance of nutritional characteristics relative to unobservable taste in explaining consumers' responses to the crisis.[42]

We calculate the counterfactual purchased quantity of poultry after the mad cow event if the shock had been to poultry as in (6). Likewise, to obtain a measure of the price variation necessary to lead to the same demand response but in the absence of the shock, we calculate simulated prices using (6).

Results for Counterfactual 3

The third line of Table 10 shows the results of counterfactual 3. If the safety shock had happened to poultry, the average consumer would have purchased 11% less poultry on average per month in the four months following the mad cow event. The monetary equivalent of this demand variation is in Column 4: prices should vary by 28% to lead to the same purchased quantity as with the simulated shock. Note that this counterfactual demand drop is only slightly higher than the demand drop associated with the safety shock on beef calculated in counterfactual 1 (10%).

6.2.4 Counterfactual 4: consumer reaction due to changes in prices

This counterfactual exercise compares factual quantities to simulated quantities per category if average prices had remained the same in the four months after the event. It isolates price effects on demand from effects of changes in safety perception and product observable and unobservable attributes. Note that as shown in Section 3.1, we find that prices were altogether nonresponsive to the safety crisis. Hence, we do not expect to find differences between factual and simulated quantities.

The simulated average monthly purchases per category j if average prices had remained the same in the four months after the event are calculated as follows:

$$\bar{y}(\text{same price})_j = \left(\hat{\Psi}_j + \hat{\delta}_j + \hat{\xi}_j\right) / \left(\bar{p}_j - \sum_{c=1}^{C} \hat{\beta}_c \bar{a}_{jc}\right)$$

The percentage differences are calculated as

$$\frac{\bar{y}(\text{same price})_j - \bar{y}_j}{\bar{y}(\text{same price})_j} \tag{7}$$

Results of Counterfactual 4

The fourth line of Table 10 reports the results for the price counterfactual, which simulates monthly average purchased quantities per category after the event considering average prices before the event. The results reiterate that relative price variation played a small role in

[42] Alternatively, we could calculate the effect of the safety shock on a counterfactual product that is identical to beef except for the unobservable taste, which would be replaced by that of poultry.

explaining purchase responses to the crisis as simulated and factual purchased quantities are mostly the same.

6.3 Analysis of heterogeneous consumers' responses

In order to further analyze the role of substitutability on consumers' responses, we now study how the response to the shock at the household level varies with unobserved idiosyncratic taste. We focus on substitutability in terms of unobservable product characteristics because Counterfactual 2 shows that it is a key determinant of choice.

For this purpose, we regress individual responses to the safety shock as calculated in Counterfactual 1, i.e., the difference between simulated beef purchases if there had been no safety shock and factual purchases, on households' estimated absolute and relative taste for beef. We study how different households responses correlate with their absolute and relative unobserved preferences for the affected product. Here we use idiosyncratic taste estimated using a subsample of the data that excludes the 18 months following the safety crisis.[43] By excluding this period from the estimation sample, we guarantee that taste estimates do not capture other effects of the safety crisis (this also serves as a robustness exercise to our taste estimates). Results are very similar when using the whole sample and the subsample excluding the crisis period. We define the taste of beef relative to the taste of category k as the percentage difference between household i's estimated taste for beef $\hat{\delta}_{i,j=Beef}$ and its estimated taste for category k, $\hat{\delta}_{i,j=k}$.[44] We regress the percentage variation in quantities' purchased in the four months following the safety shock on these estimated measures of relative taste.

Table 11 shows the results of an OLS regression (first and second columns). To further investigate heterogeneity in the responses, we also study quantile regressions at quantiles 0.25, 0.50, and 0.75 (third, fourth, and third columns, respectively). In line with Figure 5, households' beef purchases response to the shock decrease with their estimated idiosyncratic (absolute) taste for beef. Furthermore, households' response to the safety shock also decrease with their estimated taste for beef relative to the other meat categories. These correlations persist when we include further controls for household characteristics such as region of residence and education level (Columns 2-5). Except for the relative taste with respect to poultry, the negative correlation between reaction to the crisis and relative taste for other meat categories is especially strong and significant among the consumers on the top of the reaction distribution (quantiles 0.5 and 0.75).

These results on relative taste are in line with a central message of our paper: consumers' responses to product-harm crises are constrained by the absence of close enough substitutes, especially with respect to their unobserved taste. Hence, consumers whose taste for beef are lower with respect to pork, for example, that is, consumers that see beef and pork as more substitutable, decrease more their consumption of beef after the crisis.

[43] Excluding this period does not affect the average household's order of preferences for the different categories reported in Table 9.

[44] We calculate these percentage differences as $\frac{\hat{\delta}_{i,j=Beef}-\hat{\delta}_{i,j=k}}{\hat{\delta}_{i,j=Beef}}$.

7 Alternative empirical strategy and robustness

In this section, we test the robustness of our utility parameter results to an alternative identification strategy. We follow an empirical strategy based on Allcott et al. (2019). They derive their estimable equation from the aggregate first-order condition (2), but then depart from Dubois et al. (2014) by solving Equation (2) for quantities and obtaining a nonlinear estimable equation. Their approach has the advantage of allowing for the introduction of an unobservable product characteristic. However, the nonlinearity of the estimable equation makes it difficult to introduce household taste heterogeneity. Not considering household heterogeneity in preferences would limit our analysis because we would not be able to separate responses to the safety crisis from differences across households in terms of preferences over product characteristics and idyosincratic taste. Therefore, to attune it to the needs of our application, we modify Allcott et al. (2019)'s methodology by linearly approximating their estimable equation such that we can allow for both the unobservable product characteristic and household-category fixed effects.

7.1 Alternative estimable equation

To derive the alternative estimable equation following Allcott et al. (2019), we start by rewriting the aggregate first order condition (2) in terms of average prices and average nutritional characteristics such that:

$$\frac{\sum_k p_{ikj} y_{ikj}}{\sum_k y_{ikj}} \sum_k y_{ikj} = p_0 \frac{\mu_{ij}\theta_{ij}}{\gamma_i} + \sum_c p_0 \frac{\beta_c}{\gamma_i} \frac{\sum_k a_{kjc} y_{ikj}}{\sum_k y_{ikj}} \sum_k y_{ikj}. \tag{8}$$

Adding time subscripts and in order to save on notation, define $\tilde{p}_{ijt} \equiv \frac{\sum_k p_{ikj} y_{ikjt}}{\sum_k y_{ikjt}}$ and $\tilde{a}_{ijct} \equiv \frac{\sum_k a_{kjc} y_{ikjt}}{\sum_k y_{ikjt}}$, i.e., respectively the average price paid per kg of category j and the average amount of characteristic c per kg of category j for household i's purchases during period t. Hence, normalizing $p_0 = 1$, Equation (8) can be rewritten as:

$$\tilde{p}_{ijt} Y_{ijt} = \sum_{c=1}^{C} \tilde{\beta}_c \tilde{a}_{ijct} Y_{ijt} + \left(\frac{\mu_{ijt}\theta_{ijt}}{\gamma_i} \right), \tag{9}$$

where $Y_{ijt} \equiv \sum\limits_k y_{ikjt}$ and $\tilde{\beta}_c \equiv \frac{\beta_c}{\gamma_i}$.

