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Publication Date
2008-06-17

University of California, Berkeley
Department of Agricultural &
Resource Economics

CUDARE Working Papers

Year 2008 *Paper 1023R3*

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We examine how consumers and financial markets in the United States react to two health warnings about mad cow disease: the first discovery of an infected cow in December 2003 and an Oprah Winfrey show on the potentially harmful effects that aired seven years earlier. Using a unique product-level scanner data set of a national grocery chain, we find a pronounced and significant reduction in beef sales following the first discovered infection, which dissipates slowly over the next three months. Cattle futures show a comparable pattern of abnormal price drops 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.

Keywords: Food safety, mad cow disease, consumer behavior, scanner data, futures prices.
JEL code: D12, Q18, M31

We thank two anonymous referees, as well as Cyndi Berck, Peter Berck, George Judge, Gordon Rausser, Walter Thurman, and seminar participants at Resources for the Future, the University of Colorado, the University of Massachusetts, and Virginia Tech for helpful comments. We are grateful to Jennifer Brown for data research assistance, John Crespi and John Lawrence for help with obtaining the futures data, Reed Johnson and Steve Flaming for help obtaining the scanner data, and the Giannini Foundation of Agricultural Economics for financial support via a 2005-06 Mini-grant.

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1 Introduction

The United States has the second highest per capita beef consumption in the world behind Argentina.[1] Roughly 30 billion pounds of beef were consumed in 2004. However, beef consumption has stagnated for the last several years as consumers switched to other meats. The government-run advertisement campaign "Beef: It's What's for Dinner," which is financed by an assessment of U.S.$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 December 9, 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 April 16, 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."

More than seven years later, the first outbreak of the disease was reported in the United States on December 23, 2003. This information was provided by official government sources. There was repeated news coverage in newspapers, TV and radio for at least the next month.

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

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. This allows us to assess how consumers differentiated between warnings that are initiated by the government in comparison to the private media.

We find a large and significant drop in beef sales following both episodes. Scanner data from a large U.S. grocery chain reveal that there was an approximately 20% drop in beef sales following the discovery of the first infected cow in 2003. In the same period, no statistically significant break can be detected in the diary files of the Consumer Expenditure Survey (CES), which is a much smaller sample that relies on consumers' reports of purchases. However, because the CES sample is small, the standard error on the CES based estimate is so large that the 95% confidence includes both zero as well as the estimate we find in the scanner data.

Unfortunately scanner data are deleted for old time periods, so we do not have scanner data following the Oprah Winfrey show aired in 1996. However, market reactions to the same episodes can be assessed with the help of changes in cattle futures prices. In theory, financial markets should give an accurate assessment of consumer responses, as financial markets are forward-looking. Systematic differences between the futures market and consumer purchasing behavior would indicate that there might be inaccurate assessment by futures markets, e.g., through excess volatility. Rausser and Walraven (1990) find that agricultural markets can overreact to disturbances, with repercussions in other markets.

For the 2003 incident, our results show a discontinuous drop in cattle futures for futures with a two months maturity. The pattern is comparable to the consumer response obtained in the scanner data set. The drop in abnormal returns is smaller in absolute value as we look at futures with longer maturities, suggesting that the market expected the change in buying habits to be transitory.

Since we don't have scanner data for 1996, we use futures prices. Since the futures data exhibit a comparable pattern in abnormal changes to our scanner data set in 2003, we compare abnormal changes in future prices following the discovery of the first infected cow in 2003 with abnormal changes in future prices following the Oprah Winfrey show in 1996. We find abnormal futures market returns in the aftermath of this TV show to be more than half the abnormal return following the first discovery of an infected cow.

The remainder of this paper is organized as follows. The next section provides a brief discussion of the literature on food safety in general and particularly meat markets, setting up the background for analyzing health warnings about mad cow disease. Section 3 outlines our data. Section 4 describes the model, and Section 5 presents our empirical results. Section 6 concludes and discusses the implications of our findings.

2 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 in the medium or long-term.

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 et al. (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. Consumers tend to be susceptible to "scares," but it is much harder to restore consumer confidence once the damaging health effects have been resolved. Foster and Just (1989) use the same event to construct a model that examines the welfare losses associated from withholding "safety information" (leaving consumers in the dark) 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. The response to risk-related information has significant economic consequences for food businesses. Some authors have used these findings to suggest that food-retailers should seize on food safety as a market segmentation mechanism (see for example Caswell et al. (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. Examples include the case of cholesterol in shell eggs (Yen et al. 1996, Brown and Schrader 1990) and Alar contamination in apples (van Ravenswaay and Hoehn 1991). Traditional demand modeling becomes inadequate, as there is a clear structural break in the relationship between the dependent variable (food consumption) and the explanatory variables (prices, income, or other socio-economic characteristics). Chavas (1983) presents a framework of how to deal with structural breaks in meat demand models. It is even more difficult to determine whether these structural changes are permanent. Structural demand models often require some assumptions on the time pattern around a crisis in order to recover information.

There has also been an interest in assessing heterogenous responses of various socio-economic groups. Burton et al. (1996) show that the influence of socio-economic characteristics on meat consumption changes in Great Britain over the years 1973-1993. Shimshack et al. (2007) use a reduced-form approach to evaluate the effect of government warnings about mercury on fish consumption in the U.S. using the Consumer Expenditure Survey, and find that responses vary greatly by socio-economic 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 socio-economic 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. The occurrence of BSE (mad cow) scares throughout Europe have recently led several researchers to investigate how consumers react to news about BSE. 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 U.S. there has been a shift away from beef to fish and chicken. In order to pick up location-specific shifts in consumption patterns, we hence 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. For example, Crowley and Shimazaki (2005) use aggregate demand data from the pre-BSE period to develop an ARIMA model for changes in demand. In addition to the one-month-ahead forecast, they develop a dynamic forecast to estimate revenue loss due to the announcement. While previous studies usually rely on aggregate data, our analysis makes use of a unique set of micro-level scanner data from one of the largest national grocery chains.

Previous studies of consumer responses had to rely on aggregate data due to the lack of micro-level data. The one exception is the diary files of the Consumer Expenditure Survey, which track purchasing decisions of individual households for two weeks. Each week, approximately 100 households are recruited and stay in the sample. The sample size of 200 households in the entire U.S. is hence rather limited. The advantage of the Consumer Expenditure Survey is that it includes detailed socio-economic information of each person in the survey; the potential downside is the limited sampling size and the fact that it is a revolving cross-section.

On top of measuring consumer responses directly, one can also revert to indirect market assessments using financial data. Economists are often interested in the impact of certain events on the value of a firm or the demand for a product. This might appear to be a difficult undertaking, for example, requiring detailed analysis of the impact on individual firm's productivity or the marginal willingness to pay for a product. Financial event studies, however, provide a relatively straightforward way in which to undertake such an analysis. The assumption is that measurement of the short-term impact of a food safety announcement on financial markets reflects the assessment of shareholders regarding the firm-level impact of the announcement, or a shift in marginal willingness to pay for a product. Thus, a measure of the economic impacts can be derived based on changes in security or futures prices. An excellent review of the event study methodology is given by MacKinlay (1997), and Binder (1998) provides a survey of empirical issues raised by recent event studies.[2] Event study methodology has since been applied to assess the impact of a wide range of firm-specific and economy-wide events which include new government regulations (Broder and Morrall III 1991, Maloney and McCormick 1982), financial market predictions (Dimson and Marsh 1986), and product- and workplace-related deaths (Borenstein and Zimmerman 1988, Chalk 1987, Broder 1990, Broder and Morrall III 1991, Mitchell 1989). It has also been applied to food security issues. Commodity futures are forwarding-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. In this paper we also measure the reduced-form response of future price movements net of changes in the commodity market index. Finally, Marsh et al. (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.

[2] The use of event studies dates back to the late 1960s when a number of attempts were made to assess the impact of new information about annual earnings on security prices (Fama et al. 1969). These early studies, however, were hampered by the lack of readily available data on daily security prices. This made it difficult to isolate the impact of the specific event from other background influences. The subsequent availability and use of daily price series has improved the scope and precision of event analysis, but at the same time has necessitated the use of more sophisticated statistical techniques.

