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Consumer and Market Responses to Mad Cow Disease

Wolfram Schlenker and Sofia B. Villas-Boas

We examine how consumers and financial markets in the United States reacted to two health warnings about mad cow disease: the first discovery of an infected cow in December 2003 and an Oprah Winfrey show that aired seven years earlier on the potentially harmful effects of mad cow disease. We find a pronounced and significant reduction in beef sales following the first discovery of an infected cow in a product-level scanner data set of a national grocery chain. Cattle futures show a pattern of abnormal price drops comparable to the scanner data. Contracts with longer maturity show smaller drops, suggesting that the market anticipated the impact to be transitory. Cattle futures show abnormal price drops after the Oprah Winfrey show, that are, more than 50% of the drop following the 2003 discovery of an infected cow.

Key words: consumer behavior, food safety, futures prices, mad cow disease, scanner data.

The United States has the second highest per capita beef consumption in the world behind Argentina.[1] Roughly 30 billion pounds of beef was consumed in 2004. However, beef consumption has stagnated for the last several years as consumers have switched to other meats. The government-run advertisement campaign "Beef: It's What's for Dinner," which is financed by an assessment of $1.00 on every head of cattle sold, made it to the Supreme Court, where justices debated whether producers can be forced to pay for a marketing program, established in the 1985 Beef Promotion and Research Act, even if they do not agree with its message (New York Times 9 December, 2004). Part of the argument involved whether the government speaks with one voice if it advocates beef consumption as beneficial, as the surgeon general recommends eating meat moderately. While there are campaigns advertising the benefits of beef, there are also recurring health warnings associated with its consumption. The empirical question is how consumers react to various, sometimes conflicting, advisories and how consumers value information that is provided by the government compared to information that is provided by independent news media.

This paper examines how consumers react to information about the potential health hazards of beef consumption. Specifically, we examine how consumers in the United States reacted to two highly publicized warnings about bovine spongiform encephalopathy (BSE), also known as mad cow disease. In each case we examine how the warning changed consumption of meat, especially beef. The two warnings are the discovery of the first infected cow in the United States and a TV show about the potential harmful effects of mad cow disease. The warning about the harmful effects of eating beef aired on 16 April 1996 on the Oprah Winfrey show, an afternoon show with a large audience of women who usually make food purchase decisions in a household. Oprah Winfrey's show is best described as a talk show format, a forum for the opinions of the host and guests, rather than a news show. In the show, Oprah Winfrey mentioned that her guest had said that "the disease could make AIDS look like the common cold." Ms. Winfrey later commented on the fact that the disease spreads by feeding ground-up cows to other cows by saying: "It has just stopped me cold from eating another burger." The show claimed to summarize the existing knowledge on the subject. Its purpose was to highlight the potential dangers

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[1] Foreign Agricultural Service: http://www.fas.usda.gov/dlp/circular/2006/06-03LP/bpppcc.pdf

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of mad cow disease rather than to present new evidence.

More than seven years later, on 23 December 2003, the first outbreak of the disease was reported in the United States by official government sources, who previously had insisted that mad cow disease cannot be found in the United States. For the next month, there was repeated coverage in newspapers, as well as on TV and the radio.

We contrast the impact in the aftermath of a government warning, accompanied by news reporting, with the one following the concerns raised by a TV talk show. The government warning constituted new information, as it was the first infected cow ever to be discovered, while the TV show summarized existing knowledge on the potential health risks associated with mad cow disease. There is evidence that highlighted news coverage in popular outlets can lead to sharp information updates even though no "new" information is revealed (Huberman and Regev 2001). This has important policy implications as it is not only information itself that matters to consumers and financial markets, but also how it is presented.

Our study uses a detailed scanner data set from a large U.S. grocery chain that consists of daily store-level purchases for each UPC. Q1 As a result, we get much tighter confidence intervals than if we were to use the Consumer Expenditure Survey (CES), which uses a much smaller and more aggregate sample frame. We also assess the impact of the two BSE-related food scares on futures markets, and whether they vary by the maturity of the contract.

We find a large and significant drop in beef sales following both episodes. The 2003 event induced (*a*) a discontinuous drop in beef sales by approximately 20%; (*b*) a similar discontinuous drop in cattle futures for futures with a two months maturity; (*c*) a more moderate drop for futures with longer maturities; (*d*) an increase in pork and chicken consumption; (*e*) finally, the 1996 TV show that highlighted potential risks had more than 50% of the effect that followed the 2003 discovery of the first infected cow.

Background and Motivation

Food safety alerts can result in "food scares," a sudden heightened level of concern about the safety of a particular product that can stimulate rapid and significant reductions in demand that may or may not eventually recover to pre-scare levels.

A number of previous studies have examined the impact of food safety-related information on consumer demand and, in some cases, the consequent implications for consumer and producer welfare. For example, Smith, van Ravenswaay, and Thompson (1988) analyze the impact of an incident involving contamination of milk with heptachlor in Hawaii during 1982 and find that negative media coverage has a larger impact than positive coverage. Foster and Just (1989) use the same event to construct a model that examines the welfare losses associated from withholding safety information, as well as losses due to artificially exaggerating the true nature of the threat. The latter arises as consumers respond not only to an actual food crisis, but also to information about the potential risk associated with consuming various products. Some authors have suggested that food retailers should seize on food safety as a market segmentation mechanism (Caswell, Roberts, and Lin 1994; Henson and Northen 1998; Caswell 1998). While the Hawaiian milk scare was eventually resolved, new medical evidence about food-related health problems can sometimes permanently alter preferences and traditional demand modeling becomes inadequate (Yen, Jensen, and Wang 1996; Brown and Schrader 1990; van Ravenswaay and Hoehn 1991; Chavas 1983).