An advantage of this approach is that we can introduce a product characteristic that is unobserved to the econometrician, defined as $\zeta = \tilde{\beta}_1 \tilde{a}_{ij1t}$. Solving the above equation for quantities, Y_{ijt}, and assuming ζ to be constant across households, we get:

$$\left(\tilde{p}_{ijt} - \sum_{c=1}^{C} \tilde{\beta}_c \tilde{a}_{ijct} \right) Y_{ijt} = \frac{\mu_{ijt}\theta_{ijt}}{\gamma_i}. \tag{10}$$

Now, we take logs in both sides and isolate Y_{ijt}. Moreover, similar to our main model, we assume that $\ln \left(\frac{\mu_{ijt}\theta_{ijt}}{\gamma_i} \right) = \Psi_{ijt} + \delta_{ij} + \xi_t + \epsilon_{ijt}$.[45] We get:

[45]In our main approach we use the same Greek letters for the combination of terms assumed to capture the

$$\ln Y_{ijt} = -\ln\left(\tilde{p}_{ijt} - \sum_{c=2}^{C}\tilde{\beta}_c\tilde{a}_{ijct} - \zeta\right) + \Psi_{ijt} + \delta_{ij} + \xi_t + \epsilon_{ijt}. \tag{11}$$

At this point, we depart from Allcott et al.'s strategy by doing a linear approximation of the above equation. This linear approximation allows us to estimate the coefficients while including a rich set of controls for household unobserved heterogeneity, which was impractical in the nonlinear model.

We use the fact that $\ln(1+x) \approx x$ if x is small. So, if $\left|\sum_{c=2}^{C}\tilde{\beta}_c\tilde{a}_{ijct} + \zeta\right| \ll \tilde{p}_{ijt}$, then:

$$\begin{aligned}
\ln\left(\tilde{p}_{ijt} - \sum_{c=2}^{C}\tilde{\beta}_c\tilde{a}_{ijct} - \zeta\right) &= \ln\left[\tilde{p}_{ijt}\left(1 - \frac{\sum_{c=2}^{C}\tilde{\beta}_c\tilde{a}_{ijct} + \zeta}{\tilde{p}_{ijt}}\right)\right] \\
&= \ln\tilde{p}_{ijt} + \ln\left(1 - \frac{\sum_{c=2}^{C}\tilde{\beta}_c\tilde{a}_{ijct} + \zeta}{\tilde{p}_{ijt}}\right) \\
&\approx \ln\tilde{p}_{ijt} - \frac{\sum_{c=2}^{C}\tilde{\beta}_c\tilde{a}_{ijct} + \zeta}{\tilde{p}_{ijt}}
\end{aligned}$$

Using the linear approximation above, the estimable equation becomes:

$$\ln Y_{ijt} = -\ln\tilde{p}_{ijt} + \sum_{c=2}^{C}\tilde{\beta}_c\frac{\tilde{a}_{ijct}}{\tilde{p}_{ijt}} - \frac{\zeta}{\tilde{p}_{ijt}} + \Psi_{ijt} + \delta_{ij} + \xi_t + \epsilon_{ijt}. \tag{12}$$

Assuming that $\tilde{p}_{ijt}$ is the dominant effect, then $\frac{\sum_{c=2}^{C}\tilde{\beta}_c\tilde{a}_{ijct} - \zeta}{\tilde{p}_{ijt}}$ is small by construction. We should however check whether $\tilde{p}_{ijt} - \sum_{c=2}^{C}\tilde{\beta}_c\tilde{a}_{ijct} - \zeta > 0$.[46]

7.2 Identification and Instruments

Average nutritional content $\tilde{a}_{ijct}$ and category average prices $\tilde{p}_{ijt}$ may be correlated with ϵ_{ijt} in Equation (12). To see why, note that different mixes of meat cuts in consumers' baskets may result in different category average nutritional characteristics and different category average prices. Therefore if the choice of the meatcut composition of consumers' baskets is correlated in unobserved ways to their willingness to pay for each of the meat categories, then average nutritional characteristics and the error term could be correlated.

We use instrumental variables to correct for the potential endogeneity of average nutritional content and average prices. Valid instruments for average nutritional characteristics should be correlated with the nutritional content of households' purchased baskets but uncorrelated with unobservable idiosyncratic temporal shocks affecting consumers' willingness to pay. Hence, the instruments that we use in our main specification (see section 5.2) work here too, as they proxy for nutritional availability and are therefore highly correlated with purchased nutritional

strength of consumers' preferences. This is an abuse of notation as there we have $\frac{\mu_{ijt}\theta_{ijt}}{\gamma_i}$ instead of $\ln\left(\frac{\mu_{ijt}\theta_{ijt}}{\gamma_i}\right)$. We choose to maintain the notation for simplicity as the economic interpretation of such terms is very similar.

[46] Once we estimate the model, we test this condition in Table 13.

baskets, but are uncorrelated with the willingness to pay for the different products, conditional on the rich controls we use for household preference heterogeneity.

To address the potential endogeneity of category average prices, we need instruments that are correlated to the prices paid for individual meat cuts in the consumers' basket, but uncorrelated to the willingness to pay for the meat category. Our price instruments follow a similar strategy to Allcott et al. (2019), which exploit retail chains' heterogeneous comparative advantages supplying some products due to their sourcing and distribution costs relative to other products and retail chains. This comparative advantage results in some chains offering some products cheaper than others. Additionally, as the geographical distribution of chains is heterogeneous, the relative prices of different products also vary across regions. The Allcott et al. instrument draws upon these relative price differences across markets due to regional differences in retail chain presence. The instruments are correlated with prices paid by households in each market and uncorrelated with households' willingness to pay, conditional on household preference heterogeneity.

Let $\ln(p_{krt,-m})$ be the average log price for product k in the same retail chain r in all markets excluding m; and $\ln(p_{kt,-m})$, the national average log price of product k in period t in all markets excluding m. Then $\Delta \ln(p_{krt,-m}) = \ln(p_{krt,-m}) - \ln(p_{kt,-m})$ is retail chain r's cost advantage in supplying product k relative to the national average. The price instrument P_{jmt} consists of the weighted average cost advantage that retail chains in a given market m have for products in a given product category j. The main difference between Allcott et al. (2019)'s price instrument and ours is the weights used. They construct their weights using the number of stores retail chain r has in market m in period t. Our weights use the probability of sampling a given retail chain in market m in period t, Φ_{rmt}.[47]

To calculate this probability, Φ_{rmt}, we use data on all store visits that generated a purchase in any food product category, not only fresh meat and fish. The sampling probability a store of retail chain r in market m in period t is the ratio of the total number of visits to retail chain r across all households in market m in period t and the total number of store visits to any retail chain in market m and period t. That is, Φ_{rmt} considers all households of the full dataset and all store visits that led to a purchase of a food product by those households. We include all possible food categories (rather than only fresh meat and fish) in order to reduce the possibility of unobservable shocks (e.g., on preferences) affecting both the dependent variable and the sampling probability.

Finally, we let N_{jrt} be the average sales per store of a product in category j at retailer chain r in year t, and N_{kt} be the total quantity of product k sold nationwide in period t. Then the price instrument is:

[47] We have also used the number of stores as weights, using additional data on the number of stores per market. However, our favorite specification uses the store sampling probabilities because the available store number data is only available for one given year and is from several years after our period of analysis. In the meantime there was entry and exit especially due to supermarket mergers, which might have changed the retail chain spatial distribution with respect to our period of interest.

$$P_{jmt} = \frac{\sum_{r \in m} \Phi_{rmt} N_{jrt} \sum_{k=1}^{K_j} N_{kt} \Delta \ln(p_{krt,-m})}{\sum_{r \in m} \Phi_{rmt} N_{jrt} \sum_{k=1}^{K_j} N_{kt}}$$

7.3 Robustness results

Table 12 shows the utility parameter estimates from Equation (12). The first column shows results without instrumental variables, the second column shows results from an instrumental variable estimation in which the response to the safety shock is constrained to be the same across all households, whereas the third column shows results from an instrumental variables estimation in which we allow the response to the safety shock to vary across observable heterogeneous consumers. As before, the dimensions of heterogeneity that we consider are the region of residence and education level.