3 Data

We use various data sources to estimate the impact of the health warnings about mad cow disease on consumer purchasing decisions and futures prices. The first is a unique scanner data set from one of the largest U.S. grocery chains. Our data set includes 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, e.g., Store 15 sold 3 pounds of Oscar Mayer beef franks for a total of $18.50 on December 23, 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 November 18 through March 23 in the winters 2001/2002 through 2004/2005, thus spanning the period 5 weeks prior to and 13 weeks past the event date.[3] The scanner data report both sales revenues and quantity sold, and we are hence able to construct the price.[4] Prices are fixed for seven days from Wednesday to the next Wednesday when new promotional flyers are printed and distributed. The summary statistics are given in Table A1 in the appendix. Closely related products (e.g., lean ground beef, less than 10% fat) can have various UPCs, and we hence 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, e.g., all "Beef Rib Steaks", or "Beef Rib Roasts." The next aggregation level is a meat *class* which groups similar meat types together, e.g., all "Beef Rib" (both steak and roast), or "Beef Loin". Beef products are furthermore grouped into three *subcategories* for (i) ground beef, (ii) a company-specific national brand chain, and (iii) locally-supplied beef products. All other meats have only one category. When we use the aggregation measure *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 1 unit is sold would show a 700 percent increase in sales above the average level. As

[3] The end date is March 22, 2004, as it is a leap year. A Lexis-Nexis search gave us the daily count of articles that appeared on the topic as shown in Figure A2 in the appendix. Media attention subsided well before the end of the 13-week period.

[4] Roughly 7% of the entries are excluded because the quantity measure is missing.

the data appendix reveals, our daily store-level data show not a single turkey or lamb sale for 12 and 17 percent of our observations, respectively. To avoid potentially erratic relative changes of infrequently sold products, we sometimes exclude all UPCs that on average get sold on less than 30 days a month.

We obtain the exact location for each of the 298 stores and are able to match the location with socio-economic statistics from the U.S. Census based on the zip code in which a store is located. Summary statistics of the socio-economic variables are given in the appendix in Table A1.

The analysis is replicated using the diary files of the Consumer Expenditure Survey (CES) for the same years 2001-2004. We use the CES 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 hence not a panel but a repeated cross-section. In contrast, the scanner data set is much larger. There are on average more than 76,000 purchases per week of beef products at the UPC level in our scanner data set, while there are on average 133 purchases of beef products in the Consumer Expenditure Survey in a week.

Daily cattle futures prices are obtained from Iowa State University.[5] We use futures price data for two, four, and six months maturities, and the net growth of cattle should hence be limited as the cows are maturing. The futures market data is 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.

4 Analytical Framework

Our goal is to estimate the abnormal change in purchase quantities following the two mad-cow related events. We first examine average effects for areas close to the actual outbreak (stores in Washington State) and a control group comprised of Maryland, Virginia, and D.C. In a later part, we examine whether there are heterogeneous impacts for various demographic subgroups.

The baseline reduced form econometric model for estimating the effect of a mad cow

[5]http://www.econ.iastate.edu/faculty/lawrence/Futures.html. We would like to thank John Crespi and John Lawrence for assisting us in obtaining these data.

event on meat purchases is:

$$y_{asnt} = \alpha_{ast} + \sum_{n=1}^{N}[\beta_{1,n}I_n + \beta_{2,n}I_nI_{\text{WA}}] + \gamma p_{asnt} + \sum_{n=1}^{N}[\delta_{1,n}I_{n,event} + \delta_{2,n}I_{n,event}I_{\text{WA}}] + \epsilon_{asnt} \quad (1)$$

where y_{asnt} is the log quantity sold by aggregation level a (e.g., subclass, class, or overall meat total) in store s in month number n of winter / period t.[6] The total number of months in the post-event period is denoted by N.[7] The fixed effects α_{ast} allow for a shift of average purchases in each store s by aggregation level a and period t, i.e., they pick up trends in buying habits of individual products between years in each store. I_n is a dummy variable that is set to one if the purchase occurred in month n following the event, while I_{WA} is one if the store is located in Washington State. The coefficient $\beta_{1,n}$ picks up the seasonal effect of month n following the event, e.g., ham sales might always be higher around Christmas. For the regressions examining consumer responses to the first infected cow, Month 1 is the 35-day month (5 weeks) after Christmas from December 24 until January 27 in the next calendar year. For the regression that examines the effects of the Oprah-Winfrey show, Month 1 is the 35-day month starting eight days past Easter Sunday.[8] These event days are chosen such that the fixed effects for the month pick up seasonal holiday effects of Christmas (which occurs on the same day every year) and Easter (which is based on a lunar calendar and occurs on different days between years). The coefficient $\beta_{2,n}$ captures the *additional* effect in Washington State where the first infected cow was discovered. We control for log price p_{asnt}, which is the log of the average price of all products in aggregation level a in store s in month n of period t. Finally, $I_{n,event}$ is a dummy that is set to one for month n in the event period (2003 for the infected cow and 1996 for the Oprah Winfrey show). The coefficient $\delta_{1,n}$ hence picks up the treatment effect, representing the abnormal changes in consumption in month n in the event period on top of the seasonal effect $\beta_{1,n}$. The treatment effect is allowed to be different in Washington State, which would be captured by $\delta_{2,n}$.

Our identification comes from changes within an aggregation level and store in the year of interest, net of seasonality effects. In other words, we look at the seasonal difference in purchasing behavior in a given year (e.g., by how much are sales in the month following

[6]Since news of the first infected cow was published on December 23, 2003, the 35-day month following the event includes days from two calendar years.

[7]Our baseline model pairs the pre-event month with one post-event month, i.e., $N = 1$ to avoid problems with auto-correlation as discussed below. In a sensitive check, we also include a second post-event month and hence $N = 2$.

[8]We define a month as a multiple of weeks so we do not have to worry about weekday fixed effects, as sales are always higher on weekends.

the event higher than in the preceding month) and compare this difference to the one we obtained in years other than the event period. The only reason to include additional years before and after the event is to obtain an estimate of the seasonality component $\beta_{1,n}$ and $\beta_{2,n}$. Since both events in our study happened around major holidays (Christmas and Easter), a simple before-after comparison within a single period might wrongfully attribute an observed change in beef purchases to the event in question, as beef purchases exhibit seasonal patterns.

We expect that beef purchases show abnormal drops (i.e., net of seasonality effects) when new information about potentially harmful health effects are revealed, i.e., $\delta_{1,n} < 0$. If the effect is different in Washington State, where the first infected cow was discovered, then $\delta_{2,n} \neq 0$. It is harder to hypothesize what happens to other meats (chicken, pork, etc). 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.

Any hypothesis test requires an unbiased estimate of the variance-covariance matrix. There are two potential sources of concern in our data set: (i) contemporaneous correlation of the error terms of purchases in a given month and region;[9] and (ii) temporal correlation across months. To address the former we cluster the error terms ϵ_{anst} by month and region, thereby allowing the error terms of various products within a store and other stores in a region to be correlated.[10] If there are shocks in a given month, e.g., dismal weather that causes inhabitants to postpone shopping trips, all observations will show lower sales. Second, since we rely on a difference-in-difference estimate, auto-correlation might give incorrect estimates of the error term and lead us to reject the null hypothesis too often if several pre- and post-observations are included (Bertrand et al. 2004). In our baseline model, we therefore include only one observation before the event and one after, i.e., $N = 1$.

Other authors have emphasized that responses might differ by socio-economic subgroups. We therefore include interaction effects with the abnormal change. The estimated regression

[9] Our two regions are Washington State and the D.C. metropolitan area.