There has also been an interest in assessing heterogeneous responses of various socioeconomic groups (Burton, Dorsett, and Young 1996). Recently, Shimshack, Ward, and Beatty (2007) use a reduced form approach to evaluate the effect of government warnings about mercury on fish consumption in the United States using the CES, and find that responses vary greatly by socioeconomic characteristics of consumers. We follow their approach and rely on a reduced form to assess heterogeneous responses to the first reported discovery of an infected mad cow by matching each grocery store with the socioeconomic characteristics of the zip code in which it is located.

Beyond the general literature on food safety, there are several articles that focus on beef. For instance, Burton and Young (1996) find that the continued BSE scare in the United Kingdom has resulted in a long-term reduction of the beef market share by 4.5%, yet it is unclear how much of this shift is attributable to long-run trends. Moschini and Meilke (1989) argue that in the United States there has been a shift away from beef to fish and chicken. In order to pick up location-specific shifts in consumption patterns, we include store-by-product-by-year fixed effects in our approach. There are also studies examining the effects of the BSE scare on purchasing decisions in the United States (Crowley and Shimazaki 2005). While previous studies usually rely on aggregate data, our analysis makes use of a micro-level scanner data set from one of the largest national grocery chains.

On top of measuring consumer responses directly, one can also revert to financial markets. Commodity futures are forward-looking predictions of how commodity prices will develop, and any unforeseen event that will lower prices in the future should immediately be reflected in futures prices. On one hand, Robenstein and Thurman (1996) find no evidence that traders of cattle futures revise their forecasts when significant information is released on the negative health effects of red meat. On the other hand, Lusk and Schroeder (2002) find that medium-size beef recalls and large pork recalls have a marginally negative effect on short-term live cattle and lean hog futures prices; however, the results are not robust across recall size and severity. Finally, Marsh, Brester, and Smith (2008) investigate cattle futures price changes after the 2003 BSE food scare in a structural econometric model accounting for import, export, demand and supply equilibrium conditions and conclude that the demand for beef was predominantly impacted by the ban of foreign governments and not U.S. households.

Data

We use various data sources to estimate the impact of health warnings about mad cow disease on consumer purchasing decisions and futures prices. The first is a scanner data set from one of the largest U.S. grocery chains, which includes observations from 164 stores in Washington State, where the first infected cow was discovered, as well as 134 stores in the D.C. metropolitan area (Maryland, Virginia, and the District of Columbia). Observations in this data set are daily sales at the product and store level; for example, Store 15 sold 3 pounds of Oscar Mayer beef franks for a total of $18.50 on 23 December 2004, where a product is represented by a unique bar-code (UPC). The data set includes all meat (beef, lamb, pork, chicken, and turkey) sales for the period 18 November through 23 March in the winters 2001/2002 through 2004/2005, thus spanning the period five weeks prior to and thirteen weeks past 23 December of each winter. Since the scanner data report both sales revenues and quantity sold we are able to construct the price.[2] For administrative reasons, prices are typically fixed for seven days from Wednesday to the following Tuesday when new promotional flyers are printed and distributed. The summary statistics are given in table A1 in Schlenker and Villas-Boas (2009). Because closely related products (e.g., lean ground beef with different levels of fat) can have various UPCs, we use several measures to aggregate sales and quantity sold of comparable products for a given day and store. The variable *subclass* groups together UPCs with closely comparable product characteristics, for example, all "Beef Rib Steaks," or "Beef Rib Roasts." The next aggregation level is a meat *class* which groups similar meat types together, for example, all "Beef Rib" (both steak and roast), or "Beef Loin." Beef products are furthermore grouped into three *subcategories* for (*a*) ground beef, (*b*) a company-specific national brand chain, and (*c*) locally supplied beef products. All other meats have only one category. When we aggregate to the *category*, we add all purchases of a particular meat.

One potential concern is that not all UPCs are sold in each store on every single day. Specialty products are sometimes sold only a few times a month. This is potentially troublesome as products that are sold infrequently can show large relative changes. To illustrate this concern, consider a hypothetical example where a package of a product is sold on average once a week. The average sales quantity is 0.14 packages per unit of time. However, days when one unit is sold would show a 700% increase in sales above the average level. As the data appendix reveals (Schlenker and Villas-Boas 2009), our daily store-level data show not a single turkey or lamb sale for 12 and 17% of our observations, respectively. To avoid potentially erratic relative changes of infrequently sold products, we sometimes exclude all UPCs that on average are sold on fewer than thirty days in our five-week (thirty-five-day) period.

We obtain the exact location for each of the 298 stores and are able to match the location with socioeconomic statistics from the U.S. Census based on the zip code in which a store is located. Summary statistics of the socioeconomic variables are given in table A1 in Schlenker and Villas-Boas (2009).

The analysis is replicated using the diary files of the Consumer Expenditure Survey for the same years 2001–2004. We use the CES

[2] Roughly 7% of the data are excluded because the quantity measure is missing.

as a cross-check to the results we obtain in the scanner data set. The CES only reports total expenditures and not the purchased quantity. It has the advantage of more detailed household characteristics. The potential downside is a much smaller sampling frame of 200 households per week. Each household stays in the survey for only two weeks and the sample frame is thus not a panel but a repeated cross-section. In contrast, the scanner data set is much larger. On average, there are more than 76,000 daily UPC-by-store-level beef purchases per week in our scanner data set, while there are on average 133 purchases of beef products in the CES in a week. In other words, we have more than 76,000 observations per week in the scanner data set, while there are only about 133 in the CES.

Daily cattle futures prices are obtained from the Chicago Merchantile Exchange for 1995–2005. We use futures price data for two, four, and six months maturities.[3] The futures market data are merged with daily closing values of the Dow Jones Commodity Market index. This allows us to construct price movements net of changes in the market index.

Analytical Framework

We estimate the abnormal change in purchase quantities following a mad cow-related event. By abnormal changes we mean changes net of movements that are predictable by seasonal buying patterns. In other words, we derive the difference between purchases following the event and the pre-event average in the winter 2003/2004 and compare this difference to the one we obtain in winters other than 2003/2004.