For the linearization of the estimable regression to be valid, $\tilde{p}_{ijt} - \sum_{c=2}^{C} \tilde{\beta}_c \tilde{a}_{ijct} - \zeta$ should be positive, as discussed in Subsection 7.1. Table 13 shows descriptive statistics for the estimated value of $\tilde{p}_{ijt} - \sum_{c=2}^{C} \tilde{\beta}_c \tilde{a}_{ijct} - \zeta$. The table shows that the mean, the 90th, 5th, and 1st quantiles are all positive. There are negative values in the extreme left of the distribution, but these constitute less than 1% of the values.

Consistent with estimation results from our main specification (see Table 8), nutritional preference instrumental variables estimates (Columns 2 and 3) are significant and have the same sign. In terms of magnitudes, the estimated coefficients are smaller here than in our main specification, but the differences are small, especially for iron (2.24 in our main specification and 2.09 here, considering the results from the instrumental variables estimations).

Note that the coefficients capturing the unobserved characteristic, β, are estimated to be zero. We interpret this as further evidence supporting our main specification choice because its principal downside compared to this alternative specification is that it does not include unobserved product characteristics.

A noticeable difference between the estimation results here and the ones from our main specification refers to the sizes of the standard deviations of the idiosyncratic household unobservable taste per category. This could be due to differences in units across both estimable equations due to the linearization. In the instrumental variables regressions, the instruments are weaker than in our main specification but relevant.[48]

Overall, the main message implied by the results of our alternative strategy is very similar to the main message from our main strategy. There are small differences in the magnitudes of the estimated demand coefficients but not in the signs. Table 14 shows the estimated average household's tastes for the different product categories. Even though the values differ due to the different strategy, we find a ranking of product categories comparable to the one from our main specification.

[48]The Cragg-Donald test is lower than in our main specification. The cluster robust F-tests of first stage regressions are 67.76 for $\frac{1}{\tilde{p}_{ijt}}$, and 149.20, 310.37, and 93.44 for $\frac{\tilde{a}_{ijct}}{\tilde{p}_{ijt}}$ where $c = proteins, lipids, iron$.

8 Conclusion

This paper formalizes and quantifies the tradeoffs that consumers face in responding to product-harm crises. In a setting without close substitutes for the affected product category, we find that avoiding purchases of the unsafe product can lead to substantial utility loss for consumers. Due to the lack of close substitutes, consumers have to weigh the utility loss of shifting away from their originally preferred basket and the costs associated with consuming a potentially unsafe product. One implication of this tradeoff concerns the effect of the crisis on consumers' nutritional baskets. In our application, we show how the substitution patterns following the product-harm crisis led to a decrease in the consumption of nutrients considered to be essential in a healthy diet, such as iron.

Our demand estimates show that consumers derive utility from products' observable characteristics and from (perceived) product safety. Moreover, our counterfactual exercises show that unobservable taste is a crucial driver of consumers' responses. We also find that consumers respond heterogeneously to the safety shock depending not only on their idiosyncratic unobservable taste for the affected category but also their idiosyncratic taste for the affected category relative to their taste for the substitute categories.

These results highlight the relevance of substitutability in understanding consumers' reaction to a product-harm crisis. Indeed, although consumers may want to avoid exposure to the safety risk, this may be too costly if they cannot find products with similar characteristics to the affected product. Our analysis thus points to the importance for policymakers of considering market structure, especially regarding product differentiation and product substitutes, when designing policies to deal with product-harm crises. From our analysis, we can conclude that when product-harm crises affect products with fewer substitutes, the demand response is weaker. As a consequence, public policy should focus particularly in highly differentiated markets where consumers will be less likely to switch away from unsafe products.

Managerial implications

Our results have several implications for the design of managerial responses to product-harm crises. First, firms should be aware that short- and medium-run demand responses do not generally reflect the severity of the crisis on consumers' valuations. In particular, when the crisis affects markets with highly differentiated products or with fewer substitutes, consumers' responses are constrained by their idiosyncratic taste for the affected product and by the costs of substituting to alternative products with different characteristics. As our results show, using sales as an indicator of how much consumers are concerned by the product-harm crisis could lead to the incorrect conclusion that consumers still buying the product are not affected by the safety shock or do not update their safety perceptions. Those consumers could have a "foot out the door," waiting for the entry of new products, for example, to switch away.

Second, firms should consider that, although products' observed characteristics are relevant in explaining consumers' choices, consumers' idiosyncratic tastes drive substitution patterns. In our application, we find that consumers substitute mainly from beef to poultry, although other product categories (e.g., pork) are more similar in terms of nutritional characteristics. That implies that understanding the relative importance of the different demand determinants (price, product characteristics, safety, and taste) in consumers' choices is crucial to assessing the intensity of the consumers' response. In addition, the analysis of heterogeneity across consumers' reactions helps to design tailored strategies to handle product-harm crises. By analyzing consumers' preferences, firms can identify which product categories are prone to face stronger demand contractions following a crisis. It can also help determining possible positive or negative spillovers on alternative products.

References

Adda, J. (2007). Behavior towards health risks: An empirical study using the "mad cow" crisis as an experiment. *Journal of Risk and Uncertainty 35*(3), 285–305.

Ahluwalia, R., R. E. Burnkrant, and H. R. Unnava (2000). Consumer response to negative publicity: The moderating role of commitment. *Journal of marketing research 37*(2), 203–214.

Al-Zoughool, M., D. Krewski, and M. G. Tyshenko (2010). Risk management for bovine spongiform encephalopathy and variant creutzfeldt-jakob disease in france: policy analysis and lessons learned. *International Journal of Risk Assessment and Management 14*(1), 103–120.

Alexander, D., M. Ball, J. Mann, et al. (1994). Nutrient intake and haematological status of vegetarians and age-sex matched omnivores. *European Journal of Clinical Nutrition 48*(8), 538–546.

Allcott, H., R. Diamond, J.-P. Dubé, J. Handbury, I. Rahkovsky, and M. Schnell (2019). Food deserts and the causes of nutritional inequality. *The Quarterly Journal of Economics 134*(4), 1793–1844.

Anderberg, D., A. Chevalier, and J. Wadsworth (2011). Anatomy of a health scare: Education, income and the mmr controversy in the uk. *Journal of Health Economics 30*(3), 515–530.

Atkin, D. (2016). The caloric costs of culture: Evidence from indian migrants. *American Economic Review 106*(4), 1144–1181.

Barkeling, B., S. Rössner, H. Björvell, et al. (1990). Effects of a high-protein meal (meat) and a high-carbohydrate meal (vegetarian) on satiety measured by automated computerized monitoring of subsequent food intake, motivation to eat and food preferences. *International Journal of Obesity 14*(9), 743.

Berry, S., J. Levinsohn, and A. Pakes (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of Political Economy 112*(1), 68–105.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, 242–262.

Black, R. E., C. G. Victora, S. P. Walker, Z. A. Bhutta, P. Christian, M. De Onis, M. Ezzati, S. Grantham-McGregor, J. Katz, R. Martorell, et al. (2013). Maternal and child undernutrition and overweight in low-income and middle-income countries. *Lancet 382*(9890), 427–451.

Boizot-Szantai, C. and P. Sans (2014). Évaluation des élasticites-prix de la demande des produits d'origine animale en france entre 1999 et 2009. *15èmes Journées Sciences du Muscle et Technologies des Viandes, 4 November 2014 - 5 November 2014 (Clermont-Ferrand, France).*

Borah, A. and G. J. Tellis (2016). Halo (spillover) effects in social media: do product recalls of one brand hurt or help rival brands? *Journal of Marketing Research 53*(2), 143–160.

Bordalo, P., N. Gennaioli, and A. Shleifer (2012). Salience theory of choice under risk. *Quarterly Journal of Economics 127*(3), 1243–1285.