[10] In a sensitivity check, we only cluster observations in a given store in a given month, which results in smaller standard errors than the ones we present. We hence cluster all observations across all stores in a region and month, as this gives us more conservative estimates. Moreover, many of the stores are within close proximity and hence susceptible to the same shocks.

equation becomes:

$$\begin{aligned} y_{asnt} &= \alpha_{ast} + \sum_{n=1}^{N}[\beta_{1,n} I_n + \beta_{2,n} I_n I_{\mathrm{WA}}] + \gamma p_{asnt} + \sum_{n=1}^{N}[\delta_{1,n} I_{n,event} + \delta_{2,n} I_{n,event} I_{\mathrm{WA}}] \\ &\quad + \sum_{n=1}^{N}[\lambda_{1,n} I_n C_s + \lambda_{2,n} I_n I_{\mathrm{WA}} C_s] + \sum_{n=1}^{N}[\theta_{1,n} I_{n,event} C_s + \theta_{2,n} I_{n,event} I_{\mathrm{WA}} C_s] + \epsilon_{asnt} \end{aligned} \quad (2)$$

The first line is the same as in equation (1), while the new interaction terms appear on the second line. C_s is the demeaned socio-economic characteristic of the zip code in which store s is located. The parameters $\lambda_{1,n}$ and $\lambda_{2,n}$ allow the seasonality components $\beta_{1,n}$ and $\beta_{2,n}$ to be different by socio-economic subgroups, e.g., more affluent people might increase their ham consumption and correspondingly decrease their beef consumption more than less affluent groups around Christmas. The terms $\theta_{1,n}$ and $\theta_{2,n}$ capture whether the abnormal changes following the health warnings differ by socio-economic characteristics.

So far, we have aggregated quantities by month n in order to avoid the potential pitfalls of difference-in-difference estimators when there is serial correlation in the error term. To demonstrate how purchasing decisions develop over time, we also estimate a model of daily abnormal changes:

$$y_{asdt} = \alpha_{ast} + \sum_{d=1}^{D} \beta_d I_d + \gamma p_{asdt} + \sum_{d=1}^{D} \delta_d I_{d,event} + \sum_{w=1}^{6} \eta_w I_{\text{weekday w}} + \rho I_{\text{Thanksgiving}} + \epsilon_{asdt} \quad (3)$$

The above equation differs from our baseline model in equation (1) in several ways. First, the time scale is switched from months n to days d. In other words, β_d now picks up daily seasonality effects,[11] where we include dummies ranging from 34 days before the event to 91 days past the event.[12] 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 ρ for the analysis following the discovery of the first infected cow. Third, we do not allow the effects to be different for Washington State and thus drop all interaction terms with I_{WA}. The rationale is to obtain the average *overall* abnormal change which we can then compare to abnormal futures returns (which capture the average effect on the overall market as well).

[11] In the regression analysis following the discovery of the first infected cow day number 0 is December 23 of each year. In the regression analysis following the Oprah Winfrey show, day number 0 is the eighth day past Easter Sunday.

[12] We drop the 35th day before the event to avoid perfect multicolinearity with the constant. The event date (day 0) is excluded as well as the information became available throughout the day and it is unclear when consumers in the Eastern and Western United States updated their beliefs.

In the second step, we smooth the sum of the daily abnormal impacts and the residuals $\nu_{asdt} = \sum_{d=1}^{D} \delta_d I_{d,event} + \epsilon_{asdt}$ from regression (3) using a locally weighted regression.[13] 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.[14]

Finally, in our fourth model, we examine abnormal 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:

$$r_d = \alpha + \beta R_d + \epsilon. \tag{4}$$

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.

5 Empirical Results

In Section 5.1, we report how consumers respond to the first discovery of an infected cow by examining monthly *beef* purchases in our scanner data as well as the Consumer Expenditure Survey. In Section 5.2, we discuss purchases of other meats. Smoothed abnormal daily changes in purchases are presented in Section 5.3. In Section 5.4, we turn to futures market responses, following both the first discovery of an infected cow in 2003 and the Oprah Winfrey show that aired in 1996.

5.1 Analysis of Monthly 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

[13]The product-by-store-by-period fixed effects α_{ast} pick up overall shifts between years, and hence the ν_{asdt} are forced to sum to zero for each product aggregation a and store s in the pre-event days $d = -34$ to $d = -1$ in the event period t. Thus, the smoothed ν_{asdt} for $d \geq 1$ give the abnormal returns net of price changes and product-by-store-by-period, seasonality, weekday, and Thanksgiving fixed effects.

[14]The window is not allowed to cross the event date, i.e., day 3 includes observations from day 1 to day 13.

for each beef subclass. As described in the data section, a *subclass* groups together all UPC with closely comparable product characteristics, e.g., all “Beef Rib Steaks.” Local events and customs might lead to error terms that are correlated for a given month. For example, due to exceptional weather, more or fewer shopping trips might be done, causing all to be higher or lower than usual. We therefore cluster error terms within a month and region (Washington State or the D.C. metropolitan area) in each column.

The baseline model is given in column (1), where we include one observation before and one after the event date. The 35-day period following the outbreak is labeled month 1. The reported coefficients are the abnormal monthly change $\delta_{1,1}$ from equation (1) in row “Month 1” and the *additional* abnormal change $\delta_{2,1}$ in Washington State in row “Month 1 x WA.” The price elasticity γ is given in row “Log Beef Price.” Each row gives the point estimate and t-value in brackets. Beef purchases decreased by 21 percent in the first month following the discovery of the first infected cow.[15] 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; this is also highly statistically significant.

Columns (2) allows for heterogeneity by socio-economic subgroups as specified in equation (2). Rows (4)-(6) display the coefficients $\theta_{1,n}$ and $\theta_{2,n}$ of the interaction term with the demeaned socio-economic characteristics. Stores that are located in zip codes with higher median income show larger drops: an additional 1.3 percent for each \$10,000 in median income. Similarly, stores located in zip codes with a higher percentage of minority population (black and Hispanic) show larger drops: an additional 0.18 percent for each percentage point of minority residents. While this coefficient is opposite of what we originally expected, 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. Finally, a word of caution is in order: we are only able to match the socio-economic characteristics for the zip code in which a store is located. It is possible that more affluent people would go to high-end grocery stores (like Whole Foods or Wild Oats), and our estimates could hence suffer from selection bias. However, the authors have visited several stores in our data set and found that the socio-economic groups in our store sample are consistent with the demographic heterogeneity from the Census data.

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

Column (3) includes a second month past the event ($N = 2$ 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 35-day month. The point estimate is again roughly -0.23. The interaction terms with the socio-economic characteristics remain robust as well. The one exception is the interaction of income and month 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.[16] We fix the quantity-weights at pre-event levels to ensure that the average price is not confounded with changing buying habits 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, though, the estimated abnormal drop in beef consumption in rows (1) and (2) of column (4) are hardly any different from column (3). In other words, stores did not appear to significantly alter substitute prices in response to the event.

Column (5) reports the estimated drop in beef purchases without any controls for price, not even for beef products. The estimated coefficient is -0.200, slightly lower than the coefficient in column (1). This suggests that omitting consideration of price changes underestimates the drop in beef purchases, since an immediate response to the drop in beef demand would be to lower prices in order to increase beef demand.

Column (6) of Table 1 therefore 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. Given the estimated price-elasticity of approximately 2, such a price drop would increase beef consumption by approximately 3.2%, which is roughly the difference in the estimated impact between column (1), where we account for price changes, and column (5), where we do *not* account for these price changes.[17] The large national supermarket chain that provided us their scanner data mentioned to us that they did *not* systematically change prices as a response to the reported mad cow event, at least initially, as they were unprepared for such an incident.[18] This might explain the rather small price change of 1.6 percent.

[16]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.

[17]Our estimated demand elasticity is larger in absolute magnitude than the estimate of -0.570 by Eales and Unnevehr (1988). However, the latter estimate an AIDS demand system for *aggregate* beef demand. Elasticities will be higher for a supermarket chain than for overall beef purchases as customers can switch to other stores.

[18]Prices are changed once a week, on Wednesdays, and then are valid for at least a week. There was no

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 35-day span in 2001 instead of 2003. Since the first infected cow was discovered in 2003 and not 2001, we should not observe a significant abnormal return by using the wrong time 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 set of individual purchasing decisions is 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 4 years: one for the month prior to December 23 and one for the month following December 23 of each year. 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 even at an aggregate level of scanner data, with 8 observations and without controlling for price, we find 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. Note, however, 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, i.e., respondents drop in and out every week. Similarly, a monthly 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.

Finally, Table A2 of the online appendix 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 also robust to these changes in aggregation. In summary, the drop in beef purchases is robust to various specification checks.

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system in place to react to the mad cow outbreak quickly enough to change prices right away.

5.2 Analysis of Monthly 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, it is hard to predict the changes in the purchased quantities of these goods.

