What Food Purchase Data Can Tell Us about Campylobacteriosis in the U.S.?

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ABSTRACT

This paper presents a new approach to estimating the relationship between food exposures and foodborne illness in the U.S. It complements similar efforts by other federal agencies. We conduct cross-sectional time series analysis of daily data on disease and on food purchases for home consumption across the U.S. Foodborne *Campylobacter* infections are widely thought to be a chicken problem and their marked seasonality primarily driven by temperature. We find that chicken purchased for consumption at home is *not* a driver of *Campylobacter* infection and that seasonality rather than temperature has the strongest effect on the rate of *Campylobacter* infections.

KEYWORDS

Campylobacter, food source attribution, foodborne illness, big data, FoodNet surveillance, Homescan purchase data, food exposures, foodborne disease epidemiology, food safety, poultry exposure, berries, leafy greens

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INTRODUCTION

Foodborne illness continues to be a major concern to consumers and the food industry in the United States. The U.S. Centers for Disease Control and Prevention (CDC) estimates that each year roughly 48 million, or 1 in 6, Americans contract a foodborne illness. Of these, approximately 128,000 are hospitalized and 3000 die (Scallan et al., 2011a). These illness and efforts to prevent them, are costly to society. The USDA Economic Research Service (ERS) estimates that the cost of illness from the 15 leading sources of foodborne pathogens was over $15.5 billion (2013 dollars) (Hoffman et al., 2015). Routine food safety management to prevent foodborne contamination pose substantial costs for food producers, transporters, processors and marketers. Consumers' response to outbreaks and other food safety events, such as food recalls, also financially affect industry. For example, a 2016 paper by Taylor et al. found that ground beef purchases declined by $97 million in the two week period following a 2003 nationwide recall related to Bovine Spongiform Encephalopathy (a.k.a. "mad cow disease") concerns.

Government and industry both need information about which foods are causing foodborne illnesses to efficiently manage efforts to prevent them. Quantitative information on the foods that have caused foodborne illnesses due to specific pathogens can help speed outbreak investigations, set food safety management priorities, measure program performance, and target inspection activities. A relatively new area of research, called food source attribution, focuses on estimating the contributions of different exposure routes to causing foodborne infectious diseases (Batz et al. 2005). Evaluations of source attribution research have concluded that multiple analytical methods are needed to get a reliable and complete picture of the causes of foodborne

illnesses (Pires et al. 2009, WHO 2012). In recent years, U.S. federal agencies have been focusing on development of new food source attribution research methods (CDC 2018).

This study develops a new source attribution method that focuses on the causes of foodborne illnesses due to food prepared at home. It uses cross-sectional time series analysis of daily data on illnesses and food purchased for home consumption in urban markets in the U.S. to estimate associations between specific foods and foodborne illnesses in these areas. Many foodborne infectious diseases vary regionally and have marked seasonality (Lal et al. 2012). One strength of our method is that it can distinguish between the influence of regional and seasonal variation, and food purchases on illnesses.

Our study focuses on illnesses due to *Campylobacter*. We do so for two reasons. First, *Campylobacter* is one of the five leading causes of foodborne illnesses and deaths in the U.S. (Scallan et al. 2011). *Campylobacter* exposures in the U.S. are estimated to cause roughly 1,060,000 cases of illness each year, of which roughly 80 percent are foodborne (Scallan et al. 2011). The cost of foodborne *Campylobacter* infections is estimated to be roughly $2 billion per year ($2013) (Hoffmann et al. 2015). Second, new source attribution methods are needed to study *Campylobacter*. In the U.S., the primary method used to attribute foodborne illnesses to food sources is analysis of outbreak investigation data (Painter et al. 2013). But, this method is ill-suited to studying *Campylobacter* because outbreaks account for less than 1 percent of total *Campylobacter* infections in the U.S. with the rest being sporadic (non-outbreak) cases which may have different food exposure routes than outbreak cases (Taylor et al. 2013, Friedman et al. 2004). Developing new source attribution methods for *Campylobacter* has been a priority for the federal government since 2011 (IFSAC 2012).

Our new method is possible due to significant federal and state investments in both food purchase data and disease surveillance data. The U.S. Economic Research Service (ERS) has led efforts to aggregate and use scanner purchase data originally collected for marketing purposes for research into consumers' food purchase behavior. Our study uses Nielsen Homescan© data as a proxy for food consumed at home. A strength of scanner data for source attribution research is that it provides detailed information on product characteristics that are believed to affect the riskiness of the product, for example, whether a meat is ground or whole, or whether poultry has ever been frozen. ERS has invested in consumer panel food purchase scanner data (Homescan data from 1998 through 2010 and IRI data from 2008 to 2016) to use in its research on consumer food demand and expenditures. CDC and a small group of state governments have collaborated since 1996 to actively collect data on illnesses due to leading causes of foodborne (CDC FoodNet 2018). This program, called FoodNet, now involves ten states across the country. Active surveillance, like FoodNet, provides a more complete picture of the illnesses that are actually occurring than passive surveillance does.[4]

Campylobacter is a good test case for evaluating our new method because the incidence of *Campylobacter* is high in most FoodNet sites. Our method relies on having a relatively large number of cases over time and across space to provide adequate statistical power to identify relationships between food purchases and illnesses. If we cannot show a relationship between

[4] There are two fundamental approaches to collecting information on health conditions in a population, passive surveillance and active surveillance. In passive surveillance systems, public health authorities depend on health care providers to report information on health events to them. In active surveillance systems, the public health agencies contact health care providers seeking reports. Generally, active surveillance is believe to provide more complete reporting of health conditions than passive surveillance. CDC, "Public Health 101 Series: Introduction to Public Health Surveillance". https://www.cdc.gov/publichealth101/documents/introduction-to-surveillance.pdf accessed July 12, 2018.

food purchases and foodborne *Campylobacter* infections, then we will not be able to do so with pathogens that have a lower disease incidence.

Our new method allows us to explore several unsolved puzzles about the sources of *Campylobacter* infections in the U.S. One is whether it is temperature or other factors that drives the marked seasonality seen in *Campylobacter* cases. Another is what explains the substantial regional variation in *Campylobacter* infections in the U.S. A final question is how the food exposures that cause sporadic foodborne campylobacteriosis differ from those that cause outbreak-associated cases.

BACKGROUND

Effective food safety management requires information about risks (NAS 2003). Since the mid-1980s, federal food safety agencies have been working to develop ways to use information on risk to develop stronger food safety systems (NAS 1985, NAS 1987, GAO 1992, FSIS 1996, FDA juice HACCP, NAS 2003, FSIS 2006, NAS 2009). An important piece of information about risk of foodborne disease is quantitative information on the relative riskiness of different foods (Batz et al. 2005). This information can be used to improve the speed of outbreak and recall investigations, to help food safety managers set priorities, and to better target inspections. Recent efforts at improving the effectiveness of food safety policy have explicitly relied on information on the relative riskiness of foods. The USDA Food Safety and Inspection Service (FSIS) uses food attribution research to inform program priorities, develop strategic plans and evaluate program performance (FSIS 2017a, 2017b). The Food Safety Modernization Act of 2011 requires FDA to use information on the riskiness of different foods to inform record keeping requirements and in developing import safety programs (FDA 2011).

Over the past decade and a half there has been a growing effort, both in the U.S. and in other high income countries, to develop methods to estimate the relative contribution of different food exposures to the incidence or burden of specific foodborne diseases (see CDC 2017, EFSA 2008). These studies are collectively referred to as "food source attribution" studies because they attribute the incidence of foodborne diseases to various food exposure routes.

Pires et al. (2009) reviewed the food source attribution and identified four basic approaches: 1) microbiological methods, 2) epidemiological methods, 3) intervention studies, and 4) expert elicitation. These four methods continue to be the primary approaches used or under development. Microbiological methods sample animal reservoirs, food, water and environment and compare the microbial subtypes isolated from each to microbiological subtypes isolated from human cases. Unfortunately, adoption of new genetic methods of identifying pathogens may result in fewer microbial isolates being available to support microbial source attribution studies in the future. Epidemiological approaches used to study food source attribution include case-control studies, cohort studies, case-series studies and analysis of outbreak investigation data. Intervention studies may be intentionally designed treatments or trials, or may be natural experiments created by a change in exposure or behavior. Finally, structured expert elicitation studies are used where there are significant data gaps or deficiencies. Different methods have different strengths and limitations and significant gaps hinder our ability to attribute foodborne disease to their food exposures (CDC 2017, Pires et al. 2009, EFSA 2008). A World Health Organization (WHO) consultation on campylobacteriosis noted the need for multiple approaches to source attribution to gain a comprehensive understanding of the causes of foodborne infections (WHO 2012).

["**Box 1: Attribution Methods**" goes here]

The three principal federal food safety agencies, FSIS, FDA, and the CDC saw the need for new source attribution research methods to be so important to their work that they organized the Interagency Food Safety Analytics Collaboration (IFSAC) in 2011 to work collaboratively on analytical methods needed to support their food safety work (IFSAC 2016). Research focused on attributing illness caused by specific pathogens to specific food commodities was identified as a priority area of work in IFSAC's original charter and remains a priority in its current charter and strategic plan (IFSAC 2016, IFSAC 2017a, 2017b). Source attribution of foodborne campylobacteriosis was also identified as a priority in IFSAC's original strategic plan and remains so in its current action plan (IFSAC 2012, IFSAC 2017).

While there is a large body of research on causes and patterns of illnesses from *Campylobacter* in the U.K., continental Europe, Canada and New Zealand, less work has been done in the U.S. We are aware of one national case-control study (Friedman et al 2004), a national study of *Campylobacter* outbreaks (Taylor et al. 2013), and a national study examining regional variation in the *Campylobacter* species causing sporadic illnesses (Patrick et al. 2018). State level studies in Maryland, Georgia, Michigan and Arizona have looked at environmentally and agriculturally related exposures to *Campylobacter* (Paturie et al. 2013, Davis et al. 2013, Soneja et al. 2016, Vereen et al. 2007, Potter et al. 2018) or multiple factors, including food consumption (Cha et al. 2016, Pogreba-Brown et al. 2016). Several U.S. studies have looked at the prevalence of *Campylobacter* in farm animals or on meat but without directly linking this to foodborne illness (Tyson et al. 2016, Berrang et al. 2016, Besser et al., 2005, Horrocks et al., Sahin et al., 2015, Noormohamed and Fakhr 2013).