Bordalo, P., N. Gennaioli, and A. Shleifer (2013). Salience and consumer choice. *Journal of Political Economy 121*(5), 803–843.

Borraz, O., J. Besançon, and C. Clergeau (2006). Is it just about trust? the partial reform of french food safety regulation. *Ansell C. et Vogel D.(éds.) What's the Beef*, 125–152.

Bronnenberg, B. J., J.-P. H. Dubé, and M. Gentzkow (2012). The evolution of brand preferences: Evidence from consumer migration. *American Economic Review 102*(6), 2472–2508.

Chambers, R. G. and T. A. Melkonyan (2013). Food scares in an uncertain world. *Journal of the European Economic Association 11*(6), 1432–1456.

Chatard-Pannetier, A., S. Rousset, D. Bonin, S. Guillaume, and S. Droit-Volet (2004). Nutritional knowledge and concerns about meat of elderly french people in the aftermath of the crises over bse and foot-and-mouth. *Appetite 42*(2), 175–183.

Choi, A. H. and K. E. Spier (2014). Should consumers be permitted to waive products liability? product safety, private contracts, and adverse selection. *Journal of Law, Economics, and Organization*, ewt019.

Daughety, A. F. and J. F. Reinganum (2012). Cumulative harm and resilient liability rules for product markets. *Journal of Law, Economics, and Organization*, ews045.

Dawar, N. and M. M. Pillutla (2000). Impact of product-harm crises on brand equity: The moderating role of consumer expectations. *Journal of marketing research 37*(2), 215–226.

Deaton, A. and J. Muellbauer (1980). An almost ideal demand system. *American Economic Review 70*(3), 312–326.

Dubé, J.-P., G. J. Hitsch, and P. E. Rossi (2010). State dependence and alternative explanations for consumer inertia. *RAND Journal of Economics 41*(3), 417–445.

Dubois, P., R. Griffith, and A. Nevo (2014). Do prices and attributes explain international differences in food purchases? *American Economic Review 104*(3), 832–67.

Epple, D. (1987). Hedonic prices and implicit markets: estimating demand and supply functions for differentiated products. *Journal of political economy 95*(1), 59–80.

Freedman, S., M. Kearney, and M. Lederman (2012). Product recalls, imperfect information, and spillover effects: Lessons from the consumer response to the 2007 toy recalls. *Review of Economics and Statistics 94*(2), 499–516.

Ganuza, J. J., F. Gomez, and M. Robles (2016). Product liability versus reputation. *Journal of Law, Economics, and Organization*, ewv031.

Goldberg, J. C. and B. C. Zipursky (2010). The easy case for products liability law: A response to professors polinsky and shavell. *Harvard Law Review*, 1919–1948.

Griliches, Z. (1961). Hedonic price indexes for automobiles: An econometric of quality change. In *The Price Statistics of the Federal Goverment*, pp. 173–196. NBER.

Hartman, R. S. (1987). Product quality and market efficiency: The effect of product recalls on resale prices and firm valuation. *The Review of Economics and Statistics*, 367–372.

Hendel, I., S. Lach, and Y. Spiegel (2017). Consumers' activism: the cottage cheese boycott. *The RAND Journal of Economics 48*(4), 972–1003.

Hercberg, S., P. Preziosi, and P. Galan (2001). Iron deficiency in europe. *Public health nutrition 4*(2B; SPI), 537–546.

Hill, A. J. and J. E. Blundell (1986). Macronutrients and satiety: the effects of a high-protein or high-carbohydrate meal on subjective motivation to eat and food preferences. *Nutrition and Behavior 3*.

Hut, S. and E. Oster (2018). Changes in household diet: determinants and predictability. Technical report, National Bureau of Economic Research.

Jin, G. Z. and P. Leslie (2003). The effect of information on product quality: Evidence from restaurant hygiene grade cards. *Quarterly Journal of Economics 118*(2).

Lei, J., N. Dawar, and Z. Gürhan-Canli (2012). Base-rate information in consumer attributions of product-harm crises. *Journal of Marketing Research 49*(3), 336–348.

Lesdos-Cauhapé, C. and D. Besson (2007). Les crises sanitaires dans la filière viande. impact fort à court terme, plus limité à long terme. *Insee première* (1166), 4.

Liu, Y. and V. Shankar (2015). The dynamic impact of product-harm crises on brand preference and advertising effectiveness: An empirical analysis of the automobile industry. *Management Science 61*(10), 2514–2535.

Ma, B., L. Zhang, F. Li, and G. Wang (2010). The effects of product-harm crisis on brand performance. *International Journal of Market Research 52*(4), 443–458.

Marsh, T. L., T. C. Schroeder, and J. Mintert (2004). Impacts of meat product recalls on consumer demand in the usa. *Applied Economics 36*(9), 897–909.

McFadden, D. et al. (1973). Conditional logit analysis of qualitative choice behavior.

Morabia, A., M. Bernstein, S. Heritier, and S. Beer-Borst (1999). A swiss population-based assessment of dietary habits before and after the march 1996 'mad cow disease'crisis. *European journal of clinical nutrition 53*(2), 158.

Novak, S. and S. Stern (2008). How does outsourcing affect performance dynamics? evidence from the automobile industry. *Management Science 54*(12), 1963–1979.

Okrent, A. and J. Alston (2012). The demand for disaggregated food-away-from-home and food-at-home products in the united states. *USDA-ERS Economic Research Report* (139).

Pennings, J. M., B. Wansink, and M. T. Meulenberg (2002). A note on modeling consumer reactions to a crisis: The case of the mad cow disease. *International Journal of research in Marketing 19*(1), 91–100.

Polinsky, A. M. and S. Shavell (2010). The uneasy case for product liability. *Harvard Law Review 123*, 1437–2096.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy 82*(1), 34–55.

Schlenker, W. and S. B. Villas-Boas (2009). Consumer and market responses to mad cow disease. *American Journal of Agricultural Economics 91*(4), 1140–1152.

Setbon, M., J. Raude, C. Fischler, and A. Flahault (2005). Risk perception of the "mad cow disease" in france: determinants and consequences. *Risk Analysis: An International Journal 25*(4), 813–826.

Siomkos, G. J. and G. Kurzbard (1994). The hidden crisis in product-harm crisis management. *European Journal of Marketing 28*(2), 30–41.

US Consumer Product Safety Commission (2016). Samsung expands recall on galaxy note7 smartphones based on additional incidents with replacement phones; serious fire and burn hazards.

Wolfer, B. (2004). Une décision sous influence: l'interdiction des farines. *Les Dossiers de l'environnement de l'INRA* (28), 136–148.

Yamoah, F. A. and D. E. Yawson (2014). Assessing supermarket food shopper reaction to horsemeat scandal in the uk. *International Review of Management and Marketing 4*(2), 98–107.

Zhao, Y., Y. Zhao, and K. Helsen (2011). Consumer learning in a turbulent market environment: Modeling consumer choice dynamics after a product-harm crisis. *Journal of Marketing Research 48*(2), 255–267.