Table 2 reports the regression results of abnormal changes of other meat purchases controlling for price as well as month and store-by-year-by-category level fixed effects. As outlined in the data section, some UPCs or entire meat categories get sold infrequently. This problem is more pervasive for meats that have lower average purchase volumes than beef.[19] We therefore aggregate all purchases for each meat and only include UPCs that are sold on average on at least 30 days of the 35-days month. Columns (1)-(4) suggest that, based on scanner data, 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.

5.3 Analysis of Daily Beef Purchases

To investigate how consumers' responses evolve over time, we relax the monthly aggregation and present results of a locally weighted regression of daily abnormal beef purchases. This is outlined in equation (3). Our bandwidth stretches 10 days and the weights decrease quadratically in time. In other words, any abnormal change in consumption on the day in question receives a relative weight of one, while abnormal changes one, two, seven, or nine days apart receive a relative weight of 0.99, 0.96, 0.51, and 0.19, respectively.[20] The window is not allowed to cross the event day, e.g., the smoothed abnormal return for day 2 will only include days *after* the first outbreak (days 1 through 12), even though day -1 would theoretically be within 10 days of day 2.[21]

The locally weighted regression of abnormal changes in beef purchases net of price, day-

[19]The data appendix reveals that not a single turkey or lamb product is sold in 12 and 17 percent of our daily store-level data.

[20]Recall that prices, including special sales items, are usually fixed for seven days.

[21]This is purposefully done to ensure that the effect of the outbreak is not diluted by pre-event data.

number, weekday, Thanksgiving, and store-by-year-by-aggregation level fixed effects 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 grey. 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 December 23, 2003, as we otherwise should see a downward trend before day 0. By the same token, the new information reaches consumers very rapidly: the largest drop is observed within the first 7 days.[22]

Similar to Smith et al. (1988), we observe that consumers react more strongly to negative than to positive news. On December 30, 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 upward trend, that is, a recovery from the initial drop, following day 7. The upward trend of recovery is of smaller size than the drop following the discovered cow. Moreover, beef purchases (adjusted for price changes) only recover very slowly in our 91-day period after the event for which we have data.

5.4 Analysis of Daily Cattle Futures Prices

In an efficient market, futures prices will give an accurate forecast of predicted changes in cattle prices, which are directly tied to changes in beef demand. Thus, futures price data identify the market assessment of the first discovery of an infected cow. We ccompare the market assessment to the change we observe in the scanner data set. Moreover, since futures data are available for the time when the Oprah Winfrey show aired (while the scanner data set is not), we can use futures data to compare the response following the TV show to the response following the first discovery of an infected cow. Figure 2 displays the abnormal changes in live cattle futures prices following the first reported mad cow outbreak in the U.S. in 2003 (left column) as well as corresponding changes following the Oprah Winfrey show (right 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

[22] Figure A3 in the appendix displays the results from a locally weighted regression of daily abnormal changes in substitute meat purchases. A discontinuity is much less apparent.

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. Our estimates are:

$$\begin{array}{ccccc} r_d & = & \text{-}0.000096 & + & 0.142 \quad R_d \\ & & (0.51) & & (5.97) \end{array}$$

where t-values are given in brackets. Thus, a one percent change in the commodity index is predicted to increase Live Cattle futures prices by 0.142 percent. 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.[23]

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.[24] 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 as well be the result of other events that occurred after the outbreak. New precautionary systems were put in place, e.g., 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 return of futures with a longer maturity are lower.

Because futures prices match scanner data responses for 2003, and are available for a longer time 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 wide-spread reporting following the actual outbreak in 2003. The right panel

[23]There are limited overall commodity market movements, and hence we obtain an almost identical figure if we net out market movements, or use other references for the overall market index. This figure is shown in the appendix.

[24]Rucker et al. (2005) show that lumber futures prices respond more quickly to trade show events than to news about endangered species.

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.[25] 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.

6 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 drop in beef purchases using a unique 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 a "control" 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.

We replicate this analysis using the diary files of the Consumer Expenditure Survey (CES), a data set compiled specifically to examine consumer purchasing decisions. The survey is a repeated cross-section, where each week about 100 representative households enter the survey and remain in it for two consecutive weeks. This makes it harder to detect changes following a particular event as the sample size is too small and the population changes frequently, since the sample frame lacks power. Accordingly, the estimated impact using the CES is neither significantly different from zero nor different from our predicted impact. 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 includes more detailed socio-economic characteristics than the store-level

[25] Unfortunately, we don't 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 the appendix. 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 pre-existing buying habits.

scanner data. 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.

Surprisingly to us, a report about the potential danger of mad cow diseases seven years earlier on the Oprah Winfrey TV show resulted in future price drops of more than 50% of the drop we observed following the first discovery of an infected cow. 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.

In our analysis, the fact that a speculative, unofficial comment produced such a large proportion of the response to a confirmed, official report shows that consumers respond strongly to media comments. 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 sizable way compared to government warnings combined with continued general news coverage.

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Table 1: Abnormal Monthly Changes For Beef 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
Month 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)
Month 1 x 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)		
Month 2			-0.236	-0.230					
			(3.79)**	(4.45)**					
Month 2 x WA			-0.00185	-0.0188					
			(0.03)	(0.33)					
Month 1 x Income		-0.0133	-0.0134	-0.0138					
		(2.53)*	(2.80)*	(2.68)*					
Month 2 x Income			-0.00313	-0.00466					
			(0.75)	(0.90)					
Month 1 x Minority		-0.00176	-0.00168	-0.00174					
		(8.88)**	(6.96)**	(8.01)**					
Month 2 x 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
Min. Days	0	0	0	0	0	0	0	0	n.a.
Aggregation	subclass	subclass	subclass	subclass	subclass	subclass	subclass	all beef	all beef
Observations	56077	56077	84598	83146	56077	56077	56077	8	8
R-squared	0.973	0.973	0.945	0.945	0.960	0.944	0.973	0.977	0.469

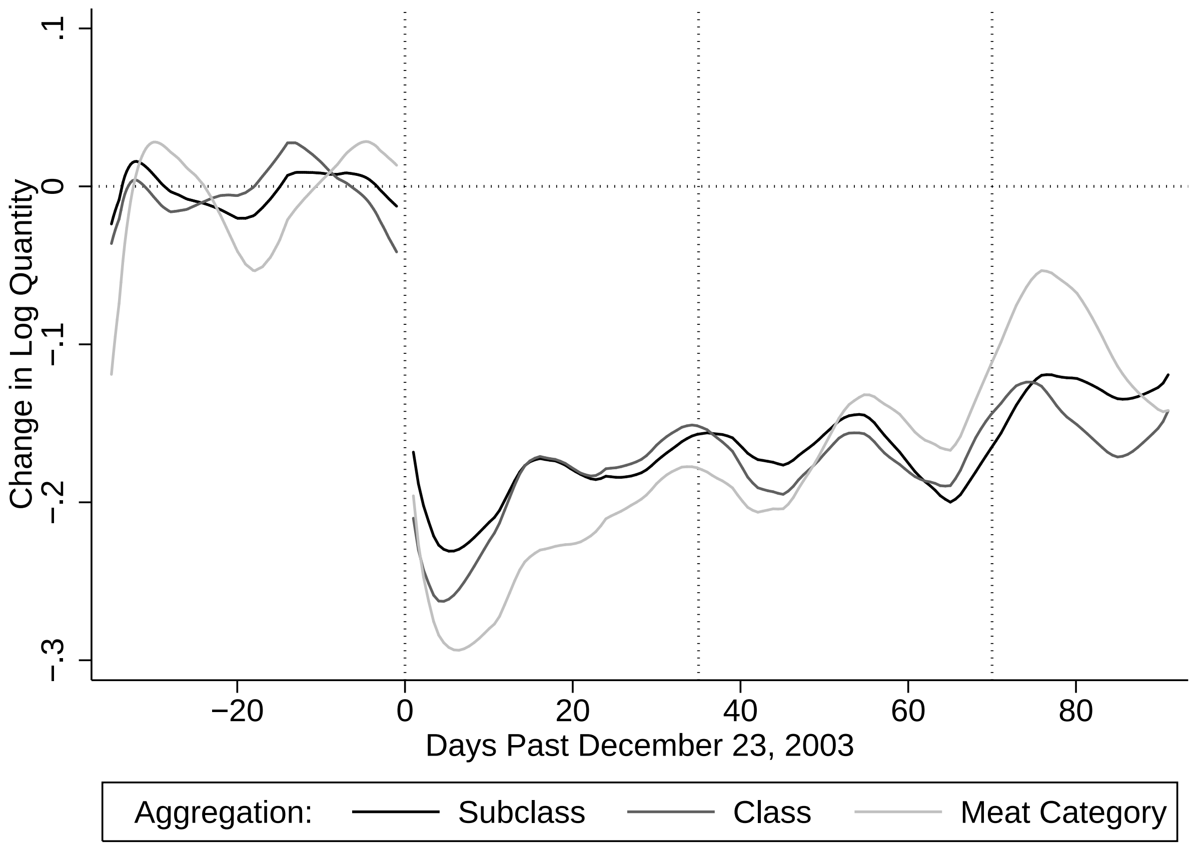
Notes: Table displays abnormal monthly changes in the variables listed in the top of each column (1)-(9) and t-values in brackets. Columns labeled "log Q" use as dependent variable the log of the purchased quantity, while "log P" uses log price and "log R" uses log revenues / expenditures. Columns (1)-(7) use subclass-by-period-by-store fixed effects while columns (8) and (9) use store-by-period fixed effects. All columns use months fixed effects to account for seasonal purchasing patterns. Months are five-week aggregates, i.e., month 1 is December 24, 2003 - January 27, 2004, while month 2 is January 28, 2004 - March 2nd, 2004. Column (8) uses the month following December 23, 2001 as a control, 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 dollars). Minority is the demeaned percentage of the population that is either Black or Hispanic. The row "minimum day" indicates on how many days out of the 35-day month a product has to be sold in a store to be included in the data set.