Epidemiological research on the sources of *Campylobacter* exposure has produced mixed results. A nationwide U.S. case-control study found drinking raw milk, eating undercooked chicken, raw seafood and eating restaurant-prepared poultry or meat were associated with higher risk of having a *Campylobacter* infection (Friedman et al. 2004). In their study, univariate, but not multivariate analysis found that consumption of chicken grilled outdoors at a large social gathering to be risk factor for campylobacteriosis. Non-food exposures were also important risk factors. Having a pet puppy, drinking untreated water from a lake, river or stream, having contact with animal stool, or being a child aged 2 to 12 in contact with farm animals were all associated with a higher risk of *Campylobacter* infection (Friedman et al. 2004). Studies in Europe, Canada, the UK and New Zealand also found eating chicken grilled outdoors increased *Campylobacter* infection risk (Domingues et al. 2012, MacDonald et al. 2015, Mullner et al. 2010). A case-control study of illnesses in Arizona found eating cantaloupe or queso fresco and handling raw poultry were associated with higher risks of *Campylobacter* infections (Progreba-Brown et al. 2016). An analysis of U.S. outbreak data found 29 percent of U.S. foodborne *Campylobacter* outbreaks between 1997 and 2008 were associated with diary, 11 percent with poultry and 5 percent with produce (Taylor et al. 2013). Other studies of sporadic illnesses outside the U.S. identify salad vegetables and fresh or frozen berries as risk factors for *Campylobacter* infection (Evans et al. 2003, Verhoeff-Bakkenes et al. 2011, *c.f.* Denis et al. 2016).

But the question of which foods are the largest risk factors for foodborne *Campylobacter* infections in the U.S. is far from settled. A leading hypothesis has been that poultry is the primary source of foodborne *Campylobacter* infection and that vegetables are cross-contaminated during food preparation on kitchen surfaces and utensils previously contaminated by raw poultry (Cools et al. 2005, Verhoeff-Bakkense et al. 2011). But Friedman et al. 2004 found eating fried chicken,

chicken and non-poultry meat that was prepared at home or eating fresh berries was associated with a lower risk of *Campylobacter* infection. And a Dutch study found *Campylobacter* prevalence levels in fruits and vegetables at retail were adequate to pose a meaningful risk given the amount of fruits and vegetables consumed (Verhoeff-Bakkenes et al. 2011). They also found that the prevalence of the *Campylobacter* in packaged raw vegetables was about 50 percent higher than in non-packaged raw vegetables (Verhoeff-Bakkenes et al. 2011). In a recent analytical review of the last decade's research on the causes of *Campylobacter* infections, Nelson and Harris (2017) argue that the focus on chicken consumption as the dominant source of these human illnesses is mistaken and that the evidence suggests that *Campylobacter* foodborne exposures routes are more diverse than implied by the poultry hypothesis.

Seasonality may also provide some evidence on the food sources of campylobacteriosis. Summer peaks in the incidence of campylobacteriosis in temperate climates have been well documented (Nylen et al. 2002, Kovats et al. 2005, Tam et al. 2006, Patrick et al. 2018,). Researchers in the U.S. and Europe have begun exploring the use of time series analysis to study the seasonality of campylobacteriosis. A small number of studies have used univariate time series analysis to forecast human campylobacteriosis incidence, disease burden and the prevalence *Campylobacter* in poultry flocks (Weisent et al. 2010, Wei et al., 2015, Noordhout 2017). Multivariate time series analysis has also provided some evidence on likely food sources of campylobacteriosis. Williams et al. (2015) conducted multivariate analysis of monthly sporadic human campylobacteriosis cases and the proportion of *Campylobacter* positive samples of chicken at retail and in slaughter facilities in the U.S. Using multiple measures of association, they concluded that these data did not suggest that a seasonal increase in chicken contamination levels is the primary driver of the seasonal pattern of human *Campylobacter* cases in the U.S. A similar time series study in Canada looking

at the relationship between disease surveillance data on human *Campylobacter* cases, sampling data on *Campylobacter* prevalence on retail chicken breasts and recreational water samples, and survey data on the frequency of swimming and barbequing also found evidence that the increase in summer *Campylobacter* cases was driven more by changes in human activities than increases in either food or water contamination (David et al. 2017).

A small set of studies have looked at the influence of ambient temperature and other weather variables on human campylobacteriosis rates (Kovats et al. 2005, Louis et al. 2005, and Tam et al. (2006). All found that temperature and precipitation were significantly associated with campylobacteriosis rates. Louis et al. (2005), in a study of England and Wales between 1990 and 1999, found that average weekly temperature influences the incidence of campylobacteriosis. While Louis et al. (2005) found no difference between using a the average weekly temperature or a 1-, 2-, or 3-week lagged temperature, in an analysis of campylobacteriosis cases during the 1990s in multiple EU countries, Kovats et al. (2005) found only temperature 10-14 weeks prior to infection was significant. In a study that is more similar to ours, Tam et al. (2006) explored the influence of temperature in England and Wales during the 1990s, while controlling for seasonality and long term time trends. They looked at average temperature over the week, 2 weeks, 3 weeks etc. prior to infection and found that after controlling for seasonality and long-term time trends, that average temperature over the 6 weeks prior to infection had the greatest influence on risk of campylobacteriosis.

METHOD

We use cross-sectional time series analysis of data on sporadic cases of campylobacteriosis in the U.S., appropriately lagged food purchase data and control variables for region, season and

temperature. We explore the influence of 21 different food groups. This methods section first describes the Homescan food consumption data used in this study. It then describes the FoodNet data on *Campylobacter* incidence. The subsequent subsection describes how we link these two data sources. Finally, the statistical analysis is described.

Food Purchase Data

Detailed, high frequency data on food purchases is increasingly being used to study food demand and consumption (see e.g., Rahkovsky and Snyder, 2015; Dong and Stewart, 2013; Mancino and Kuchler, 2012). Because scanner data is generally daily in frequency and can be very locationally specific, it is well suited to use in regional, time-series analysis. However, sampling properties may not be well defined and purchases may be tied to stores rather than households. To overcome these data issues, we use a curated type of purchase data, Homescan©, collected from panels of U.S. households by Nielsen, a major U.S. marketing firm. USDA ERS purchased Nielsen data between 1998 and 2010 and since then has purchased similar food purchase data, IRI InfoScan©.

[Box 2 Food Consumption Data Sources goes here]

Nielsen recruited households to meet demographic criteria, and then weighted the households to be representative of each of 52 market areas and of the entire contiguous United States for a given year. Households were identified as being located in one of 52 market areas (some of which are Major Markets) and of the entire contiguous United States. Household demographic data, including number of people in a household, is included in the Homescan dataset. ERS analysis of Nielsen methodology and data determined that it is representative of purchases at a national and market level (Einav et al. 2008).

Homescan households record all food purchases from all sources, including farmers' markets and non-food stores as well as grocery stores, supermarkets, and club and warehouse stores. It does not include food eaten in restaurants or other food service facilities. Usually, a scanner is used to scan the food item's UPC code. Information collected on each purchase includes the purchase date, and details about the specific items purchased including UPC code (if available), total quantity purchased, package size, and other descriptive characteristics. Foods sold without UPC codes are often those sold in varying weights (random-weight items). Fresh meats, produce and some deli items, foods that are important for studying foodborne illness, are often sold by weight. Nielsen only collected Homescan data on "random-weight" foods between 1998 and 2006. In 2012, IRI resumed collecting data on expenditures, but not on the quantity, of foods sold by "random weight". As a result, we cannot use this more recent IRI data in our analysis.[5]

Like any data, Homescan food purchase data has limitations. Because the data track purchases, they are only an approximation for consumption. However, food consumption is likely closely linked to the purchase date, especially for perishable items like dairy products, fresh fruits, and fresh vegetables. The data do not track food eaten at restaurants or other places outside the home, which compose about one-third of food calories consumed in the U.S. (Lin and Guthrie, 2012). Only households that report data for at least 10 of 12 months during the calendar year are included in a year's analysis sample. Some households participate for several years. A requirement that households must report purchases for 10 out of 12 months in a calendar year results in a considerable decline in participation in the final two months of each year.[6] As a

[5] ERS researchers are working on research that would impute the quantity of random-weight food sold from this IRI expenditure data. This imputation may make IRI random weight data useful for food source attribution research at a future date.

[6] Although households are brought into the sample continuously, those that enter after February and stay on at least 10 continuous months will not be included in their entry-year dataset because they only report for 9 of the 12

result, there is a consistent decline in the total purchases reported in November and December of each year. Finally, the Homescan sample expanded over time. Between 2000 and 2003, about 8,000 households reported both UPC-coded and varying-weight food-at-home purchases. In 2004, the sample size collecting UPC-coded items, but not random weight products, was greatly expanded to 32,000 households. By 2006, 38,000 households were participating in the full Homescan panel, of which, 7,526 collected random weight food purchases.

Food Categories

Most prior U.S. source attribution studies have partitioned the food supply based on broad food "commodity" types e.g., beef or eggs (Painter et al., 2013, DeWaal et al. 2006, Batz et al. 2012) (Figure 1). A new food categorization scheme was developed by the U.S. Interagency Food Safety Analytics Consortium (IFSAC) for analysis of outbreak data subsequent to this study, but would not substantially our analysis (Richardson et al. 2017). Case-control studies use structured interviews in which participants recall their activities including food consumption; this often reveals more specific food characteristics, like whether a food was frozen or fresh, the degree of cooking involved, or whether a vegetable was eaten raw or cooked.

[Figure 1. Painter et al. Food Categorization for Food Source Attribution of Outbreak Disease Data. Figure 1 goes here.]

calendar-year months. In contrast, those that begin in January (or the previous year) and report purchases through October will appear in the data, even though they do not report in November or December. Those that leave prior to October will not be included at all.

A strength of Homescan and other scanner data for use in studying foodborne disease exposure routes is that they provide detailed information on product characteristics that can be used to categorize foods according to foodborne disease risk characteristics. There are general characteristics of food that can affect the likelihood of pathogen presence, growth, or survival. For example, ground meat has more surface area for pathogen growth than intact cuts of meat, foods that are eaten raw do not have the additional "kill step" provided by cooking, packaging may affect the likelihood of contamination or pathogen survival, and freezing kills some types of bacteria. Scanner data relies on UPC codes which contain detailed product information on each food purchase, e.g., product is identified as "frozen breaded-chicken-breast fillets" or "10-oz-bagged-pre-washed spinach". In Homescan, information on random weight foods includes product descriptions like, ground-beef, chicken legs, chicken gizzards, whole chicken, frozen whole turkey etc. as well as package weight. We use this detailed information to categorize foods not only by type of food, but also by processing and handling (e.g., frozen vs. fresh) and form of food (e.g., sliced vs. block cheese) that can influence the presence or growth of pathogens on foods.

[Table 1 goes here]

Table 1 presents a data categorization relevant to the study of foodborne pathogen exposures based on information from UPC and other "random weight" product descriptions (Table 1). This categorization was designed to reflect risk factors that have been associated with illness or

pathogen presence or growth in a wide range of foodborne pathogens (Gould et al. 2013, Voetsch et al. 2007, DuPont 2007). The categorization structure is designed to be compatible with aggregation to broader food "commodity" categorization used in past food source attribution studies (Fig. 1).

In order to aggregate from individual food items into broader categories, we converted purchase quantities of each item to kilograms. We then used the Nielsen household weights to estimate the kilograms of each food category purchased in each market. Using county-level population data from the U.S. Census Bureau, we then calculated the per capita daily amounts purchased of each food category in each market. Both Homescan and FoodNet use counties as their smallest geographic unit.