Tables

Table 1: Average quantity purchased per month and household, average category prices, average number of households purchasing each category per month, and average monthly volume market share per category

Category	Monthly Quantity per Household (in kg)	Average Price	Average Number of Households	Volume Market Share
Beef	1.92	10.29	1754.46	0.281
Offal	0.77	9.25	286.99	0.018
Poultry	2.12	6.68	1535.30	0.272
Pork	1.70	6.03	1263.60	0.181
Fish	1.95	9.54	1014.60	0.165
Other	1.30	9.95	761.45	0.084

Notes: All values reported are conditional on purchase. There are 3618 households that buy at least one kind of fresh meat or fi

Table 2: Mean price of nutrients and mean nutrient content across meat cuts per meat category

Nutrient	Category	Mean Nutrient Price (euros per 1 mg)	Content (mg per 100 g)			
			Mean	Std. dev.	Min.	Max.
		Panel A				
Iron	Beef	0.55	2.36	0.66	0.90	3.30
	Offal	0.25	4.54	1.48	1.10	7.30
	Poultry	0.89	1.24	1.20	0.40	9.40
	Pork	0.65	1.64	3.68	0.80	23.30
	Fish	2.31	1.41	1.41	0.00	5.50
	Other meat	0.44	2.68	2.29	1.12	41.89
		Panel B				
Lipids	Beef	0.26	6.76	4.34	2.30	18.85
	Offal	0.21	5.84	3.81	2.59	14.20
	Poultry	0.23	5.09	5.01	0.00	24.20
	Pork	0.06	12.22	5.66	2.59	26.60
	Fish	0.93	3.11	3.77	0.50	15.80
	Other meat	0.13	9.86	3.55	3.09	18.30
		Panel C				
Proteins	Beef	0.05	21.30	0.93	19.35	23.00
	Offal	0.05	18.09	3.35	15.10	27.90
	Poultry	0.03	27.25	2.11	16.40	32.40
	Pork	0.02	24.04	2.15	16.30	27.50
	Fish	0.05	19.06	3.73	6.36	30.00
	Other meat	0.04	24.96	3.12	10.80	32.60

Table 3: Price changes for beef, poultry, and pork after the event

	Beef Price Index		Poultry Price Index		Pork Price Index	
	Variable	Fixed	Variable	Fixed	Variable	Fixed
1 month after X category	0.20	-0.31	-0.94	-0.77	-0.81	-1.23
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
2 months after X category	0.07	-0.10	-0.77	-0.59	-1.17	-0.98
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
3 months after X category	0.11	0.01	-0.82	-0.60	-1.45	-1.53
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
4 months after X category	0.04	-0.04	-0.87	-0.57	-0.72	-1.04
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
5 months after X category	0.23	0.06	-0.81	-0.38	-0.42	-0.78
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
6 months after X category	0.16	-0.19	-1.06	-0.55	-0.14	-0.43
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
7 months after X category	0.06	-0.25	-1.16	-0.64	-0.39	-0.54
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
8 months after X category	0.14	-0.22	-1.14	-0.44	-0.34	-0.25
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
9 months after X category	0.13	-0.05	-1.22	-0.42	-0.48	-0.25
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
10 months after X category	0.41	-0.01	-0.73	0.01	-0.20	-0.27
	(0.57)	(0.52)	(2.93)	(3.02)	(2.93)	(3.02)
Obs.	390.00	390.00	390.00	390.00	390.00	390.00
r2	1.00	1.00	0.92	0.91	0.92	0.91
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year, season, Christmas FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; prices are in euros, and market shares are in volume; 't months after X category' is a dummy variable that indicates purchases of the category (beef , poultry, or pork) over t months after the events, $t = 1, ..., 10$. All specifications include product category, year, season (i.e. quarter) and Christmas (i.e. last month of the year) fixed effects. The dependent variables are variable and fixed price indexes for each of the 6 product categories in each 4 week period over the 5 years (65 periods of 4 weeks).

Table 4: Changes in quantities and market shares of beef, poultry, and pork, and in quantities of total fresh meat and fish after the event

	Beef		Poultry		Pork		Total Meat & Fish	
Variable	Market Share	Quantity	Market Share	Quantity	Market Share	Quantity		Quantity
category	0.28***	3276.35***	0.27***	3071.06***	0.18***	2051.51***		
	(0.003)	(55.73)	(0.00)	(57.89)	(0.00)	(58.95)		
1 month after	0.01*	217.06*	-0.01	-19.71	-0.00	55.44	1 month after	-298.53
	(0.01)	(125.77)	(0.01)	(130.62)	(0.01)	(133.01)		(582.12)
2 months after	0.02**	389.29***	-0.01	11.99	0.01	251.98*	2 months after	-280.510
	(0.01)	(138.10)	(0.01)	(143.42)	(0.01)	(146.05)		(648.23)
3 months after	0.00	-282.93	0.00	-293.00	-0.01	-519.83***	3 months after	1023.59
	(0.01)	(181.42)	(0.01)	(188.41)	(0.01)	(191.86)		(830.68)
4 months after	-0.00	-441.03**	0.00	-345.92*	-0.01	-603.39***	4 months after	932.11
	(0.01)	(181.42)	(0.01)	(188.41)	(0.01)	(191.86)		(830.68)
5 months after	-0.00	-430.61**	0.00	-372.45**	-0.01	-557.40***	5 months after	957.62
	(0.01)	(181.42)	(0.01)	(188.41)	(0.01)	(191.86)		(830.68)
6 months after	-0.00	-252.60	0.00	-191.19	-0.00	-346.77*	6 months after	-160.29
	(0.01)	(180.06)	(0.01)	(187.00)	(0.01)	(190.42)		(838.82)
1 month after X category	-0.07***	-833.50***	0.043**	587.17*	0.01	136.27	7 months after	-344.94
	(0.02)	(290.53)	(0.02)	(301.72)	(0.02)	(307.25)		(838.82)
2 months after X category	-0.11***	-1256.47***	0.07***	1007.31***	-0.04**	-432.63	8 months after	-278.64
	(0.02)	(290.53)	(0.02)	(301.72)	(0.02)	(307.25)		(838.82)
3 months after X category	-0.06***	-714.33**	0.02	329.24	0.01	119.74	9 months after	-161.12
	(0.02)	(290.53)	(0.02)	(301.72)	(0.02)	(307.25)		(838.82)
4 months after X category	-0.03	-314.59	0.01	97.90	0.01	72.28	10 months after	-298.21
	(0.02)	(290.53)	(0.02)	(301.72)	(0.02)	(307.25)		(838.82)
5 months after X category	-0.02	-224.01	0.0336*	410.18	-0.01	-50.60		
	(0.02)	(290.53)	(0.02)	(301.72)	(0.02)	(307.25)		
6 months after X category	-0.03	-277.74	0.03	336.94	-0.03	-300.06		
	(0.02)	(290.53)	(0.02)	(301.72)	(0.02)	(307.25)		
Obs.	390	390	390	390	390	390	Obs.	390
Year, season, Christmas FE	Yes	Yes	Yes	Yes	Yes	Yes		Yes

Notes: Standard errors in parentheses;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; quantities are in kg, and market shares are in volume; 't months after X category' is the interaction of a dummy variable indicating t periods after the event, and category is respectively beef, poultry, and pork. The explanatory variable "category" is a placeholder for beef in columns 1 and 2, for poultry in columns 3 and 4, and for pork in columns 5 and 6. The dependent variable is volume market share (within fresh meat and fish) and total quantities for each of the 6 product categories, and overall total quantities of fresh meat and fish, in each 4 week period over the 5 years (65 periods of 4 weeks). All specifications include year, season (i.e., quarter) and Christmas (i.e., last month of the year) fixed effects.

Table 5: Change in average nutritional content of meat purchases after the event

	Proteins	Lipids	Iron
1 month after	0.32***	-0.27***	-0.11***
	(0.06)	(0.07)	(0.02)
2 month after	0.29***	-0.10	-0.11***
	(0.08)	(0.08)	(0.03)
3 month after	-0.00	-0.20*	-0.04
	(0.07)	(0.08)	(0.03)
4 month after	0.26***	-0.04	-0.11***
	(0.05)	(0.07)	(0.02)
5 month after	0.34***	-0.21**	-0.15***
	(0.06)	(0.07)	(0.03)
6 month after	0.02	-0.31***	-0.03
	(0.05)	(0.07)	(0.02)
7 month after	0.14**	-0.25***	-0.04
	(0.05)	(0.07)	(0.03)
8 month after	0.31***	0.04	-0.06
	(0.05)	(0.07)	(0.03)
Obs.	145813	145813	145813
Year, Season, Christmas FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.10$, $^{**}p < 0.05$, *** $p < 0.01$. All specifications include year, season (i.e., quarter) and Christmas (i.e., last month of the year) fixed effects, and standard error clustered at the household level. The dependent variable is average nutritional content of purchases per household and period. Proteins and lipids are in g per 100 grams. Iron is in mg per 100 grams. 't months after' is a dummy variable that indicates t months after the event.