The publication of the first infected mad cow event occurred on 23 December 2003, two days before Christmas. A simple pre-post comparison might wrongfully attribute seasonal changes in beef purchases to the event in question. Therefore, we include analogous pre- and postperiods for the years 2001, 2002, and 2004 in our analysis to obtain an estimate of the seasonality component. We have one preperiod and two postperiods, where periods are thirty-five-day aggregates.[4] The time line of the data and our definition of periods is as follows:

	Period 0	**Period 1**	**Period 2**
Winter 2001/2002	18 Nov to 22 Dec	24 Dec to 27 Jan	28 Jan to 2 Mar
Winter 2002/2003	18 Nov to 22 Dec	24 Dec to 27 Jan	28 Jan to 2 Mar
Winter 2003/2004	18 Nov to 22 Dec	**24 Dec to 27 Jan**	**28 Jan to 1 Mar**
Winter 2004/2005	18 Nov to 22 Dec	24 Dec to 27 Jan	28 Jan to 2 Mar 2

National news media reported the first discovery of an infected cow as a cover story throughout the United States and as a result we do not have a cross-sectional control group to perform a spatial difference in difference analysis. However, we investigate whether there was a different effect on purchases in the region where the first infected cow was discovered (Washington State) relative to the Eastern United States.

The baseline reduced form econometric model for estimating the effect of the discovery of the first infected cow in the event winter 2003/2004 (marked in boldface in the above time line) on meat purchases is

$$y_{asnt} = \delta_{n,2003} + \delta^{WA}_{n,2003} + \alpha_{ast} + \beta_n + \beta^{WA}_n + \gamma p_{asnt} + \varepsilon_{asnt} \tag{1}$$

where y_{asnt} is the log quantity sold by aggregation level a (e.g., subclass, class, or overall meat total) in store s and period n in winter t. In particular, n indicates whether the data correspond to before ($n = 0$), during ($n = 1$), or after ($n = 2$) the holiday/New Year period for each winter.[5] The fixed effects α_{ast} allow for a shift of average purchases in each store s by aggregation level a and winter t as others have argued before that there are long-term shifts (Moschini and Meilke 1989). The coefficient β_n picks up the seasonal effect of period n, for example, ham and turkey sales might always be higher around Christmas.[6] The coefficient β^{WA}_n captures the additional seasonal effect of period n in Washington State. The coefficients $\delta_{n,2003}$ and $\delta^{WA}_{n,2003}$ capture the effects of the discovery of the infected cow and the differential

[3] The growth of cattle should be limited as the cows are maturing. We therefore do not incorporate any cattle growth in the arbitrage condition of holding cattle futures in the analytical section below.

[4] We define a period as a multiple of weeks so we do not have to worry about weekday fixed effects, as sales are always higher on weekends. Moreover, we pick five-week aggregates to ensure that the period before 23 December always includes Thanksgiving. A four-week period would not include Thanksgiving in some years and hence not fully capture the seasonality effects.

[5] We cannot include dummies for all three periods as they would be perfectly collinear with α_{ast} and hence exclude β_0, $\delta_{0,2003}$, and $\delta^{WA}_{0,2003}$ in our empirical specification.

[6] The sensitivity to various seasonality estimates is discussed in Table A3 of Schlenker and Villas-Boas (2009).

effect on Washington, in the first ($n = 1$) and second ($n = 2$) five-week period after the publication.

We expect that beef purchases show abnormal drops when new information about potentially harmful health effects is revealed, i.e., $\delta_{1,2003} < 0$. If the effect is different in Washington State, where the first infected cow was discovered, then $\delta^{WA}_{1,2003} \neq 0$. It is harder to hypothesize what happens to other meats (e.g., chicken and pork). On the one hand, one would expect that consumers substitute away from beef to other meat products (a within-meat substitution effect). On the other hand, some concerned consumers might choose to reduce all meat consumption, leading to a decline in chicken or pork consumption. Which of the two effects dominates is an empirical question.

We control for log price p_{asnt} in some of our regressions, which is the log of the average price of all products in aggregation level a in store s in period n of winter t. One possible response of stores to a drop is quantity sold is to lower the price, which would increase $\delta_{1,2003}$ toward zero. It should be noted that the coefficient γ might be inconsistent as prices are endogenous. However, the main purpose of this study is not to derive the price elasticity. Instead, our regressions with and without price controls, as well as the derived price changes, are included to demonstrate that our estimate $\delta_{1,2003}$ is not driven by price responses of stores.

Any hypothesis test requires an unbiased estimate of the variance-covariance matrix. There are two potential sources of concern in our data set: (a) contemporaneous correlation of the error terms of purchases in a given period and region; and (b) temporal correlation across periods. To address the former we cluster the error terms ε_{anst} by period and region, thereby allowing the error terms of various products within a store and other stores in a region to be correlated.[7] If there are shocks in a given period, for example, dismal weather that causes inhabitants to postpone shopping trips, all observations will show lower sales. Temporal correlation is a potential problem as it might lead us to reject the null hypothesis too often if several pre- and postobservations are included (Bertrand, Duflo, and Mullainathan 2004).[8] In our baseline model, we therefore include only one period before the event and one after the event in each of the four winters where we have data.

Other authors have emphasized that responses might differ by socioeconomic subgroups. We therefore include interaction effects with the abnormal change. The estimated regression equation becomes

$$\text{(2)}\quad y_{asnt} = \delta_{n,2003} + \delta^{WA}_{n,2003} + \theta_{n,2003} C_s + \alpha_{ast} + \beta_n + \beta^{WA}_n + \lambda_n C_s + \gamma p_{asnt} + \varepsilon_{asnt}$$

Two new terms appear compared to equation (1) that both include C_s, the demeaned socioeconomic characteristic of the zip code in which store s is located. The parameters λ_n allow the period fixed effects to be different by socioeconomic subgroups. For example, more affluent people might increase their ham consumption and correspondingly decrease their beef consumption more than less affluent groups around Christmas. The terms $\theta_{n,2003}$ capture whether the abnormal changes following health warnings differ by socioeconomic characteristics.

