Essays on Price Analysis of Livestock Market

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(ABSTRACT)

This dissertation consists of three chapters. The first chapter titled “U.S. Grass-fed Beef Price Premiums” examined monthly retail-level price premiums for grass-fed beef (relative to conventional grain-fed beef) in the U.S. from 2014 through 2021. We found that premiums were heterogeneous, with premium cuts (such as sirloin steak, tenderloin, ribeye and filet mignon) enjoying the highest premiums. Premiums were not consistent with price levels, as the lowest premiums were observed for short ribs, skirt steak and flank steak. Our findings suggest that grass-fed beef price premiums were negatively affected by the consumption of food away from home. Changes in income, increased information about taste, protein and minerals, fat, revocation of the USDA grass-fed certification program in 2016 and COVID-19 pandemic, also affected premiums for several individual cuts. Premiums were not sensitive to changes in information about climate change.

The second chapter, “Impact of Animal Disease Outbreaks on The U.S. Meat Demand”, examined the impact of the mad cow (BSE) and bird flu (AI) outbreaks on the demand for beef, pork, and broilers in the U.S from 1997 to 2019. Using time-varying elasticities obtained from a Rotterdam model with animal disease cases, we found that BSE outbreaks reduced beef consumption by 0.64 percent and increased pork consumption by 2.34 percent, on average. While BSE outbreaks reduced beef demand, these effects were short lived and did not extend beyond one quarter. On the other hand, broiler consumption decreased during the HPAI outbreaks while beef and broiler consumption increased after such outbreaks. Our time-varying cross-price elasticities indicated that substitution between beef and broilers and beef and pork strengthened after Quarter 4 of 2003.

The third chapter is titled “Impact of North American Mad Cow Disease Outbreaks on The U.S.
Cattle Futures”. Our study developed a distributional event response model (DERM) framework to show the duration and magnitude of market responses of the U.S. cattle futures market during episodes of mad cow disease (BSE) in North America between 2010 and 2019. Our results indicated that the 2017 U.S. BSE outbreak reduced the returns of live cattle futures. Additionally, the average duration of the BSE event response was about 8.5 days.
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(GENERAL AUDIENCE ABSTRACT)

This dissertation focused on the price analysis of the U.S. livestock market. The first chapter analysed the pattern of grass-fed beef price premiums measured as the difference between grass-fed beef price and conventional beef price. We mainly explored how the premiums were affected by consumers’ income, food consumption away from home, and information on climate change, beef taste, and nutrition. We found that consumption of food away from home reduced the grass-fed beef price premiums. In addition, increased information about taste, protein and minerals, fat, and COVID-19 pandemic, could also affected the grass-fed premiums for several individual cuts.

The second chapter explored how mad cow diseases and bird flu diseases affected the demand for beef, pork, and chicken. We particularly investigated how each disease outbreak affected the meat demand. My result showed that in the presence of mad cow diseases in the U.S., people bought more pork. This result that retailers should have higher pork demand when mad cow diseases are detected.

The third chapter explored how mad cow diseases in North America affected the U.S. live cattle futures. We showed that the U.S. mad cow disease in 2017 reduced the returns of U.S. cattle futures and this impact lasted about 8.5 days. Simultaneously, we found that mad cow disease outbreaks in Canada did not significantly affect the U.S. cattle futures.
Dedication

To my mom, my dad, Yuetong, and my dear friends.
Acknowledgments

I would like to thank my Ph.D. advisors Dr. Olga Isengildina Massa and Dr. Shamar Stewart. Thank you both for providing me with comments and suggestions regarding studies, work, and life. I would also like to thank my committee members Dr. Matthew Holt and Dr. John Bovay for their help and guidance over the last few years. I am also grateful to all the professors and classmates who helped me in my four-year studies at Virginia Tech. Thank you to all my friends who helped me and shared your experiences with me. With all your love and help, I could successfully finish my studies at Virginia Tech.
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1 U.S. Grass-fed Beef Price Premiums

1.1 Introduction

Consumer demand for specialized markets of healthier and environmentally friendly goods is on the rise, with large supermarket chains continually increasing their assortment of organic and eco-friendly products Wong et al. (2010). Grass-fed beef is one of the production claims, along with naturally raised (raised without antibiotics and/or hormones) and certified organic, that aims to distinguish these products from conventionally raised grain-fed beef. Buoyed by growing interest among American producers and consumers, the grass-fed beef market has gained traction as a rapidly growing niche market (see McCluskey et al., 2005; Gillespie et al., 2016). The U.S. grass-fed beef retail sales increased from less than $5 million in 1998 to $400 million in 2012 (Williams, 2013; Qushim et al., 2018). According to Nielsen data published in a report by Bonterra Partners, retail sales of grass-fed beef doubled every year from 2012 to 2016, growing from $17 million to $272 million (Cheung and McMahon, 2017; Bayless, 2018). While the grass-fed beef market has been rapidly growing, it remains a relatively small portion of the beef market. In 2019, only about 4% of total beef sales are marketed with some type of label claim (Cattlemen’s Beef Board, 2020). Moreover, beef products classified as grass-fed account for only 1.82% of total retail beef volume (Cattlemen’s Beef Board, 2020). This pattern of rapid growth and a small current market share points to a strong growth potential of the grass-fed beef market.

Consumer interest in grass-fed beef is motivated by a number of factors. Chief among them is the belief that it offers more nutrition and is more environmentally friendly than conventional grain-fed beef (Cheung and McMahon, 2017; Shinn and Pledger, 2021). Cheung and McMahon (2017) argue that some consumers believe that grass-fed beef has a lower total fat content, better omega-6 and omega-3 fatty acid ratio, higher levels of antioxidants, a lower risk of E. coli infection, and higher levels of conjugated linoleic acid (CLA), a cancer fighter, making it a healthier meat. Other
primary drivers of consumer demand for grass-fed beef include concerns regarding health and animal welfare, as well as concerns regarding the use of growth-inducing, sub-therapeutic antibiotics and hormones. A study by Consumer Reports (2015) compared multi-drug resistant samples in grass-fed and conventional beef, and found that the former had three times lower likelihood of containing multi-drug resistant bacteria. Consumers are often concerned about environmental stewardship. A recent wave of information highlighting the regenerative aspects of grass-fed grazing has further prompted consumer interest in grass-fed beef (Cheung and McMahon, 2017; Shinn and Pledger, 2021). If managed properly, grass-fed grazing has been shown to improve soil quality, promote the growth of healthy grasses, and sequester carbon in the ground to mitigate climate change (Shinn and Pledger, 2021). However, other studies show that soil carbon sequestration is unstable and reversible (Hayek and Garrett, 2018). Additionally, when combating environmental impacts, people are more interested in discussing plant-based products rather than grass-fed meat (Davis et al., 2022). Ultimately, grass-fed cattle of the right breed, produced at the highest standards, can result in beef that is more tender, well-marbled and better-tasting than grain-fed beef (Cheung and McMahon, 2017). However, achieving this quality of grass-fed meat is rare, and it is important to note that few consumers are buying it just for the flavor, and many would still prefer the flavor of conventional beef over grass-fed (Umberger et al., 2002).

The growth of the grass-fed market has precipitated several studies focusing on consumer demand for grass-fed beef. For example, Cheung and McMahon (2017) concluded that “baby boomers” and others who care about health and fitness would be likely buyers of grass-fed beef. A 2014 survey by the Consumer Reports National Research Center also showed that when shopping for food, consumers feel that it is important that their purchases “support local farmers, protect the environment, support companies that treat workers well, provide better living conditions for animals, and reduce the use of antibiotics” (Consumer Reports, 2015, p.6). Gwin et al. (2012) found that at baseline, uninformed consumers in Portland, Oregon, would pay $0.90-$0.94/pound more for grass-fed ground beef. Moreover, information about production and nutritional factors increased this premium. Similarly, Umberger et al. (2002) showed that 23% of U.S. consumers are willing to pay a premium of $1.36 per pound for Argentine grass-fed beef relative to U.S. grain-fed
beef. Furthermore, Tonsor et al. (2018) found that media reports, especially those related to climate change and sustainability, could have a significant effect on meat demand by altering preferences. These examples show that consumer preferences for claims-based foods are typically elicited using the data from interviews, written surveys, and experimental auctions (see Umberger et al., 2002; Steenkamp et al., 2010; Alphonce and Alfnes, 2012; Lim et al., 2013, for example). However, these approaches may be riddled with hypothetical biases in survey and/or experimental design.

The goal of our study is to estimate premiums consumers paid for grass-fed beef based on observed national retail-level data from the U.S. Department of Agriculture (USDA)’s Agricultural Marketing Service (AMS) over the period 2014-2021. Our study explores the heterogeneity in premiums across the 12 most common cuts of grass-fed beef as well as the factors that affect these premiums. Figure 1 shows the relative shares of market sales across various beef cuts in 2021 indicating larger market shares of more expensive cuts, like ribeye, tenderloin and filet mignon. Thus, 10 out of 12 beef cuts that we discuss in this paper cover more than half of the total beef cut sales. To the best of our knowledge, market-based grass-fed beef premiums and premium variation across different cuts of beef have not been explored in the extant literature.

Consistent with the consumer-focused nature of our study, we explore the effects of consumers’ real income, food consumption away from home, and media information on observed price premiums. Specifically, we assess the determinants of price premiums for each beef cut, both individually and jointly in a panel framework. Our findings indicate that the grass-fed beef price premiums were negatively affected by consumption of food away from home. The premiums for some individual cuts were sensitive to changes in information about beef’s protein, mineral, and fat content, its taste, the revocation of the USDA grass-fed certification program in 2016 and the COVID-19 pandemic. However, premiums were not sensitive to changes in information about climate change.

The rest of this paper is organized as follows. Section 1.2 presents the conceptual framework. Section 1.3 offers a description of the data and the relevant sources. In Section 1.4, we present our empirical results and conduct relevant sensitivity analyses regarding our model specification. Our concluding remarks are presented in Section 1.5. Section 1.6 provides limitation and approaches to
1.2 Conceptual Framework

Price premiums measure consumers' willingness to pay for claims-based food (food with specific attributes such as organic, GMO-free, and grass-fed) relative to conventional food. Previous studies have used raw price premiums (Wang et al., 2008) and relative price premiums (Steenkamp et al.,
as measures of price premiums. The raw price premiums, $RPP$, in $$/lb are calculated as:

$$RPP_t = P_{GF,t} - P_{CB,t}$$ (1)

where, $P_{GF}$ and $P_{CB}$ represent the price of grass-fed and conventional beef, respectively. While straightforward and easily traceable to changes in its components, this method ignores the inherent differences in price levels of various cuts (expensive steaks vs inexpensive stew meat).

In order to circumvent this issue, we obtain a relative price premium by dividing the raw price premium by the conventional beef price and express it in percentage form

$$PP_t = \frac{RPP_t}{P_{CB,t}} \times 100\%$$ (2)

The relative price premium form ($PP$) will serve as the base of our analysis while the raw price premium measure ($RPP$) will serve as a test of robustness of our results.

We derive reduced form price premium models from the structural grass-fed beef price and conventional beef price equations, as commonly done across a wide range of topics (Contoyannis and Jones, 2004; Wooldridge, 2010; Goodwin, 2015; Mason et al., 2017). Specifically, we assume that beef prices are determined by the following equations:

$$P_{GF} = f(X, Y)$$ (3)

$$P_{CB} = g(X, Z)$$ (4)

where $P_{GF}$ and $P_{CB}$ are as defined in equations (1) and (2). The matrices $Y$ and $Z$ denote exogenous variables that could differentially affect the price of grass-fed beef and conventional beef at the production level. Among others, these might include the cost of finishing grass-fed vs grain-fed cattle. In general, grass-finished cattle tend to stay on the pasture much longer than grain-finished cattle and are also much lighter on average (Harvest Returns, 2018).\footnote{Grain finished beef ready for sale weighs between 1,200 to 1,400 pounds. At this weight, the cattle are between 15 to 22 months old. Grass finished beef, on the other hand, when ready for sale weighs between 1,000 to 1,200 pounds. At this weight, the cattle are between 20 to 26 months old Harvest Returns (2018).} $X$, on the other hand, denotes the matrix of exogenous variables affecting the retail price of grass-fed beef and conventional beef. Our specification of factors that should be included in the $X$ matrix is
based on the findings of previous survey-based studies.

Previous studies suggest that consumers’ income positively affects premia in various niche markets, such as naturally produced beef (Umberger et al., 2009) and Raised Carbon Friendly (RCF) beef (Li et al., 2016). Specifically, Umberger et al. (2009) indicated that consumers with a higher income are more likely to pay a higher premium for natural products. Li et al. (2016) showed that higher income consumers will support and pay more for RCF-certified beef.

Furthermore, Umberger et al. (2002) suggested that consumers’ habit of eating at home is likely to affect the price premiums as well. Specifically, using survey data, Umberger et al. (2002) found that consumers who more frequently eat at home would prefer grass-fed beef steak to corn-fed beef steak. This suggests that food consumption patterns may affect price premiums. This factor may also be growing in relevance as Sakse na et al. (2018) found that “over the past 30 years, FAFH’s share of U.S. households’ food budgets and total food spending grew steadily.”

Beef has important nutrients including high-quality protein, iron, and zinc, which are potentially beneficial to good health for human beings (McAfee et al., 2010; Van Wezemael et al., 2014). Unsurprisingly, consumers’ beliefs regarding beef’s nutritional value and taste can also affect beef demand and price premiums (Tonsor et al., 2010, 2018). These beliefs are often influenced by media reports. In particular, information on human health impacts of zinc, iron and protein became prevalent. Additionally, medical journal articles linking nutrition including protein and minerals such as iron and zinc, have been positively linked to beef demand by Tonsor et al. (2010). Thus, more publications and media information on such nutritional elements leads to more consumer interest in products containing these characteristics. In this regard, Tonsor et al. (2010) found that the number of published articles related to fat negatively affected beef demand. Using a food demand survey (FooDS) from 2013 to 2017, Tonsor et al. (2018) argued that food taste is the most important food value and nutrition is the fourth most important food value to participating consumers. Furthermore, based on a rank of factors describing consumer perceptions regarding steak and ground beef, Tonsor et al. (2018) showed that “consumers, on average, perceive steak to be convenient, tasty, attractive, and novel but they also perceive steak to be poor for animal
welfare, nutrition, and environment while also being expensive.” (p.29)

While some of these factors, such as consumers’ income and media articles regarding protein and minerals, may affect both grass-fed and conventional beef prices, others, such as the media information related to climate change, may be more specific to grass-fed beef premiums. Based on equation (3) and equation (4), we can hypothesize the reduced-form expression:

\[ PP = h(X) \]  

(5)

where \( PP \) is again the grass-fed beef (relative) price premium observed at the retail level, \( X \) includes consumer disposable income, consumption of food away from home (FAFH), and several measures that capture the intensity of media information that may affect consumer preferences.\(^2\)

Examination of grass fed beef price premiums has to take into account relevant policy changes during the period of study. On January 12, 2016, the USDA revoked the “USDA Grass-fed” label, while leaving the standards for the claim on their website for producers to follow USDA-AMS (nd).\(^3\) At the same time, the USDA Grass Fed Small and Very Small Producer Program (SVS), administered by AMS, remained intact. Consequently, the AMS continued to collect and disseminate price information for meat products labeled grass-fed. The revocation meant that ranchers and restaurants became the third party certifying grass-fed beef. Yet little is known about whether the revocation of the USDA label affected the premiums for beef marketed as grass-fed. As such, we will explicitly investigate this issue in this study.

Another important market shock during the period of study was associated with COVID-19 pandemic. On January 20, 2020, the U.S. Center for Disease Control and Prevention (CDC) confirmed the first U.S. laboratory-confirmed case of COVID-19 of a domestic case in Washington state. By March 2020, cases were dispersed throughout the country. This culminated in the U.S. Government declaring a nationwide emergency on March 13, 2020.\(^4\) The pandemic led to a growth in demand for organic and sustainable foods worldwide (Ecovia, 2020) and in the U.S. (Askew, 2020). To the

\(^2\)The reader is directed to Table 3 for a more detailed explanation of these media-related variables.