Final selection of food categories for use in our multi-variate cross-sectional time series analysis of sporadic *Campylobacter* infections was based on preliminary univariate analysis and results from prior scientific research literature. In our final analysis, discussed below, we include food variables that are likely risk factors as well as foods, like canned foods, that biologically should not pose a risk of *Campylobacter* infection. These low risk foods are included to test the reliability of modeling results.

FoodNet

Time series analysis relies on having a high frequency of events per time period for statistical power. We use Foodborne Diseases Active Surveillance Network (FoodNet) active surveillance data for disease incidence because active surveillance is designed to do the best job possible at capturing the full set of illnesses that have occurred. Most disease surveillance is passive. Passive

surveillance system relies on the cooperation of health-care providers to report cases of notifiable diseases. In active surveillance public health officials routinely communicate with laboratories and care providers to identify new cases of illness. FoodNet routinely contacts more than 650 clinical laboratories serving the surveillance area to identify new cases and conducts periodic audits to ensure that all cases are reported (CDC 2018).

FoodNet is a collaborative effort by CDC, 10 state departments of public health, FSIS, and FDA (CDC 2013). It was established in 1996 and conducts population-based active surveillance of laboratory-diagnosed cases of illness caused by each of 8 major pathogens commonly transmitted through food. While these 8 pathogens are leading causes of foodborne illness, they can also be transmitted through other exposure routes. FoodNet does not determine whether a single infection was acquired through food. FoodNet collects information on the pathogen identified, laboratory testing methods, and whether a case was associated with an outbreak. In our analysis, we do not include outbreak associated FoodNet cases; we only use data on sporadic infections. FoodNet sporadic case data has been used extensively in case-control and cohort studies (Friedman et al. 2004, Fullerton et al. 2007, Kimura 2004, Kassenborg 2004, Voetsch 2007).

FoodNet surveillance began in 1996 in Minnesota, Oregon, and select counties in California, Connecticut, and Georgia. In 1997, catchment expanded to include additional counties in Georgia. In 1998, catchment expanded to include all Connecticut counties, and select counties in Maryland and New York. In 1999, all Georgia counties were included as well as additional counties in New York. In 2000, an additional county in California and select counties in Tennessee were added. In 2001, catchment expanded to include select counties in Colorado, and additional counties in Maryland. In 2002, all counties in Maryland and additional counties in Colorado and New York

were added. In 2003, all counties in Tennessee and additional counties in New York were added. In 2004, catchment expanded to include New Mexico and additional counties in New York. The FoodNet catchment area has been stable since 2004.

We see *Campylobacter* as providing a "best case scenario" for the use time series analysis to detect an association between food purchases and foodborne disease because of its high incidence. Our methods relies on there being a relatively large number of cases over time to provide statistical power adequate to identify relationships between cases and food purchases. In 2000 and in 2006, *Campylobacter* caused a large or the largest number of cases in all FoodNet regions (Table 2). We obtained FoodNet data on all laboratory-confirmed sporadic infections of *Campylobacter* occurring during 2000-06 including the date of specimen collection and patient's county of residence.

[Table 2 goes here]

Linking FoodNet and Homescan data sets

Neither Homescan nor FoodNet cover all areas of the U.S. Geographically, the FoodNet surveillance area is a subset of the Homescan markets. FoodNet and Homescan data were linked by county, the smallest geographic unit used in the FoodNet data. Since Homescan data are constructed to be representative of markets, there is no direct relationship between the geographic units of Homescan data and the counties in the FoodNet catchment area. To identify the representative Homescan market for each FoodNet county, ArcGIS was used to overlay Homescan markets on FoodNet counties and the percentage of the FoodNet population included in each market was determined. Table 3 presents a list of the Homescan markets in which at least

some of the counties were active FoodNet sites. We conducted robustness checks based on the population coverage (percentage of the Homescan population in the active FoodNet counties).

[Table 3 goes here]

Lag Structure

Our analysis relies on the logic that a causal event must precede the effect it causes; this logic underlies statistical concepts of causation (Granger 1969). In our context, this means that food exposure must precede an illness in order to cause of that illness. We face the complication that we cannot observe either food exposure or onset of symptoms directly.

We aggregate daily FoodNet and HomeScan© data to weekly frequency in order to have enough illnesses in each observation period and assure adequate statistical power for analysis. FoodNet provides the date of specimen collection and the date of laboratory confirmation of the illness. The incubation period between consumption of *Campylobacter* on food and illness is 2-5 days (CDC 2018 *Campylobacteriosis*). Therefore, prior to aggregating FoodNet data to the weekly level, for each infection, the date of specimen collection was use as a proxy for the illness onset date and end of an incubation period. Also, in order to take into account the lag between food purchase, storage, and consumption behavior in the HomeScan© data and the onset of illness and seeking care, we explored alternative lag structures through sensitivity analysis. We found that the best performing lag structure was that which defined food purchases in a particular week as the sum of the purchases in the time period 5 to 18 days prior to the day the illness.

RESULTS

Our analysis uses pooled cross-sectional time series analysis of weekly FoodNet illness data for 17 U.S. metropolitan areas between 2000 and 2006. This methodological approach relies on variability across time, space and foods to estimate a relationship between food purchases and foodborne disease and to test for the relative influences of temperature, seasonality, and region on *Campylobacter* incidence.

Descriptive Analysis

As expected from prior literature, we see strong mid-summer peaks in sporadic campylobacteriosis case rates in most market areas during the study period (Figs. 2a and 2b). The exceptions were Hartford and the ex-urban New York area which have multiple peaks. Incidence rates vary across Homescan markets with the highest incidence rates being in the San Francisco area and the lowest in the Memphis, Tennesee market area (Figs. 3a, 3b). Time trends in incidence rates varied by market (Figs. 3a, 3b). Illness rates fell during the study period on average and in the San Francisco Bay, Minneapolis, and Buffalo-Rochester areas. In a few markets, incidence rates fluctuated greatly. In many makets, incidence rates remained relatively flat over the study period. From a statistical perspective, there appears to be enough variance in incidence rates across markets, across seasons, and across time to allow for estimation of relationships beween incidence rates and explanatory factors like food.

[Figures 2 -3 go here]

We also see considerable variation over both time and markets in food purchases by food categories. Chicken has been implicated as a reservoir for *Campylobacter* (Agunos et al. 2014).

Freezing chicken kills *Campylobacter* (Archer 2004). Figure 2a and 2b show purchases of fresh (not-frozen) chicken in 18 Homescan markets. On average purchases peak in the winter and again in the summer with substantial regional variation. Purchase levels show strong variation between regions. Syracuse and Pittsburg are well above average purchase levels of fresh chicken, while Denver and Minneapolis fall well below. Large variations in purchases are helpful in identifying regional and seasonal effects on illness in statistical analysis. Fresh berries and salad greens have also been implicated as exposure routes for foodborne *Campylobacter*. Across most markets, purchases of fresh berries show a strong summer seasonal peak (Figs. 4). In contrast, leafy greens purchases show seasonal peaks only about a third of the markets (Figs. 5). Again, we see substantial variation in the share of total food purchases in the market represented by these foods, both across foods and across markets.

Information on the seasonality of food purchases may be useful to researchers and public health officials working on food safety. This information has not generally been available for reasons explained above. Appendix 1 presents time series plots of Homescan© food purchase data in the U.S. developed in this project for categories of food likely to be of greatest interest to analysts working in foodborne illness research and public health programs.

[Figures 8 and 9 go here]

Temperature has been implicated as a factor that influences *Campylobacter* incidence (Louis et al. 2005, Tam 2005). Our analysis uses National Oceanic and Atmospheric Administration temperature data. As one would expect, weekly average temperature varies seasonally, generally peaking in mid-July (Fig. 6). The exception is San Francisco, where temperature peaks in September. We also see regional differences in temperature. July peaks range from below 70 in

Portland to over 80 in Memphis. Low temperatures range from about 20 in Minneapolis to about 50 in San Francisco in early January (Fig. 6).

[Figure 10 goes here]

Statistical model

We model sporadic weekly cases of *Campylobacter* infections in the U.S., *C*, as a function of lagged food purchases, region, season, temperature, and year:

$$C_{r,w} = \alpha_{r,w} + \sum_{\boldsymbol{i}} \boldsymbol{\beta}_1^i \boldsymbol{F}_{r,w}^i + \boldsymbol{\beta}_2 \boldsymbol{T}_{r,w-x} + \sum_j \boldsymbol{\beta}_3^j \boldsymbol{Z}^j + e_{r,w}$$

where *C* are the number cases of illness observed weekly in each Homescan region, with *r* indexing Homescan Market regions, and *w* indexing weeks starting with the first week of 2000 and ending with the last week of 2006. ***F*** are kilograms per capita of food *i* purchased 5 to 18 days before a day when a case was laboratory confirmed during week *w* in market region *r*. ***T*** is a vector of average weekly temperatures for each region. ***Z*** is a matrix of *j* fixed effects including: year, month, market, and region; *a* is a constant and *e* is measurement error for each Homescan region and week of the study period. To accommodate the fact that the dependent variable, *C*, is a count data (e.g., 0, 1, 3 cases per day) we use Poisson models.

Market fixed effects are included to control for unobserved regional differences that could affect the risk of campylobacteriosis. These may include differences in food preparation practices, differences in care seeking or medical treatment practices, and regional differences in population

age structure, level and types of outdoor activities, consumption of food from farmers markets or home gardens, or pathogen prevalence in livestock, poultry, wildlife, or recreational waters. The year fixed effects control for broader time-specific effects common across all markets such as changes in Homescan and FoodNet data or nationwide shifts in demand. Month or season fixed effects account for disease seasonality, seasonal cooking and food consumption patterns, seasonal patterns in behavior unrelated to food purchased for home consumption, as well as seasonal changes in the Homescan sample.

REGRESSION RESULTS

Regression results for 6 alternative models are reported in Table 4. Model 1 includes only foods as explanatory variables. Model 2 adds market fixed effects. Model 3 includes foods, market and year fixed effects. Model 4 adds average daily temperature averaged over the six weeks prior to the day the case was laboratory confirmed lagged 4 days to allow for incubation (the average of temperature on days t-5 to t-46 where *t* is the day the case is laboratory confirmed. Models 5 and 6, our preferred specifications, then add a control for Season or for month fixed effects. We present regressions exploring alternative temperature averaging periods in an appendix to this report. We conducted sensitivity analysis that found that model results are unaffected by excluding markets with less than 15 percent coverage.

[Table 4 goes here]

All results are presented as incidence rate ratios (IRR) and their standard errors. The IRRs are the ratio of the incidence (cases per 100,000 people) expected if the corresponding variables was increased by one unit relative to the original expected incidence. An IRR of one indicates that an

increase in the variable made no difference to the incidence of disease. IRRs less than one indicate variables that reduce incidence while those over one indicate variables that increase incidence. Coefficient significance is measured relative to one, which is no effect. One, two, and three stars indicate p-values of less than .1, .05, and .01 levels of significance, respectively.