We also perform an analysis using daily scanner data and compare the results to abnormal daily futures market responses in 2003. We have daily futures data for 1996, while the scanner data are deleted after four years. The futures data allow us to contrast the market response following the Oprah Winfrey show in 1996, with the market responses following the first discovery of an infected cow in 2003. Moreover, while aggregating quantities by period n gives consistent test statistics for the estimates, even when there is serial correlation in the error terms, a daily analysis gives a more detailed look at how purchasing decisions develop over time. We use a two-stage estimation strategy in our daily model using the scanner data.

In a first stage we estimate seasonality components and the price elasticity using days from the winters 2001/2002, 2002/2003, and 2004/2005, as well as days prior to 23 December in the event winter 2003/2004. This is, we exclude all days in the event winter that were past 23 December. Days prior to 23 December 2003 are necessary to identify the

[7] Clustering allows for nonzero off-diagonal elements in the variance-covariance matrix of the error terms, which correspond to the average correlation between various error terms in the same period and region. If we only cluster observations *in a given store* in a given period we obtain smaller standard errors. The chosen clustering structure is therefore more conservative about the significance levels.

[8] Intuitively, if there is a large positive autocorrelation that we do not correct for, then a one-time random shock will phase out slowly and could be wrongfully interpreted as a permanent shift.

aggregation-by-store-by-winter fixed effects α_{ast}. The regression equation becomes

$$(3)\quad y_{asdt} = \alpha_{ast} + \beta_d + \gamma p_{asdt} + \eta_w + \rho_{\text{Thanks giving}} + \mu_{\text{Thanks giving Fr}} + \varepsilon_{asdt}$$

The above equation differs from our baseline model in equation (1) in several ways. First, the time scale is switched from periods n to days d. In other words, β_d now picks up day fixed effects, 0 is 23 December of each year, and we include days ranging from −35 to 91 for each of our four winters.[9] Second, since we are dealing with daily data, we include weekday fixed effects η_w (purchases are always higher on weekends) and a dummy for Thanksgiving/the Friday following Thanksgiving with coefficients ρ and μ, respectively. Third, we do not allow the effects to be different for Washington State.[10] The rationale is to obtain the average overall abnormal change, which we can then compare to abnormal futures returns (which captures the average effect on the overall market as well).

In the second step, we use the regression coefficients from equation (3) to derive residuals ε_{asdt} for all observations in the event winter 2003/2004. The first-stage regression removed the portion of the residuals that are due to changing prices or seasonality effects. These remaining residuals are then smoothed using a locally weighted regression. We use Epanechnikov Kernel weights with a window of 10 days, or roughly a week and a half as prices are fixed for seven consecutive days, and the window is not allowed to cross the event date.

Finally, in our fourth model, we examine abnormal changes in cattle futures prices. While we control for seasonality effects in previous regressions of purchase quantities, we now construct abnormal price movements net of overall commodity market movements. Futures prices are responsive to changes in the risk-free interest rate and other overall market factors, which are captured in the commodity market index. This is captured by a market model of the form:

$$(4)\quad r_d = \alpha + \beta R_d + \varepsilon$$

Daily futures price changes r_d are regressed on the market return R_d, which we approximate by the Dow Jones Commodities Market index. The abnormal returns are hence $r_d - \hat{\alpha} + \hat{\beta} R_d$. We construct a time series relative to the price of the commodity for the day before the event took place by applying the daily abnormal returns (net of overall commodity market movements) successively on the days prior to and following this day.

Empirical Results

Analysis of Thirty-Five-Day Aggregate Beef Purchases

Abnormal changes in beef purchases following the first discovery of an infected cow are shown in table 1. In columns (1)–(5), the dependent variable is the log of the purchased quantity for each beef subclass. As described in the data section, a *subclass* groups together all UPC with closely comparable product characteristics.

The baseline model is given in column (1), where we include one thirty-five-day period before and one after 23 December for each store and subclass for each of the four winters in our data. The reported coefficients are the change $\delta_{1,2003}$ from equation (1) in row "Period 1," and the additional abnormal change $\delta^{WA}_{1,2003}$ in Washington State in row "Period 1 × *WA*." The price elasticity γ is given in row "Log Beef Price." Each row gives the point estimate and t-value in parentheses. Beef purchases decreased by 21% in the thirty-five days following the discovery of the first infected cow.[11] The effect is not significantly different in Washington State where the discovery was made. The impact is not only large in magnitude, but also highly statistically significant. The estimated price elasticity is −1.91, also highly statistically significant.

Column (2) allows for heterogeneity by socioeconomic subgroups as specified in equation (2). Rows (5) and (7) display the coefficients θ_n of the interaction term with the demeaned socioeconomic characteristics. Stores that are located in zip codes with higher median income show larger drops: an additional 1.3% for each \$10,000 in median income.

[9] The event date (day 0) is excluded as it is unclear when consumers in various time zones in the United States updated their beliefs during that day. We also exclude day fixed effects for the first day to avoid perfect multicolinearity.

[10] Table A4 in Schlenker and Villas-Boas (2009) allows the coefficient ρ and μ to be different in Washington.

[11] Kennedy (1981) has pointed out that the conditionally unbiased percent reduction will be $e^{b-\frac{1}{2}(\frac{b}{t})^2} - 1$, where b is the coefficient estimate and t is the t-value. Using the results given in table 1, we get $e^{-0.231-\frac{1}{2}(\frac{-0.231}{21.37})^2} - 1 = -0.21$, or −21%.