\(^3\)The standards for the claims: see details at https://www.ams.usda.gov/services/auditing/grass-fed-SVS

\(^4\)https://www.cdc.gov/museum/timeline/covid19.html
best of our knowledge, the effect of the pandemic on grass-fed beef premiums has not been explored in the previous literature, but will be explicitly examined in our study.

To assess the potential heterogeneity in the grass-fed price premiums across beef cuts, we first estimated individual models for each cut:

$$\Delta^{(12)}PP_{i,t} = \psi_i'X + \beta_iREV_t + \gamma_iCOVID_t + \theta_i t + \varepsilon_{i,t}, \quad i = \{1, 2, ..., 12\}$$  \hspace{1cm} (6)

where $\Delta^{(12)}PP_{i,t}$ denotes the annual difference of the price premium.$^5$ $i$ refers to each particular meat cut; and $X$ represents the matrix of exogenous variables in annual percentage changes (computed as log-differences). $REV_t$ is an indicator variable for the period following the revocation of “grass-fed” label by USDA in January 2016:

$$REV_t = \begin{cases} 
0 & \text{for } t < \text{January, 2016} \\
1 & \text{otherwise}
\end{cases}$$ \hspace{1cm} (7)

$COVID_t$ is an indicator variable for the post-national emergency declaration of COVID-19 pandemic period. The value is equal to 1 after February 2020, and 0 otherwise.

$$COVID_t = \begin{cases} 
0 & \text{for } t < \text{March, 2020} \\
1 & \text{otherwise}
\end{cases}$$ \hspace{1cm} (8)

The vector of parameters $\psi_i$ captures the impact of the (annual) percentage changes of the exogenous variables on our grass-fed beef premium measure. The parameters $\beta_i$ and $\gamma_i$ capture the impact of the grass-fed label revocation and COVID-19 pandemic, respectively. $\theta_i$ shows the effect of time trend, $t$; and $\varepsilon_i$ denotes the error term.

We estimated equation (6) using two approaches. First, we use OLS models to show the differential effects of the various factors on the grass-fed price premium for each individual cut. Second, we utilize a cut-panel estimation to examine whether these factors commonly affect price premiums.

$^5$The annual difference form of price premiums can get rid of the problem of seasonality and unit roots in price premiums. The reader is directed to Data section for the findings of seasonality and unit roots in relative price premiums and the specifications of annual difference of the relative price premium.
1.3 Data

Monthly retail price data for the 12 most common cuts of grass-fed and conventional beef from January 2014 to December 2021 were obtained from the National Monthly Grass Fed Beef and National Retail Beef Activity Reports, respectively. Both are published by USDA-AMS.

Figures 2 and 3 present the price levels (of grass-fed and conventional beef) and our computed premiums. Specifically, Figure 2 shows that the gap between the grass-fed and conventional beef varies over time and across cuts (ordered from least to most expensive). When expressed in premium terms, some more intriguing dynamics emerge. Figure 3 shows a decreasing trend in the beef premiums for some beef cuts (such as filet mignon and short ribs), whereas others (such as rump roast and chuck roast) exhibit an increasing trend before 2018 and a decreasing trend after 2018. Figure 3 also captures spikes in the premiums of the expensive beef cuts such as filet mignon and tenderloin in 2016 due to the higher conventional beef prices shown in Figure 2.

Table 1 corroborates these patterns. On average, the grass-fed beef premiums were between 48% and 193% of conventional beef prices. The “premium-quality” cuts seem to enjoy the largest average price premiums with sirloin steak (193.15%), tenderloin (165.46%), ribeye steak (156.08%), and filet mignon (150.02%) being the top contenders. Despite being some of the cheaper cuts of beef, roasts generated substantial premiums in the grass-fed beef market. The average premium for chuck roast and rump roast is as high as 105.54% and 132.80%, respectively. On the other hand, several cuts had average premiums of less than 2 times (100%) the conventional price. These include stew meat (93.39%), flank steak (77.31%), and skirt steak (74.72%). The lowest average premiums were observed for short ribs (48.25%). We interpret this as a signal that these cuts are less attractive (relative to others) in the grass-fed market. In general, these observations demonstrate heterogeneity in premiums of grass-fed beef cuts.

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6Ribeye roast, bottom round roast, tri tip, and sirloin roast had multiple missing values and thus were excluded from the estimation. Of the remaining 12 cuts, less than 2.4% (28 data points) were missing and would be useful for further inference. To preserve potential seasonality in the raw data, missing values were imputed using the relevant monthly averages over the sample period.

7This pattern is likely caused by instances of steak thefts at supermarkets and cattle rustling in 2016 (Tuttle, 2016).
Figure 2: Monthly Beef Prices ($/lb)

Data source: USDA-AMS
Figure 3: Beef Price Premiums (%)

Note: The premium measure is computed based on equation (2).
It is well documented that prices within the meat market are seasonal in nature (see Chavas and Mehta, 2004; Wang and Tomek, 2007, for example). Table 2 shows considerable seasonality in some cuts, especially brisket, with higher premiums both in the warmer (May, June, and August) and cooler (February, March, and November) months relative to January.\(^8\) Premiums for premium steaks, like filet mignon and tenderloin, were higher during the summer. On the other hand, premiums for flank steak and chuck roast were lower during the summer months. There is also evidence that premiums for filet mignon, tenderloin as well as short ribs and stew meat have declined over time.

In order to eliminate the effect of seasonality in some premiums, we transformed the premiums calculated in equation (2) to annual percentage changes, as follows:

\[
\Delta^{(12)} PP_t = PP_t - PP_{t-12} = \left( \frac{RP_{P}t}{P_{CB,t}} \right) \times 100\% - \left( \frac{RP_{P}t-12}{P_{CB,t-12}} \right) \times 100\% \tag{9}
\]

where \(PP_t\) and \(PP_{t-12}\) denote the relative price premiums at time \(t\), and one year prior, respectively. This effectively removes seasonality in our series via annual differencing. The relevant descriptive statistics for the annual changes are presented in the bottom panel of Table 1.

We conducted tests of stationarity to determine whether any transformations were necessary to avoid potential spurious regression issues in our empirical analysis. We checked the stationarity of price premiums using unit root tests including the Augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1981), Phillips-Perron tests (Phillips and Perron, 1988), and Kwiatkowski, Phillips, Schmidt, Shin (KPSS) tests (Kwiatkowski et al., 1992). Stationarity test results, shown in the bottom panel of Table 1, support the conclusion that the annual changes in price premiums are largely stationary at the 5% level of significance.\(^9\)

Table 3 describes the data sources and variable specifications. We measured the impact of changes in income on grass-fed beef premiums using the seasonally adjusted monthly real disposable personal

\(^8\)The equivalent results for the grass-fed premiums, measured as raw price premiums, are presented in Table A1 of the Appendix A.

\(^9\)Before conducting the seasonal differencing, we conducted a unit root test of the premium as defined in equation (2). Save for sirloin steak and stew meat, the ADF tests failed to reject the null hypothesis of unit root. The KPSS tests failed to reject the null of stationary in all but 3 cuts (filet mignon, flat iron steak, and short ribs).
income per capita published by the U.S. Bureau of Economic Analysis. These data were collected from the Federal Reserve Economic Data (FRED) at the Federal Reserve Bank of St. Louis. Food away from home (FAFH) and food at home (FAH) data were collected from USDA-ERS and combined to derive the FAFH share of total food expenditures.\footnote{The data on FAFH sales and FAH sales are based on final-purchase estimates. FAFH sales included full-service restaurants, retail stores, schools and colleges, etc. Purchases from food stores, warehouse clubs and home production were counted as FAH sales. See details at https://www.ers.usda.gov/data-products/food-expenditure-series/documentation/revisions.}

Following the approach of Tonsor et al. (2018), we used media and medical information to measure the environmental concerns, beef taste, and nutritional information such as protein, minerals and fat. Specifically, environmental information included news related to climate change and cattle. Taste consisted of the number of released articles regarding beef taste. Protein and minerals included the numbers of published literature on the topics of protein, zinc or iron in beef, respectively. Similarly, fat consisted of the number of published articles regarding fat in beef. The news releases associated with climate change and beef taste were collected from NewsBank. The published literature related to beef protein, minerals and beef fat was collected from PubMed. The monthly released news and published articles from 2014 to 2021 were collected by searching the articles with specific keywords listed in Table 3. These numbers of articles would represent the variables for climate change, beef taste, protein & minerals, as well as fat. However, we acknowledge that we cannot distinguish between the positive or negative news using this approach.

Where possible, the independent variables entered equation (6) in percentage change form. This facilitates easier interpretation of the model results in equation (6). Descriptive statistics in Table 3 indicate that real disposable income increased by about 2.59 percent annually within our sample. With respect to news and information, the number of articles related to climate change increased by 20.87 percent annually, while the number of articles discussing fat decreased by 0.19 percent annually.
1.4 Empirical Results

1.4.1 Main Results

Columns (1) – (8) in Table 4 show the OLS estimation results of differential effects of the exogenous variables on premiums for specific cuts of grass-fed beef and column (9) shows the results of a cut panel model that measured the average effects across cuts. In this table and the discussion that follows, we will focus our discussion on the cuts described by models that are overall significant. According to the low explanatory power indicated by the F-tests, we will omit the models for filet mignon, skirt steak, brisket, and chuck roast and focus our discussion on the remaining eight cuts.

A number of key tests were performed before estimating the cut panel. First, we used the panel structural break tests established by Ditzen et al. (2021). The novelty of their approach is that we are able to estimate and test for many known and unknown breaks in the panel data. Specifically, we conducted the hypothesis test of 2 unknown breaks during the sample period. We rejected the null of no breaks and hence the test detected 2 structural breaks in August 2016 and August 2017. With the break date known, we conducted the panel unit root tests developed by Karavias and Tzavalis (2014). This test permits structural breaks in panel data with known break dates. We rejected the null of unit roots and concluded that our data are panel stationary. We also checked the slope heterogeneity for the model using the tests established by Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013). The results showed that all slope coefficients are identical across panels. In effect, this indicates that the effects of exogenous variables on grass-fed beef premiums are similar across the beef cuts. Thus, a pooled panel estimation would yield meaningful insights into our research question. In addition, serial correlation tests established by Drukker (2003) and Wooldridge (2010) suggested that the idiosyncratic errors have an autocorrelation structure. Therefore, we estimated equation (6) using a pooled feasible GLS with an autocorrelation AR(1) process common to all the 12 beef cuts.

\[ \text{Note: We also conducted the hypothesis test of 1 unknown break as the null versus 2 unknown breaks as the alternative. We rejected the null of 1 break.} \]
The OLS model results regarding the effect of income on the price premiums were mixed. In fact, only three cuts indicated a statistically significant relationship. A 1 percent growth in real annual disposable income increased the sirloin steak and short rib premiums by 7.90 and 1.28 percent, respectively, but decreased premiums for rump roasts by 3.31 percent. When pooled in the panel framework (Column 9), we observed that the overall effect of income on grass-fed beef premiums was positive, albeit not statistically significant.

Consumption of food away from home (FAFH) was the strongest negative driver of price premiums for grass-fed beef with significant effects observed for the panel specification and several individual beef cuts. For individual beef cuts, notable examples were the tenderloin and sirloin steak. In fact, tenderloin and sirloin steak appear to be the most sensitive to the increase in FAFH's share of the total food budget. Specifically, a 1 percent increase in FAFH resulted in a 5.67 and 6.22 percent decrease for tenderloin and sirloin steak premiums, respectively. The pooled panel results, on the other hand, revealed an average effect of -0.98 percent across all cuts following a 1 percent rise in FAFH. These results show that as the share of FAFH increased grass-fed beef premiums declined. These findings of a negative relationship between FAFH and grass-fed beef price premiums are consistent with the survey-based findings of Umberger et al. (2002).

Increased media attention to climate change and cattle did not appear to affect grass-fed beef premiums. From the individual and pooled regressions, climate change information did not have significant effects on the premiums. On the other hand, media information about taste was positively associated with the grass-fed premium for ribeye steak. In particular, a 1 percent rise in media information on taste led to a 0.84 percent increase in price premiums for ribeye steak. The average effect across all cuts, however, was not statistically significant as per the pooled panel results.

The increase in articles related to nutritional information about protein and minerals had different effects on grass-fed beef premiums. Specifically, a 1 percent rise in articles associated with protein and mineral led to an increase of rump roast and stew meat premiums by 0.36 and 0.17 percent, respectively. On average, this effect was not significantly different from zero across all cuts.
Table 1: Descriptive Statistics and Unit Root Tests for Monthly Prices and premiums

<table>
<thead>
<tr>
<th>Beef Cuts</th>
<th>Conventional ($/lb)</th>
<th>Grass-fed Prices ($/lb)</th>
<th>Price Premiums (%)</th>
<th>Annual Change of Price Premiums (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>S.D.</td>
<td>Mean</td>
</tr>
<tr>
<td>Filet Mignon</td>
<td>13.98</td>
<td>13.96</td>
<td>2.29</td>
<td>33.83</td>
</tr>
<tr>
<td>Tenderloin Steak</td>
<td>11.20</td>
<td>11.20</td>
<td>1.85</td>
<td>28.78</td>
</tr>
<tr>
<td>Ribeye Steak</td>
<td>8.66</td>
<td>8.41</td>
<td>0.96</td>
<td>21.99</td>
</tr>
<tr>
<td>Sirloin Steak</td>
<td>5.76</td>
<td>5.51</td>
<td>1.13</td>
<td>16.39</td>
</tr>
<tr>
<td>Skirt Steak</td>
<td>7.72</td>
<td>7.74</td>
<td>1.43</td>
<td>12.89</td>
</tr>
<tr>
<td>Flat Iron Steak</td>
<td>6.93</td>
<td>6.92</td>
<td>0.76</td>
<td>15.76</td>
</tr>
<tr>
<td>Flank Steak</td>
<td>7.98</td>
<td>7.80</td>
<td>0.98</td>
<td>14.01</td>
</tr>
<tr>
<td>Rump Roast</td>
<td>4.16</td>
<td>3.99</td>
<td>0.76</td>
<td>9.46</td>
</tr>
<tr>
<td>Brisket Chuck Roast</td>
<td>4.30</td>
<td>4.01</td>
<td>1.35</td>
<td>9.26</td>
</tr>
<tr>
<td>Short Ribs</td>
<td>4.41</td>
<td>4.26</td>
<td>0.56</td>
<td>8.96</td>
</tr>
<tr>
<td>Stew Meat</td>
<td>5.38</td>
<td>5.25</td>
<td>0.80</td>
<td>7.85</td>
</tr>
</tbody>
</table>

Notes: Price premiums and annual changes are specified in equations (2) and (9), respectively. The number of observations is 96. S.D. denotes the standard deviation and ADF denotes the Augmented Dickey-Fuller (ADF) tests. C.V. denotes coefficient of variation. The appropriate lag length is selected based on the BIC criterion. PP and KPSS are the Phillips-Perron and Kwiatkowski, Phillips, Schmidt, Shin tests, respectively. The maximum lags of the KPSS test are chosen by Schwert criterion. *, **, and *** reflect significance at the 10%, 5%, and 1% levels of significance, respectively.
<table>
<thead>
<tr>
<th>Estimation Method</th>
<th>Beef Cuts</th>
<th>Trend</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>181.03***</td>
</tr>
<tr>
<td>(1)</td>
<td>Filet Mignon</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(2)</td>
<td>Tenderloin</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(3)</td>
<td>Ribeye</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(4)</td>
<td>Sirloin</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(5)</td>
<td>Skirt</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(6)</td>
<td>Flank</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(7)</td>
<td>Rump</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(8)</td>
<td>Brisket</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(9)</td>
<td>Chuck</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(10)</td>
<td>Short Ribs</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(11)</td>
<td>Stew Meat</td>
<td>-1.27***</td>
<td>-0.75***</td>
<td>0.04</td>
<td>-0.09</td>
<td>0.27</td>
<td>0.56***</td>
<td>0.11</td>
<td>0.10</td>
<td>0.24</td>
<td>0.09</td>
<td>-0.51***</td>
<td>-0.17**</td>
<td>0.43</td>
</tr>
<tr>
<td>(12)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>181.03***</td>
</tr>
</tbody>
</table>