The average daily campylobacteriosis rate is 0.739 per 100,000 people. In Model 1, which does not control for regional differences, time trends, seasonality, or temperature, many foods are highly significant (Table 4). Without controlling for these confounders, we see results that are inconsistent with prior research, for example, non-frozen chicken ($\beta = 0.770 < 0$) is associated with lower and frozen chicken ($\beta = 2.590 > 0$) with higher levels of campylobacteriosis. Freezing is known to kill *Campylobacter*.

Patterns of significance on food variables change substantially once we control for confounding effects. Accounting for market and time trends, but not season, (Models 2 and 3), ground beef, berries, fruit that is eaten without peeling, and non-leafy fresh vegetables are associated with a statistically significant higher rate of campylobacteriosis, which is not surprising given prior research, but so do processed snack foods and deli meat which have not been associated with increased campylobacteriosis rates and have generally effective kill steps. Several foods that are typically processed or pasteurized (canned foods, dairy, juice) are all associated with lower campylobacteriosis rates, as are fruits that are peeled before eating, but so are ground meat other than beef, and seafood which are not highly processed.

Controlling only for temperature, ground beef, berries, non-leafy fresh vegetables, and deli meats continue to be associated with higher rates of campylobacteriosis, but not fruits not typically eaten peeled. Once temperature and seasonality are also accounted for (Models 4 and 5), only

ground beef, berries, non-leafy green vegetables, and whole meat are associated with increased campylobacteriosis rates. In model 6, which uses month fixed effects, whole cuts of red meat are associated with higher campylobacteriosis risk, the only model in which this occurs. There is a large difference in the size of the risk ratio for berries in Models 4, 5, and 6. When month rather than season is used to control for seasonality, the estimated influence of berries on campylobacteriosis is lower than when season is not controlled for or when seasonal fixed effects are included as quarterly seasons (Model 5). But even when season is represented by a month dummy variable, berries have one of the largest risk ratios we estimate. As expected, frozen chicken is associated with lower campylobacteriosis rate in Model 4 as are dairy, peeled fruit, juice, leafy greens, and ground meat other than beef. Chicken, which would generally be regarded as one of the major exposure routes for foodborne campylobacteriosis, is not associated with an increase in campylobacteriosis.

While the influences of these foods on campylobacteriosis incidence may be statistically significant, they are not numerically large. In Model 5 and 6, ground beef has an IRR of 1.5 and 1.37 respectively, or an increase in the campylobacteriosis incidence rate of 1.4 to 1.5 cases per 100,000 population associated with purchasing an extra kilogram (2.2 pounds) of ground beef per person in a two week period. On average, consumers purchased 11 grams of ground beef per person in a 2-week period.

Models 2 through 6 in Table 4 include market fixed effects, with the Albany Homescan Market as the omitted market. The results indicate that there are differences in the incidence rates across markets, even after accounting for food purchase quantities, time trend, temperature and

seasonality, so the coefficients on the market dummies included provide estimates of the IRR in each market relative to Albany.

Our results show that seasonality has a large and highly significant impact on campylobacteriosis incidence even after controlling for temperature (Table 4). On average across regions, risk peaks in June and is lowest in February. Temperature has a statistically significant, but small, effect of increasing campylobacteriosis rates beyond the impacts of seasonality, whether seasonality is represented by season or month. There is no systematic trend in campylobacteriosis rates over the study time period other than their being estimated to be higher in 2000 than in other study years. Following Tam et al. (2005), we explored sensitivity of results to different averaging periods and found more stable results on the role of temperature when we use a 6 week averaging period.

We also ran analysis to look at the impact of omitting Homescan markets that had less overlap with FoodNet. Omitting these markets little effect. For instance, ground beef's IRR changes from 1.57 to 1.67, when Homescan markets with less than 15 percent coverage are omitted in a model including season dummies and temperature.

DISCUSSION

One of the basic questions about campylobacteriosis is whether it is driven by season, temperature or both. Past research has shown clear seasonality in *Campylobacter* incidence with a summer peak (Nylen et al. 2002, Miller et al., 2004, Strachan et al., 2013, Weisent et al. 2010). Several studies have looked at either the influence of temperature or the influence of seasonality on *Campylobacter* incidence, but not the two together, finding that human campylobacteriosis incidence rises with temperature or lagged temperature (Louis et al. 2005, Kovats et al. 2005). This

study confirms results found by Tam et al. 2005 in England, i.e., that season and temperature independently influence *Campylobacter* infections. The only U.S. study we found exploring this relationship reached a different conclusion. Soneja et al. (2016) conducted a multivariate analysis of campylobacteriosis in Maryland regressing 4 seasonal dummy variables, state-level count data on monthly extreme heat and precipitation events, and county level demographic variables on monthly campylobacteriosis cases in Maryland from 2000-2012. They did not find an association between extreme heat or precipitation events and campylobacteriosis once seasonality was accounted for. They estimated an IRR of 2.63 for summer compared to winter after accounting for the influence of extreme weather events.

We find that seasonality and temperature each have independent impacts on campylobacteriosis incidence in the U.S., but that the influence of season is much larger than that of temperature. At a national level, season, modeled either with 3 month seasons or with monthly dummy variables, had a large and highly significant effect on weekly *Campylobacter* incidence over and above the impact of regional weekly temperature levels. Our estimates indicate that holding temperature, region, and foods constant, there were on average between 2000 and 2006 roughly 815 more monthly cases of campylobacteriosis nationally in June and in July than in January (IRRs of roughly 1.25). In addition, we also found that temperature had a smaller, but statistically significant, impact on national campylobacteriosis incidence even after accounting for seasonality. A one degree increase in average weekly temperature across the year was associated with roughly 16 additional cases of campylobacteriosis per week over and above what was accounted for by season, region or food exposure.

Previous research has explored why there are seasonal peaks and geographic variability in *Campylobacter* infections. Higher temperatures can enhance pathogen survival and growth (D'Souza et al. 2004). This may lead to higher prevalence in animal populations, water, and temperature abuse in food transport, storage or handling (Jore et al. 2010, Boysen 2011). But seasonal factors may also be at play separately. Human activities vary seasonally, potentially leading to greater human exposure to pathogens through travel, contaminated recreational water, and greater direct contact with livestock, other animals or even flies (Neal et al. 1995, Mullner et al. 2010, Ekhald et al. 2005). Methods or location of food preparation may vary seasonally. Prior research has found that barbeques, a summer outdoor activity, pose an increased risk for *Campylobacter* infection (Domingues et al. 2012, Ravel et al. 2010). We cannot observe food preparation methods. Our data only captures food purchased for preparation at home. There may be seasonal differences in consumption of food prepared outside the home that affect the seasonality of campylobacteriosis in the U.S. An additional factor that may play a role, but has not been studied is the fact that produce is sourced from different geographic regions both within and outside the U.S. over the course of a year (Plattner et al. 2014).

We also find that regional differences in human *Campylobacter* incidence persist even after controlling for food, season and temperature. Relative to Albany, Memphis had the lowest incidence risk ratio, 0.54, and San Francisco the highest 2.2. Most demographic variables were highly correlated with region over a six year period, so it was not possible using the data and method we develop in this paper to explore what it is about region that affects campylobacteriosis incidence rates. But clearly there are differences that bear investigation. Possible influences include differences in the human population age structure, health status, health care systems/disease reporting, or human activity patterns across regions. Differences in the prevalence

Campylobacter in reservoirs in the region coupled with regional differences in human outdoor activity could also be a factor in regional differences in incidence. Prior research has identified direct contact with livestock or manures to be a risk factors. Prior research has also found that hogs are more likely to be infected with *Campylobacter jejuni* and chickens with *Campylobacter coli* (FDA 2015). There may be regional differences in contact with livestock and with different species of livestock. Patrick et al. 2018 study found roughly two-thirds of human *C. jejuni* and *C. coli* cases occur in the Midwest and South while roughly half of *C. upsaliensis* cases occur in Western and Pacific states.

Poultry consumption is widely viewed as a major risk factor for foodborne campylobacteriosis (Nelson and Harris 2017). But like the U.S. case-control study of sporadic *Campylobacter* infections, we find that eating chicken at home actually reduced *Campylobacter* infection risk (Friedman et al. 2004). However, contrary to the findings in the case-control study, we find fresh berry purchases for home consumption increased rather than decreased *Campylobacter* infection risk. Neither consumption of ground beef nor consumption of non-leafy vegetables were identified as increasing risk in Friedman et al.'s case-control study, but they were in our analysis. Major food risk factors identified in the case-control study involved either eating meats prepared at a restaurant or eating raw or undercooked seafood or chicken or unpasteurized dairy products, features that we cannot measure with our data. Foods that should have lower risks due to their processing do have lower risks in Model 6, namely frozen chicken and dairy products (predominantly pasteurized). Canned foods, which are estimated to be slightly protective when season is not taken into account, is not significant in models 5 and 6; cereal is not significant in all but model1. We take these results that foods that should have lower risks do or are simply not

significant predictors of campylobacteriosis as some verification that the model is correctly reflecting food-related campylobacteriosis risk.

Our results broadly support the suggestion by Nelson and Harris (2017) that foodborne campylobacteriosis is not just a chicken story. Among foods that were purchased for home consumption, chicken did not increase risk of *Campylobacter* infection, but berries, non-leafy fresh vegetables, ground beef consistently did. Studies of sporadic *Campylobacter* infections outside the U.S. have also identified salad vegetables and fresh or frozen berries as risk factors for *Campylobacter* infection (Evans et al. 2003, Verhoeff-Bakkenes et al. 2011, *c.f.* Denis et al. 2016), though a Canadian study did not find *Campylobacter* in a national study sampling fresh produce in grocery stores. Notably, over half of the produce in this Canadian study was imported. It is interesting that we find fresh vegetables other than leafy greens are consistently associated with higher campylobacteriosis risk but leafy greens are not. This may indicate that cross-contamination in the home kitchen is playing a role, as fresh vegetables other than leafy greens are typically chopped and processed more than leafy greens. A strength of our study is that it provides insight into the role of foods purchased for "at-home" food consumption. A limitation is that it does not provide insight into the role of foods consumed at restaurants or other food service establishments in causing foodborne illness.

Methodologically, this study shows that at least for a pathogen with incidence as a high as *Campylobacter* in the U.S., cross-sectional time series analysis that combines disease surveillance data and food purchase data can enhance our understanding of the causes of common foodborne diseases. We were able to provide new evidence on the influence of season and temperature on sporadic *Campylobacter* incidence in the U.S. Our results on chicken

purchased for consumption at home are consistent with major findings from the single national case-control study of campylobacteriosis in the U.S. and we provided additional evidence to support the hypothesis that the *Campylobacter* food exposures routes are broader than poultry. This method was also able to shed additional light on regional differences in the incidence of *Campylobacter*. We were able to show that these regional differences persist even after controlling for season, temperature and food purchase patterns. However, because of the relatively small number of regions in the U.S. in which there is active surveillance of campylobacteriosis, it is not possible to use this method to explore whether demographic, behavioral or biological factors are drivers behind these regional differences. A likely limitation for this method is statistical power. We use *Campylobacter* to explore use of this method because *Campylobacter* incidence is high. In a companion paper we compare results from *Campylobacter* to those for STEC O157:H7 to examine the extent to which this method can be used to study pathogens with lower incidence rates.