Table 6: Monthly household purchases of non-animal iron-rich food, and overall iron amount from purchased non-animal and meat sources

	Non-animal iron-rich food		Iron amount from purchased	
	Quantities	Expend. Share	Non-animal	Meat
1 month after	0.06**	0.00	0.96*	-8.28***
	(0.03)	(0.01)	(0.58)	(2.21)
2 months after	-0.05	0.00	-0.89	-1.60
	(0.04)	(0.01)	(0.79)	(2.90)
3 months after	0.00	0.01	-0.09	-6.32**
	(0.03)	(0.01)	(0.63)	(2.45)
4 months after	-0.10***	-0.01*	-1.99***	-15.63***
	(0.02)	(0.01)	(0.50)	(2.20)
5 months after	-0.07**	0.01*	-1.28**	-17.00***
	(0.03)	(0.01)	(0.62)	(2.34)
6 months after	-0.02	-0.00	-0.15	-2.90
	(0.03)	(0.01)	(0.61)	(1.82)
7 months after	-0.07**	-0.01	-1.42**	-13.02***
	(0.03)	(0.01)	(0.58)	(1.76)
8 months after	-0.04	0.02**	-0.60	-13.43***
	(0.04)	(0.01)	(0.78)	(1.88)
9 months after	-0.00	-0.01	0.01	-9.63***
	(0.04)	(0.01)	(0.78)	(1.79)
10 months after	0.01	-0.01	0.16	-9.93***
	(0.04)	(0.01)	(0.78)	(1.89)
Obs.	17785	10508	17785	79451
Household FE	Yes	Yes	Yes	Yes
Year, season, Christmas FE	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include year, season (i.e., quarter) and Christmas (i.e., last month of the year) fixed effects, and standard error clustered at the household level. The dependent variables in the first and second columns are, respectively: household monthly purchases of lentils, chickpeas, and other beans in quantites (kg) and expenditure share; and in the third and fourth columns, repectively, overall iron amount from the above purchased non-animal iron sources per month and household (in mg), and overall iron amount purchased from fresh meat and fish sources per month and household (in mg); 't months after' is a dummy variable indicating t months after the event. Years included are 1999-2001.

Table 7: Effect of the crisis on purchases of non-meat categories

	Cheese		Other dairy and Eggs	
	Expenditure	Expend. Share	Expenditure	Expend. Share
1 month after	2.74*	0.01***	1.49	-0.00
	(1.50)	(0.00)	(1.49)	(0.00)
2 months after	7.46***	0.00	6.21**	0.00
	(2.09)	(0.00)	(2.16)	(0.00)
3 months after	-2.90*	-0.00	-4.85**	-0.01**
	(1.59)	(0.00)	(1.58)	(0.00)
4 months after	-6.81***	0.01***	-5.41***	0.01*
	(1.56)	(0.00)	(1.55)	(0.00)
5 months after	-4.50**	0.01***	-6.72***	0.01**
	(1.59)	(0.00)	(1.54)	(0.00)
6 months after	1.43	0.00	3.95**	-0.00
	(1.52)	(0.00)	(1.55)	(0.00)
7 months after	-14.38***	0.01**	-14.80***	0.01**
	(1.49)	(0.00)	(1.48)	(0.00)
8 months after	-6.63**	-0.00	-8.46***	0.01**
	(2.40)	(0.00)	(2.35)	(0.00)
9 months after	-0.84	-0.01**	0.18	0.01**
	(1.52)	(0.00)	(1.54)	(0.00)
10 months after	-8.72***	0.01**	-10.10***	0.01*
	(1.64)	(0.00)	(1.63)	(0.00)
Obs.	119617	119617	120941	120941
Household FE	Yes	Yes	Yes	Yes
Year, season, Christmas FE	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include year, season (i.e., quarter) and Christmas (i.e., last month of the year) fixed effects, and standard error clustered at the household level. Expenditures are in euros. We compute expenditure shares relative to the overall expenditure on fresh meat and fish, dairy, eggs, and beans. 't months after' corresponds to a dummy variable indicating t months after the event. Years included are 1999-2001.

Table 8: Utility parameter estimates

	(1) OLS		(2) IV		(3) IV and Heterogeneous shocks	
Proteins	0.03***	(0.00)	-0.05***	(0.01)	-0.05***	(0.01)
Lipids	-0.01***	(0.00)	0.03***	(0.01)	0.03***	(0.01)
Iron	1.58***	(0.20)	2.24**	(0.91)	2.38**	(0.93)
1 month after	0.09	(0.09)	1.72***	(0.46)	1.39	(1.05)
2 months after	0.28**	(0.13)	3.17***	(0.69)	2.24*	(1.31)
3 months after	0.96***	(0.14)	1.40***	(0.42)	2.02	(1.27)
4 months after	0.23**	(0.11)	-1.43***	(0.49)	-1.53	(1.05)
5 months after	0.15	(0.11)	-0.95**	(0.42)	-1.00	(1.03)
6 months after	0.17	(0.11)	0.51	(0.37)	0.67	(1.16)
7 months after	-0.08	(0.10)	-1.75***	(0.47)	-1.10	(1.08)
8 months after	-0.07	(0.11)	-1.03**	(0.42)	-2.38**	(1.19)
1 month after X beef	-0.30	(0.20)	-5.13***	(1.13)	-2.70	(2.49)
2 months after X beef	-1.71***	(0.22)	-10.96***	(1.72)	-12.48***	(2.80)
3 months after X beef	-0.85***	(0.20)	-4.33***	(0.92)	-5.86**	(2.42)
4 months after X beef	-0.47***	(0.18)	-0.89	(0.69)	-3.15	(2.11)
5 months after X beef	-0.09	(0.18)	-0.82	(0.75)	-4.88**	(2.07)
6 months after X beef	-0.24	(0.18)	-1.74**	(0.70)	-2.90	(1.92)
7 months after X beef	-0.52***	(0.17)	-1.36**	(0.67)	-2.73	(1.78)
8 months after X beef	-0.65***	(0.17)	-3.88***	(0.84)	-8.35***	(2.15)
Obs.	422719		422719		422719	
Household FE	Yes		Yes		Yes	
Year, Season, Christmas FE	Yes		Yes		Yes	
Weak IV test			10.67		10.57	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include year, season (i.e., quarter) and Christmas (i.e., last month of the year) fixed effects, and standard error clustered at the household level. The first column reports estimates of OLS with household-category fixed effects; the second column, with household-category fixed effects and instrumental variables; while the third column shows estimates of a model with instrumental variables, household-category fixed effects, and heterogeneous responses to the shock. The weak IV test is the Cragg-Donald Wald F-statistic. 't months after X beef' is the interaction of a dummy variable indicating t months after the event and purchases of beef.

Table 9: Mean household taste per category

	Mean	Std. dev.
Beef & Veal	36.927	21.703
Offal	11.911	5.268
Poultry	39.290	19.785
Pork	25.668	11.617
Fish	31.989	21.987
Other meat	25.241	10.726

Notes: The table reports the mean and standard deviation of the idiosyncratic taste for the average consumer. In order for the average consumer to be representative, we weight subcategories based on purchase frequency.