Notes: Number of observations is 96 for each beef cut. Robust standard errors are presented in parentheses. Trend refers to a simple time trend. *, **, and *** reflect significance at the 10%, 5%, and 1% levels of significance, respectively.
### Table 3: Descriptions of Independent Variables

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>ABR.</th>
<th>DESCRIPTIONS</th>
<th>UNIT</th>
<th>DATA SOURCE OR CALCULATIONS</th>
<th>MEAN</th>
<th>MEDIAN</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>INC</td>
<td>Real disposable personal income: per capita, monthly, seasonally adjusted annual rate</td>
<td>Chained 2012 Dollars</td>
<td>FRED, Federal Reserve Bank of St. Louis. <a href="https://fred.stlouisfed.org/series/A229RX0">https://fred.stlouisfed.org/series/A229RX0</a></td>
<td>43944.67</td>
<td>43419</td>
<td>2996.97</td>
</tr>
<tr>
<td>FAFH</td>
<td>FAFH</td>
<td>FAFH’s share of food expenditure</td>
<td>%</td>
<td>FAFH = FAFHS + FAHS × 100</td>
<td>51.18</td>
<td>52.17</td>
<td>2.63</td>
</tr>
<tr>
<td>Climate Change</td>
<td>CLIM</td>
<td>The number of published news on the U.S. newspapers, with keywords “climate change” or “greenhouse gas” or “global warming” and “cattle”</td>
<td>#</td>
<td>Access World News from NewsBank</td>
<td>208.18</td>
<td>135.50</td>
<td>162.49</td>
</tr>
<tr>
<td>Taste</td>
<td>TAS</td>
<td>The number of published news on the U.S. newspapers, searched by keywords “taste” or “tasty” or “tender” or “juicy” or “flavor” or “savor” and “beef”</td>
<td>#</td>
<td>Access World News from NewsBank</td>
<td>2615.98</td>
<td>2548.50</td>
<td>408.80</td>
</tr>
<tr>
<td>Protein &amp; Minerals</td>
<td>PM</td>
<td>The number of published literatures, searched by keywords “zinc” or “iron” or “protein” and “beef”</td>
<td>#</td>
<td>PubMed</td>
<td>29.41</td>
<td>28.00</td>
<td>9.98</td>
</tr>
<tr>
<td>Fat</td>
<td>FAT</td>
<td>The number of published literatures, searched by keywords “fat” or “cholesterol” or “heart disease” or “arteriosclerosis” and “disease” and “beef”.</td>
<td>#</td>
<td>PubMed</td>
<td>7.36</td>
<td>7.00</td>
<td>3.12</td>
</tr>
<tr>
<td>Revocation</td>
<td>REV</td>
<td>Dummy variable to indicate the revocation of “grass-fed” label in January 2016 (1 for Jan 2016 and the months after, 0 otherwise)</td>
<td>#</td>
<td></td>
<td>0.75</td>
<td>1.00</td>
<td>0.44</td>
</tr>
<tr>
<td>COVID pandemic</td>
<td>COVID</td>
<td>Dummy variable to indicate the COVID-19 pandemic that started in March 2020</td>
<td>#</td>
<td></td>
<td>0.23</td>
<td>0.00</td>
<td>0.42</td>
</tr>
</tbody>
</table>

#### Annual Percentage Differences

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>ABR.</th>
<th>DESCRIPTIONS</th>
<th>UNIT</th>
<th>DATA SOURCE OR CALCULATIONS</th>
<th>MEAN</th>
<th>MEDIAN</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>D.LINC</td>
<td>Annual log-differences of real disposable personal income (in 2012 dollars)</td>
<td>D.LINC = ln(INCt/INCt−12) × 100</td>
<td></td>
<td>2.59</td>
<td>2.47</td>
<td>3.83</td>
</tr>
<tr>
<td>FAFH</td>
<td>D.FAFH</td>
<td>Annual difference of FAFH’s share of food expenditure</td>
<td>D.FAFH = FAFHt − FAFHt−12</td>
<td></td>
<td>0.59</td>
<td>0.75</td>
<td>4.04</td>
</tr>
<tr>
<td>Climate Change</td>
<td>D.LCLIM</td>
<td>Annual log-differences of CLIM</td>
<td>D.LCLIM = ln(CLIMt/CLIMt−12) × 100</td>
<td></td>
<td>20.87</td>
<td>16.81</td>
<td>64.48</td>
</tr>
<tr>
<td>Taste</td>
<td>D.LTAS</td>
<td>Annual log-differences of TAS</td>
<td>D.LTAS = ln(TASt/TASt−12) × 100</td>
<td></td>
<td>0.82</td>
<td>3.28</td>
<td>16.71</td>
</tr>
<tr>
<td>Protein &amp; Minerals</td>
<td>D.LPM</td>
<td>Annual log-differences of PM</td>
<td>D.LPM = ln(PMt/PMt−12) × 100</td>
<td></td>
<td>6.16</td>
<td>6.55</td>
<td>26.76</td>
</tr>
<tr>
<td>Fat</td>
<td>D.LFAT</td>
<td>Annual log-differences of FAT</td>
<td>D.LFAT = ln(FAt/FAt−12) × 100</td>
<td></td>
<td>-0.19</td>
<td>0.00</td>
<td>56.25</td>
</tr>
</tbody>
</table>

Notes: ABR. and S.D. represent abbreviation and standard deviation, respectively. Since the annual difference of FAFH (D.FAFH) represents the annual percentage change of food away from home, it is not necessary to take the logarithmic form of annually differenced FAFH.
### Table 4: Individual Estimates and Cut-Panel Estimates

<table>
<thead>
<tr>
<th>Estimation Methods:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beef Cuts</td>
<td>Tenderloin</td>
<td>Ribeye</td>
<td>Sirloin</td>
<td>Flat Iron</td>
<td>Flank</td>
<td>Rump</td>
<td>Short</td>
<td>Stew</td>
<td>Cut-Panel</td>
</tr>
<tr>
<td>(OLS)</td>
<td>Steak</td>
<td>Steak</td>
<td>Steak</td>
<td>Steak</td>
<td>Steak</td>
<td>Roast</td>
<td>Ribs</td>
<td>Meat</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>61.70**</td>
<td>0.98</td>
<td>28.10</td>
<td>-39.14***</td>
<td>-9.7</td>
<td>34.75***</td>
<td>4.32</td>
<td>6.99</td>
<td>6.63</td>
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<td>0.78</td>
<td>7.90***</td>
<td>1.12</td>
<td>0.46</td>
<td>-3.31***</td>
<td>1.28***</td>
<td>0.83</td>
<td>0.12</td>
</tr>
<tr>
<td>FAFH</td>
<td>-5.67*</td>
<td>1.15</td>
<td>-6.22***</td>
<td>2.51</td>
<td>0.26</td>
<td>1.42</td>
<td>-0.68</td>
<td>-1.02</td>
<td>-0.98*</td>
</tr>
<tr>
<td>Climate Change</td>
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<td>-0.01</td>
<td>0.32</td>
<td>-0.08</td>
<td>-0.08</td>
<td>-0.12</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
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<tr>
<td>Taste</td>
<td>0.21</td>
<td>0.84*</td>
<td>-0.62</td>
<td>-0.67</td>
<td>-0.21</td>
<td>0.08</td>
<td>0.05</td>
<td>-0.25</td>
<td>0.04</td>
</tr>
<tr>
<td>Protein &amp; Minerals</td>
<td>0.64</td>
<td>0.12</td>
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<td>0.18</td>
<td>-0.15</td>
<td>0.36**</td>
<td>0.06</td>
<td>0.17*</td>
<td>0.07</td>
</tr>
<tr>
<td>Fat</td>
<td>-0.33**</td>
<td>0.02</td>
<td>-0.21</td>
<td>-0.17*</td>
<td>0.02</td>
<td>0.12</td>
<td>-0.04</td>
<td>-0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td>Revocation</td>
<td>0.53</td>
<td>0.23</td>
<td>(0.30)</td>
<td>(0.22)</td>
<td>(0.09)</td>
<td>(0.16)</td>
<td>(0.07)</td>
<td>(0.10)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>COVID</td>
<td>0.17</td>
<td>(0.10)</td>
<td>0.15</td>
<td>(0.09)</td>
<td>(0.04)</td>
<td>(0.08)</td>
<td>(0.04)</td>
<td>(0.06)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Trend</td>
<td>-29.48</td>
<td>19.74</td>
<td>-1.77</td>
<td>58.74***</td>
<td>23.65*</td>
<td>-2.28</td>
<td>-15.63</td>
<td>-25.32*</td>
<td>3.05</td>
</tr>
<tr>
<td>COVID</td>
<td>-20.53</td>
<td>43.21</td>
<td>(19.45)</td>
<td>(12.20)</td>
<td>(18.41)</td>
<td>(10.54)</td>
<td>(13.66)</td>
<td>(9.66)</td>
<td>(9.66)</td>
</tr>
<tr>
<td>Trend</td>
<td>52.44</td>
<td>8.59</td>
<td>23.09</td>
<td>5.29</td>
<td>-16.97</td>
<td>-4.07</td>
<td>-7.70</td>
<td>-22.46*</td>
<td>-2.59</td>
</tr>
<tr>
<td>Trend</td>
<td>74.44</td>
<td>26.27</td>
<td>(41.95)</td>
<td>(34.21)</td>
<td>(12.08)</td>
<td>(21.24)</td>
<td>(7.93)</td>
<td>(11.89)</td>
<td>(10.94)</td>
</tr>
<tr>
<td>Trend</td>
<td>-1.55</td>
<td>-0.57</td>
<td>-1.41</td>
<td>-0.28</td>
<td>-0.13</td>
<td>-0.55</td>
<td>0.02</td>
<td>0.35</td>
<td>-0.09</td>
</tr>
<tr>
<td>R2</td>
<td>0.122</td>
<td>0.131</td>
<td>0.274</td>
<td>0.203</td>
<td>0.194</td>
<td>0.272</td>
<td>0.211</td>
<td>0.129</td>
<td></td>
</tr>
<tr>
<td>p value of F test</td>
<td>0.007</td>
<td>0.060</td>
<td>&lt;0.001</td>
<td>0.001</td>
<td>0.100†</td>
<td>&lt;0.001</td>
<td>0.016</td>
<td>0.052</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The dependent variables are annual differences of the respective price premiums, specified in equation (9). Separate OLS models are estimated for each cut. Trend refers to a simple time trend. The number of observations for each individual cut is 84 and for the panel estimates is 1,008. t-statistics are presented in parentheses. OLS estimates for meat cuts without overall significance (as determined by the F-test) are not presented above. The p-value of Wooldridge test for serial autocorrelation in the panel data is 0.0003. Hence, we reject the null hypothesis of no first order autocorrelation. FGLS-AR(1): pooled feasible GLS estimators with a heteroskedastic error structure with cross-sectional correlation and AR(1) autocorrelation structure. Cut-Panel is a beef panel including all the 12 cuts. Standard errors are robust standard errors. See Table 3 for the descriptions for each independent variable. *, **, and *** reflect significance at the 10%, 5%, and 1% levels of significance, respectively. † denotes the actual p-value that is smaller than 0.100.
Increased media information regarding fat had negative impacts on the grass-fed price premiums. Specifically, a 1 percent rise in media information on fat results in a fall in price premiums for tenderloin and flat iron steak by 0.33 and 0.17 percent, respectively. However, the average effect of increased media attention to fat on grass-fed premiums was not statistically significant.

The revocation of the grass-fed beef certification by USDA had a heterogeneous impact on the 8 cuts estimated. In the case of a flat iron steak and flank steak, the revocation increased that cut’s premium. Stew meat premium was negatively affected in the period following the discontinuation of this certification. When assessed in the pooled framework, the average effect was positive but not statistically significant. We attribute this to the fact that grass-fed labeling continues to be used by grocers and consumers may not be aware of the fact that this information is self-certified in most cases.

Lastly, our panel model showed that grass-fed stew meat premiums were roughly 22.46 percent lower during the COVID-19 pandemic. However, the panel results suggested that the average grass-fed beef premiums have not changed significantly across all cuts during COVID-19. Our findings for the trend also indicated that annual changes in grass-fed premiums did not change significantly over time.

### 1.4.2 Sensitivity Analysis

We assessed the robustness of our estimates using the raw price premiums as an alternative measure of price premiums. Table A2 in Appendix A shows the estimation results. The F-tests revealed that the regression for the flank steak was not statistically significant. Therefore, flank steak was omitted in Table A2. Since we did not detect structural breaks in the raw price premium series, we also used the Levin, Lin, and Chu panel unit root tests (Levin et al., 2002) to test for panel stationarity. We concluded that there was no unit root present in the series. The panel estimations did not display an autocorrelation structure in the idiosyncratic errors, but captured the panel heteroskedasticity, which indicates the raw price premiums varied by beef cuts. Therefore, the last column of Table A2 shows the estimates for the panel model using pooled feasible GLS estimators with panel-corrected
standard errors (PGLS-PCSE) to adjust for heteroskedasticity across the panel.

While the magnitude of our coefficient estimates is different due to the differences in premium measurements applied, most of the OLS results in Table A2 are qualitatively similar to Table 4. For example, our estimates for the effects of income and food away from home on the relative price premiums (Table 4) are consistent with the effects on raw price premiums (Table A2) in terms of signs and significance levels for individual cuts.

1.5 Summary and Conclusions

This study examined price premiums for various cuts of grass-fed beef in the U.S. retail markets over the period January 2014 - December 2021. To the best of our knowledge, this is the first study to examine price premiums in grass-fed beef markets using observed market data rather than surveys or experiments.

Our results show that the observed premiums for grass-fed beef were heterogeneous across cuts. The highest premiums of 150 - 193 percent were observed for premium stakes, specifically, sirloin, tenderloin, ribeye and filet mignon. The lowest premiums of 48 - 77 percent were observed for flank steak, skirt stake and short ribs. This evidence indicates that grass-fed beef premiums are not consistent with the price levels of various cuts, but rather driven by certain quality characteristics consumers are looking for and highlights the fact that grass-fed beef is more attractive for some cuts but not for others.

Since market data is not accompanied by quality characteristics, we attempted to measure them through general media attention to certain attributes, such as taste, protein, minerals and fat. Our findings suggest that ribeye premiums were positively affected by information about taste, while rump roast and stew meat premiums were positively related to increased concerns and information flows regarding protein and minerals. While grass-fed beef is considered leaner and healthier (Cheung and McMahon, 2017), these health benefits may result in negative taste implications, as less marbled beef usually appears to be less tender. Our findings show that increased information
about fat decreased grass-fed premiums for tenderloin and flat iron steaks. However, our study did not find any significant impacts of information on fat on grass-fed premiums for other beef cuts. As the grass-fed beef industry continues to grow, these findings can be used to develop efficient marketing strategies that would help motivate grass-fed beef consumption and enhance premiums. Specifically, increasing information about protein and minerals would enhance purchases of grass-fed rump roast and stew meat while promotion of grass-fed ribeye steaks should focus on their superior taste.

Since Tonsor et al. (2018) demonstrated that beef is not viewed as an environmentally friendly product, we attempted to assess whether the grass-fed production claim examined in this study appears to address consumer concerns about climate change and enhance the premiums they are willing to pay. However, we did not find any evidence that information about climate change is associated with changes in grass fed beef premiums.

According to our results, the biggest driver of grass-fed beef premiums in our sample was consumption of food away from home. In fact, as consumers increased their consumption of food away from home by one percent, the premiums accrued to grass-fed beef decreased by 0.98 percent. This finding is consistent with survey-based results in Umberger et al. (2002) study. Given the long-term trend of increasing consumption of food away from home highlighted in Saksena et al. (2018), this trend may lead to lower grass-fed beef premiums on average in the long run.

Consumption of food away from home also likely captured the impact of COVID-19 pandemic on grass-fed beef premiums. For example, in April of 2020, consumption of food away from home decreased by 16.2 percent from the previous year. This period was also associated with increase in premiums for ribeye steak, tenderloin, sirloin steak, brisket, short ribs, and stew meat by 0.05, 1.11, 90.64, 149.36, 8.35 and 1.95 percent, respectively. At the same time an indicator variable for COVID-19 pandemic did not capture many additional effects, as it was only significant and negative for stew meat, but not in any other cases.