Conventionally, research on the association between foodborne illness and food exposures has relied on dietary recall. The food purchase data developed for this study provides an additional, and, as we have shown, useful source of information for studying foodborne exposures. In Appendix 1 to this report, we provide graphs of regional food purchases categorized by commonly recognized foodborne disease risk factors.

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[**Box 1. Attribution Methods**]

Microbial subtyping has provided strong evidence of association between food sources and human disease where it has been supported by integrated disease surveillance and collection of isolates at critical points in the food chain (Pires et al. 2009). It is particularly useful in identifying linkages between primary animal reservoirs and human disease. Source attribution through genetic subtyping depends on heterogeneity in the pathogen type across food sources. As a result, to date, it has been used successfully with a limited number of pathogens, primarily *Salmonella* and *Campylobacter*. Source attribution using microbial subtyping also depends on the quality of human disease surveillance and on extensive isolate collection with sufficiently large and representative samples across potential food sources (Pires et al. 2009). The most advanced application of the method has been developed in Denmark, which maintains an integrated surveillance program of *Salmonella* in the food chain and human salmonellosis (Hald et al. 2004). Microbial subtyping has also been used in the United Kingdom (Dingle et al. 2001) and New Zealand (French 2007) to study campylobacteriosis source attribution.

Comparative exposure assessment estimates human exposure to a pathogen through different exposure routes either through a combination of modeling and sampling. Disease is attributed to exposure routes proportionately to the exposure dose estimate for each route. This is a form of risk modelling which is less detailed than conventional microbial risk assessment and more focused on partitioning the disease burden among all known exposure routes. Use of comparative exposure assessment is often limited by a lack of data on prevalence or exposure for different routes. Models for *Campylobacter* exposure have been developed for the Netherlands (Evers et al. 2008) and New Zealand (McBride et al. 2005).

Conventional epidemiological methods (case-control studies, cohort studies and case-series studies) have all been used to identify potential risk factors for foodborne disease. Case control studies are used more widely in foodborne disease epidemiology than cohort or case-series studies. They identify risk factors through comparison of matched ill and non-ill population samples. Systematic reviews and meta-analyses of several individual studies can be used to estimate the fraction of specific foodborne diseases attributable to specific risk factors, including specific food exposures, but the narrow scope of these studies generally limits their usefulness in partitioning disease across all likely exposure sources (Batz 2005). In contrast, analyzing data from outbreak investigations may be the most widely used and flexible method of attributing foodborne illness to food exposures. Identification of whether an illness is foodborne and of the specific food exposure route is a central task of outbreak investigations. As a result, outbreak investigations ideally provide the major source of hard data on the distribution of foodborne disease across food exposures. Aggregate data from outbreak investigations have been used to partition foodborne disease among food exposure routes (Painter et al. 2013). Where foods are mixed in preparation, modeling must be used to estimate the proportion of exposure attributable to specific foods (Painter et al. 2013). Such outbreak attribution studies are feasible in countries with strong surveillance systems. But even in these countries, outbreak attribution has limitations. In the U.S., outbreaks accounted for less than 1 percent of FoodNet *Campylobacter* cases, about 5 percent of FoodNet *Listeria* and *Salmonella* cases, and about 20 percent of FoodNet *E. coli* 0157:H7 cases (Ebel et al. 2016). Furthermore, in many outbreaks, the pathogen and/or the exposure route are not identified. Small outbreaks, those causing mild illness, or illnesses with long incubation periods are less likely to be reported. As a result, outbreak investigation may not accurately represent source attribution and the level of accuracy may vary by pathogen (Batz et al. 2005)

Current methods rely heavily on data from outbreak investigations (Painter et al. 2009). But outbreaks account for less than 10 percent of foodborne illness annually and may not be caused by the same foods that cause sporadic illnesses.

Intervention studies, whether of intentional or "natural experiments," are primarily useful for estimating the risk attributable to specific exposures. For example, withdrawal of chicken and eggs from Belgium food markets in 1999 due to dioxin-contamination of chicken feed, provided a natural experiment that allowed estimation of the percent of campylobacteriosis attributable to chicken consumption in Belgium (Velling and Van Lock 2002).

Expert elicitation is a structured means of aggregating expert judgment to provide information on data gaps. It should be seen as a more transparent, rigorous alternative to modelers using their own judgments about critical model parameters rather than a replacement for primary data and research. Several methods have been developed and applied to a wide range of scientific questions (cites). Scientifically, these methods represent alternative attempts to address the tendency for humans to have systematic biases in the way they assess uncertainty (Tversky and Kahneman 1974, Cooke and Shrader-Frechette 1991, Morgan and Henrion 1992, U.S. EPA 2012). Expert elicitations have been used for source attribution research in the United Kingdom (Henson 1997), United States (Hoffmann et al. 2007), the Netherlands (Havelaar et al., 2008), New Zealand (Lake et al. 2010), and recently in the WHO's global burden of disease initiative (Aspinall et al. 2016).

Box 2. Food Consumption Data Sources.

Conventionally, in modeling of the relationship between food consumption and foodborne disease in the U.S. has relied on the "What We Eat in America" (WWEIA) component of the National Health and Nutrition Examination Survey (NHANES) (USDA ARS 2017). NHANES continuously surveys a sample of approximately 5,000 Americans from 15 counties across the U.S. each year. The data are released every 2 years and are weighted to provide nationally representative sample for each two-year cycle. The WWEIA component of NHANES asks individuals detailed questions about their food intake during two separate 24-hour periods and can be used to estimate usual intake for the population or population subgroups. Because the geographic coverage is limited in each year of the survey, and can be correlated with time of year (northern counties more likely to be sampled in the summer and southern counties in the winter) the data are not suitable for seasonal or regional analyses across the U.S.

The other major data conventionally used to gain insight into food consumption in the U.S. is food availability data (USDA ERS 2017). Food availability data measures the annual supply of basic commodities (e.g., fluid milk, cottage cheese, tangerines, turkey, and broilers) available for human consumption in the United States. Annual commodity supply available for human consumption is defined as "Available Commodity Supply (stocks at the beginning of the year + production + imports) – Measurable Nonfood Use (farm inputs + exports + end-of-year stocks)." A related data series, the Loss-Adjusted Food Availability data, adjusts food availability estimates for food loss at different states in the food chain to more closely approximate actual food intake in the U.S. (USDA ERS 2017). Like NHANES, these data are also annual and national and therefore do not provide information about the seasonality of food availability or its

regional variation. Similar food availability datasets (i.e., supply and use balance sheets) are constructed by countries around the world and are compiled into the FAO Food Balance Sheets (FAO 2017).

Tables:

Figures:

Appendix:

Table 1. Food Categories

Aggregate Categories	Disaggregated Food Categories
Canned	Canned Fruits and Vegetables
	Canned Meat
	Canned Seafood
Cereal	Cereal
Dairy	Milk
	Block Cheese (Random Weight)
	Block Cheese (UPC)
	Processed Block Cheese (UPC)
	Processed Sliced Cheese (UPC)
	Sliced Cheese (Random Weight)
	Sliced Cheese (UPC)
	Other Dairy (Random Weight)
	Other Dairy (UPC)
Deli/Sliced/Precooked	Mixed Deli Meat (UPC)
	Precooked Beef Sausages (UPC)
	Precooked Beef Sausages (Random Weight)
	Precooked Mixed Sausages (UPC)
	Precooked Mixed Sausages (Random Weight)
	Precooked Pork Sausages (UPC)
	Precooked Pork Sausages (Random Weight)
	Sliced Beef (Random Weight)
	Sliced Beef (UPC)
	Sliced Mixed Meat (Random Weight)
	Sliced Mixed Meat (UPC)
	Sliced Pork (Random Weight)
	Sliced Pork (UPC)
	Sliced Turkey (UPC)
	Sliced Turkey (Random Weight)
Eggs	Eggs (UPC)
Fresh Vegetables, Herbs, and Roots	Ready-to-Eat Carrots (UPC)
	Ready-to-Eat Celery (UPC)
	Beets (Random Weight)
	Broccoli (Random Weight)
	Brussel Sprouts (UPC)
	Brussel Sprouts (Random Weight)

	Carrots (UPC)
	Carrots (Random Weight)
	Cauliflower (Random Weight)
	Celery (UPC)
	Celery (Random Weight)
	Corn (Random Weight)
	Cucumbers (Random Weight)
	Eggplant (Random Weight)
	Greens (UPC)
	Greens (Random Weight)
	Head of Cabbage (Random Weight)
	Herbs (UPC)
	Herbs (Random Weight)
	Mixed Vegetables (UPC)
	Mixed Vegetables (Random Weight)
	Mushrooms (UPC)
	Mushrooms (Random Weight)
	Onions and Scallions (Random Weight)
	Peas (UPC)
	Peas in the Pod (UPC)
	Peppers (UPC)
	Pepper (Random Weight)
	Potatoes (UPC)
	Potatoes (Random Weight)
	Radishes (UPC)
	Shredded Cabbage (UPC)
	Sprouts (UPC)
	Squash (UPC)
	Squash (Random Weight)
	String Beans (UPC)
	String Beans (Random Weight)
	Tomatoes (UPC)
	Tomatoes (Random Weight)
	Other Root Vegetables (Not Carrots, Onions and Scallions, Potatoes, or Radishes)
	Other ready-to-eat vegetables (UPC)
	Other Vegetables (Not listed above)
Leafy Greens	Leafy Lettuce (Random Weight)
	Lettuce Head (UPC)
	Lettuce Head (Random Weight)
	Ready-to-Eat Lettuce (UPC)

	Ready-to-Eat Spinach (UPC)
	Spinach (Random Weight)
Frozen Fruits and Vegetables	Frozen Fruits and Vegetables (UPC)
Fruits Eaten without Peeling (Not Peeled Fruits)	Grapes (Random Weight)
	Grapes (UPC)
	Peaches (Random Weight)
	Pears (Random Weight)
	Plums (Random Weight)
	Prunes (Random Weight)
	Apples (Random Weight)
	Apples (UPC)
	Raisins
	Dry Dates
	Other Dry Fruit (Not Raisins or Dates)
Berries	Blueberries (UPC)
	Raspberries (UPC)
	Strawberries (UPC)
	Other Berries (Not Blueberries, Raspberries or Strawberries) (UPC)
Fruits Eaten Peeled (Peeled Fruits)	Bananas (Random Weight)
	Grapefruit (UPC)
	Kiwi (UPC)
	Lemons (UPC)
	Limes (UPC)
	Mangos (Random Weight)
	Melons (Random Weight)
	Oranges (UPC)
	Papayas (Random Weight)
	Pineapples (Random Weight)
	Tangerines (UPC)
	Avocado (UPC)
Juice	Pasteurized Citrus Juice (UPC)
	Pasteurized Grape Juice (UPC)
	Pasteurized Pineapple Juice (UPC)
	Pasteurized Vegetable Juice (UPC)
	Other Pasteurized Juice (UPC)
	Other Juice (UPC)
Whole Meat	Fresh Whole Beef (Random Weight)
	Fresh Whole Beef (UPC)
	Fresh Whole Lamb (Random Weight)
	Fresh Whole Lamb (UPC)