Table 10: Counterfactual Exercise Results

Counterfactuals	Factual Quantities	Simulated Quantities	% Variation in Quantities	Equivalent % Variation in Prices
Cf 1 - No shock	1914.21	2114.29	0.10	0.17
Cf 2 - Taste	1746.28	1413.84	-0.19	0.37
Cf 3 - Nutrition	2346.22	2091.12	-0.11	0.28
Cf 4 - Prices as before	1914.21	1923.64	0.00	-

Notes: Average consumer's simulated monthly purchased quantities in the four months after the event if: (Cf 1) there was no change in safety perceptions, (Cf2) if the shock had been to pork; (Cf 3) if the shock had been to poultry, and (Cf 4) if prices were the same as before the event. *Equivalent % variation in p* is the price variation that would lead to the same percentage variation in the demand as in Column 4.

Table 11: Substitutability Analysis - Idiosyncratic taste and consumers' response

	% Variation in Beef Quantities after the Shock				
	OLS		Quantile		
			Q(0.25)	Q(0.50)	Q(0.75)
	(1)	(2)	(3)	(4)	(5)
Taste for beef	-0.003***	-0.003***	-0.002***	-0.002***	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Beef relative to poultry	-0.004	-0.004	-0.006*	-0.006	-0.016
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Beef relative to pork	-0.037**	-0.038**	-0.001	-0.030***	-0.065***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Beef relative to fish	-0.019**	-0.021***	-0.005*	-0.011***	-0.017**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Beef relative to other meat	-0.056***	-0.052***	-0.018***	-0.038***	-0.072***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Obs.	1881	1881	1881	1881	1881
Region and Education FE	No	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is % Variation in beef quantities per household between factual purchases after the crisis and simulated purchases after the crisis if there was no safety updating after the crisis. 'Beef relative to k' refers to percentage difference between household i's estimated taste for beef and its estimated taste for category k. Column 1 and 2 show the result from OLS. Columns 2, 3, and 4 show the results from quantile regressions: quantile 0.25, 0.50, 0.75, respectively. 'Region' are regional fixed effects and 'Education' control for the education level of the person of reference in the household.

Table 12: Alternative identification strategy: Utility parameter estimates

	(1) OLS		(2) IV		(3) IV and Heterogeneous shocks	
ξ	0.00***	(0.00)	-0.00*	(0.00)	-0.00*	(0.00)
Proteins	-0.01***	(0.00)	-0.02***	(0.00)	-0.02***	(0.00)
Lipids	-0.00***	(0.00)	0.01***	(0.00)	0.01***	(0.00)
Iron	-0.87***	(0.05)	2.09**	(0.94)	2.08**	(0.95)
1 month after	0.07***	(0.01)	0.02	(0.02)	0.01	(0.03)
2 months after	0.11***	(0.01)	0.00	(0.04)	-0.01	(0.05)
3 months after	0.03**	(0.02)	-0.08	(0.07)	-0.13*	(0.08)
4 months after	-0.05***	(0.02)	-0.14**	(0.06)	-0.12*	(0.07)
5 months after	-0.03*	(0.02)	-0.15**	(0.07)	-0.15**	(0.07)
6 months after	0.03**	(0.02)	-0.08	(0.07)	-0.09	(0.07)
7 months after	-0.03*	(0.02)	-0.14**	(0.07)	-0.13*	(0.08)
8 months after	-0.00	(0.02)	-0.13*	(0.07)	-0.12*	(0.07)
1 month after X beef	-0.15***	(0.02)	-0.19***	(0.03)	-0.21***	(0.05)
2 months after X beef	-0.27***	(0.02)	-0.25***	(0.04)	-0.21***	(0.06)
3 months after X beef	-0.14***	(0.02)	-0.11***	(0.03)	-0.06	(0.05)
4 months after X beef	-0.05***	(0.02)	-0.03	(0.03)	-0.08*	(0.04)
5 months after X beef	-0.06***	(0.02)	-0.05*	(0.03)	-0.05	(0.04)
6 months after X beef	-0.08***	(0.02)	-0.05*	(0.03)	-0.04	(0.05)
7 months after X beef	-0.03*	(0.02)	0.01	(0.03)	-0.01	(0.05)
8 months after X beef	-0.11***	(0.02)	-0.09***	(0.03)	-0.10**	(0.04)
Obs.	462328.00		408475.00		408475.00	
Household FE	Yes		Yes		Yes	
Year, Season, Christmas FE	Yes		Yes		Yes	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include year, season (i.e., quarter) and Christmas (i.e., last month of the year) fixed effects, and standard errors clustered at the household level. The first column reports estimates of OLS with household-category fixed effects; the second column, household FE and instrumental variables, while the third column shows estimates of a model with instrumental variables, household-category fixed effects, and heterogeneous responses to the shock. 't months after X beef' is the interaction of a dummy variable indicating t months after the event and purchases of beef.

Table 13: Sign test for the validity of the linearization in the alternative estimable equation

	$\tilde{p}_{ijt} - \sum_{c=2}^{C} \tilde{\beta}_c \tilde{a}_{ijct} - \zeta$
Mean	0.585
Standard Deviation	0.448
Maximum Value	106.410
Minimum Value	-3.082
1st Percentile	0.132
5th Percentile	0.212
90th Percentile	1.077
Obs.	462328

Table 14: Alternative identification strategy: Mean household taste per category

	Mean	Standard Deviation
Beef	2.84	0.64
Offal	1.72	0.66
Poultry	3.27	0.66
Pork	2.68	0.58
Fish	2.91	2.82
Other meat	2.71	0.49

Notes: The table reports the mean and standard deviation of the idiosyncratic taste, δ_{ij}, for the average consumer based on the alternative identification assumptions. In order for the average consumer to be representative, we weight subcategories based on purchase frequency.

Appendix

A.1 Effect of the crisis on the outside good

Table A1 shows the effect of the crisis on the outside good. More specifically, the changes that happened 1 up to 10 months after the event on (i) total quantities of food except alcoholic beverages and fresh meat (Column 1), (ii) total expenditure in food except for alcoholic beverages and fresh meat (Column 2), (iii) total food expenditures except for alcoholic beverages, but including fresh meat (Column 3), and (iv) the expenditure market share of fresh meat relative to total expenditure on food except alcoholic beverages (last column). All regressions include household fixed effects and, also, quarter, Christmas and year dummies.

The results indicate that there was an increase on the expenditure of food other than fresh meat and fish in the first months following the event (around 6 euros which represent an approximate 3% increase). This is consistent with the increase in cheese consumption found in Subsection 3.2. Total food expenditure food increases by around 5 euros in the same period. In the second month following the crisis, both expenditures on food other than fresh meat and total food expenditure significantly increase by around 10 euros. From the third month after the crisis onward, however, both expenditures on food other than fresh meat and total food expenditures go significantly down. With respect to the market share of fresh meat expenditures over total food expenditures, we see a significant decrease in the first two months after the crisis of 1 percentage points. This is followed by an increase of 1 percentage points in the market share of fresh meat in the third month after the crisis onwards.

Overall, there seems to be a significant effect on nonmeat expenditures in the 2 months following the event. Nevertheless, the evidence is consistent with most substitution happening within the fresh meat categories. In Table A1 consumers appear to be spending less on fresh meat because they are purchasing less beef, which is the most expensive fresh meat category. As a consequence, they are freeing up income to spend in other food categories, in particular, cheese. However, the effect is short-lived and small compared to the effect of the crisis on beef and poultry consumption.