Changes in disposable income had a positive impact on premiums for grass-fed sirloin steak and short ribs, but not for other cuts. The lack of a significant positive link between income and grass-
fed beef premiums in our panel results is not consistent with other studies (e.g. Umberger et al., 2009; Li et al., 2016) and may be a limitation resulting from our aggregated national level data. Our measure of real income reflects general income trends in the US population, but it is not able to segment consumers in various income brackets to capture higher preferences for grass-fed beef among higher income consumers. Furthermore, lack of the impact of the revocation of the grass-fed certification is likely associated with the fact that many consumers are not aware of this change as the program continues for small farms and the labeling continues to be observed at the grocery stores.

1.6 Limitations and Avenues for Further Research

Although our models explain a relatively small proportion of annual variation in grass-fed beef premiums, our findings shed light on their relative magnitude and some of the main motivations behind grass-fed beef consumption. While we rely on indirect measures of consumer preferences as captured by media release information, it is important to recognize that our findings are largely consistent with survey-based conclusions of previous studies, as mentioned above. Confirming survey-based findings of previous studies with observed market data available from public sources is important and valuable, but it carries several limitations. We already mentioned that our aggregated national income data is unable to differentiate preferences for grass-fed beef across various income groups. Similarly, our aggregated national price data is unable to pick up any regional differences in price premiums in the niche markets that were highlighted in the previous literature (Umberger et al., 2009; Chang et al., 2010; Greene and McBride, 2015; Badruddoza et al., 2022). These limitations may be addressed by using disaggregated transaction level data in future studies.

In addition, our study focused on the level of grass-fed beef price premiums. However, the volatility of grass-fed prices and conventional prices was not analyzed in this paper. We reserve this for future studies. Moreover, using current data from USDA, we can only show the market share of general beef in the market, but we are not able to show the market of grass-fed beef and conventional beef.
Future work can use surveys to collect the market share of grass-fed beef and conventional beef of each beef cut.
2 Impact of Animal Disease Outbreaks on The U.S. Meat Demand

2.1 Introduction

The U.S. meat demand is a complex and multi-faceted system, with numerous demand drivers that are changing and evolving over time (Tonsor et al., 2010). Data from the Food and Agriculture Organization (FAO) show that U.S. meat consumption increase from 88.66 kg per capita per year in 1961 to 124.10 kg per capita per year in 2017 (Ritchie and Roser, 2017). In more recent decades, changes in meat consumption by type, shown in Figure B1 in Appendix B.1, reveal a rapid expansion of poultry consumption since 1960s at the expense of beef. Over the same period, poultry’s market share has risen from less than 20% in the early 1960s to more than 40% in 2017 (Ritchie and Roser, 2017). Lower retail prices of poultry relative to beef and pork, rapid development, and marketing, as well as consumers’ health-related concerns are likely the three main contributors to the rising demand for poultry (Spiegel, 2017; Bentley, 2019). Pig and hog consumption remain relatively steady at around 25% of total meat demand over this period.

Underpinned by health-related concerns, animal diseases have been demonstrated to be important determinants of meat demand (Ishida et al., 2010; Wang and de Beville, 2017). From a global perspective, animal diseases have caused serious problems for meat market in the last few decades (OECD/FAO, 2018). For instance, highly pathogenic avian influenza (HPAI), a more severe variant of avian influenza, was detected in a commercial poultry flock for the first time in British Columbia, Canada in early April 2022 (Scott, 2022a). Meanwhile, governments of Canada and Manitoba invest C$2.2 million to protect the food supply (Kelly, 2022). This shows the massive damage of HPAI.

1However, due to expanding beef prices and decreasing broiler prices from 1997 to 2019, the total expenses of beef and broilers do not change as much as the consumption of beef and broilers. Therefore, we do not capture a distinct increasing or decreasing trend in the budget shares of beef and broilers during this period. See Figure B2 in Appendix B.1.
outbreaks on local market.

So far two animal diseases that have widely affected the U.S. meat market include Bovine Spongiform Encephalopathy (BSE), and avian influenza (AI) virus. The first case of BSE (also known as mad cow disease) is confirmed in the UK in 1986 (Smith and Bradley, 2003). Since then, BSE has spread around the world and disrupted global beef consumption. U.S. detected its first case of BSE in 2003 in Washington State in the cattle imports from Canada (CDC, 2018a). By the end of 2018, the United States has identified six BSE cases.

AI, most known as bird flu, was first reported in China in 1996 (Ku and Chan, 1999; Barral et al., 2008). The AI virus could infect both poultry and wild birds and could also infect humans if enough bird flu gets into people’s eyes, noses, or mouth (CDC, 2018b). The AI has two variants: highly pathogenic avian influenza (HPAI) and low pathogenicity avian influenza (LPAI). HPAI is a serious disease and requires a rapid response (USDA, 2021), while the infection of poultry with LPAI viruses is less dangerous (CDC, 2017). Before the AI virus spread to the U.S., it was detected in the form of H5N1 in Asia and Europe. But after it occurred in the U.S., the virus has mutated to other highly pathogenic forms such as H7N2 and H5 (Wang and de Beville, 2017; CDC, 2018b). The U.S. reported H7N2 cases in Virginia in 2002, H5N2 cases in Texas in 2004 (USDA, 2015; Wang and de Beville, 2017), and three types of H5 (H5N1, H5N2, and H5N8) cases in 21 states from December 2014 to mid-June 2015 (Wang and de Beville, 2017; CDC, 2018b). USDA reports show that from 2014 to 2015 Minnesota confirmed 110 cases and Iowa confirmed 77 cases while the other states had at most 10 cases (1521). More recently, USDA reports detected HPAI cases in flocks in 29 states merely in 2022 (Ricci, 2022). Since fall 2021 the HPAI cases in the number of commercial ducks was about 17,200, resulting in restrictions on the import of U.S. poultry products from more than 80 countries (Scott, 2022b). Additionally, in 2022 USDA planed to devote $400 million to support the birds infected by HPAI outbreaks (Scott, 2022c).

Furthermore, the world meat market has suffered from African swine fever (ASF) for decades. The pork market in China has suffered from ASF outbreaks since 2019 (Ma et al., 2021). According to Swine Disease Global Surveillance Project, the U.S. has not detected any ASF outbreaks to
Another prevalent disease in the U.S. is Porcine Epidemic Diarrhea (PED). However, as the pork products from hogs infected by PED are safe for humans (Paarlberg, 2014), we hence did not include PED in our study.

The impact of animal diseases on meat demand has attracted a lot of attention in previous studies (Burton and Young, 1996; Jin and Koo, 2003; Ishida et al., 2010; Mu et al., 2015; Wang and de Beville, 2017; Ma et al., 2021; Ning et al., 2022). A group of papers examined the foreign animal disease outbreaks’ impacts on the local meat market. In particular, Burton and Young (1996) explored demand for beef and other meats under BSE in Great Britain. They indicate a reduction in beef market share by 4.5% due to the impact of BSE. Jin and Koo (2003) explored the BSE outbreak’s effect on Japanese consumers’ demand for meat. A structural change in Japanese meat demand was detected which was synchronized with the BSE outbreak that happened in 2001. Other studies (e.g., Mu et al., 2015; Wang and de Beville, 2017) explored the impact of domestic animal disease outbreaks of BSE and AI on U.S. meat markets. For example, Mu et al. (2015) examined the impacts of the BSE and AI on the U.S. meat demand and used media coverage to measure AI and dummy variables to measure BSE. They find that beef is replaced by pork during BSE outbreaks. Wang and de Beville (2017) showed that poultry demand would be easily substituted by beef and pork given negative news of bird flu. However, these studies only showed a fixed elasticity in a certain period and failed to indicate the effect of animal diseases on the dynamic compensated elasticities over time. Ning et al. (2022) shows that own-price elasticities for the U.S. beef imports became more price elastic after the BSE outbreak in December, 2003. However, the time-varying estimates for the U.S. meat consumption has not been studied yet.

Many previous studies measured the animal disease impacts using media coverage that either discriminate between negative and positive reports (Verbeke and Ward, 2001; Wang and de Beville, 2017) or do not (Burton and Young, 1996; Piggott and Marsh, 2004; Attavanich et al., 2011). For instance, Verbeke and Ward (2001) used a media index of TV coverage and advertising expenditures. Their simulation results showed that fresh meat advertising had only a minor impact compared

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2Source: https://cahfs.umn.edu/swine-disease-global-surveillance-project
with negative press. Wang and de Beville (2017) puts weights on each article according to their own intuitive thoughts. Their results showed that poultry consumption was easily substituted by pork and beef given the negative news of bird flu virus. Burton and Young (1996) found the cumulative number of articles regarding BSE affected consumers’ meat expenditure allocations in Great Britain. However, using media coverage to measure animal diseases has its challenges as it is difficult to disentangle positive versus negative news coverage and construct an objective measure of news information. An alternative method is to measure animal diseases using identified animal disease cases (Marsh et al., 2008; Mu et al., 2015). The advantage of this method is that it can precisely measure the identified dates and numbers of disease cases.

This study extends the previous literature by assessing the impacts of domestic outbreaks of two animal diseases, i.e., BSE and AI, on the U.S. meat demand. Implied by Figure B1 in Appendix B.1, our study concentrates on three types of meat products in the U.S. meat market, that is, beef, pork, and broilers. We focus on HPAI because HPAI is extremely infectious avian influenza whereas LPAI is not. To examine the change in consumption due to animal disease outbreaks, we calculated time-varying compensated elasticities over the study period. We showed that BSE outbreaks reduced beef consumption by 0.64 percent and increased pork consumption by 2.34 percent on average. We also showed that while BSE outbreaks reduced beef demand, these effects were short lived and did not extend beyond one quarter. The BSE outbreak in Quarter 4 of 2003 and Quarter 2 of 2012 increased pork demand by 1.64 percent and 2.94 percent, respectively. On the other hand, our findings suggest that an initial increased in pork demand due to BSE was reinforced in the following quarter, suggesting a longer duration of this impact. We also showed that the broiler consumption decreased during the HPAI outbreaks whereas beef and broiler consumption increased after the HPAI outbreaks. The HPAI outbreak in Quarter 2 of 2015 reduced the broiler demand by 1.76 percent in the current period and increased broiler demand by 3.78 percent in the successive period. These large impacts were due to a large number of identified cases during the outbreak. Using time-varying cross-price elasticities, we also showed that the substitution between beef and broilers and between beef and pork became stronger after Quarter 4 of 2003. In addition, the substitution between broilers and pork was relatively stable from 1997 to 2019.
The rest of this paper is organized as follows. Section 3.3 describes our data. Section 3.4 introduces the econometric method. Section 3.5 shows the main results. Section 3.6 makes a summary and draws the conclusion.

2.2 Data

The retail prices and consumption of beef, pork, and broilers over the periods 1997-2019 were obtained from USDA-Economic Research Service (USDA-ERS). Real retail meat prices were calculated using the consumer price index (CPI) for all urban consumers from the U.S. Bureau of Labor Statistics. The CPI was rebased to 2012 instead of 1982-1984 to reflect current prices more closely. Following Tonsor et al. (2010) and Tonsor and Olynk (2011), we obtained total food consumption as the ratio of total food expenditure to the consumer price index (CPI) for food. Consumption of other food was specified as the difference between total food consumption and total consumption of beef, pork and broilers. The price for other food was derived as a ratio of the other food expenditure to the consumption of other food. The food expenditure data represents sales of food for all purchasers collected from USDA-ERS. Food CPI was obtained from the U.S. Bureau of Labor Statistics.

One concern is that the elasticities of meat products may be not necessarily changed by animal diseases. Other factors such as consumers’ tastes may also change elasticities. Previous studies have considered the elasticities’ effect from health concerns that change consumers’ tastes over time (Gao and Shonkwiler, 1993; Acharya and Molina, 2004). Particularly, Gao and Shonkwiler (1993) and Acharya and Molina (2004) used the ratio of low-fat milk and whole milk consumption per capita to proxy for health concerns. Following their approach, our study also controlled the effect of the milk consumption ratio. Our data on per capita consumption of skim milk and whole milk was also collected from USDA-ERS.

Table 5 shows that during our study period, beef had the highest average consumption at 20.24 lb/capita, followed by broilers (19.25 lb/capita) and pork (13.14 lb/capita). Real retail prices of beef
were on average most expensive at $4.83/lb, followed by pork ($3.42/lb) and broilers ($1.93/lb). Table 5 also indicates that meat products comprised about 18.33 percent of the total food expenditure.

Table 5: Summary Statistics of Quarterly Data Used in Model Estimation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>S.D.</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beef Consumption (lb/capita)</td>
<td>20.24</td>
<td>20.66</td>
<td>2.03</td>
<td>23.8</td>
<td>16.89</td>
</tr>
<tr>
<td>Pork Consumption (lb/capita)</td>
<td>13.14</td>
<td>13.13</td>
<td>1.85</td>
<td>17.15</td>
<td>9.72</td>
</tr>
<tr>
<td>Broiler Consumption (lb/capita)</td>
<td>19.25</td>
<td>19.00</td>
<td>1.77</td>
<td>23.42</td>
<td>15.78</td>
</tr>
<tr>
<td>Other Food Consumption (lb/capita)</td>
<td>1060.79</td>
<td>1009.73</td>
<td>107</td>
<td>1261.16</td>
<td>910.23</td>
</tr>
<tr>
<td>Real Retail Beef Prices ($/lb)*</td>
<td>4.83</td>
<td>4.69</td>
<td>0.62</td>
<td>6.21</td>
<td>3.87</td>
</tr>
<tr>
<td>Real Retail Pork Prices ($/lb)*</td>
<td>3.42</td>
<td>3.43</td>
<td>0.19</td>
<td>4.04</td>
<td>3.00</td>
</tr>
<tr>
<td>Real Retail Broiler Prices ($/lb)*</td>
<td>1.93</td>
<td>1.90</td>
<td>0.14</td>
<td>2.20</td>
<td>1.67</td>
</tr>
<tr>
<td>Real Retail Other Food Prices ($/lb)*</td>
<td>0.77</td>
<td>0.80</td>
<td>0.14</td>
<td>0.99</td>
<td>0.55</td>
</tr>
<tr>
<td>Expenditure Shares for Beef on Total Food (%)</td>
<td>9.90</td>
<td>9.82</td>
<td>0.84</td>
<td>12.46</td>
<td>8.51</td>
</tr>
<tr>
<td>Expenditure Shares for Pork on Total Food (%)</td>
<td>4.63</td>
<td>4.40</td>
<td>0.89</td>
<td>6.39</td>
<td>3.26</td>
</tr>
<tr>
<td>Expenditure Shares for Broilers on Total Food (%)</td>
<td>3.80</td>
<td>3.72</td>
<td>0.45</td>
<td>4.85</td>
<td>2.96</td>
</tr>
<tr>
<td>Expenditure Shares for Other Food on Total Food (%)</td>
<td>81.67</td>
<td>82.08</td>
<td>1.88</td>
<td>84.48</td>
<td>77.41</td>
</tr>
<tr>
<td>Lower Fat and Skim Milk consumption (gallon/capita)</td>
<td>3.42</td>
<td>3.57</td>
<td>0.34</td>
<td>3.79</td>
<td>2.56</td>
</tr>
<tr>
<td>Whole Milk Consumption (gallon/capita)</td>
<td>1.65</td>
<td>1.53</td>
<td>0.27</td>
<td>2.06</td>
<td>1.32</td>
</tr>
<tr>
<td>Low-whole Milk Consumption Ratio (100%)</td>
<td>2.11</td>
<td>2.04</td>
<td>0.32</td>
<td>2.66</td>
<td>1.70</td>
</tr>
<tr>
<td>Identified BSE Cases in US (#)</td>
<td>271.50</td>
<td>0.00</td>
<td>2595.08</td>
<td>24892.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Identified HPAI Cases in US (#)</td>
<td>0.07</td>
<td>0.00</td>
<td>0.25</td>
<td>1.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: Number of observations is 92. *: Inflation-adjusted dollars (deflated by Consumer Price Index base year = 2012).

We recorded the outbreaks of the identified animal diseases in the U.S using data from World Organization for Animal Health (OIE) and Animal and Plant Health Inspection Service at USDA for HPAI (USDA-APHIS), and from Center for Disease Control (CDC) for BSE. Since the data on individual cases of LPAI were not available and HPAI was a more severe illness and had to be reported, our study focused only on the HPAI cases for AI. Table 6 shows the specific dates of identified BSE and HPAI cases in the U.S. from 1997 to 2019. In short, six BSE outbreaks and five HPAI outbreaks were collected.