	Fresh Whole Pork (Random Weight)
	Fresh Whole Pork (UPC)
	Frozen Whole Beef (Random Weight)
	Frozen Whole Pork (Random Weight)
Ground Meat (No Beef)	Frozen Ground Pork
	Fresh Ground Lamb (Random Weight)
	Fresh Ground Lamb (UPC)
	Fresh Ground Pork (Random Weight)
	Fresh Ground Pork (UPC)
Processed Not-Ready-to-Eat Meat	Raw Beef Sausage (Random Weight)
	Raw Beef Sausage (UPC)
	Raw Pork Sausage (Random Weight)
	Raw Pork Sausages (UPC)
	Raw Mixed Sausage (Random Weight)
	Raw Mixed Sausage (UPC)
	Pork Bacon (UPC)
	Other Bacon (UPC)
Ground Beef	Fresh Ground Beef (Random Weight)
	Fresh Ground Beef (UPC)
	Frozen Ground Beef (UPC)
Frozen Chicken	Frozen Ground Chicken (UPC)
	Frozen Whole Chicken (Random Weight)
	Frozen Whole Chicken (UPC)
Fresh Chicken	Fresh Whole Chicken (Random Weight)
	Fresh Whole Chicken (UPC)
	Fresh Ground Chicken (Random Weight)
	Fresh Ground Chicken (UPC)
Turkey	Fresh Ground Turkey (Random Weight)
	Fresh Ground Turkey (UPC)
	Fresh Whole Turkey (Random Weight)
	Fresh Whole Turkey (UPC)
	Frozen Ground Turkey (Random Weight)
	Frozen Ground Turkey (UPC)
	Frozen Whole Turkey (Random Weight)
Seafood, fish, etc.	Fresh Crustaceans (Random Weight)
	Fresh Fish (Random Weight)
	Fresh Mollusks (Random Weight)
	Fresh Oysters (Random Weight)
	Frozen Crustaceans (UPC)
	Frozen Fish (UPC)
	Frozen Mixed Seafood (UPC)

	Frozen Mollusks (UPC)
	Ready-to-Eat Fish and Seafood (Random Weight)
	Ready-to-Eat Fish and Seafood (UPC)
Nuts and Seeds	Raw Seeds (UPC)
	Raw Seeds (Random Weight)
	Raw Shelled Mixed Nuts (UPC)
	Raw Shelled Peanuts (UPC)
	Raw Shelled Peanuts (Random Weight)
	Raw Shelled Tree Nuts (UPC)
	Raw Shelled Tree Nuts (Random Weight)
	Raw Unshelled Mixed Nuts (UPC)
	Raw Unshelled Mixed Nuts (Random Weight)
	Raw Unshelled Peanuts (UPC)
	Raw Unshelled Peanuts (Random Weight)
	Raw Unshelled Tree Nuts (UPC)
	Raw Unshelled Tree Nuts (Random Weight)
	Roasted Seeds (UPC)
	Roasted Seeds (Random Weight
	Roasted Shelled Mixed Nuts (UPC)
	Roasted Shelled Mixed Nuts (Random Weight)
	Roasted Shelled Pecan (UPC)
	Roasted Shelled Pecan (Random Weight)
	Roasted Shelled Tree Nuts (UPC)
	Roasted Shelled Tree Nuts (Random Weight)
Snacks	Snacks (UPC)

Table 2. FoodNet Cases by Pathogen

Table 2a. Infections caused by specific pathogens, reported by FoodNet sites, 2000									
Pathogen	CA	CT	GA	MD	MN	NY	OR	TN	Total
Campylobacter	1186	586	591	189	1079	343	558	181	4713
Cryptosporidium	67	29	178	7	197	23	21	13	535
Cyclospora	6	2	13	0	0	1	0	0	22
Escherichia coli O157	46	84	42	16	216	74	114	34	626
Non-O157 STEC	0	13	12	0	28	0	3	1	57
Listeria	13	18	20	10	8	21	6	9	105
Salmonella	460	418	1491	379	612	254	293	423	4330
Shigella	577	69	319	82	903	22	118	265	2355
Vibrio	22	6	8	7	3	0	7	1	54
Yersinia	28	13	46	8	10	8	9	11	133

Source: CDC. 2000. Foodborne Disease Active Surveillance Network (FoodNet) 2000 Surveillance Report. https://www.cdc.gov/foodnet/PDFs/2000final_report.pdf (accessed May 12, 2017)

Table 2b. Number of laboratory-confirmed infections caused by specific bacterial pathogens reported, by site, FoodNet, 2006											
Pathogen	CA	CO	CT	GA	MD	MN	NM	NY	OR	TN	Total
Campylobacter	866	479	532	580	432	899	383	522	634	443	5,770
Listeria	8	5	19	20	28	7	5	22	11	14	139
Salmonella	486	358	506	1841	776	725	259	495	401	842	6,689
Shigella	244	180	67	1375	128	259	172	48	94	198	2,765
STEC O157	42	35	41	41	40	147	20	53	83	88	590
STEC non-0157	6	16	34	18	33	44	23	19	9	10	212
*STEC O Antigen undetermined.	0	0	0	4	17	0	0	0	0	5	26
Vibrio	41	3	19	25	31	4	2	12	10	9	156
Yersinia	10	6	18	32	11	23	5	14	15	29	163

Total	1,703	1,082	1,236	3,936	1,496	2,108	869	1,185	1,257	1,638	16,510

Table 2c. Number of laboratory-confirmed infections caused by specific parasitic pathogens reported, by site, FoodNet, 2006

Pathogen	CA	CO	CT	GA	MD	MN	NM	NY	OR	TN	Total
Cryptosporidium	47	37	38	276	20	242	41	54	77	47	879
Cyclospora	0	0	11	19	2	4	1	0	2	4	43
Total	47	37	49	295	22	246	42	54	79	51	922

Source: CDC. 2006. Foodborne Disease Active Surveillance Network (FoodNet) 2006 Surveillance Report. https://www.cdc.gov/foodnet/PDFs/2006_Annual_Report.pdf (accessed May 12, 2017)

Table 3. Relationship between Homescan and FoodNet Geographic and Temporal Coverage

Markets	Number of counties that are active in FoodNet	Coverage[1]	Overlap[2]	First year all FoodNet counties were active
Baltimore	12	100%	100%	2002
Atlanta	57	98%	92%	1999
Buffalo-Rochester	13	96%	81%	2003
Minneapolis	38	93%	83%	1998
Portland	24	86%	83%	1998
Nashville	41	82%	69%	2003
Hartford-New Haven	6	78%	67%	1998
Albany	12	62%	71%	2004
Denver	7	62%	23%	2002
Memphis	16	55%	30%	2003
San Francisco	3	46%	27%	2000
Washington, D.C.	11	39%	25%	2002
NY Exurban	1	33%	25%	1998
Syracuse	6	14%	30%	2004
Jacksonville	8	12%	40%	1999
Boston	1	1%	5%	1998
Pittsburg	1	1%	3%	2002

[1] Percentage of Homescan population in the active FoodNet counties
[2] FoodNet counties as percentage of Homescan counties

Table 4. Regression Results: Incidence Rate Ratios for Campylobacter Regressions

	Model					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Consumption	+ Market FE	+ Year FE	Temperature L6	+ Season FE	+ Month FE (no season)
Food: Total Kgs. Sold per Capita (lagged t=5 to t=18 days)						
Ground Beef	0.527***	1.840***	1.589***	1.485***	1.501***	1.370***
	(0.0453)	(0.153)	(0.135)	(0.135)	(0.137)	(0.126)
Berries	9.214***	6.511***	7.688***	4.840***	3.015***	1.800***
	(1.088)	(0.739)	(0.891)	(0.599)	(0.439)	(0.297)
Canned Goods	0.727***	0.814***	0.836***	0.917***	1.000	1.016
	(0.0242)	(0.0269)	(0.0272)	(0.0303)	(0.0346)	(0.0354)
Cereal	4.891***	0.815	1.086	1.207	1.060	1.003
	(0.850)	(0.149)	(0.200)	(0.234)	(0.206)	(0.196)
Frozen Chicken	2.590***	0.969	0.904	0.928	0.841	0.710**
	(0.297)	(0.137)	(0.127)	(0.134)	(0.123)	(0.108)
Not Frozen Chicken	0.770***	1.068	1.087	1.111*	1.095	1.029
	(0.0445)	(0.0630)	(0.0636)	(0.0657)	(0.0645)	(0.0619)
Dairy	1.213***	0.953***	0.957**	0.950***	0.956**	0.958**
	(0.0179)	(0.0180)	(0.0182)	(0.0188)	(0.0188)	(0.0188)
Deli meat (all)	0.788***	0.955	1.147**	1.109*	1.097	1.067
	(0.0404)	(0.0517)	(0.0645)	(0.0652)	(0.0647)	(0.0633)
Eggs	0.498***	0.908	0.908	0.971	0.935	1.213
	(0.0758)	(0.145)	(0.144)	(0.158)	(0.152)	(0.200)
Frozen Fruits and Vegetables	0.108***	0.908	0.879	0.991	1.050	1.088
	(0.0127)	(0.116)	(0.112)	(0.131)	(0.137)	(0.142)
Fruits not typical eaten peeled	3.944***	2.314***	2.199***	1.076	0.756***	0.850
	(0.283)	(0.178)	(0.169)	(0.0977)	(0.0742)	(0.0896)
Fruits eaten peeled	1.446***	0.545***	0.513***	0.823***	0.843***	0.824***
	(0.0655)	(0.0312)	(0.0299)	(0.0494)	(0.0511)	(0.0513)
Juice	0.582***	0.807***	0.837***	0.917*	0.916*	0.912*