Table 1. Changes in Thirty-Five-Day Aggregate Log Beef Purchases Following Discovery of First Infected Cow

	(1) log Q	(2) log Q	(3) log Q	(4) log Q	(5) log Q	(6) log P	(7) Placebo log Q	(8) log R	(9) log R
Period 1	−0.231	−0.194	−0.200	−0.202	−0.200	−0.0166	0.0563	−0.216	0.338
	(21.37)**	(21.61)**	(5.20)**	(5.84)**	(14.71)**	(3.20)**	(0.82)	(11.44)**	(0.32)
Period 1 × *WA*	0.044	−0.021	−0.032	−0.059	0.056	−0.007	−0.124		
	(0.94)	(0.49)	(0.61)	(1.27)	(1.65)	(0.28)	(1.24)		
Period 2			−0.236	−0.230					
			(3.79)**	(4.45)**					
Period 2 × *WA*			−0.00185	−0.0188					
			(0.03)	(0.33)					
Period 1 × income		−0.0133	−0.0134	−0.0138					
		(2.53)*	(2.80)*	(2.68)*					
Period 2 × income			−0.00313	−0.00466					
			(0.75)	(0.90)					
Period 1 × minority		−0.00176	−0.00168	−0.00174					
		(8.88)**	(6.96)**	(8.01)**					
Period 2 × minority			−0.00193	−0.00200					
			(8.00)**	(6.81)**					
Log beef price	−1.91	−1.91	−2.16	−2.20			−1.90		
	(9.61)**	(9.62)**	(12.22)**	(11.71)**			(9.77)**		
Log pork price				−0.0546					
				(0.60)					
Log chicken price				0.296					
				(1.51)					
Log turkey price				−0.0485					
				(2.36)*					
Log lamb price				0.186					
				(2.20)*					
Data set	Scanner	Scanner	Scanner	Scanner	Scanner	Scanner	Scanner	Scanner	CES
Minimum days	0	0	0	0	0	0	0	0	n.a.
Aggregation	Subclass	Subclass	Subclass	Subclass	Subclass	Subclass	Subclass	All beef	All beef
Observations	5,6077	5,6077	8,4598	8,3146	5,6077	5,6077	5,6077	8	8
R-squared	0.973	0.973	0.945	0.945	0.960	0.944	0.973	0.977	0.469

Notes: Table displays changes in the variables listed in the top of each column. Columns labeled "log Q" use as dependent variable the log of the purchased quantity, while "log P" uses log price and "log R" uses log revenues/expenditures. Columns (1)–(7) use subclass-by-period-by-store fixed effects, while columns (8) and (9) use store-by-period fixed effects. All columns use period fixed effects to account for seasonal purchasing patterns. Periods are five-week aggregates; that is, period 1 is 24 December to 27 January, while period 2 is 28 January to 2 March. Column (8) uses the thirty-five-day period following 23 December 2001, as the event period to test whether a placebo effect can be detected in another year. Income is the demeaned average income in the zip code in which the store is located (in $10,000). Minority is the demeaned percentage of the population that is either African American or Hispanic. The row "minimum day" indicates on how many days out of the thirty-five-day period a product has to be sold in a store to be included in the data set. *T*-values are given in parentheses. Single asterisk (*) indicates significance at the 5% level, while two asterisks (**) indicate significance at the 1% level.

Similarly, stores located in zip codes with a higher percentage of minority population (African American and Hispanic) show larger drops: an additional 0.18% for each percentage point of minority residents. This coefficient is opposite of what we originally expected, but it might be explained by the fact that both ethnic groups have a higher per capita beef consumption to begin with than other socioeconomic groups. While we are only able to match the socioeconomic characteristics for the zip code in which a store is located, we observed ethnic compositions of the customers that were similar to zip code averages when we visited various stores.

Column (3) includes a second thirty-five-day period past the event in equation (2) to see whether the effect started to phase out. The magnitude of the average abnormal reduction in beef consumption appears to remain roughly the same through the second thirty-five-day period. The point estimate is again roughly −0.23. The interaction terms with the socioeconomic characteristics remain robust as well. The one exception is the interaction of income and period 2, which is no longer significant.

Column (4) controls for the price of substitute meats, which are the quantity-weighted average price of all UPCs that belong to each meat.[12] We fix the quantity weights at pre-event levels to ensure that the average price is not confounded with changing buying habits

[12] In contrast, the price of beef is the average price of all UPCs with the same subclass. The quantity-weighted overall price indices of the substitute meats are more aggregated measures and the *t*-values are much lower.

induced by the event itself. The cross-price elasticities are significant for turkey and lamb. The former is a complement while the latter is a substitute. More importantly, the estimated abnormal drop in beef consumption in rows (1) and (2) of column (4) is hardly any different from column (3).

Column (5) reports the estimated drop in beef purchases without controlling for price, not even for beef products. The estimated coefficient is -0.200, slightly lower than the coefficient in column (1). We conclude that while adding price as a covariate improves the R^2 of our regression, it has a negligible effect on the magnitude and significance of our estimated treatment effect.

Column (6) of table 1 replicates the analysis with log price as the dependent variable to see whether stores lowered prices in response to the first discovery of an infected cow. We detect a small but statistically significant drop of 1.6% in average price. Using various published estimates of the price elasticity, the important implication is that the effect on $\delta_{1,2003}$ of such a price drop will be small.[13]

Column (7) runs a placebo experiment to validate our approach using the scanner data. We estimate the abnormal change in beef purchases for the same thirty-five-day span in 2001, the first winter of our four-year sample, instead of 2003. Since the first infected cow was discovered in 2003 and not 2001, we should not observe a significant abnormal change by using the wrong period. This procedure gave us the expected result; the coefficient in column (7) is not only lower in magnitude but also not statistically significant.

Historically, the only available micro-level data sets of individual purchasing decisions are the diary files of the CES. Columns (8) and (9) of table 1 contrast our results using the scanner data to results from the CES. Column (8) uses scanner data and aggregates all beef expenditures over all stores, leaving us with two observations for each of our four winters: one for the thirty-five-day period prior to 23 December and one for the thirty-five-day period following 23 December of each winter. Since the goal is to compare the results to the CES, we switch the dependent variable from log quantity to log revenues (log expenditures), as the CES lists expenditures, not the quantity purchased, for various goods, including beef.