Figure 4 shows the plots of meat prices (Panel A), meat supply (Panel B) and demand (Panel C) with the outbreaks of BSE and HPAI. Panel A shows that the broiler price had a downward trend from 1997 to 2019 whereas the price of beef increased over time. Pork prices were relatively steady during the study period.
Figure 4: Changes in Descriptive Statistics of U.S. Meat Markets over 1997-2019.

Panel A. Real Retail Meat Prices ($/lb), Base Year 2012
Panel B. Supply of Meat in lbs per capita
Panel C. Consumption of Meat in lbs per capita
The change in meat prices can be explained by the variation in meat demand and supply. Animal disease outbreaks typically led to a drop in consumer demand due to safety concerns associated with the affected product. At the same time, the supply of the affected product also fell as the affected products are discarded from the supply chain. The effect of the simultaneous drop in demand and supply on equilibrium price was ambiguous, but can be determined empirically. The descriptive statistics shown in Figure 4, Panel C, demonstrate that following the first BSE outbreak in the U.S. in Quarter 4 of 2003, the U.S. beef consumption decreases from 21.81 lbs/capita to 19.43 lbs/capita, the lowest level during the period 1997 to 2008. Furthermore, Figure 4, Panel B shows that in Quarter 4 of 2003 U.S. beef supply falls by 3.02 lbs/capita. This means that the beef supply decrease outweighed the demand decrease, leading to an increase in price. As shown in Figure 4, Panel A, beef price increased from $4.60/lb in Quarter 3 of 2003 to $5.16/lb in Quarter 4 of 2003 and remained elevated until Quarter 2 of 2013.

<table>
<thead>
<tr>
<th>Disease</th>
<th>Year</th>
<th>Quarter</th>
<th>Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSE</td>
<td>2003</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2005</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2006</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2018</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2004</td>
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<td>1</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>1</td>
<td>65</td>
</tr>
<tr>
<td>HPAI</td>
<td>2015</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>2</td>
<td>24892</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>3</td>
<td>9</td>
</tr>
</tbody>
</table>

Data Sources: OIE, USDA-APHIS and CDC.

However, inferring the impacts of animal diseases on meat demand merely based on descriptive statistics such as Figure 4, Panel C may fail to comprise the impacts from other variables such as meat prices. Therefore, we employed an empirical model to control these effects and will discuss the model in the following section.
2.3 Methodology

Our study aims to explore how meat demand is affected by each individual animal disease outbreak. We have several concerns about the selected model. First, in order to incorporate the impact of animal diseases on meat demand, Marsh et al. (2004) and Tonsor and Olynk (2011) estimated demand models such as Almost Ideal Demand System (AIDS) models and Rotterdam models with exogenous demand shifters of animal diseases. Second, the compensated elasticities derived from demand models may change over time shown by Mazzocchi (2003) and Barnett and Kanyama (2013). Third, Barnett and Kanyama (2013) showed that the Rotterdam model with time-varying coefficients outperformed the time-varying AIDS model in terms of recovering the signs of all the time-varying elasticities. Our study hence followed their findings and used a Rotterdam model with time-varying coefficients. Particularly, we implemented a two-step procedure in this method. In the first step, our Rotterdam model with time-varying coefficients was specified as

\[
 w_{it} \Delta \log q_{it} = \phi_{it} + \sum_{s=1}^{3} \psi_{is,t} S_s + \theta_{it} \Delta Q + \sum_{j=1}^{4} \pi_{ijt} \Delta \log p_{jt} + \sum_{k=0}^{1} \beta_{ikt} \Delta \log (\text{BSE}_{i,t-k}) \\
+ \sum_{k=0}^{1} \gamma_{ikt} \Delta \log (\text{HPAI}_{i,t-k}) + \alpha_{it} \Delta \log \text{Milk}_t + v_{it}, \forall i \in \{1, 2, 3, 4\} \tag{10}
\]

where \( i = 1, 2, 3 \) and 4 refers to beef, pork, broilers and other food, respectively; \( w_{it} \) is the \( i \)-th good expenditure share at time \( t \); \( q_{it} \) is the meat \( i \) consumption per capita; \( S_s \) denotes the quarterly seasonal dummies; \( \Delta Q_t = \sum_{i=1}^{n} w_{it} \Delta \ln q_{it} \) is the Divisia quantity index, representing the proportional change in real total expenditure (Deaton and Muellbauer, 1980); \( p_{jt} \) denotes the price for commodity \( j \); \( \text{Milk}_t \) denotes the ratio of low fat milk over the whole milk consumption per capita to control the consumers’ health concern; \( \text{BSE}_{t-k} = \text{BSE}_{t-k} + 1 \) and \( \text{HPAI}_{t-k} = \text{HPAI}_{t-k} + 1 \) denote the indicators for BSE and HPAI diseases at time \( t - k, \forall k \in \{0, 1\} \), respectively; \( \beta_{ikt} \) and \( \gamma_{ikt} \) are the estimated coefficients; \( v_{it} \) is the error term; and \( \psi_{i,0}, \theta_{i}, \pi_{ij}, \gamma_{it}, \kappa_{it}, \delta_{it} \) and \( \phi_{i,s} \) are parameters to be estimated. Particularly, \( \pi_{ij} \) is the Slutsky coefficient indicating the total substitution effect of the change in the price of

\[\text{We use the indicators of animal diseases (BSE}_{t-k} \text{ and } \text{HPAI}_{t-k}) \text{ rather than actual animal diseases (BSE}_{t-k} \text{ and } \text{HPAI}_{t-k}) \text{ because some periods did not capture animal diseases so that their logarithmic forms are meaningless.}\]
Based on economic theory, general demand restrictions were imposed using parameter constraints (Marsh et al., 2004). The adding-up condition is imposed as
\[
\begin{align*}
\sum_{i=1}^{4} \theta_{it} &= 1, \sum_{i=1}^{4} \phi_{it} = 0, \sum_{i=1}^{4} \pi_{ijt} = 0, \sum_{i=1}^{4} \psi_{its} = 0, \sum_{i=1}^{4} \alpha_{it} = 0, \\
\sum_{i=1}^{4} \beta_{ikt} &= 0, \sum_{i=1}^{4} \gamma_{ikt} = 0, \forall j, s, \forall k \in \{0, 1\}
\end{align*}
\] (11)
which requires that the marginal budget shares on each good summed to unity (\(\sum_{i=1}^{4} \theta_{i} = 1\)) and that the net effect of a price change on the budget equaled zero (\(\sum_{i=1}^{4} \pi_{ij} = 0\)) (Deaton and Muellbauer, 1980). The rest of the adding-up conditions requires that the net effect of a preference change on the budget sum to zero. The homogeneity and symmetry restrictions are specified as
\[
\begin{align*}
\sum_{j=1}^{4} \pi_{ijt} &= 0, \forall i, \\
\pi_{ijt} &= \pi_{jit}, \forall i, j
\end{align*}
\] (12) (13)
As our error variance-covariance matrix is unknown, we applied an time-varying feasible seemingly unrelated regression (SUR) with local constant estimators developed by Casas and Fernandez-Casal (2019) to estimations.\(^4\)\(^5\) In practice, similar to traditional SUR estimation, the time-varying feasible SUR approach dropped one equation of commodity \(i\) and built a system of three equations under the adding-up constraint. The coefficients and the variances of the dropped equation were recovered using a series of nonlinear combination calculations.

In the second step, given the estimates in equation (10) derived from local constant estimators, we obtained the time-varying compensated elasticities specified as
\[
\begin{align*}
\varepsilon_{ijt} &= \frac{\pi_{ijt}}{w_{it}}, \eta_{it} = \frac{\theta_{it}}{w_{it}}, \lambda_{BSE,ikt} = \frac{\beta_{ikt}}{w_{it}}, \lambda_{HPAI,ikt} = \frac{\gamma_{ikt}}{w_{it}}, \forall i, j, \forall k \in \{0, 1\}
\end{align*}
\] (14)
where \(\varepsilon_{ijt}\) refers to time-varying own-price elasticities if \(i = j\) and time-varying cross-price elas-
\(^4\)The SUR estimation assumes of exogeneity of meat prices. We tested the exogeneity of prices based on the estimation of fixed-coefficient Rotterdam model equation B.1 in Appendix B.2.
\(^5\)As the package for time-varying 3SLS estimation is not available, we used time-varying feasible SUR estimation.
ticities otherwise; \( \eta_{it} \) denotes time-varying expenditure elasticities; \( \lambda_{BSE,ikt} \) and \( \lambda_{HPAI,ikt} \) are the elasticities of the demand for meat \( i \) at time \( t \) with respect to BSE and HPAI at time \( t - k \), respectively.

Since we are interested in the impact of each individual animal disease outbreak on the meat demand, we derived the actual reactions of meat demand to animal disease outbreaks as follows

\[
\% \Delta q_{it+k} = \lambda_{BSE,ikt} \cdot \% \Delta BSE_t \tag{15}
\]

or

\[
\% \Delta q_{it+k} = \lambda_{HPAI,ikt} \cdot \% \Delta HPAI_t
\]

where \( \% \Delta BSE_t \) and \( \% \Delta HPAI_t \) represent the percentage change of animal diseases BSE and HPAI at time \( t \), respectively; \( \% \Delta q_{it+k} \) denotes the percentage change of meat \( i \) consumption at time \( t + k \), which can be caused by either BSE\(_t\) or HPAI\(_t\).

Our study focused on the meat demand response to animal disease outbreaks (i.e., \( \% \Delta q_{it+k} \)) instead of elasticities for meat demand with respect to animal disease outbreaks (i.e., \( \lambda_{BSE,ikt} \) and \( \lambda_{HPAI,ikt} \)). The reasons are twofold. First, as each animal disease outbreak may contain various outbreaks, it is more practical for stakeholders such as retailers to concentrate on how much changes in consumers’ meat consumption during each outbreak. Second, our data show that most of the study periods did not capture any animal disease outbreaks. In those periods, the time-varying compensated elasticities had little practical use. Therefore, our focus was on the actual consumption change affected by each animal disease outbreak (i.e., \( \% \Delta q_{it+k} \)).

2.4 Empirical Results

In this section, we will first show the impact of animal diseases on meat demand, and then interpret the time-varying expenditure, own-price, and cross-price elasticities, followed by the robustness check with a Rotterdam model with fixed coefficients.
2.4.1 Main Results: Impact of Animal Diseases on Meat Consumption

The elasticity estimates for meat demand with respect to animal diseases were shown in Figure 5 Panel A. We also showed the values of elasticities in the disease periods in Table 7 columns (5) - (10). As we discussed in Section 3.3 and Section 3.4, we focused on the estimated effects of animal diseases on the meat demand in Table 7 columns (11) - (16) which were calculated based on equation (15).

In general, our estimates show that BSE outbreaks reduced beef demand and increased pork demand. This finding was consistent with that of Burton and Young (1996). Table 7 shows that BSE outbreaks reduced beef consumption by 0.64 percent and increased pork consumption by 2.34 percent on average. Specifically, in Quarter 3 of 2018, the BSE outbreak hampered beef demand by 0.71 percent while the BSE outbreak in Quarter 2 of 2012 enhanced the pork demand by 2.95 percent. We also found that the magnitude of BSE’s effects on pork and beef demand increased after 2006. For example, the BSE outbreak hampered the beef demand by 0.60 percent in Quarter 1 of 2006 whereas this effect expanded to 0.69 percent, 0.68 percent, and 0.71 percent in 2012, 2017, and 2018, respectively.

Table 7 columns (14) - (16) also show the longer-term effects of BSE diseases on meat demand. In the quarter following the outbreak, the BSE disease in 2003 led to a 0.82 percent rise in beef demand, indicating a reversal of the original effect. This was larger than the contemporaneous effect of the BSE outbreak on beef demand (−0.63%). This implies that the beef demand rebounded after a BSE outbreak in a larger magnitude than the reduction in beef demand during the BSE outbreak. Furthermore, the BSE disease led to a 1.20 percent and 1.21 percent growth in beef consumption in Quarter 3 of 2017 and Quarter 3 of 2018, respectively. This suggests while BSE outbreaks reduced beef demand, these effects were short-lived and did not extend beyond one quarter. On the other hand, our findings suggest that an initial increase in pork demand due to BSE was reinforced in the following quarter by 0.47 percent in Quarter 1 of 2004, suggesting a longer duration of this impact, despite falling by 1.17 percent points from 1.64 percent in Quarter 4 of 2003.
Table 7 column (13) illustrates that HPAI outbreaks reduced broiler consumption, similar to the findings of Wang and de Beville (2017). However, the broiler demand increased affected by the HPAI outbreak in Quarter 3 of 2015. This is because, unlike other periods, in Quarter 3 of 2015 the identified HPAI cases (9 cases) were much fewer than the 24892 cases in Quarter 2 of 2015, resulting in falling HPAI cases and a rising broiler demand in Quarter 3 of 2015. Additionally, the effect of HPAI outbreaks on broiler demand was highly linked to the number of identified HPAI cases. For instance, the HPAI outbreak in Quarter 2 of 2015 had the largest impact on broiler demand (-1.76%) due to its much larger number of identified cases (24892 cases) than the rest of the periods. On the other hand, the HPAI outbreak in Quarter 1 of 2004 had the smallest impact on broiler demand (-0.13%) because of the small cases detected (1 case).

Additionally, we also found the reversal effects of HPAI outbreaks on the broiler demand in the successive period in Table 7 column (16). The HPAI outbreak increased broiler demand by 3.78 percent in Quarter 2 of 2015 and reduced broiler demand by 4.34 percent in Quarter 3 of 2015. These effects were also greater than the contemporaneous effects of HPAI outbreaks. Furthermore, Table 7 column (14) shows that beef demand was enhanced following an HPAI outbreak with expanding HPAI cases. In Quarter 1 of 2004 and in Quarter 2 of 2015, the beef demand grew by 0.22 percent and 2.89 percent, respectively.

### 2.4.2 Time-varying Expenditure, Own-price and Cross-price Elasticities

**Time-varying Expenditure Elasticities**

Expenditure elasticity indicates how much one product’s consumption will change due to a variation in total food expenditure. Expenditure elasticities for beef are expected to drop in magnitude after the BSE outbreaks, which means that beef is less sensitive to changes in total food expenditure. Figure 5 Panel B indicates that the time-varying expenditure elasticities for beef declined rapidly after the 2003 BSE case with a magnitude of 0.177 percent point. This means that a one percent increase in the food budget was linked to a 0.177 percent point growth in the share of beef consumption in the budget after the 2003 BSE outbreak. This effect lasted two years until Quarter
4 of 2005 when the expenditure elasticities (1.290) surpassed the elasticities in Quarter 4 of 2003 (1.276). This was mostly compensated by the low total meat demand in Quarter 4 of 2003 in which the meat consumption decreased to the lowest level (54.42 lb/capita) during the period 2003-2007 (see Figure B3). Our estimates show that expenditure elasticities for broilers were larger than the expenditure elasticities for beef and pork in all the periods. This implies that demand for broilers was the most sensitive to the changes in total food expenditure. These estimates supported the findings of Chen (1998) and Huang and Lin (2000).

Using a demand system with the time-varying parameters, Mazzocchi (2003) detected a negative trend in time-varying expenditure elasticities for meat and concluded that a change in taste is likely to be affected by consumers’ health concerns. Our study extends Mazzocchi (2003) by ruling out the role of health concerns in the expenditure elasticities. Specifically, our study controlled the health concerns by augmenting the low-whole milk ratio to our Rotterdam model. We found that meat expenditure elasticities had a rising trend for beef, pork, and broilers. The alternative reason to explain the upward trends in time-varying expenditure elasticities might be that U.S. consumers had an increasing demand for protein in general.