	(0.0234)	(0.0387)	(0.0398)	(0.0456)	(0.0453)	(0.0455)
Leafy Greens	1.695***	0.923	1.002	0.781*	0.798	0.721**
	(0.166)	(0.114)	(0.123)	(0.112)	(0.113)	(0.107)
Ground Meat (excl. beef)	0.379	0.0967**	0.105**	0.156*	0.147*	0.152*
	(0.394)	(0.109)	(0.118)	(0.169)	(0.160)	(0.163)
Whole cuts of meat (excl. poultry)	0.938	1.052	1.001	1.057	1.056	1.115**
	(0.0470)	(0.0548)	(0.0543)	(0.0573)	(0.0579)	(0.0613)
Nuts	2.883***	0.707**	0.846	0.942	0.857	1.184
	(0.386)	(0.125)	(0.146)	(0.165)	(0.153)	(0.216)
Seafood	0.0427***	0.144***	0.244***	0.616	0.492**	0.577
	(0.0171)	(0.0540)	(0.0886)	(0.220)	(0.176)	(0.208)
Turkey	1.004	0.947	0.961	0.914*	0.920	0.989
	(0.0492)	(0.0471)	(0.0474)	(0.0453)	(0.0480)	(0.0549)
Snacks	0.700***	1.525***	1.233**	0.992	0.979	0.947
	(0.0640)	(0.138)	(0.115)	(0.0987)	(0.0980)	(0.0950)
Fresh Vegetables (excl. leafy greens)	1.160***	1.223***	1.161***	1.195***	1.205***	1.196***
	(0.0422)	(0.0509)	(0.0491)	(0.0519)	(0.0527)	(0.0526)
Market Fixed Effects:						
Atlanta		0.762***	0.769***	0.717***	0.714***	0.714***
		(0.0246)	(0.0247)	(0.0238)	(0.0237)	(0.0238)
Baltimore		0.823***	0.834***	0.785***	0.789***	0.790***
		(0.0292)	(0.0295)	(0.0284)	(0.0285)	(0.0286)
Boston		1.262***	1.281***	1.216**	1.220**	1.241***
		(0.0941)	(0.0955)	(0.0952)	(0.0955)	(0.0972)
Buffalo - Rochester		1.195***	1.218***	1.125***	1.137***	1.141***
		(0.0421)	(0.0425)	(0.0406)	(0.0410)	(0.0414)
District of Columbia		0.696***	0.717***	0.659***	0.672***	0.674***
		(0.0287)	(0.0296)	(0.0281)	(0.0286)	(0.0288)
Denver		1.483***	1.501***	1.492***	1.499***	1.486***
		(0.0520)	(0.0531)	(0.0540)	(0.0541)	(0.0537)
Hartford - New Haven		1.238***	1.256***	1.182***	1.211***	1.222***
		(0.0457)	(0.0460)	(0.0439)	(0.0449)	(0.0456)
Jacksonville		1.246***	1.257***	1.144**	1.139*	1.126*

	(0.0778)	(0.0782)	(0.0761)	(0.0757)	(0.0749)
Memphis	0.541***	0.550***	0.551***	0.538***	0.537***
	(0.0270)	(0.0274)	(0.0278)	(0.0272)	(0.0271)
Minneapolis	1.583***	1.545***	1.497***	1.512***	1.531***
	(0.0532)	(0.0517)	(0.0514)	(0.0518)	(0.0526)
New York Exurban	1.669***	1.682***	1.576***	1.622***	1.640***
	(0.0667)	(0.0672)	(0.0646)	(0.0666)	(0.0679)
Nashville	0.722***	0.752***	0.698***	0.681***	0.688***
	(0.0290)	(0.0301)	(0.0287)	(0.0281)	(0.0285)
Pittsburg	0.730	0.774	0.716	0.718	0.730
	(0.172)	(0.182)	(0.177)	(0.178)	(0.181)
Portland	1.539***	1.584***	1.443***	1.442***	1.427***
	(0.0559)	(0.0587)	(0.0555)	(0.0555)	(0.0551)
San Francisco	2.249***	2.285***	2.126***	2.181***	2.195***
	(0.0723)	(0.0733)	(0.0699)	(0.0719)	(0.0729)
Syracuse	1.482***	1.537***	1.421***	1.474***	1.500***
	(0.0967)	(0.100)	(0.0929)	(0.0965)	(0.0982)
Year Fixed Effects					
2001		0.900***	0.894***	0.893***	0.891***
		(0.0169)	(0.0170)	(0.0169)	(0.0169)
2001		0.876***	0.866***	0.869***	0.877***
		(0.0178)	(0.0190)	(0.0191)	(0.0194)
2002		0.834***	0.856***	0.860***	0.859***
		(0.0171)	(0.0180)	(0.0181)	(0.0180)
2003		0.849***	0.852***	0.861***	0.858***
		(0.0175)	(0.0176)	(0.0178)	(0.0178)
2004		0.871***	0.862***	0.869***	0.872***
		(0.0179)	(0.0177)	(0.0180)	(0.0181)
2005		0.853***	0.834***	0.844***	0.850***
		(0.0176)	(0.0173)	(0.0176)	(0.0180)
Average 6 Week Temperature Lagged (average of t-5 to t-46)			1.008***	1.006***	1.005***
			(0.000525)	(0.000851)	(0.00162)
Month Fixed Effects					

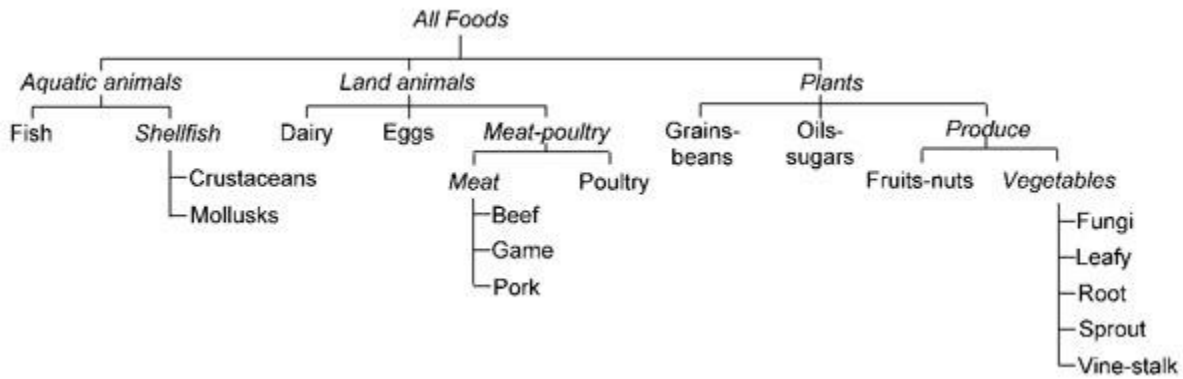
February						0.937**
						(0.0270)
March						0.944*
						(0.0287)
April						0.910***
						(0.0330)
May						1.058
						(0.0491)
June						1.251***
						(0.0711)
July						1.220***
						(0.0819)
August						1.108
						(0.0770)
September						0.978
						(0.0618)
October						0.917*
						(0.0456)
November						0.863***
						(0.0361)
December						0.841***
						(0.0269)
Season Fixed Effects***						
Spring (March-May)					1.002	
					(0.0198)	
Summer (June-August)					1.190***	
					(0.0373)	
Fall (September-November)					0.978	
					(0.0252)	
Constant	1.89e-05***	1.51e-05***	1.74e-05***	1.04e-05***	1.12e-05***	1.25e-05***
	(4.26e-07)	(5.69e-07)	(7.29e-07)	(5.62e-07)	(6.51e-07)	(9.43e-07)
Observations	41,666	41,666	41,666	38,871	38,871	38,871

Average campylobacteriosis Cases Per 100K	0.739	0.739	0.739	0.739	0.739	0.739
Pseudo R-squared	0.0584	0.114	0.115	0.117	0.119	0.121

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: At least 4 days in the 1-week consumption lag (n-5 to n-18) occurred during this Year/Month/Season
Omitted Dummies: Market=Albany, Year=2000, Season=Winter, and Month=January
2-week Lagged Consumption Year == 2001 [See Note]
2-week Lagged Consumption Month == February [See Note]
Seasonal Dummy: Season of mode of 2-week period prior to laboratory confirmation (t-5 to t-18)
Temperature L6: lagged 6 week average daily temperature (the average of t-5 to t-46 days, with *t* being the day the case is laboratory confirmed)

Figures:

Figure 1. Painter et al. (2013) Food Categorization for Food Source Attribution of Outbreak Disease Data



Italics indicate commodity groups.