Table 2: Abnormal Monthly Changes in Other Meat Purchases Following Discovery of First Infected Cow

	(1) Pork	(2) Pork	(3) Chicken	(4) Chicken	(5) Turkey	(6) Turkey	(7) Lamb	(8) Lamb
Month 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)
Month 1 x 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)
Month 2		-0.0865		-0.0415		-0.209		-0.172
		(2.27)*		(1.63)		(2.41)*		(4.47)**
Month 2 x WA		0.111		0.110		0.268		0.405
		(2.58)*		(3.07)**		(1.15)		(5.89)**
Month 1 x Income		0.00088		0.00784		0.00409		0.0169
		(0.20)		(2.02)		(0.50)		(2.02)
Month 2 x Income		0.00201		-0.00248		-0.00681		0.00300
		(0.43)		(0.65)		(0.78)		(0.40)
Month 1 x Minority		-0.00025		0.00148		-0.00103		0.00014
		(0.82)		(3.03)**		(0.62)		(0.28)
Month 2 x 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
Min. Days	30	30	30	30	30	30	30	30
Aggregation	category	category	category	category	category	category	category	category
Observations	2290	3440	2290	3440	1768	2654	1507	2264
R-squared	0.992	0.989	0.991	0.989	0.968	0.977	0.968	0.959

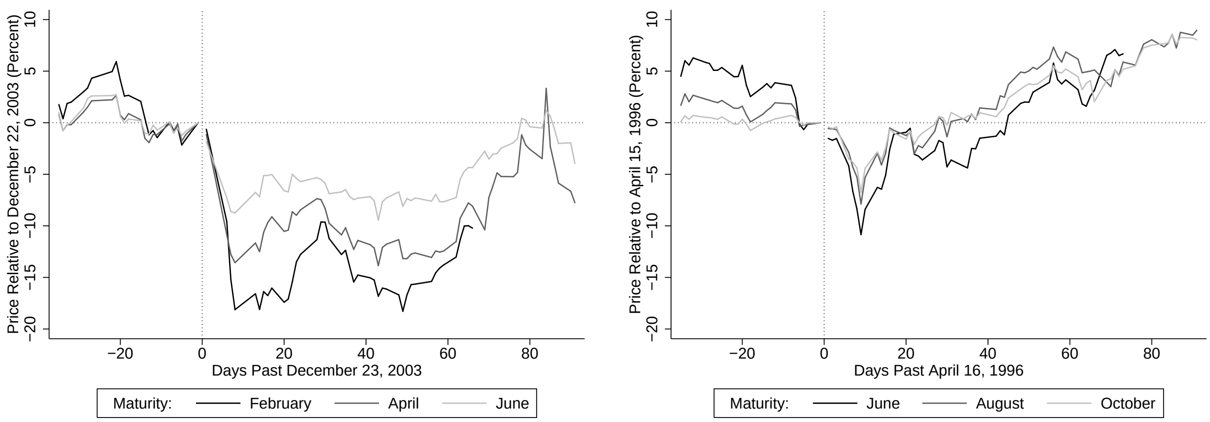
Notes: Table displays abnormal monthly changes in log meat purchases (listed on top of each column) and t-values in brackets. Columns use subclass-by-period-by-store fixed effects and months fixed effects to account for seasonal purchasing patterns. Months are five-week aggregates, i.e., month 1 is December 24, 2003 - January 27, 2004, while month 2 is January 28, 2004 - March 2nd, 2004. Income is the demeaned average income in the zip code in which the store is located (in 10,000 dollars). Minority is the demeaned percentage of the population that is either Black or Hispanic. The row "minimum day" indicates on how many days out of the 35-day month a product has to be sold in a store to be included in the data set.

Figure 1: Abnormal Daily Changes in Beef Purchases Following Discovery of First Infected Cow



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 December 23, 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 2: Abnormal Daily Changes in Cattle Futures Prices (Net of Changes in Commodity Price Index)



Notes: Panels display futures prices of Live Cattle with maturities of two, four, and six months, respectively, *net* of changes in the Dow Jones Commodity Market index. The left panel uses the first discovery of a mad cow as day 0 (December 23, 2003), while the right panel uses the report by Oprah Winfrey (April 16, 1996). Futures with a maturity of roughly two months expire before the end of the 91-day window and hence only a partial time series is displayed.

Appendix

Data Appendix

Descriptive statistics of our data set are shown in Table A1. The location of the 298 supermarkets in our scanner data are displayed in Figure A1. The variables included in the scanner data set are:

Variable	Description
date	exact date (day, month, year)
store id	id that uniquely identifies a store
UPC	Universal Product Code - unique id for each product
qtyWeight	total quantity of a UPC that is sold in a store on a given day
netSales	total sales (dollar) of a UPC that is sold in a store on a given day

We had an additional meta data set for UPCs. The variable *subclass* groups together UPCs with closely comparable product characteristics, e.g., all "Beef Rib Steaks," or "Beef Rib Roasts." The next aggregation level is a meat *class* which groups similar meat types together, e.g., all "Beef Rib" (both steak and roast), or "Beef Loin." Finally, meat category lumps together *all* beef sales in a store per month.

There are UPC codes that are not sold on every single day and hence do not show up in our data for certain days. Our daily data covers the time span of 35 days prior to the event to 91 days past the event. We exclude the event day itself (day 0) as well as Christmas, when many stores are closed, to end up with 125 days for each of our 4 winters. The maximum number of observations in each meat category is hence given by 4 winters x 125 days per winter x 298 stores = 149,000 observations. Note that most stores sell at least some beef during each day, as the number of observations is 143,298 in column 5 of Table A1, which is rather close to 149,000. On 3.8 percent of all possible store-day combinations no beef products are sold. On the other hand, there are stores that don't sell any turkey products (a highly seasonal item) or lamb products (a specialty meat) on 12 and 17 percent of all possible store-day combinations, respectively.

Figure A2 displays the number of newspaper articles that includes the word "mad cow" on any given day compared to the event dates. General newspaper coverage increased significantly following the discovery of the first infected cow (black lines), while it did not change much following the Oprah Winfrey show (gray lines).

Additional Results and Sensitivity Checks

Table A2 examines the sensitivity of our results to various aggregation levels. If products are sold infrequently, the fluctuation between zero and any positive number will induce tremendous fluctuations in log quantities (which incorporate relative changes). Therefore, we limit the sample to include only subclass, classes, or overall beef sales that are sold on average in no less than 30 days of our 35 day (5-week) month. The results are very robust to the chosen aggregation level.