Table A1: Effect of the crisis on total quantities, total expenditure and fresh meat market share

Variable	Quantity except meat	Expenditure except meat	Total expenditure	Meat Expenditure Market Share
1 month after	-625.99	6.28***	5.36***	-0.01***
	(672.18)	(1.58)	(1.80)	(0.00)
2 months after	3768.80***	9.73***	10.07***	-0.01**
	(901.63)	(2.12)	(2.42)	(0.00)
3 months after	-8171.49***	-6.47***	-4.93***	0.01***
	(662.14)	(1.56)	(1.78)	(0.00)
4 months after	-4104.71***	-14.46***	-16.40***	0.01***
	(658.84)	(1.55)	(1.77)	(0.00)
5 months after	-4518.99***	-14.60***	-16.00***	0.01***
	(657.85)	(1.55)	(1.76)	(0.00)
6 months after	-4808.26***	-7.21***	-6.96***	0.01***
	(653.10)	(1.54)	(1.75)	(0.00)
7 months after	-7176.99***	-22.73***	-26.46***	0.01***
	(653.99)	(1.54)	(1.75)	(0.00)
8 months after	625.57	-10.35***	-13.44***	0.01**
	(649.70)	(1.53)	(1.74)	(0.00)
9 months after	1721.77***	-4.70***	-6.19***	-0.00
	(656.09)	(1.55)	(1.76)	(0.00)
10 months after	-3970.01***	-13.74***	-16.83***	0.01**
	(674.63)	(1.59)	(1.81)	(0.00)
Obs.	79451	79451	79451	79451
Household FE	Yes	Yes	Yes	Yes
Year, season, Christmas FE	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Quantities are in kg; Quantity and Expenditures are in euros. Expenditure except meat are total food quantity and expenditure on food (except alcoholic beverages), respectively, except for fresh meat; Meat Expenditure Market Share is the ratio between fresh meat expenditures and total expenditures; 't months after' is a dummy variable that indicates t months after the events, $t = 1, ..., 10$. Years included are 1999-2001.

A.2 Alternative reference groups

In Table A2 we study whether the demand estimates are consistent when using alternative reference groups in the construction of the instrumental variables. Specifically, we follow two different strategies: (i) using larger reference groups based on a more aggregated geographical dimension and (ii) restricting our sample to exclude the smallest reference groups. For larger reference groups the focal household's choice has a lower weight on the instrument, and therefore, the less likely it would be that there is correlation between unweighted average nutritional availability and the focal household's taste (conditional on the rich controls for household heterogeneity that we use).

As shown below, we find that our results are robust to both strategies, as well as to implementing both of them jointly. In Column 1, to facilitate comparison, we report again the results from the specification in the paper. Column 2 shows the results when using the more aggregated geographical dimension to construct the reference groups. We construct these alternative reference groups splitting France into 8 regions rather than into 21 subregions, which implies using reference groups approximately 3 times larger (the average size of the reference group increases from 29.65 to 75.37 households and similar increment for the median size). Both columns have comparable results. In addition, Column 3 and 4 replicate the analysis in Columns 1 and 2, respectively, but restricting our sample to exclude around 10% observations from the smallest reference groups. In the four columns, we obtain comparable demand estimates.

Table A2: Alternative definitions of reference groups - Utility parameter estimates

	(1) Main specification		(2) IV with aggregate regions		(3) IV excluding smallest decile		(4) IV combination of (2) and (3)	
Proteins	-0.05***	(0.01)	-0.07**	(0.03)	-0.06***	(0.02)	-0.07**	(0.03)
Lipids	0.03***	(0.01)	0.04**	(0.02)	0.03***	(0.01)	0.05**	(0.02)
Iron	2.24**	(0.91)	4.02*	(2.21)	2.57***	(0.99)	3.80*	(2.20)
1 month after	1.72***	(0.46)	1.95***	(0.71)	1.72***	(0.48)	1.90***	(0.71)
2 months after	3.17***	(0.69)	3.62***	(1.16)	3.19***	(0.72)	3.53***	(1.17)
3 months after	1.40***	(0.42)	1.40***	(0.49)	1.42***	(0.43)	1.38***	(0.48)
4 months after	-1.43***	(0.49)	-1.76**	(0.79)	-1.50***	(0.52)	-1.73**	(0.80)
5 months after	-0.95**	(0.42)	-1.14*	(0.61)	-1.03**	(0.45)	-1.09*	(0.61)
6 months after	0.51	(0.37)	0.54	(0.44)	0.44	(0.39)	0.54	(0.43)
7 months after	-1.75***	(0.47)	-2.04***	(0.77)	-1.86***	(0.51)	-1.99***	(0.77)
8 months after	-1.03**	(0.42)	-1.22**	(0.58)	-1.09**	(0.45)	-1.18**	(0.57)
1 month after X beef	-5.13***	(1.13)	-5.58***	(1.76)	-5.28***	(1.19)	-5.32***	(1.72)
2 months after X beef	-10.96***	(1.72)	-12.22***	(3.22)	-11.23***	(1.85)	-12.05***	(3.25)
3 months after X beef	-4.33***	(0.92)	-4.63***	(1.37)	-4.29***	(0.95)	-4.64***	(1.38)
4 months after X beef	-0.89	(0.69)	-0.72	(0.79)	-0.81	(0.72)	-0.70	(0.79)
5 months after X beef	-0.82	(0.75)	-0.78	(0.86)	-0.98	(0.75)	-0.81	(0.86)
6 months after X beef	-1.74**	(0.70)	-1.84**	(0.88)	-1.70**	(0.73)	-1.75**	(0.87)
7 months after X beef	-1.36**	(0.67)	-1.38*	(0.78)	-1.22*	(0.69)	-1.35*	(0.78)
8 months after X beef	-3.88***	(0.84)	-4.30***	(1.32)	-3.97***	(0.88)	-4.20***	(1.33)
Obs.	422719		422719		418554		416607	
Household FE	Yes		Yes		Yes		Yes	
Year, Season, Christmas FE	Yes		Yes		Yes		Yes	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include year, quarter and Christmas fixed effects, and standard error clustered at the household level. Column 1 reports the result from our main specification (Column 2 of Table 8) where instrumental variables are constructed using 21 geographical subregions. In Column 2 the instrumental variables are constructed using 8 geographical regions. Column 3 reports the results of the main specification when restricting the sample to exclude the reference groups corresponding to the lowest decile in terms of size. Column 4 reports the results both excluding the lowest decile and using the 8 geographical regions to build the instrumental variables.

A.3 Counterfactual 1 at the individual level

Replacing the observed and unobserved preference components by their estimated value (indicated by a hat above the respective letter), we write individual i's average purchase in category j after the event, $\bar{y}_{ij}$, as:

$$\bar{y}_{ij} = \left(\hat{\Psi}_{ij} + \hat{\delta}_{ij} + \hat{\xi}_{ij}\right) / \left(\bar{p}_{ij} - \sum_{c=1}^{C} \hat{\beta}_c \bar{a}_{ijc}\right)$$

where

$$\hat{\Psi}_{ij} \equiv \frac{1}{4} \sum_{t=\tau}^{4} \hat{\Psi}_{ijt};$$

$$\hat{\xi}_{ij} \equiv \frac{1}{4} \sum_{i=1}^{N} \hat{\xi}_{ijt};$$

and

$$\bar{a}_{ijc} \equiv \frac{\bar{z}_{icj}}{\bar{y}_{ij}}.$$

Analogously to what we have done in the case of the average household, we set $\hat{\Psi}_{ij}$ equal to zero for the four months after the shock to obtain the counterfactual monthly mean purchases of the household i if there were no shocks to its safety perception. Using estimated values for the observed and unobserved preference parameters, the simulated quantities in this case are then given by:

$$\bar{y}(\text{no shock})_{ij} = \left(\hat{\delta}_{ij} + \hat{\xi}_{ij}\right) / \left(\bar{p}_{ij} - \sum_{c=1}^{C} \hat{\beta}_c \bar{a}_{ijc}\right).$$

We compare $\bar{y}(\text{no shock})_j$ and $\bar{y}_{ij}$. The percentage difference is calculated as:

$$\frac{\bar{y}(\text{no shock})_{ij} - \bar{y}_{ij}}{\bar{y}_{ij}}.$$