**Time-varying Own-price Elasticities**

Own-price elasticities reflect the change in the quantity of a food product due to a variation in its own price. Because of the BSE outbreak, the own-price elasticity for beef is expected to increase in magnitude. Figure 5, Panel C shows that an increasing percentage in the beef prices was associated with a diminishing ratio of beef consumption, which indicates that beef was a normal good. Additionally, our estimates show the own-price elasticities had a decreasing trend after the 2003 BSE outbreak. Specifically, a one percent decrease in beef prices led to a rise in beef demand with the magnitude of 0.417 percent in Quarter 4 of 2003 and 0.536 percent in Quarter 3 of 2018. This suggests that U.S. consumers were more price-elastic for beef products over time. Our estimate for own-price elasticities for beef was consistent with the elasticities obtained by Hahn (2001) and Yadavalli and Jones (2014).
Figure 5: Compensated Elasticities of Rotterdam Models with Time-varying Coefficients

Panel A. Elasticities for Meat Demand with Respect to Animal Diseases
Panel D: Estimated Cross-price Elasticity

Notes: The compensated elasticities of Rotterdam models with time-varying coefficients were calculated based on equation (14). Estimations in pork equation were estimated based on the restrictions of adding-up, homogeneity, and symmetry for Rotterdam models with time-varying coefficients. The time-varying estimates were local constant estimates based on R package “tvReg” developed by Casas and Fernandez-Casal (2019). Bandwidths of time-varying estimates were selected by leave-one-out cross-validations. When the search for a bandwidth does not converge, we used a bandwidth = 20. Bandwidths were equal to 20, 2.21 and 1.75 for beef, pork, and broiler equations, respectively. MSE of the time-varying estimates was 0.0018.
Table 7: Effects of The Animal Disease Outbreaks on The Meat Demand

<table>
<thead>
<tr>
<th>Names</th>
<th>Year</th>
<th>Quarter</th>
<th>Cases (#)</th>
<th>(1) Animal disease outbreaks at time $t$</th>
<th>(2) Disease elasticities of meat demand at time $t$</th>
<th>(5) Disease elasticities of meat demand at time $t + 1$</th>
<th>(8) Meat demand at time $t$</th>
<th>(11) Meat demand response at time $t + 1$</th>
<th>(14) Meat demand response at time $t + 1$</th>
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<tr>
<td>BSE</td>
<td>2003</td>
<td>4</td>
<td>1</td>
<td>-0.009 -0.024 -0.023 0.012 0.007 -0.016 -0.628 1.640</td>
<td>-0.628 1.640</td>
<td>-1.589 0.820 0.471 -1.076</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2005</td>
<td>2</td>
<td>1</td>
<td>-0.008 0.030 -0.020 0.013 0.007 -0.016 -0.547 2.082</td>
<td>-0.547 2.082</td>
<td>-1.384 0.885 0.515 -1.128</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2006</td>
<td>1</td>
<td>1</td>
<td>-0.009 0.030 -0.020 0.014 0.008 -0.018 -0.601 2.111</td>
<td>-0.601 2.111</td>
<td>-1.409 0.948 0.556 -1.250</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>2</td>
<td>1</td>
<td>-0.010 0.042 -0.022 0.016 0.006 -0.018 -0.689 2.945</td>
<td>-0.689 2.945</td>
<td>-1.555 1.088 0.442 -1.273</td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>1</td>
<td>1</td>
<td>-0.010 0.036 -0.020 0.017 0.004 -0.017 -0.679 2.496</td>
<td>-0.679 2.496</td>
<td>-1.412 1.196 0.261 -1.177</td>
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<td></td>
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<tr>
<td></td>
<td>2017</td>
<td>2</td>
<td>24892</td>
<td>-0.001 -0.004 -0.002 0.004 -0.001 0.004 -0.092 -0.207</td>
<td>-0.092 -0.207</td>
<td>-0.125 0.222 -0.100 0.310</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2018</td>
<td>3</td>
<td>1</td>
<td>-0.010 0.040 -0.021 0.017 0.003 -0.017 -0.712 2.778</td>
<td>-0.712 2.778</td>
<td>-1.455 1.210 0.238 -1.174</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>HPAI</td>
<td>2004</td>
<td>1</td>
<td>1</td>
<td>-0.001 -0.003 -0.002 0.003 -0.001 0.004 -0.092 -0.207</td>
<td>-0.092 -0.207</td>
<td>-0.125 0.222 -0.100 0.310</td>
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</tr>
<tr>
<td></td>
<td>2014</td>
<td>1</td>
<td>65</td>
<td>-0.002 -0.004 -0.002 0.004 -0.002 0.006 -0.695 -1.850</td>
<td>-0.695 -1.850</td>
<td>-1.031 1.716 -0.866 2.552</td>
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<tr>
<td></td>
<td>2015</td>
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<td>14</td>
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<td>-0.406 -1.016</td>
<td>-0.620 1.081 -0.561 1.524</td>
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<tr>
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<td>24892</td>
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<td>-1.121 -3.355</td>
<td>-1.758 2.890 -1.367 3.775</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>3</td>
<td>9</td>
<td>-0.001 -0.004 -0.002 0.004 -0.002 0.006 1.150 3.145</td>
<td>1.150 3.145</td>
<td>1.681 -3.392 1.287 -4.342</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Note: Disease elasticities of meat demand ($\lambda_{BSE,ikt}$ and $\lambda_{HPAI,ikt}$) from columns (5) - (10) were calculated based on equation (14). Meat demand responses ($\%\Delta q_{it+k}$) in columns (11) - (16) were calculated based on equation (15).
Time-varying Cross-price Elasticities

Cross-price elasticities measure the sensitivity of the demand for a product caused by a shift in the price of a corresponding product. Figure 5, Panel D uses the time-varying elasticities to capture a shift in preference for meat products. Particularly, Panel D captures an increasing trend in the cross-price elasticity curve for pork with respect to beef. Specifically, a one percent rise in beef price resulted in a 0.244 percent growth in pork demand in Quarter 4 of 2003 and a 0.438 percent growth in Quarter 3 of 2018. This implies that beef was substituted more by pork products in 2018 compared to 2003. This finding of the substitution between beef and pork was consistent with Burton and Young (1996). This finding can also be supported by the time-varying cross-price elasticity for pork with respect to beef, whose curve showed a flat trend before Quarter 4 of 2003 and an increasing trend after Quarter 4 of 2003.

Our estimates also show that time-varying elasticity for beef with respect to broilers had a similar pattern to the elasticity for beef with respect to pork, which had a decreasing trend before Quarter 4 of 2003 and a rising trend after Quarter 1 of 2004. Particularly, the cross-price elasticity for beef with respect to broilers decreased from 0.080 in Quarter 3 of 1997 to 0.059 in Quarter 4 of 2003 and increased from 0.050 in Quarter 1 of 2004 to 0.088 in Quarter 4 of 2019. Also, we spotted a similar pattern in the elasticity for broiler demand with respect to beef prices with the values falling from 0.188 in Quarter 3 of 1997 to 0.131 in Quarter 1 of 2004 and rebounding afterward. These two cross-price elasticities between broiler and beef showed that after Quarter 4 of 2003, beef and broilers became stronger substitutes.

2.4.3 Robustness Check

As a robustness check, we derived the fixed elasticities in Table B1 in Appendix B.2 based on the fixed-coefficient Rotterdam model (see details in Appendix B.2). Table B1 indicates that the U.S. BSE outbreaks contemporaneously enhanced the pork demand significantly. Specifically, a ten percent rise in the BSE cases resulted in a 0.31 percent rise in the pork demand, suggesting a substitution relationship between beef and pork. Additionally, a ten percent rise in the lagged
HPAI cases significantly increased the beef demand by 0.04 percent and broiler demand by 0.06 percent. These findings supported the results from time-varying elasticities in terms of the signs.

### 2.5 Summary and Conclusions

This study focused on U.S. meat consumption during the period from 1997 to 2019. Using fixed elasticities shown in tables and time-varying elasticities shown in figures, our research estimated the impacts of two domestic animal diseases (BSE and HPAI) on the demand for beef, pork, broilers, and other food. We derived the time-varying elasticities from a Rotterdam model with time-varying coefficients. Our study focused on the percentage change in meat consumption due to the changes in animal disease cases. We showed that pork demand was greatly enhanced due to the BSE diseases in the same period. Increasing HPAI cases result in a lower contemporaneous broiler consumption.

While beef demand was reduced during the BSE outbreak, these effects were short lived and did not extend beyond one quarter. On the other hand, HPAI outbreaks led to a smaller consumption of broiler. The bird flu outbreak reduced the broiler by 1.76 percent because of the large number of identified bird flu cases in Quarter 2 of 2015.

Additionally, using time-varying expenditure elasticities for beef fell rapidly after the 2003 BSE case with a magnitude of 0.177 percent point. Time-varying own-price elasticities indicated that U.S. consumers were more price-elastic for beef products from 2004 to 2019. Our estimates for time-varying cross-price elasticities indicate that the substitutions between beef and broilers and between beef and pork become stronger since 2004. However, the substitution relation between pork and broilers was relatively stable across time periods.

Since beef, pork, and broiler markets are the main types of meat in the U.S., the implications from our study are informative for U.S. retail markets. Our findings suggest that retailers should adjust their inventories to increase the substitutes of meat affected by a disease outbreak. For instance, if a BSE case is identified, grocery stores should add more pork products to their inventories.
2.6 Limitations and Avenues for Further Research

Despite the precise effect of animal disease outbreaks on the meat demand that we derived from the time-varying estimators, one limitation of our study is that, unlike parametric analysis, we were not able to show the significance levels of those time-varying estimators. Previous studies have shown the significance of time-varying estimates (Ning et al., 2022). Our study shows that some outbreaks led to a small change in the magnitude of meat consumption. These estimates might be not statistically significant, which we reserve for future studies.

Our study analysed the impact of animal disease outbreaks on the meat demand. We did not concentrated on the price responses to animal disease outbreaks. Previous studies have shown the price effect of market events using an inverse demand system such as inverse Rotterdam models (e.g. Barten and Bettendorf, 1989; Eales et al., 1997; Brown and Lee, 2010). Further studies can use this approach to show the impact of animal disease outbreaks on meat retailed prices.

While our study analyzed the effects of BSE and HPAI outbreaks on U.S. meat consumption, we did not examine the impact of African swine fever (ASF) on U.S. markets. ASF is confined to Africa until the mid-20th century when it spread to Europe, and further to South America (Costard et al., 2013). ASF heavily hit China’s hog and pork industry starting in August 2018 and throughout 2019. As China has the largest pork market in the world, ASF in China can indirectly influence the global pork market as well (Carriquiry et al., 2020). Our study did not include ASF as the U.S. did not have any cases of ASF so far (USDA, 2020). Further study can consider the foreign animal diseases' impacts on the domestic meat market.
3 Impact of North American Mad Cow Disease Outbreaks on The U.S. Cattle Futures

3.1 Introduction

In the U.S. livestock industry, the cattle futures markets have witnessed shocks from animal diseases detected in North America. One famous animal disease is Bovine Spongiform Encephalopathy (BSE) which causes a progressive neurological disorder in cattle (CDC, 2021). BSE was first spotted in Canada in May 2003 and later in the U.S. in December 2003. Jin et al. (2008) found that both BSE outbreaks significantly increased the volatility of U.S. cattle futures prices. From 2010 to 2019, six BSE outbreaks were detected in Canada and U.S. Literature has found that the 2012 U.S. BSE significantly affected cattle futures (Houser and Karali, 2020) while the effects of the other BSE outbreaks from 2010 to 2019 have not been examined by previous studies.

While extensive studies explored the impact of animal diseases on livestock markets (Jin et al., 2008; Schulz and Tonsor, 2015; Houser and Karali, 2020), little was known about the duration of BSE outbreaks’ effects on the livestock futures prices. As the duration of the market response is meaningful to forecast cattle futures, the goal of our study is to explore the duration and magnitude of the impact of animal diseases on cattle futures. In particular, we established an empirical model and conducted a nonlinear analysis to estimate the market response to the outbreak event.

Our results show that the U.S. BSE outbreak in 2017 reduced the nearby futures of live cattle. We also show that the duration of the BSE response was about 8.5 days. We indicate that the BSE caused a maximum effect on the cattle futures on the 15th day after the BSE case was announced in the U.S.

This study makes several contributions to the literature. First, our study is the first one that
provides a precise estimation of the duration of the market response to animal disease events. Second, we show the evidence of the market response to the animal diseases, which can be used in forecasting cattle futures.

3.2 Literature Review

An extensive literature found the magnitude of the effects of BSE (e.g. Henson and Mazzocchi, 2002; Jin et al., 2008; Houser and Karali, 2020; Ning et al., 2022) on the cattle market. Specifically, Henson and Mazzocchi (2002) showed that the returns in the U.K. beef sectors suffered from a significant fall after British BSE outbreaks. Jin et al. (2008) indicated live cattle futures contracts fell from $79.975/cwt in late January 2003 to $73.35/cwt in mid-March 2003 due to the BSE outbreak. Houser and Karali (2020) illustrated that returns for lean hog futures increased by 1.64 percentage points on average due to the 2003 U.S. BSE outbreak. However, this study excluded seventeen detected BSE outbreaks in North America during the study period and explored the market response from only two BSE outbreaks in the USA. Ning et al. (2022) estimated the impact of the 2003 U.S. BSE outbreak on the U.S. imports from three major origins. Their study showed that own-price elasticities for beef imports were more price elastic after the 2003 BSE outbreak.

While a number of studies showed the magnitude of market response, the duration of diseases’ effects was less explored. Jin et al. (2008) found that the effect of the 2003 Canada BSE outbreak on U.S. cattle futures lasted for one day. On the other hand, the 2003 U.S. BSE disease caused a persistent impact on the nearby December and February maturity futures prices for five months. However, Jin et al. (2008) failed to estimate the precise duration of the U.S. BSE effect. Park et al. (2008) estimated the precise duration of animal disease effects on retail prices of beef and pork in Korea. However, this study did not focus on the futures market. Using the estimation of several different event windows, Houser and Karali (2020) also explored the volatility in livestock futures markets when BSE and HIN1 were detected. However, these windows might not be accurate if the actual duration of the market response is not equal to the width of the given windows. Yet, no

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studies have examined the precise duration of the futures market impact of animal diseases using U.S. livestock futures.

Several studies used nonlinear estimations to derive the duration and magnitude of the disease impact on prices (Rucker et al., 2005; Karali et al., 2019; Neill and Chen, 2021). For instance, Rucker et al. (2005) established a distributional event response model (DERM) to estimate the market impact of various events on lumber futures. Other follow-up studies also developed that model for crude oil markets (Karali et al., 2019) and egg markets (Neill and Chen, 2021).\footnote{In particular, Karali et al. (2019) established a mixed event response model (MERM) that allowed for asymmetric effects.} One advantage of the DERM model is that a DERM model allows a nonlinear event response and is hence less restrictive in assumptions than the traditional linear model. Additionally, using a DERM model, we can estimate the duration and magnitude of market responses to each individual event. Therefore, following Rucker et al. (2005) and Neill and Chen (2021), we will use a DERM model in empirical analysis.

Previous studies also explored how various factors affected the distant or deferred futures (Frank et al., 2008; Karali, 2012; Houser and Karali, 2020). Different from these studies, our study did not consider distant futures. The reason is that different from the approaches used by Frank et al. (2008), Karali (2012), or Houser and Karali (2020), the DERM model can maximize the log likelihood by selecting the optimal period that could be far away from the date of disease outbreak detected. Therefore, we do not include distant futures in our empirical analysis.

3.3 Data

The dataset includes daily livestock futures prices of live cattle (LC) collected from the Chicago Mercantile Exchange (CME). To eliminate the dynamic effect of the recession during 2007-2009 as well as the COVID pandemic on the futures, we focus on the futures prices from January 1, 2010, to the latest time December 31, 2019. Livestock prices had a dynamic pattern in the financial crisis during 2007-2009 and the crisis impact lasted for months (Powell et al., 2019). Therefore,
the impact of the financial crisis on the futures market should be considered if the study period includes the observations from 2007 to 2009.

Live cattle futures expires in February, April, June, August, October, and December. We used the futures contracts that expired in one or two months to obtain the nearby futures. Table 8 shows the contracts that we use in this study. As no futures are traded on weekends or national holidays, we have a sample size of 2,519 daily cattle futures prices.