Column (8) shows that the aggregated scanner data with eight observations and without controlling for price still detect an abnormal and significant drop in beef revenues that is comparable to our results using disaggregated data and controlling for price. When replicating the analysis using data from the diary files of the CES in column (9), we do not find significant effects on expenditures. However, note the large standard errors associated with the estimate based on the CES data; while it is not statistically different from zero, it is also not statistically different from our estimate in column (8). We believe this is most likely due to the limited sample size of the CES and the fact that it is a revolving cross-section, that is, respondents drop in and out every week. Similarly, an aggregate analysis of CES data following the Oprah Winfrey show does not detect any significant changes in the CES, but the error bounds are again very large. We believe scanner data sets should be considered as a serious alternative to the CES when researchers are interested in detecting changes in buying habits. If, however, the power of the CES is sufficient to obtain small standard errors, it might be preferable for event studies as the data include more detailed socioeconomic characteristics than the store-level scanner data, and are nationally representative.

Finally, table A2 of Schlenker and Villas-Boas (2009) displays the estimated reduction in beef purchases under various other aggregation measures. We aggregate all UPC purchases to the subclass, class, or overall meat category level. The broader the aggregation, the lower the number of observations in our sample. However, our estimated abnormal reduction in beef purchases is very robust to the aggregation level.

Analysis of Thirty-Five-Day Aggregate Purchases of Other Meats

We now turn to the impact on other meats. As mentioned before, the effect of the discovery of the first infected cow could have two countervailing effects. It could induce a meat-substitution effect where consumers switch to other meats and thereby increase their consumption of these other meats, or it could lead to an overall reduction in meat purchases due to perceived health risks of all meats in general. Since these effects work in opposite directions,

[13] Our estimated demand elasticity is larger in absolute magnitude than the estimate of -0.570 by Eales and Unnevehr (1988). However, the latter is an *aggregate* beef demand elasticity, and our estimate is for a chain, and thus higher as customers can switch to other stores.

Table 2. Changes in Thirty-Five-Day Aggregate Log Purchases of Other Meats Following Discovery of First Infected Cow

	(1) Pork	(2) Pork	(3) Chicken	(4) Chicken	(5) Turkey	(6) Turkey	(7) Lamb	(8) Lamb
Period 1	0.0425	0.0394	0.0657	0.0423	0.0785	0.0653	0.00122	−0.00617
	(2.25)*	(1.36)	(9.58)**	(2.46)*	(0.83)	(0.72)	(0.05)	(0.20)
Period 1 × *WA*	0.0792	0.102	0.0960	0.140	0.109	0.0833	0.0823	0.131
	(2.01)	(2.10)*	(3.20)**	(4.16)**	(0.49)	(0.38)	(0.95)	(1.52)
Period 2		−0.0865		−0.0415		−0.209		−0.172
		(2.27)*		(1.63)		(2.41)*		(4.47)**
Period 2 × *WA*		0.111		0.110		0.268		0.405
		(2.58)*		(3.07)**		(1.15)		(5.89)**
Period 1 × income		0.00088		0.00784		0.00409		0.0169
		(0.20)		(2.02)		(0.50)		(2.02)
Period 2 × income		0.00201		−0.00248		−0.00681		0.00300
		(0.43)		(0.65)		(0.78)		(0.40)
Period 1 × minority		−0.00025		0.00148		−0.00103		0.00014
		(0.82)		(3.03)**		(0.62)		(0.28)
Period 2 × minority		−0.00028		−0.00060		−0.00092		0.00048
		(1.07)		(1.12)		(0.50)		(0.77)
Log price	−2.04	−1.95	−1.49	−1.35	−2.27	−1.97	−1.52	−1.20
	(26.41)**	(23.50)**	(25.89)**	(29.05)**	(12.88)**	(15.16)**	(5.14)**	(6.58)**
Data set	Scanner	Scanner	Scanner	Scanner	Scanner	Scanner	Scanner	Scanner
Minimum days	30	30	30	30	30	30	30	30
Aggregation	Category	Category	Category	Category	Category	Category	Category	Category
Observations	2,290	3,440	2,290	3,440	1,768	2,654	1,507	2,264
R-squared	0.992	0.989	0.991	0.989	0.968	0.977	0.968	0.959

Notes: Table displays abnormal seasonal changes in log meat purchases (listed on top of each column). Columns use subclass-by-period-by-store fixed effects and period fixed effects to account for seasonal purchasing patterns (not reported). Periods are five-week aggregates; that is, period 1 is 24 December to 27 January, while period 2 is 28 January to 2 March. Income is the demeaned average income in the zip code in which the store is located (in \$10,000). Minority is the demeaned percentage of the population that is either African American or Hispanic. The row "minimum day" indicates on how many days out of the thirty-five-day period a product has to be sold in a store to be included in the data set. T-values are given within parentheses. Single asterisk (*) indicates significance at the 5% level, while two asterisks (**) indicate significance at the 1% level.

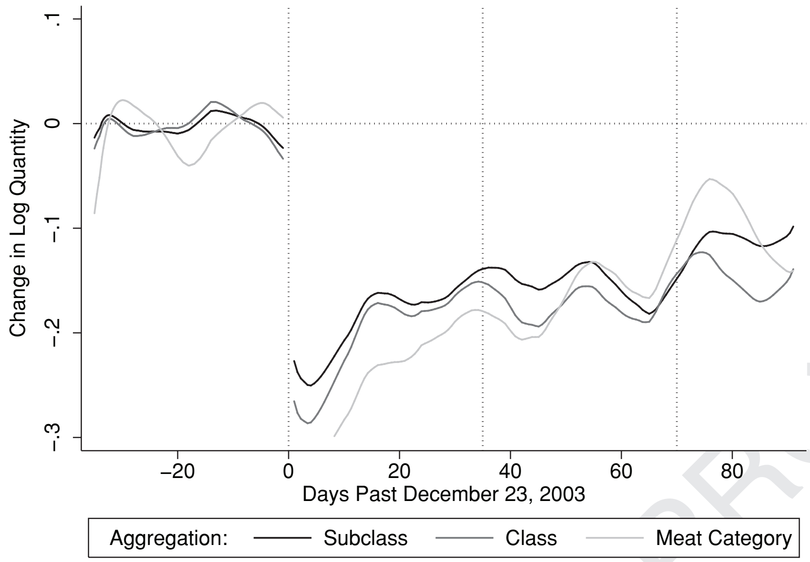
it is an empirical question which one of these effects dominates.