Table A3 displays the sensitivity of the baseline results to various assumptions about the seasonality parameters $\beta_{1,n}, \beta_{2,n}, \lambda_{1,n}$ and $\lambda_{2,n}$. If there was a sale spike/drop in one of the control periods (periods besides the event period 2003/2004) due to another event, the seasonality components might be biased. In such a case we might wrongfully attribute a reversion to mean consumption levels as an impact due to the discovery of the first infected cow in the event period.[26] In a first check, columns (1)-(3) of Table A3 use the same specification as column (1) in Table 1 except that each one of the control periods is dropped from the analysis. Analogously, one of the control periods is dropped in columns (5)-(7) of Table A3, which replicates the specification of column (3) in Table 1. The estimated abnormal change in the purchased quantity in the first row remains rather robust. In a second check, columns (4) and (8) drop all periods but the event period (and hence the seasonality components $\beta_{1,n}, \beta_{2,n}, \lambda_{1,n}$ and $\lambda_{2,n}$ can no longer be identified). The interaction with the dummy for Washington State becomes significant, suggesting that the seasonal components differ between our two regions, yet the estimated impact in the first row still remains negative and highly significant. These sensitivity checks make it unlikely that our results pick up a spurious reversion to mean consumption levels.

Figure A3 displays smoothed abnormal changes in log quantity sold for the meats besides beef. There is no clear discontinuity in purchases compared to the one we observe for beef in Figure 1 of the main paper.

Figure A4 replicates the graph of abnormal futures returns *without* accounting for movements in the commodity market index. The results are very close to the ones we obtain in Figure 2.

[26] We would like to thank one of the anonymous referees for pointing out this sensitivity check.

Table A1: Descriptive Statistics

Panel A: Scanner Data Set from Supermarket Chain							
	UPC	**Subclass**			**Meat Total**		
	Obs.	**Obs.**	**Mean**	**Std.**	**Obs.**	**Mean**	**Std.**
				Beef			
Log Quantity (lbs)	5,475,791	2,522,671	2.44	1.28	143,298	6.02	0.62
Log Price ($)	5,475,791	2,522,671	1.35	0.45	143,298	1.21	0.24
Log Sales ($)	5,475,791	2,522,671	3.79	1.22	143,298	7.23	0.57
				Pork			
Log Quantity (lbs)	2,782,412	1,563,633	2.05	1.23	143,281	4.98	0.78
Log Price ($)	2,782,412	1,563,633	1.11	0.46	143,281	1.00	0.28
Log Sales ($)	2,782,412	1,563,633	3.15	1.09	143,281	5.98	0.64
				Chicken			
Log Quantity (lbs)	2,582,363	1,189,132	2.85	1.42	143,290	5.68	0.74
Log Price ($)	2,582,363	1,189,132	0.79	0.60	143,290	0.66	0.29
Log Sales ($)	2,582,363	1,189,132	3.64	1.34	143,290	6.34	0.65
				Turkey			
Log Quantity (lbs)	608,093	377,334	2.07	1.48	131,204	3.15	1.61
Log Price ($)	608,093	377,334	0.84	0.50	131,204	0.79	0.40
Log Sales ($)	608,093	377,334	2.91	1.22	131,204	3.94	1.34
				Lamb			
Log Quantity (lbs)	391,435	292,985	0.99	0.95	123,120	1.83	1.06
Log Price ($)	391,435	292,985	1.59	0.52	123,120	1.49	0.37
Log Sales ($)	391,435	292,985	2.58	0.88	123,120	3.31	1.08

Panel B: Socio-economic Data For Zip-Code in Which Supermarket is Located					
	Obs.	**Mean**	**Min**	**Max**	**Std.**
Income ($10,000)	298	56.5	21.2	154.8	20.8
Black or Hispanic (%)	298	18.9	1.1	98.4	21.2

Panel C: Consumer Expenditure Survey					
	Obs.	**Mean**	**Min**	**Max**	**Std.**
Log Beef Sales ($)	9,562	2.01	-1.05	5.77	0.757
Log Pork Sales ($)	8,843	1.79	-1.20	5.64	0.755
Log Poultry Sales ($)	7,905	1.85	-2.04	5.01	0.648

Notes: Panel A displays descriptive statistics for the scanner data. The first column gives the number of observations in the data (observations are total UPC-levels sales in a store on a given day). The next three columns give the number of observations if we aggregate all UPCs with the same subclass. The last three columns aggregate all UPCs for each meat. Panel B displays socio-economic characteristics of the zip codes in which the stores are located. Panel C summarizes beef sales of respondents in the diary files of the Consumer Expenditure Survey during the time span that is covered by the scanner data.

Table A2: Sensitivity of Abnormal Changes in Log Beef Purchases to Various Aggregation Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Month 1	-0.231	-0.200	-0.202	-0.202	-0.200	-0.158	-0.176	-0.176
	(21.37)**	(13.68)**	(24.74)**	(15.63)**	(5.20)**	(3.76)**	(3.49)**	(6.40)**
Month 1 x WA	0.043	-0.003	-0.012	-0.067	-0.032	-0.076	-0.066	-0.111
	(0.94)	(0.07)	(0.25)	(2.93)*	(0.61)	(1.33)	(0.98)	(3.07)**
Month 2					-0.236	-0.233	-0.223	-0.194
					(3.79)**	(3.78)**	(2.92)**	(5.11)**
Month 2 x WA					0.00185	0.0308	0.00928	0.0236
					(0.03)	(0.40)	(0.10)	(0.42)
Month 1 x Income					-0.0134	-0.0146	-0.0101	-0.0113
					(2.80)*	(2.89)**	(1.99)	(2.28)*
Month 2 x Income					-0.00313	-0.00659	0.00271	-0.00741
					(0.75)	(1.51)	(0.62)	(1.14)
Month 1 x Minority					-0.00168	-0.00189	-0.00159	-0.00101
					(6.96)**	(4.76)**	(4.03)**	(2.99)**
Month 2 x Minority					-0.00193	-0.00139	-0.00096	-0.00084
					(8.00)**	(3.39)**	(2.06)	(1.70)
Log Price	-1.91	-2.07	-1.07	-1.26	-2.16	-1.99	-1.19	-1.22
	(9.61)**	(21.43)**	(9.95)**	(9.07)**	(12.22)**	(22.09)**	(10.38)**	(6.15)**
Data Set	scanner	scanner	scanner	scanner	scanner	scanner	scanner	scanner
Min. Days	0	30	30	30	0	30	30	30
Aggregation	subclass	subclass	class	category	subclass	subclass	class	category
Observations	56077	27333	17995	2290	84598	41087	27055	3440
R-squared	0.973	0.984	0.987	0.992	0.945	0.977	0.978	0.988

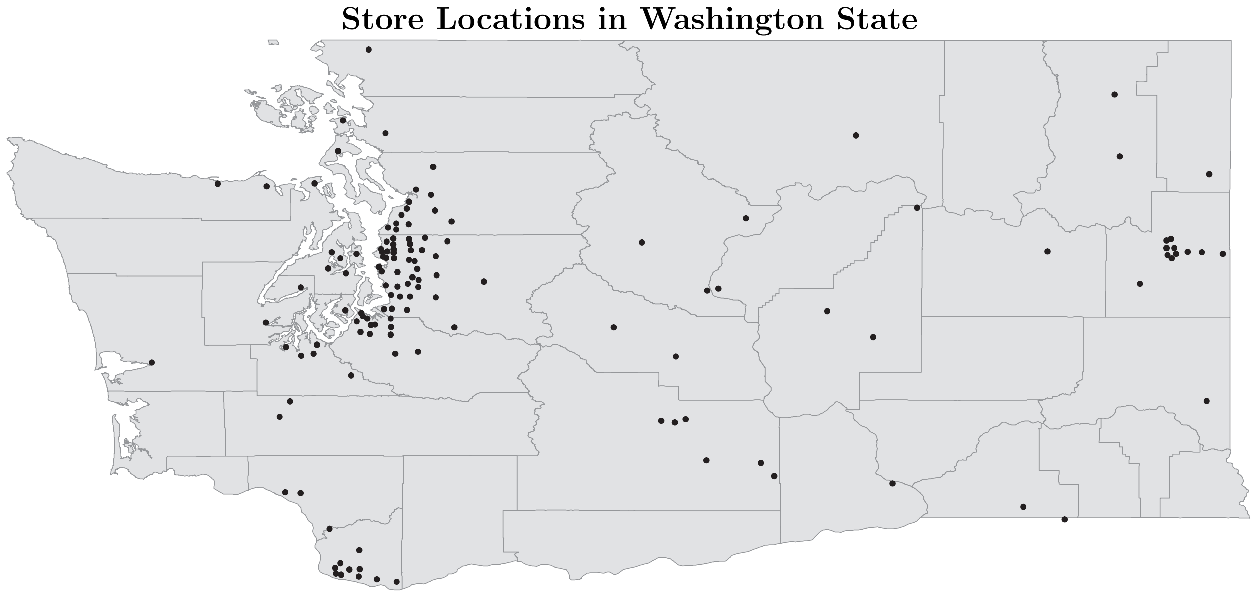
Notes: Table displays abnormal monthly changes in log meat purchases and t-values in brackets. Columns are ordered by increasing aggregation levels, i.e., an increasing number of UPCs are lumped into one observation. Column (1) and (5) are the same as columns (1) and (3) in Table 1. All columns use aggregation-class by winter by store fixed effects as well as month fixed effects. Months are five-week aggregates, i.e., month 1 is December 24, 2003 - January 27, 2004, while month 2 is January 28, 2004 - March 2nd, 2004. Income is the demeaned average income in the zip code the store is located (in 10,000 dollars). Minority is the demeaned percentage of the population that is either Black or Hispanic. The row "minimum day" indicates on how many days out of the 35-day month a product has to be sold in a store to be included in the data set.