<table>
<thead>
<tr>
<th>Calendar Month</th>
<th>Nearby Contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>January&lt;sub&gt;t&lt;/sub&gt;</td>
<td>February&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>February&lt;sub&gt;t&lt;/sub&gt;</td>
<td>April&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>March&lt;sub&gt;t&lt;/sub&gt;</td>
<td>April&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>April&lt;sub&gt;t&lt;/sub&gt;</td>
<td>June&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>May&lt;sub&gt;t&lt;/sub&gt;</td>
<td>June&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>June&lt;sub&gt;t&lt;/sub&gt;</td>
<td>August&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>July&lt;sub&gt;t&lt;/sub&gt;</td>
<td>August&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>August&lt;sub&gt;t&lt;/sub&gt;</td>
<td>October&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>September&lt;sub&gt;t&lt;/sub&gt;</td>
<td>October&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>October&lt;sub&gt;t&lt;/sub&gt;</td>
<td>December&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>November&lt;sub&gt;t&lt;/sub&gt;</td>
<td>December&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>December&lt;sub&gt;t&lt;/sub&gt;</td>
<td>February&lt;sub&gt;t+1&lt;/sub&gt;</td>
</tr>
</tbody>
</table>

Notes: \( t \) and \( t+1 \) denote the current year and the following year, respectively.

As we aim to capture the impact of animal disease events directly related to the U.S. food supply chain, our study excluded the BSE outbreaks outside of Canada and the U.S. Data on BSE outbreaks were collected from the Centers for Disease Control (CDC) and World Organization for Animal Disease (OIE). CDC documented the date of each BSE case.

From 2010 to 2019, North America had six BSE outbreaks. Among six BSE outbreaks, three of them were in the U.S., identified on April 15, 2013, July 18, 2017, and August 29, 2018, respectively, and the other three were detected in Canada on February 12, 2010, February 10, 2011, and February 12, 2015. During each BSE outbreak, only one BSE case was detected.

Figure 6 shows the time-series pattern of futures prices and returns of the live cattle. Live cattle
futures prices had an increasing trend until mid-2014 when the prices have a peak. Lean hog futures prices reached the top level in late 2014 and had a falling tendency after 2014. These patterns show that they are likely to have a unit root. On the other hand, the returns of live cattle and lean hogs oscillated around zero in the study period.

Figure 6: Futures Prices and Returns of Live Cattle (LC)

Notes: U.S. BSE outbreaks were identified on April 15, 2013, July 18, 2017, and August 29, 2018. Canadian BSE outbreaks were detected on February 12, 2010, February 10, 2011, and February 12, 2015.

Table 9 shows the descriptive statistics of the closing futures prices of live cattle that was equal to 121.942 cents/lb on average. Augmented Dickey-Fuller (ADF) test and KPSS both show that the futures prices of live cattle contained a unit root at the 95% confidence level. Hence we derived the return of futures that was specified as:

$$R_t = \ln \frac{P_t}{P_{t-1}} \times 100$$
Table 9: Summary Statistics of Cattle Futures

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>S.D.</th>
<th>Max</th>
<th>Min</th>
<th>ADF</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prices (U.S. cents per pound)</td>
<td>121.942</td>
<td>120.425</td>
<td>17.243</td>
<td>171</td>
<td>85.05</td>
<td>-2.443</td>
<td>1.610***</td>
</tr>
<tr>
<td>Returns</td>
<td>0.008</td>
<td>0.000</td>
<td>0.965</td>
<td>3.522</td>
<td>-4.434</td>
<td>-47.992***</td>
<td>0.038</td>
</tr>
</tbody>
</table>

Notes: The number of observations is 2,519. ADF tests choose the optimal lags using BIC criteria. KPSS tests use Maxlag = 26 chosen by Schwert criterion for all the futures prices and returns. *, **, and ***, reflect significance at the 10%, 5%, and 1% levels of significance, respectively.

Table 9 shows that the mean of cattle returns was 0.008 with a much smaller standard deviation (0.965) than futures prices (17.243). We also conducted seasonal analysis on the cattle returns. Figure C1 in the Appendix shows no seasonality in the series of cattle returns. Additionally, ADF and KPSS tests in Table 9 show that the returns of live cattle were stationary. Our study hence focused on the live cattle returns in the following empirical analysis.

3.4 Methodology

We first implemented a linear model as a baseline in estimations. We also added lagged cattle returns ($R_{t-s}$) as independent variables to solve a potential autocorrelation problem in the model estimation. The linear model is specified as

$$R_t = \alpha + \sum_{s=1}^{2} \beta_s R_{t-s} + \sum_{i=1}^{3} \gamma_i I_{US,i} + \sum_{j=1}^{3} \theta_j I_{CA,i} + \varepsilon_t$$ (16)

where $R_t$ and $R_{t-s}$ denote the cattle returns at time $t$ and $t-s$, respectively; $I_{US,i}$ and $I_{CA,i}$ denote the dummies for BSE outbreaks in U.S. and Canada, respectively. $I_{US,i}$ (or $I_{CA,i}$) is equal to 1 on date $t$ if a BSE outbreak is detected on that day and 0 otherwise; $\alpha$, $\beta_s$, $\gamma_i$, and $\theta_i$ are the parameters that need to be estimated.

We used a DERM model to estimate the magnitude and the duration of each animal disease’s effect on U.S. cattle returns. We assumed symmetric effects of animal diseases on the cattle futures

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2The p-value for the second order autocorrelation test for the residual in equation 16 is 0.0923, indicating no autocorrelation problem in the second order.
market. Therefore, following Rucker et al. (2005) and Neill and Chen (2021), we let the distribution to be normal and hence applied a DERM model with a normal distribution (hereafter referred to as NERM) in our empirical analysis. The NERM model is specified as

\[ R_t = \alpha + \sum_{s=1}^{2} \beta_s R_{t-s} + \sum_{i=1}^{3} \gamma_i f(D^US_i, \mu_{US}, \sigma_{US}) + \sum_{j=1}^{3} \theta_j f(D^CA_j, \mu_{CA}, \sigma_{CA}) + \epsilon_t \quad (17) \]

\( f(\cdot) \) denotes the probability density function (p.d.f) that is assumed to follow the normal distribution:

\[ f(D^k_t, \mu_k, \sigma_k) = \frac{1}{\sigma_k \sqrt{2\pi}} \exp \left( -\frac{(D^k_t - \mu_k)^2}{2\sigma_k^2} \right), \quad k = \text{US}_i \text{ or CA}_j \quad (18) \]

where \( D^k_t \) denotes a counter variable showing the difference between any date \( t \) and the date when a particular animal disease outbreak \( k \) was detected in the U.S. (US) or in Canada (CA).\(^3\) \( \epsilon_t \) is the error term that is assumed to be i.i.d.

\( \alpha, \beta, \gamma_i, \theta_i, \mu_k \) and \( \sigma_k \) are the parameters that need to be estimated. Particularly, \( \beta, \gamma_i \) and \( \theta_i \) are linear parameters. \( \beta \) denotes the impact of lagged returns on returns; the value of \( \gamma_i \) and \( \theta_i \) denote the magnitude of the cattle price response to an individual BSE outbreak in the U.S. and Canada, respectively.

\( \mu_k \) and \( \sigma_k \) denote the nonlinear parameters in the distribution function \( f(\cdot) \) for disease \( k \). Both parameters determine the pattern of the market response after a disease outbreak event. Particularly, \( \mu_k \) measures the distance between the largest effect and the outbreak dates. \( \sigma_k \) affects the dates on which futures are affected by disease outbreaks. Here, we added one restriction to the model estimation by assuming that the outbreaks of one animal disease in one country shared the same distribution.\(^4\) This means that all the outbreaks in one country had the same \( \mu_k \) and \( \sigma_k \). Despite this, the magnitude of the market impact possibly varied by outbreaks and was affected by \( \gamma_i \) and \( \theta_j \). In addition, since using five or more nonlinear parameters failed to generate estimates for all the parameters, we hence only estimated \( \sigma_{US}, \mu_{US}, \sigma_{CA}, \text{ and } \mu_{CA} \) in this study.

We used full information maximum likelihood (FIML) in model estimations for all the linear and

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\(^3\)As the cattle futures did not include holiday dates, this counter variable only include the trading dates.

\(^4\)In practice, as the FIML method in estimations might generate a negative \( \sigma_k \), we also added another restriction of \( \sigma_k > 0 \), which should be a defaulted condition.
nonlinear parameters. In particular, Gauss-Newton parameter-change vector was used for minimizing the objective function. Additionally, Breusch–Godfrey Lagrange multiplier test was applied after model estimations to detect the potential autocorrelation problem.

### 3.5 Empirical Results

Table 10 shows the estimation for the linear model and NERM model. The estimation for the linear model shows that lagged cattle return is positively connected to current return. In addition, cattle return was increased by 1.588 percent due to the 2011 Canada BSE outbreak. Cattle return was reduced by 2.634 and 1.589 percent due to the U.S. BSE in 2012 and 2017, respectively. Our estimates for the linear model indicate that Canadian BSE outbreaks can increase U.S. cattle returns while U.S. BSE outbreaks lessened U.S. cattle returns.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Linear Model</th>
<th>NERM Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t Value</td>
</tr>
<tr>
<td>Constant</td>
<td>0.009</td>
<td>0.47</td>
</tr>
<tr>
<td>Lag 1. Returns</td>
<td>0.044**</td>
<td>2.22</td>
</tr>
<tr>
<td>Lag 2. Returns</td>
<td>-0.014</td>
<td>-0.71</td>
</tr>
<tr>
<td>2010 Canada BSE</td>
<td>-0.858</td>
<td>-0.89</td>
</tr>
<tr>
<td>2011 Canada BSE</td>
<td>1.588*</td>
<td>1.65</td>
</tr>
<tr>
<td>2015 Canada BSE</td>
<td>0.086</td>
<td>0.09</td>
</tr>
<tr>
<td>( \mu_{CA} )</td>
<td>65.990***</td>
<td>34.13</td>
</tr>
<tr>
<td>( \sigma_{CA} )</td>
<td>3.320</td>
<td>1.50</td>
</tr>
<tr>
<td>2012 US BSE</td>
<td>-2.634***</td>
<td>-2.74</td>
</tr>
<tr>
<td>2017 US BSE</td>
<td>-1.589*</td>
<td>-1.65</td>
</tr>
<tr>
<td>2018 US BSE</td>
<td>0.290</td>
<td>0.3</td>
</tr>
<tr>
<td>( \mu_{US} )</td>
<td>15.277***</td>
<td>18.76</td>
</tr>
<tr>
<td>( \sigma_{US} )</td>
<td>1.514**</td>
<td>1.97</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-3470.61</td>
<td>-3468.14</td>
</tr>
<tr>
<td>AIC</td>
<td>6959.22</td>
<td>6958.28</td>
</tr>
<tr>
<td>BIC</td>
<td>7011.69</td>
<td>6980.49</td>
</tr>
</tbody>
</table>

Notes: *, **, and ***, reflect significance at the 10%, 5%, and 1% levels of significance, respectively. CA and US denotes Canada and U.S., respectively.

Table 10 also shows the estimation of the NERM model. The model estimation results indicate
that the p-value of Godfrey’s Serial Correlation Test was 0.6281, suggesting the autocorrelation problem was not detected in the model estimation at the 5% significance level. Table 10 also shows the parameters for the constant term were not significantly different from zero and the first-lagged term of the return positively affected the current return. The significant $\mu_k$ for Canadian BSE outbreaks indicate the greatest impact of Canadian BSE’s impacts on cattle returns took place on the day 65.99 after the BSE was reported. However, despite the significant $\mu_{CA}$, none of the Canadian BSE outbreaks caused significant impacts on the cattle returns.

On the other hand, the significant $\sigma_k$ and $\mu_k$ for the U.S. BSE outbreaks in Table 10 indicate the symmetric buildup and decay of animal diseases’ impacts on cattle returns. Specifically, $\mu_{US}$ and $\mu_{US}$ were equal to 1.514 and 15.277, respectively. This means that the largest change in cattle returns happened on the 15th after the U.S. BSE outbreaks.

We also show the model evaluation of the linear model and the NERM model in Table 10. As the NERM model estimates have a larger log likelihood value and smaller values of AIC and BIC, the NERM model had a better performance in modeling the impact. Table 10 also indicates a negative effect of the 2017 BSE outbreak on the cattle futures. As our estimates were based on a nonlinear estimation, we showed a figure of the NERM model estimates that were relevant to the 2017 U.S. BSE outbreak from Table 10.

Figure 7 indicates an intuitive illustration of $\hat{\gamma}_5$, $\hat{\sigma}_{US}$, and $\hat{\mu}_{US}$ estimated from Table 10. Specifically, using a 99% confidence level, Figure 7 shows that the cattle market response to the 2017 BSE outbreak took place on the 11th day after that BSE outbreak was reported. On the 15th day, the BSE effect on cattle futures reach a peak where live cattle return was reduced by 1.89 percent due to the 2017 BSE outbreak. This is the greatest impact on cattle futures caused by the U.S. BSE outbreak. The effect of the 2017 BSE outbreak lasted about 8.5 days ($19.527 - 11.027 = 8.500$) and the effect disappeared on the 19th day after the BSE outbreak was detected. Compared to the linear estimates for the 2017 U.S. BSE outbreak (-1.589), we show our estimates in the NERM model were consistent in terms of sign and magnitude.

Unlike Houser and Karali (2020), our study did not capture the significant effect of the 2012 U.S.
BSE outbreak on the deferred futures. This is expected since we can only estimate the event response in the window of [11.027, 19.527] on the nearby futures. This window, however, was not in the estimation of Houser and Karali (2020) either. Our study provides a much more accurate duration of the market response. This is our main contribution to the literature.

3.6 Summary and Conclusions

Our study investigated the impact of North American BSE outbreaks on U.S. cattle returns. We were particularly interested in the duration and magnitude of each animal disease outbreak. Using a NERM model with a normal distribution, we showed that the U.S. BSE outbreak in 2017 negatively affected nearby cattle futures. Compared to the linear estimates, we show our estimates in the
NERM model were consistent in terms of sign and magnitude. This shows that the NERM estimates are robust.

Following previous DERM studies, our study estimated the nuisance parameters including the variance parameters (or speed-of-adjustment parameters) $\sigma_{US}$ and $\sigma_{CA}$. Other studies regarding nonlinear analysis have mentioned the testing for these nuisance parameters. In particular, Davies (1977, 1987) have addressed an identification problem for the nuisance parameters under the null of “no effect”. Teräsvirta (1994) used Lagrange multiplier (LM)-type tests for these nuisance parameters. However, previous studies regarding the DERM model missed testing for these parameters. In addition, the variance parameters have a non-standard asymptotic distribution so the typical t-test does not apply in these cases. Future studies can implement tests for these nuisance parameters in the DERM model.

We assumed the outbreak from the same country had identical parameters of a distributional function. This assumption suggested that the outbreaks from one country had the same duration time. However, this assumption may be not true. In particular, previous studies found first BSE in Canada and USA might have different impacts on the cattle futures returns (Houser and Karali, 2020). Further study can relax the assumption of the same parameters (such as $\mu_k$ and $\sigma_k$) in one country in the NERM model. Additionally, our study assumes that the DERM model follows a normal distribution, but the distribution function might have a more complex form if the event has a larger impact on the global market (Karali et al., 2019). Further studies can assume a different distributional function in the DERM model.