Table 2 reports the regression results of abnormal changes in the log of other meat purchases controlling for price, as well as period and store-by-winter-by-category level fixed effects, where the fixed effects are not reported to save space. As outlined in the data section, some UPCs or entire meat categories are sold infrequently. We therefore aggregate all purchases for each meat and only include UPCs that are sold on average on at least thirty days of the thirty-five-day period. Columns (1)–(4) suggest that consumers appear to have increased their pork and chicken consumption, especially in Washington State. No significant abnormal changes can be detected for turkey or lamb purchases in columns (5)–(8). The estimates for these meats, however, exhibit larger standard errors than those for beef, as these other meats get bought less frequently and have higher seasonal components.

Analysis of Daily Beef Purchases

To investigate how consumers' responses evolve over time, we relax the temporal aggregation and present results of a locally weighted regression of daily abnormal beef purchases. The two-stage procedure of first removing all portion of the residuals that can be explained by price movements or seasonality effects and then smoothing the remaining residuals is outlined in equation (3). Our bandwidth stretches ten days and the weights decrease quadratically in time. The window is not allowed to cross the event day to ensure that the effect of the outbreak is not diluted by pre-event data.

The locally weighted regression of abnormal (i.e., net of price, day number, weekday, Thanksgiving, and store-by-winter-by-aggregation-level fixed effects) changes in beef purchases are displayed in figure 1. The baseline model using subclass aggregation is displayed as a black solid line. Successively higher aggregation levels—class and meat category—are plotted in lighter gray. There is a clear discontinuity at the event day, when beef quantity sold drops sharply compared to pre-event levels. The figure suggests that there is no news leakage before the official announcement on 23 December 2003 as we otherwise should see a downward trend before day 0. By



Notes: Figure displays changes in log beef purchases (quantity sold) using various aggregation measures for beef: UPCs are aggregated to the subclass, class levels, or all beef sales. Day 0 is 23 December 2003 when the first infected cow in the United States is made public. Abnormal changes are net of price as well as period-by-store-by-aggregation level, day-number, Thanksgiving, and weekday fixed effects.

Figure 1. Abnormal daily changes in beef purchases following discovery of first infected cow

the same token, the new information reaches consumers very rapidly: the largest drop is observed within the first seven days.[14]

Similar to Smith, van Ravenswaay, and Thompson (1988), we observe that consumers react more strongly to negative than to positive news. On 30 December 2003, the Department of Agriculture announced a new meat tracking system that should make it easier and faster to identify infected cows. Figure 1 shows that this had limited effects. The curve shows a brief recovery from the initial drop, following day 7. The recovery is of smaller size than the drop following the discovery of the first infected cow. Moreover, beef purchases (adjusted for price changes) only recover very slowly in our ninety-one-day period after the event for which we have data.

Analysis of Daily Cattle Futures Prices

We compare the futures market assessment to the change we observe in the scanner data set. Figure 2 displays the abnormal changes in live cattle futures prices following the first reported mad cow outbreak in the United States in 2003 in the left column. Various shades of gray represent futures prices with a maturity of two, four, and six months after the event day, where lighter grays indicate longer maturities. We construct daily returns around these two days (i.e., the event is called day 0, negative x-values are the number of days preceding the event, and positive x-values are the number of days following the event). The y-values are changes in futures prices compared to the last trading day preceding the event day *net of overall commodity market movements*.

We report the estimates after subtracting overall market movements as outlined in equation (4). In a first step, we regress daily futures price changes r_d on daily changes in the Dow Jones Commodity Market index R_d for contracts that have less than 150 days left until maturity in the years 1995–2005. Our estimates imply that a 1% change in the commodity index is predicted to increase Live Cattle futures prices by 0.142%. In a second step, we subtract the predicted change $\hat{r_d} = 0.142 R_d$ in cattle futures prices from the observed return to end up with the abnormal return.[15]

[14] Figure A3 in Schlenker and Villas-Boas (2009) displays the results from a locally weighted regression of daily abnormal changes in substitute meat purchases. A discontinuity is much less apparent.

[15] The estimates are $r_d = -0.000096 + 0.142\, R_d$, where only the second parameter is significant. There are limited overall commodity market movements, and hence we obtain a very similar figure if we do not net out the market index.

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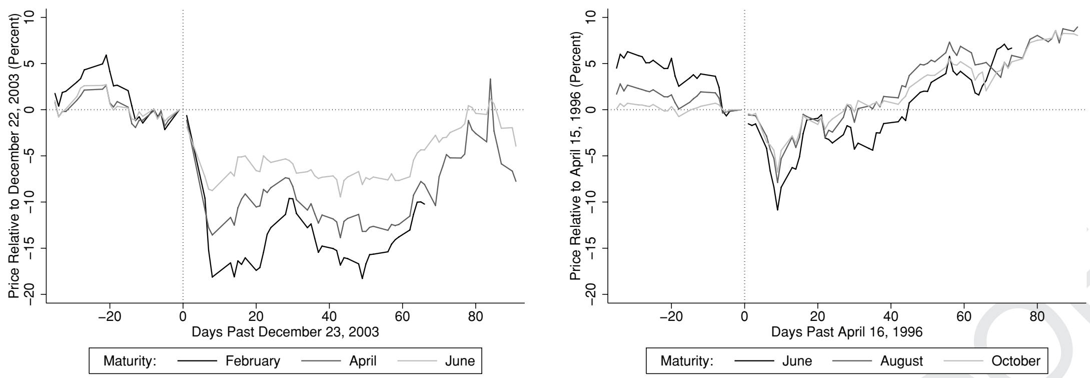

Notes: Panels display futures prices of live cattle with maturities of two, four, and six months, respectively, <i>net</i> of changes in the Dow Jones Commodity Market index. The left panel uses the first discovery of a mad cow as day 0 (23 December 2003), while the right panel uses the report by Oprah Winfrey (16 April 1996). Futures with a maturity of roughly two months expire before the end of the ninety-one-day window, and hence only a partial time series is displayed.