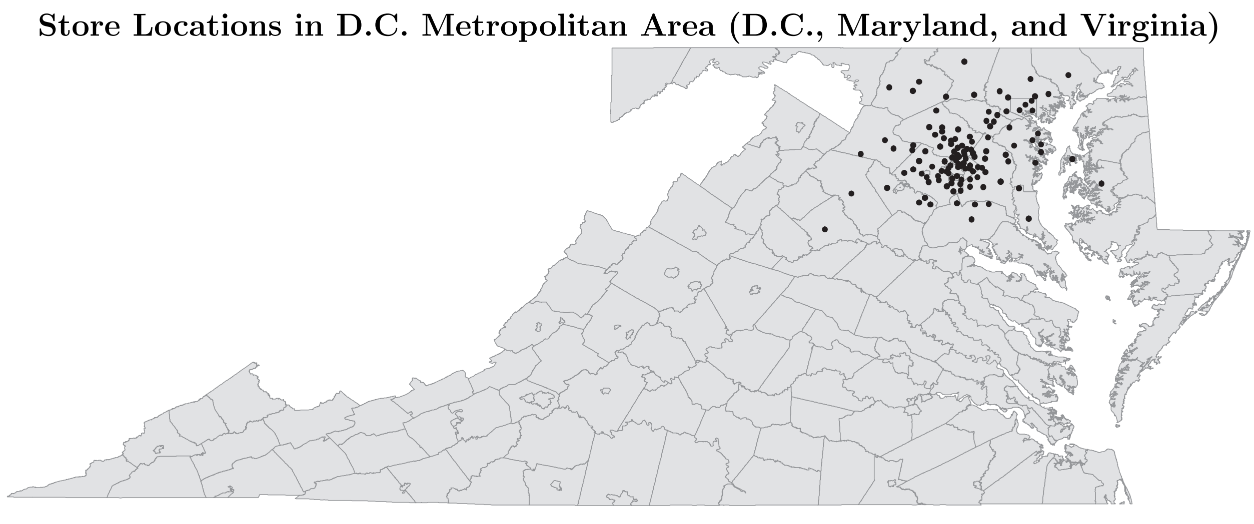
Table A3: Sensitivity of Abnormal Changes in Log Beef Purchases to Assumptions about Seasonality Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Month 1	-0.240	-0.217	-0.236	-0.194	-0.204	-0.194	-0.202	-0.162
	(19.62)**	(38.16)**	(14.27)**	(20.01)**	(3.51)**	(7.11)**	(6.68)**	(13.91)**
Month 1 x WA	-0.001	0.069	0.056	0.025	-0.073	0.005	-0.032	-0.052
	(0.02)	(1.62)	(0.77)	(67.82)**	(1.09)	(0.15)	(0.52)	(4.03)*
Month 2					-0.250	-0.168	-0.303	-0.127
					(2.63)*	(4.19)**	(5.05)**	(4.64)**
Month 2 x WA					-0.0189	-0.0315	0.0584	-0.101
					(0.19)	(0.75)	(0.93)	(8.07)**
Month 1 x Income					-0.0153	-0.0117	-0.0132	-0.0185
					(3.79)**	(2.07)	(2.21)*	(4.22)**
Month 2 x Income					-0.00170	-0.00078	-0.00694	-0.0149
					(0.41)	(0.18)	(1.55)	(4.75)**
Month 1 x Minority					-0.00181	-0.00151	-0.00176	-0.00197
					(6.65)**	(5.86)**	(5.66)**	(12.86)**
Month 2 x Minority					-0.00194	-0.00179	-0.00208	-0.00237
					(7.57)**	(6.73)**	(7.41)**	(10.24)**
Log Price	-2.08	-1.73	-1.92	-1.91	-2.30	-2.13	-2.14	-2.31
	(9.97)**	(13.39)**	(7.87)**	(6.07)**	(13.50)**	(9.07)**	(9.99)**	(5.27)**
Data Set	scanner	scanner	scanner	scanner	scanner	scanner	scanner	scanner
Min. Days	0	0	0	0	0	0	0	0
Aggregation	subclass	subclass	subclass	subclass	subclass	subclass	subclass	subclass
Periods Excl.	2001/2002	2002/2003	2004/2005		2001/2002	2002/2003	2004/2005	
Period Incl.				2003/2004				2003/2004
Observations	42622	42416	41374	14258	63824	64078	62753	21459
R-squared	0.974	0.973	0.972	0.971	0.949	0.944	0.945	0.949

Notes: Table displays abnormal monthly changes in log meat purchases and t-values in brackets. Columns use various subperiods to estimate the seasonality components. Columns (1)-(3) and (5)-(7) drop one of the three control periods from the analysis. Columns (4) and (8) only use the period in which the event occurred with *no* estimate of the seasonality component. All columns use subclass by winter by store fixed effects as well as month fixed effects. Months are five-week aggregates, i.e., month 1 is December 24, 2003 - January 27, 2004, while month 2 is January 28, 2004 - March 2nd, 2004. Income is the demeaned average income in the zip code the store is located (in 10,000 dollars). Minority is the demeaned percentage of the population that is either Black or Hispanic. The row "minimum day" indicates on how many days out of the 35-day month a product has to be sold in a store to be included in the data set.

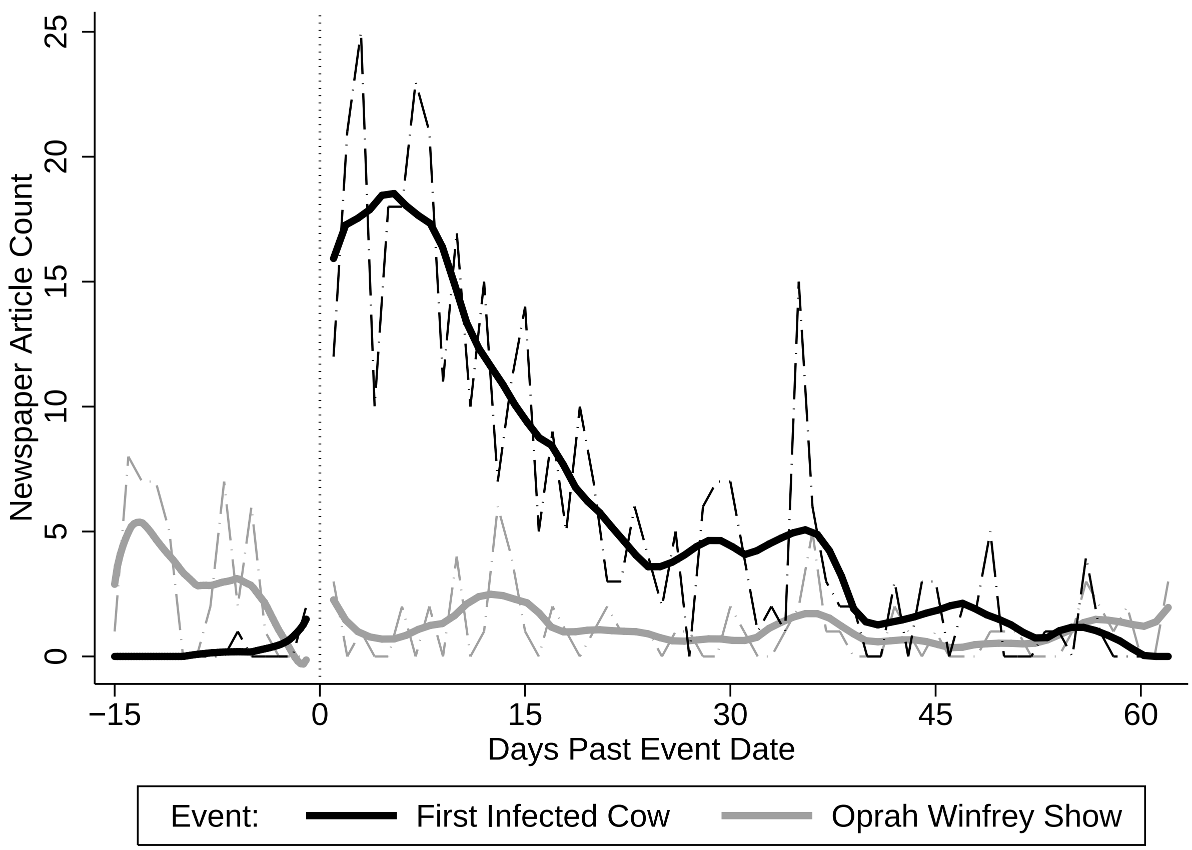
Figure A1: Store Locations in Scanner Data