Another consideration is different from African Swine Fever (ASF), which is a prevalent disease. As the U.S. has not identified any ASF cases yet while other continents such as Europe and Asia found more ASF cases last five years, future studies can explore how the U.S. livestock futures market is affected by ASF outbreaks in foreign countries. Additionally, our study only considers the impact of animal diseases on the cattle market in the U.S. We did not explore the effects on hog futures such as lean hog (LH). Future studies can take the hog futures as their main focus.
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Appendices
Appendix for Chapter 1
Table A1: OLS Estimates of Trends and Seasonality in Grass-fed Premiums Measured as Raw Price Premiums, 2014-2021

<table>
<thead>
<tr>
<th>Beef Cuts</th>
<th>Filet Mignon</th>
<th>Tenderloin</th>
<th>Ribeye Steak</th>
<th>Sirloin Steak</th>
<th>Skirt Steak</th>
<th>Flat Iron Steak</th>
<th>Flank Steak</th>
<th>Rump Roast</th>
<th>Brisket Chuck Roast</th>
<th>Short Ribs</th>
<th>Stew Meat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trend</td>
<td>-0.1448***</td>
<td>-0.0711***</td>
<td>-0.0025</td>
<td>0.0040</td>
<td>0.0402***</td>
<td>0.0165***</td>
<td>0.0078**</td>
<td>0.0077</td>
<td>0.0076***</td>
<td>-0.0216***</td>
<td>-0.0024</td>
</tr>
<tr>
<td>Feb</td>
<td>0.6536</td>
<td>5.0011*</td>
<td>1.8900*</td>
<td>0.9547</td>
<td>-0.4939</td>
<td>0.5273</td>
<td>0.3185</td>
<td>0.0665</td>
<td>0.8510</td>
<td>-0.7239**</td>
<td>0.1978</td>
</tr>
<tr>
<td>Mar</td>
<td>1.0934</td>
<td>4.3159</td>
<td>1.2812</td>
<td>1.1495</td>
<td>-0.2703</td>
<td>0.9771</td>
<td>0.2120</td>
<td>-0.4431</td>
<td>1.6433**</td>
<td>-0.2115</td>
<td>0.4144</td>
</tr>
<tr>
<td>Apr</td>
<td>2.7269</td>
<td>2.5232</td>
<td>1.2030</td>
<td>0.9729</td>
<td>-0.8893</td>
<td>0.3107</td>
<td>-0.1170</td>
<td>-0.0146</td>
<td>0.7081</td>
<td>-0.2916</td>
<td>0.2110</td>
</tr>
<tr>
<td>May</td>
<td>3.2180</td>
<td>7.0181***</td>
<td>0.5042</td>
<td>1.4952</td>
<td>-0.8782</td>
<td>1.6280*</td>
<td>0.4413</td>
<td>1.8979***</td>
<td>0.1058</td>
<td>0.2938</td>
<td>0.0005</td>
</tr>
<tr>
<td>Jun</td>
<td>1.3590</td>
<td>7.7954***</td>
<td>0.2679</td>
<td>0.3074</td>
<td>-0.7011</td>
<td>1.8615**</td>
<td>-0.7474</td>
<td>-0.0952</td>
<td>1.9102***</td>
<td>-0.2243</td>
<td>0.0892</td>
</tr>
<tr>
<td>Jul</td>
<td>3.0998</td>
<td>3.0427</td>
<td>1.3472</td>
<td>1.3695</td>
<td>-0.8060</td>
<td>1.0288</td>
<td>-0.8177</td>
<td>-0.3205</td>
<td>1.1288</td>
<td>-0.6082*</td>
<td>0.2945</td>
</tr>
<tr>
<td>Aug</td>
<td>3.2011</td>
<td>3.0300</td>
<td>0.5753</td>
<td>1.3844</td>
<td>-0.2512</td>
<td>0.4561</td>
<td>-1.1017*</td>
<td>-0.4495</td>
<td>1.5048**</td>
<td>-0.4783</td>
<td>0.1823</td>
</tr>
<tr>
<td>Sep</td>
<td>1.6347</td>
<td>2.4249</td>
<td>0.3952</td>
<td>1.0678</td>
<td>-0.3551</td>
<td>-0.0003</td>
<td>-0.3381</td>
<td>-0.0448</td>
<td>0.4809</td>
<td>-0.1309</td>
<td>-0.2386</td>
</tr>
<tr>
<td>Oct</td>
<td>1.5732</td>
<td>4.8897*</td>
<td>1.0627</td>
<td>0.9026</td>
<td>-0.7715</td>
<td>-0.3580</td>
<td>-0.3809</td>
<td>0.3886</td>
<td>1.2232*</td>
<td>-0.0160</td>
<td>-0.1133</td>
</tr>
<tr>
<td>Nov</td>
<td>2.1670</td>
<td>1.9203</td>
<td>1.2634</td>
<td>0.8270</td>
<td>-0.6672</td>
<td>0.5143</td>
<td>-0.5531</td>
<td>0.1149</td>
<td>1.5237**</td>
<td>-0.2581</td>
<td>0.2398</td>
</tr>
<tr>
<td>Dec</td>
<td>7.4041***</td>
<td>0.3783</td>
<td>0.6961</td>
<td>1.3925</td>
<td>0.8704</td>
<td>0.5557</td>
<td>-0.5336</td>
<td>0.0836</td>
<td>0.3820</td>
<td>-0.3332</td>
<td>0.6124*</td>
</tr>
<tr>
<td>R²</td>
<td>0.505</td>
<td>0.280</td>
<td>0.981</td>
<td>0.049</td>
<td>0.271</td>
<td>0.411</td>
<td>0.229</td>
<td>0.117</td>
<td>0.185</td>
<td>0.222</td>
<td>0.497</td>
</tr>
</tbody>
</table>

Notes: Number of observations is 96 for each beef cut. t-statistics in parentheses. Trend refers to a simple time trend. *, **, and *** reflect significance at the 10%, 5%, and 1% levels of significance, respectively.
Table A2: Beef Individual Estimates and Cut Panel Estimates of Independent Variables in Annual Difference of Raw Price Premiums

<table>
<thead>
<tr>
<th>Estimation Methods</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beef Cuts</td>
<td>Filet Mignon</td>
<td>Tenderloin</td>
<td>Ribeye Steak</td>
<td>Sirloin</td>
<td>Skirt Steak</td>
<td>Flat Iron Steak</td>
<td>Rump Roast</td>
<td>Brisket Roast</td>
<td>Chuck Roast</td>
<td>Short Ribs</td>
<td>Stew Meat</td>
</tr>
<tr>
<td>Constant</td>
<td>3.7775**</td>
<td>4.2580**</td>
<td>0.5204</td>
<td>1.9907</td>
<td>0.0819</td>
<td>-2.2109***</td>
<td>1.2768***</td>
<td>0.6671</td>
<td>0.6340***</td>
<td>0.2511</td>
<td>0.5995</td>
</tr>
<tr>
<td>Income</td>
<td>-0.0002</td>
<td>-0.0004</td>
<td>0.0002**</td>
<td>0.0005***</td>
<td>0.0001</td>
<td>0.0001</td>
<td>-0.0002***</td>
<td>0.0000</td>
<td>-0.0000</td>
<td>0.0001***</td>
<td>0.0001**</td>
</tr>
<tr>
<td>FAFH</td>
<td>-0.0529</td>
<td>-0.3994*</td>
<td>0.1458**</td>
<td>-0.1473*</td>
<td>-0.0475</td>
<td>0.3210***</td>
<td>0.0423</td>
<td>-0.0226</td>
<td>0.0267</td>
<td>-0.0026</td>
<td>-0.0247</td>
</tr>
<tr>
<td>Climate Change</td>
<td>0.0116*</td>
<td>0.0163*</td>
<td>0.0001</td>
<td>-0.0017</td>
<td>0.0015</td>
<td>-0.0062**</td>
<td>-0.0029**</td>
<td>0.0010</td>
<td>-0.0020*</td>
<td>-0.0005</td>
<td>-0.0009</td>
</tr>
<tr>
<td>Taste</td>
<td>-0.0027</td>
<td>0.0028</td>
<td>0.0023**</td>
<td>0.0009</td>
<td>-0.0015</td>
<td>0.0001</td>
<td>0.0005</td>
<td>0.0014</td>
<td>-0.0001</td>
<td>0.0002</td>
<td>-0.0001</td>
</tr>
<tr>
<td>Protein &amp; Minerals</td>
<td>0.0293</td>
<td>0.0680</td>
<td>0.0105</td>
<td>-0.0008</td>
<td>-0.0340</td>
<td>0.0169</td>
<td>0.0326**</td>
<td>-0.0093</td>
<td>0.0152</td>
<td>0.0147</td>
<td>0.0222</td>
</tr>
<tr>
<td>Fat</td>
<td>-0.0579</td>
<td>0.0278</td>
<td>-0.0310</td>
<td>-0.1059</td>
<td>-0.0337</td>
<td>-0.0829</td>
<td>0.0427</td>
<td>-0.0823*</td>
<td>0.0024</td>
<td>-0.0325</td>
<td>-0.0213</td>
</tr>
<tr>
<td>Revocation</td>
<td>-4.1044</td>
<td>-4.4490</td>
<td>-0.1722</td>
<td>-3.5030**</td>
<td>3.2900*</td>
<td>3.2014***</td>
<td>-0.7240</td>
<td>1.4620</td>
<td>-0.6319*</td>
<td>-1.0348**</td>
<td>-1.8244***</td>
</tr>
<tr>
<td>COVID</td>
<td>0.2750</td>
<td>0.8532</td>
<td>1.6545</td>
<td>0.6933</td>
<td>0.2428</td>
<td>1.5941</td>
<td>0.2065</td>
<td>3.8857***</td>
<td>-0.2638</td>
<td>-0.6778*</td>
<td>0.9859*</td>
</tr>
<tr>
<td>Trend</td>
<td>-0.0466</td>
<td>-0.0396</td>
<td>-0.0252</td>
<td>0.0191</td>
<td>-0.0622*</td>
<td>-0.0127</td>
<td>-0.0076</td>
<td>-0.0667**</td>
<td>0.0035</td>
<td>0.0090</td>
<td>0.0263**</td>
</tr>
<tr>
<td>R²</td>
<td>0.1212</td>
<td>0.2185</td>
<td>0.1292</td>
<td>0.3317</td>
<td>0.1773</td>
<td>0.2758</td>
<td>0.2694</td>
<td>0.1640</td>
<td>0.1627</td>
<td>0.2826</td>
<td>0.2259</td>
</tr>
<tr>
<td>p value of F test</td>
<td>0.0202</td>
<td>&lt;0.0001</td>
<td>0.0088</td>
<td>&lt;0.0001</td>
<td>0.0411</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>0.0524</td>
<td>0.0011</td>
<td>0.0047</td>
<td>0.0010</td>
</tr>
</tbody>
</table>

Notes: The number of observations for each individual cut is 84 and for panel estimates is 1,008. t-statistics in parentheses. The dependent variables are annual difference of raw price premiums. Trend refers to a simple time trend. Independent variables are as specified in Table 3. PGLS-PCSE: Pooled feasible GLS estimates with panel-corrected standard error. Cut-Panel is a beef panel including all 12 cuts. Standard errors are robust standard errors. *, **, and *** reflect significance at the 10%, 5%, and 1% levels of significance, respectively.
B Appendix for Chapter 2

B.1 Meat Consumption and Shares

Figure B1: Per Capita Meat Consumption by Type in United States, 1961 to 2017

Notes: Average per capita meat consumption breaks down by specific meat types, measured in kilograms per person per year. Data is based on per capita food supply at the consumer level, but does not account for food waste at the consumer level. Also see Figure 4 Panel C for the meat consumption from 1997 to 2019. Source: Ritchie and Roser (2017) and the UN Food and Agricultural Organization (FAO).
Figure B2: Budget share of each type of meat on total food

![Budget share of each type of meat on total food](image)

Notes: Total meat excludes veal, lamb, and mutton.

Figure B3: Total Meat Consumption and Supply from 1997 to 2019

![Total Meat Consumption and Supply from 1997 to 2019](image)

Notes: Total meat excludes veal, lamb, and mutton.
B.2 Estimates of the Rotterdam model with fixed coefficients

We introduced the second approach in the estimation of compensated elasticity, which is a conventional approach following Marsh et al. (2004) and Tonsor and Olynk (2011). Specifically, we examined the effect of animal diseases on the meat market to explore the fixed elasticities from a Rotterdam model with fixed coefficients in different periods. Our Rotterdam model with fixed coefficients is specified as

\[ w_{it} \Delta \ln q_{it} = \phi_i + \sum_{s=1}^{3} \psi_{is} S_s + \theta_i \Delta Q + \sum_{j=1}^{4} \pi_{ij} \Delta \log p_{jt} + \sum_{k=0}^{1} \beta_{ik} \Delta \log (\text{BSE}_{i,t-k}) \]

\[ + \sum_{k=0}^{1} \gamma_{ik} \Delta \log (\text{HPAI}_{i,t-k}) + \alpha_i \Delta \log \text{Milk}_t + v_{it}, \quad \forall i \in \{1, 2, 3, 4\} \]

where the variables are identical to those in equation (10). The differences are that the parameters in equation (B.1) are fixed parameters whereas those parameters in equation (10) vary over time. The adding-up, homogeneity and symmetry restrictions are also imposed on equation (B.1).

Following Tonsor et al. (2010) and Tonsor and Olynk (2011), we estimated the model in two ways. First, assuming the prices and expenditure are predetermined, we used an iterative seemingly unrelated regression (SUR) in estimations. Second, we assumed endogenous prices and expenditure and use iterative three-stage least squares (3SLS) in estimation. Following the approach of Eales and Unnevehr (1993), Kinnucan et al. (1997) and Tonsor and Olynk (2011), our instruments included lagged meat prices, lagged meat quantities, lagged total food expenditure per capita, corn prices received by producers, 90-day treasury bill yields, a price index for energy, the U.S. population, real consumer income per capita and a simple time trend. We conducted Hausman specification tests to determine the exogeneity of prices and quantities. If we failed to reject the null hypothesis of exogeneity in the Hausman tests, we employed iterative SUR estimations, otherwise we would use iterative 3SLS. Either iterative SUR or 3SLS dropped one equation of commodity \( i \) and build a system of three equations under the adding-up constraint. The coefficients and the variances of the drop equation were recovered using a series of nonlinear combination calculations.
We also derived the fixed compensated price elasticities $\varepsilon_{ijt}$, expenditure elasticities ($\eta_i$) as well as the elasticities for meat demand with respect to BSE ($\lambda_{BSE,i}$) and HPAI ($\lambda_{HPAI,i}$) from the Rotterdam model written as

$$
\varepsilon_{ij} = \frac{\pi_{ij}}{w_i}, \quad \eta_i = \frac{\theta_i}{w_i}, \quad \lambda_{BSE,ik} = \frac{\beta_{ik}}{w_i}, \quad \lambda_{HPAI,ik} = \frac{\gamma_{ik}}{w_i}, \quad \forall i, j, \forall k \in \{0, 1\} \quad (B.2)
$$

where the compensated elasticities, including $\pi_{ij}, \theta_i, \beta_{ik},$ and $\gamma_{ik}$, are derived from the Rotterdam model are listed in equation (B.1).

Table B1 shows the fixed compensated elasticities derived from the fixed-coefficient Rotterdam model.

<table>
<thead>
<tr>
<th>Demand of</th>
<th>With respect to</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beef Price</td>
<td>-0.442***</td>
<td>0.297**</td>
<td>0.142</td>
<td></td>
</tr>
<tr>
<td>Pork Price</td>
<td>0.139**</td>
<td>0.146</td>
<td>0.205</td>
<td></td>
</tr>
<tr>
<td>Broiler Price</td>
<td>0.055</td>
<td>0.168</td>
<td>-0.074</td>
<td></td>
</tr>
<tr>
<td>Expenditure</td>
<td>1.363***</td>
<td>0.717**</td>
<td>2.164***</td>
<td></td>
</tr>
<tr>
<td>BSE Cases</td>
<td>-0.010</td>
<td>0.031**</td>
<td>-0.020</td>
<td></td>
</tr>
<tr>
<td>HPAI Cases</td>
<td>-0.002</td>
<td>-0.003</td>
<td>-0.002</td>
<td></td>
</tr>
<tr>
<td>Lagged BSE Cases</td>
<td>0.015</td>
<td>0.006</td>
<td>-0.016</td>
<td></td>
</tr>
<tr>
<td>Lagged HPAI Cases</td>
<td>0.004**</td>
<td>-0.002</td>
<td>0.006*</td>
<td></td>
</tr>
<tr>
<td>Average Budget Share (%)</td>
<td>10.10</td>
<td>5.79</td>
<td>4.21</td>
<td></td>
</tr>
</tbody>
</table>

Notes: We partialled out the estimates for seasonal dummies and low-whole milk consumption ratio. *, **, and *** reflect significance at the 10%, 5%, and 1% levels of significance, respectively.
Appendix for Chapter 3

Figure C1: Autocorrelation Plots of Cattle Returns

Note: As each year has 252 trading days, we set the max lag of autocorrelation plots as $252 \times 2 = 504$. 