Figure 2. **Abnormal daily changes in cattle futures prices (net of changes in commodity price index)**

The pattern of abnormal changes in futures prices after the 2003 event is comparable to the results we obtain in the scanner data set in figure 1. Again, there seems to be no news "leakage" as there is no downward trend in prices leading up to the event. By the same token, markets reacted in phase with changes in consumer beef purchases.[16] The sharp discontinuous shift we observe in our futures data suggests that market participants in our sample react very quickly. This is not surprising as both events were highly publicized and a less than immediate adjustment would allow for arbitrage opportunities.

Futures prices revert to pre-event levels over time as the dust settles, which might well be the result of other events that occurred after the outbreak. New precautionary systems were put in place; for example, the Department of Agriculture introduced a new meat tracking system. Furthermore, no additional cases of mad cow diseases were found over the following weeks, which seems to have appeased both consumers and, accordingly, financial markets. Yet the rate of recovery is much slower than the immediate sudden drop following the announcement. An interesting side effect is that the market seems to have correctly anticipated this eventual recovery, as the abnormal returns of futures with a longer maturity are lower.

Because futures prices match scanner data responses for 2003, and are available for a longer period than our scanner data set, we can compare the response following the Oprah Winfrey show in 1996 that warned about potential health effects with the response following the widespread reporting following the actual outbreak in 2003. The right panel of figure 2 shows the response to the 1996 event and the left panel shows the response to the 2003 event. The warning in the Oprah Winfrey show led to an initial reduction of more than half the size of the one following the actual outbreak, yet futures prices recovered more quickly in response to the 1996 event than in response to the 2003 event.[17] As Foster and Just (1989) have pointed out, there is evidence that exaggerating the potential threat level can lead consumers to temporarily restrict their purchasing decisions. Such scares will induce welfare losses as consumers deviate from their first-best consumption patterns based on speculative threats.

Conclusions

We estimate the change in consumer buying habits following the first discovery of mad cow disease in the United States in December 2003. We find a statistically significant and robust

[16] Rucker, Thurman, and Yoder (2005) show that lumber futures prices respond more quickly to news about trade disputes than to news about endangered species.

[17] Unfortunately, we do not have a control group to disentangle whether futures prices recovered due to other abnormal shocks that fell within our post-event study period. A Lexis-Nexis article count of articles with the word "mad cow" is shown in figure A2 of Schlenker and Villas-Boas (2009). Newspaper covered continued for several weeks following the discovery of the first infected cow and it hence appears plausible that it indeed took longer for consumers to revert to preexisting buying habits.

drop in beef purchases using a product-level scanner panel data set from one of the largest U.S. grocery chains. The data set includes observations for stores in Washington State where the infected cow was found, and for another group of stores in the D.C. metropolitan area. The effect is comparable in both areas. Stores located in zip codes with higher mean income exhibit additional reductions in sales, as do stores located in zip codes with a higher fraction of minority groups. Our event study of cattle futures price movements net of overall commodity market movements exhibits a pattern that is comparable to the abnormal changes in beef purchases in our scanner data. Futures contracts with longer maturities show lower abnormal changes, suggesting that the market anticipated the impacts to be transitory.

From our results we conclude that the impact of the first discovery of an infected cow was quick and economically significant. The impact was geographically widespread and not limited to the areas where the scare occurred. Finally, the impact was product specific, negative in this case for the meat in question, and positive for some substitute meats.

Results also reveal a similar response to earlier coverage of the potential health risk in the Oprah Winfrey TV show. Futures prices dropped by more than 50% of the abnormal return we observed following the first discovery of an infected cow in 2003. However, it should be noted that during the show the host and a guest commented that mad cow disease could make AIDS look like the common cold, which in retrospect is a gross overstatement of the risk of mad cow disease.

The sharp response following the Oprah Winfrey show highlights how markets (and consumers) can update their expectations following highly visible media events even though no real "new" information was revealed; that is, the potential dangers of BSE had previously been discussed in the literature. Similarly, Huberman and Regev (2001) find a very sharp stock market response to a New York Times article that highlights a potential cure for cancer, even though the same information was published five months earlier in the academic journal *Nature* and had been mentioned previously in other newspaper articles (including the New York Times itself). While one could argue that the information on the effects of mad cow disease was not very widely understood, it appears that the response following the Oprah Winfrey show (which summarized the existing debate on the potentially harmful effects) was disproportionately large compared to the response following the actual outbreak, which carried new information, that is, that the disease had reached beef production in the United State for the first time.

Ms. Winfrey's comment that she would not eat another burger could be seen as framing the danger in exaggerated terms. Having identified the effect of media coverage on economic outcomes adds to existing research in this area that has focused on the impact of media expansion and media bias on political attitudes and outcomes (Stroemberg 2004; Gentzkow and Shapiro 2006; DellaVigna and Kaplan 2007). It further allows us to draw some conclusions on magnitudes of consumer reactions to different sources of information. Our estimates imply that receiving coverage in one of America's most-watched afternoon television programs can impact markets in a sizeable way compared to government warnings combined with continued general news coverage.

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