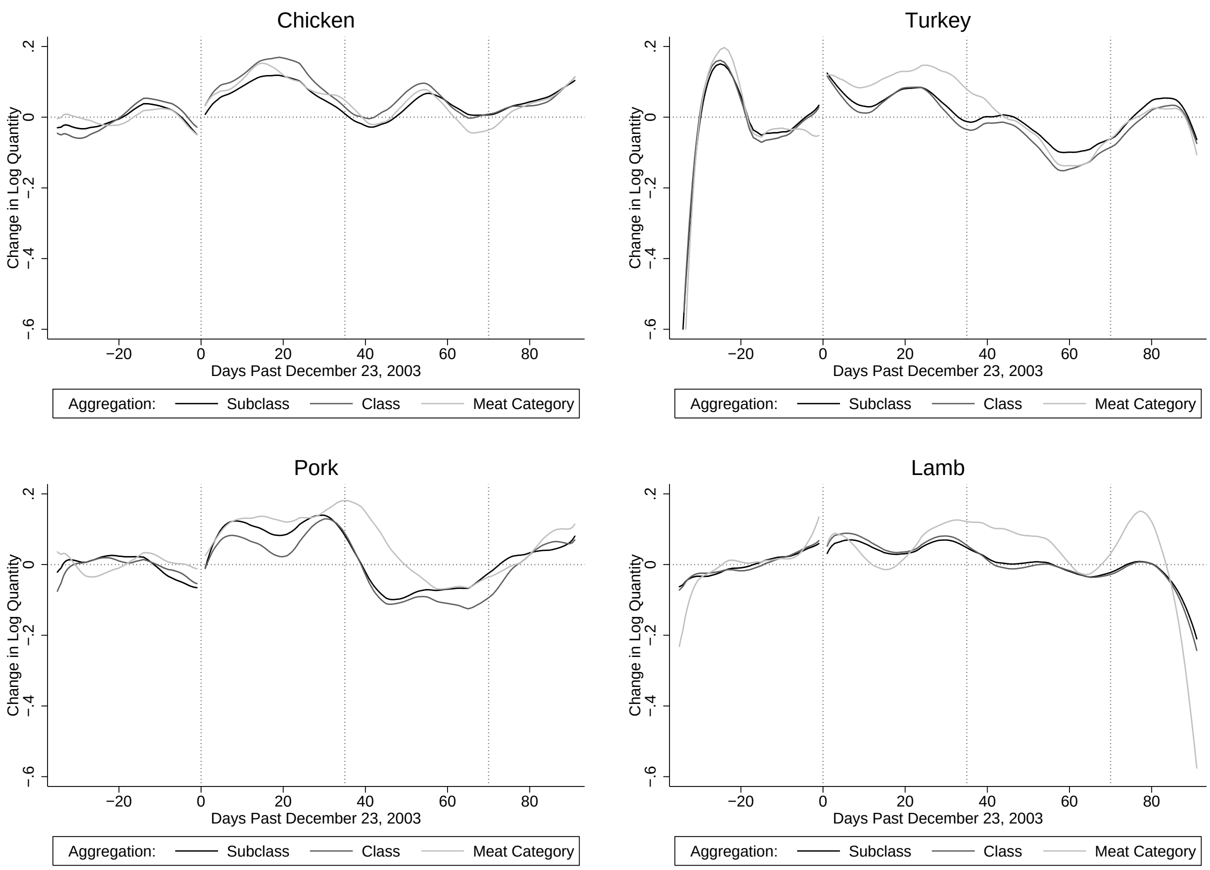
Notes: Panels display the location of the 164 stores in Washington State as well as the 134 stores in the Washington D.C. metropolitan area.

Figure A2: Newspaper Coverage



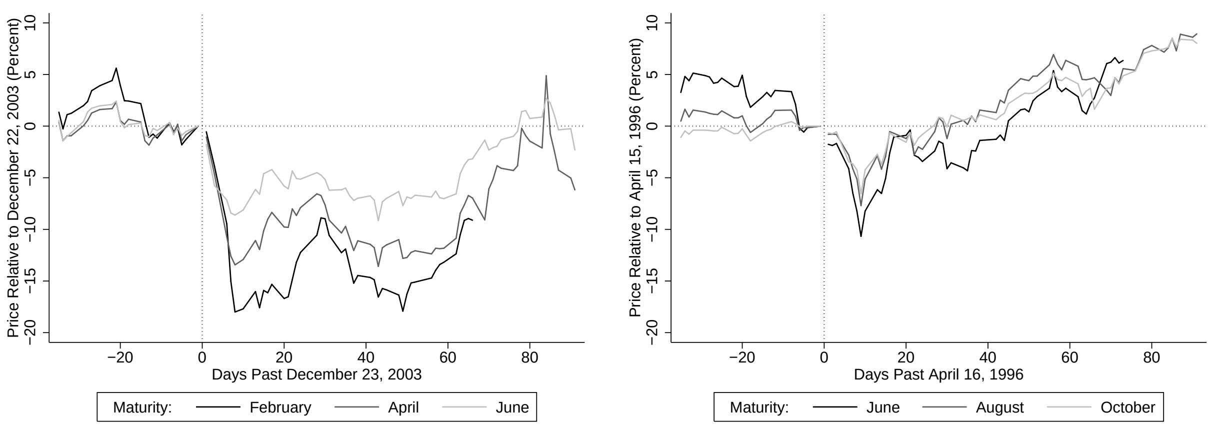
Notes: Figure displays the number of articles in major newspaper that include the word "mad cow" on a given day. Gray lines use April 16, 1996 as the event date (Oprah Winfrey show), while black lines use December 23, 2003 as event date (first infected cow is reported). Thin dashed lines plot the daily article count, while thick solid lines plot the result from a locally weighted regression with a bandwidth of 4 days.

Figure A3: Abnormal Daily Changes in Other Meat Purchases Following Discovery of First Infected Cow



Notes: Panels display changes in log quantity sold for pork, chicken, turkey, and lamb, respectively. Each panel includes three aggregation measures: the sum of all UPCs with the same subclass, class, or meat category. Day 0 is December 23, 2003, when the first case of a mad cow outbreak in the United States is made public. Abnormal changes are net of price as well as year-by-store-by-aggregation level, day-number, Thanksgiving, and weekday fixed effects.

Figure A4: Gross Abnormal Daily Changes in Cattle Futures Prices (Without Adjustments for Movements in Commodity Market Index)



Notes: Panels display futures prices of Live Cattle with maturities of two, four, and six months, respectively. The left panel uses the first discovery of a mad cow case as day 0 (December 23, 2003), while the right panel uses the comments by Oprah Winfrey (April 16, 1996). Futures with a maturity of roughly two months expire before the end of the 91-day window and hence only a partial time series is displayed.