Figure 2. Seasonality in campylobacteriosis rates by market

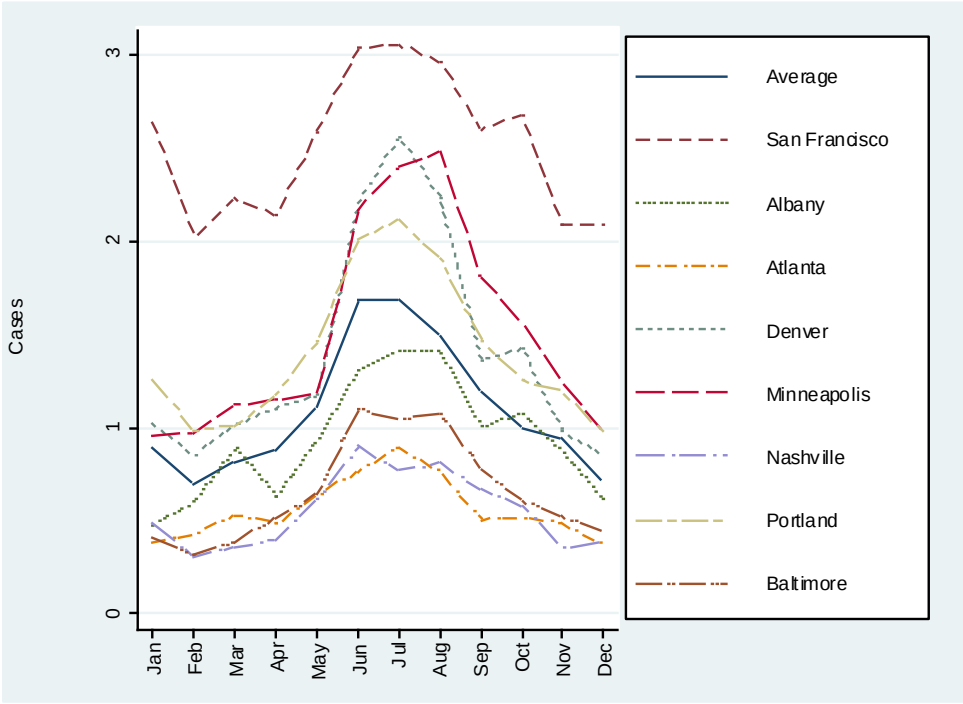


Figure 2a. *Campylobacter* Cases per 100K by Market and Month

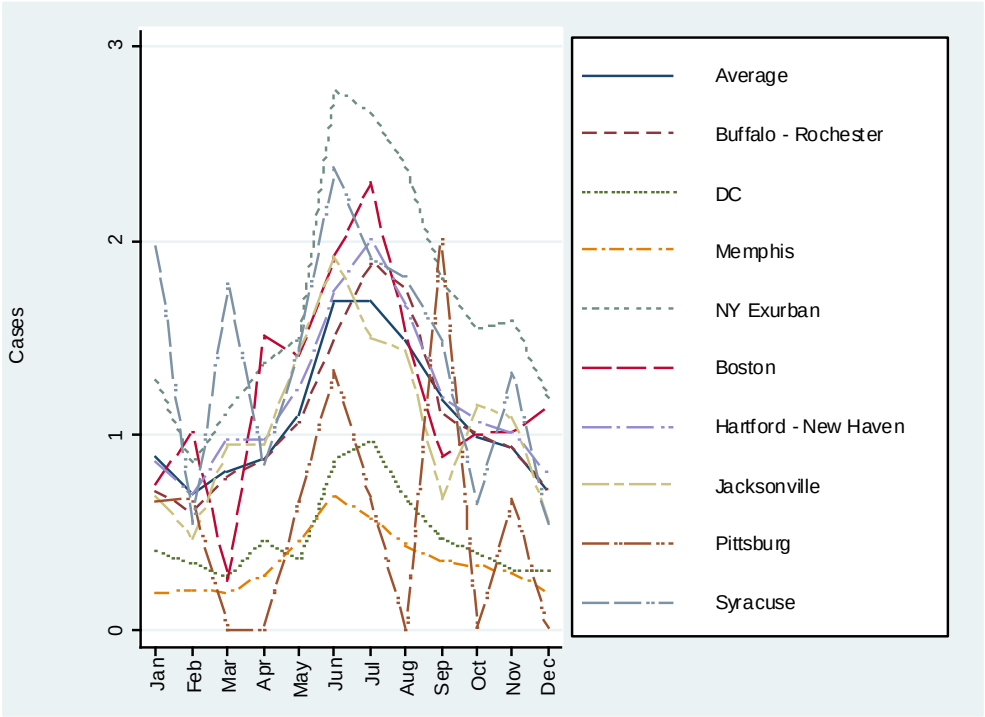


Figure 2b. *Campylobacter* Cases per 100K by Market and Month

Figure 3. Time trends in campylobacteriosis rates by market.

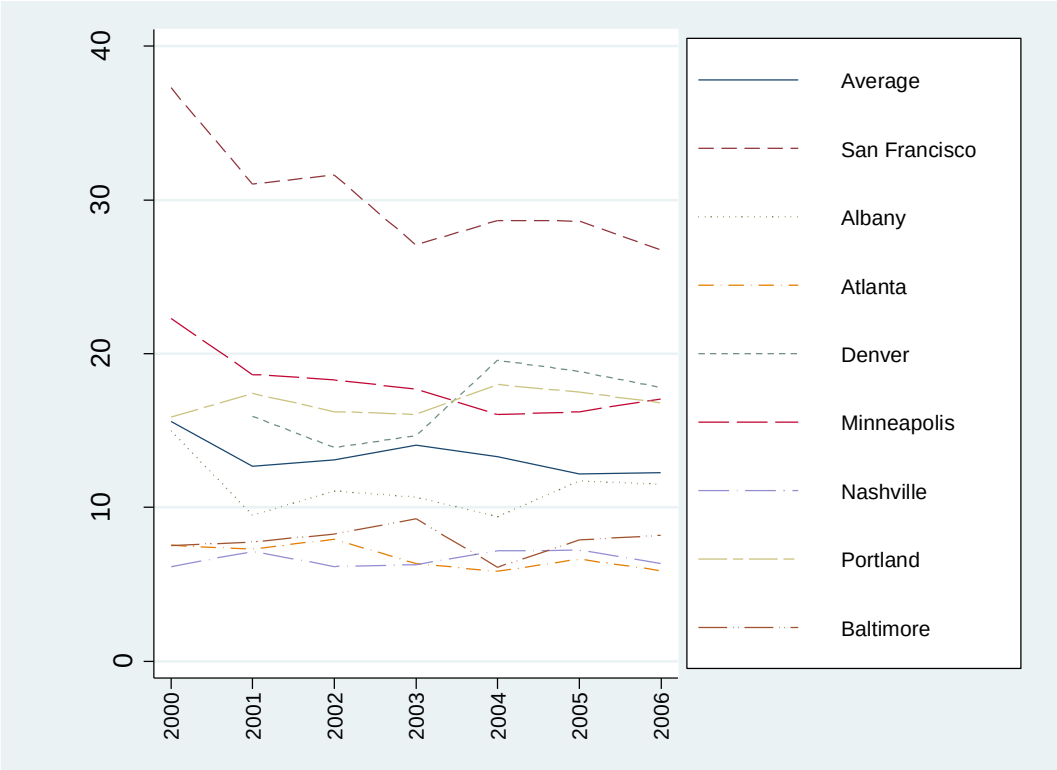


Figure 3a. *Campylobacter* Cases per 100K by Market and Year

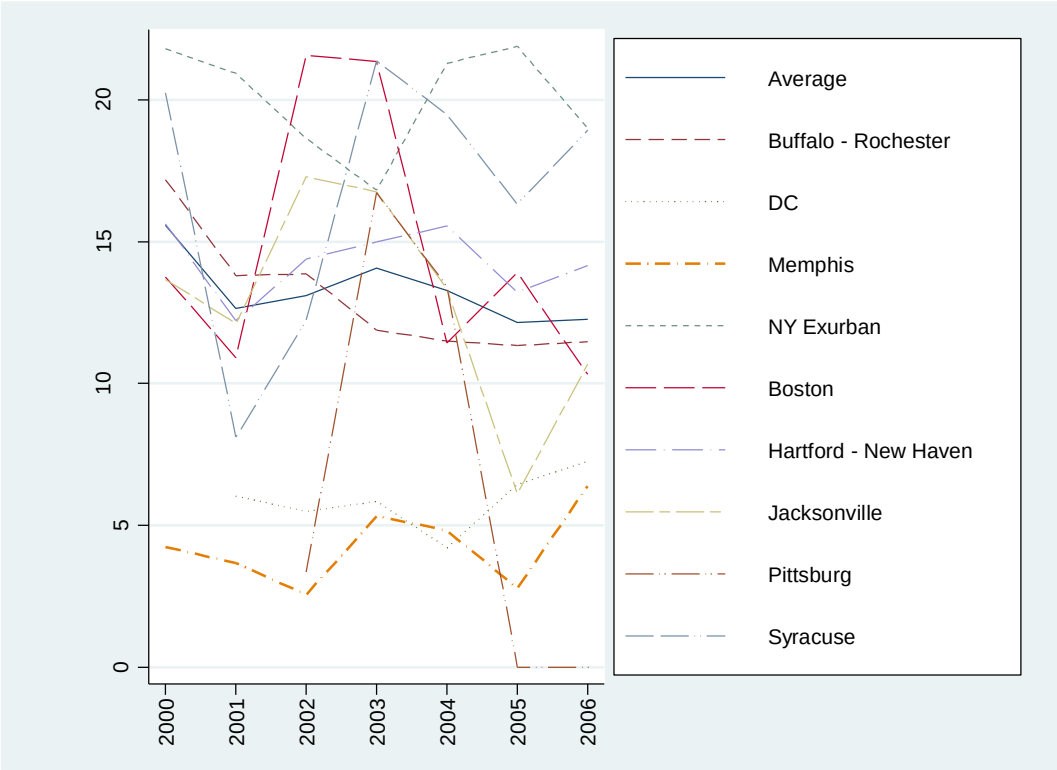
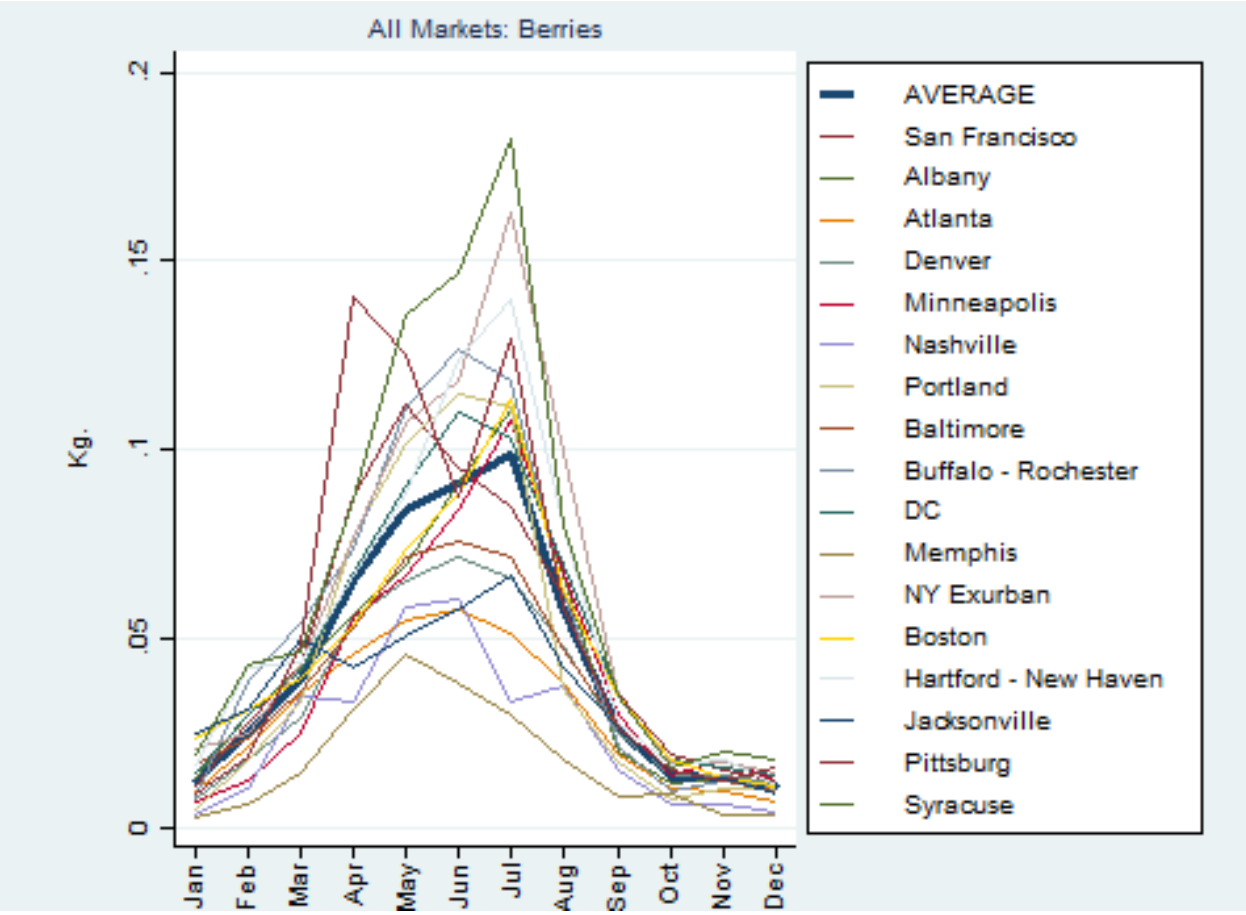


Figure 3b. *Campylobacter* Cases by Market and Year

Figure 4. Seasonality in berry purchases by market



Figures 5. Seasonality in leafy greens purchases by market

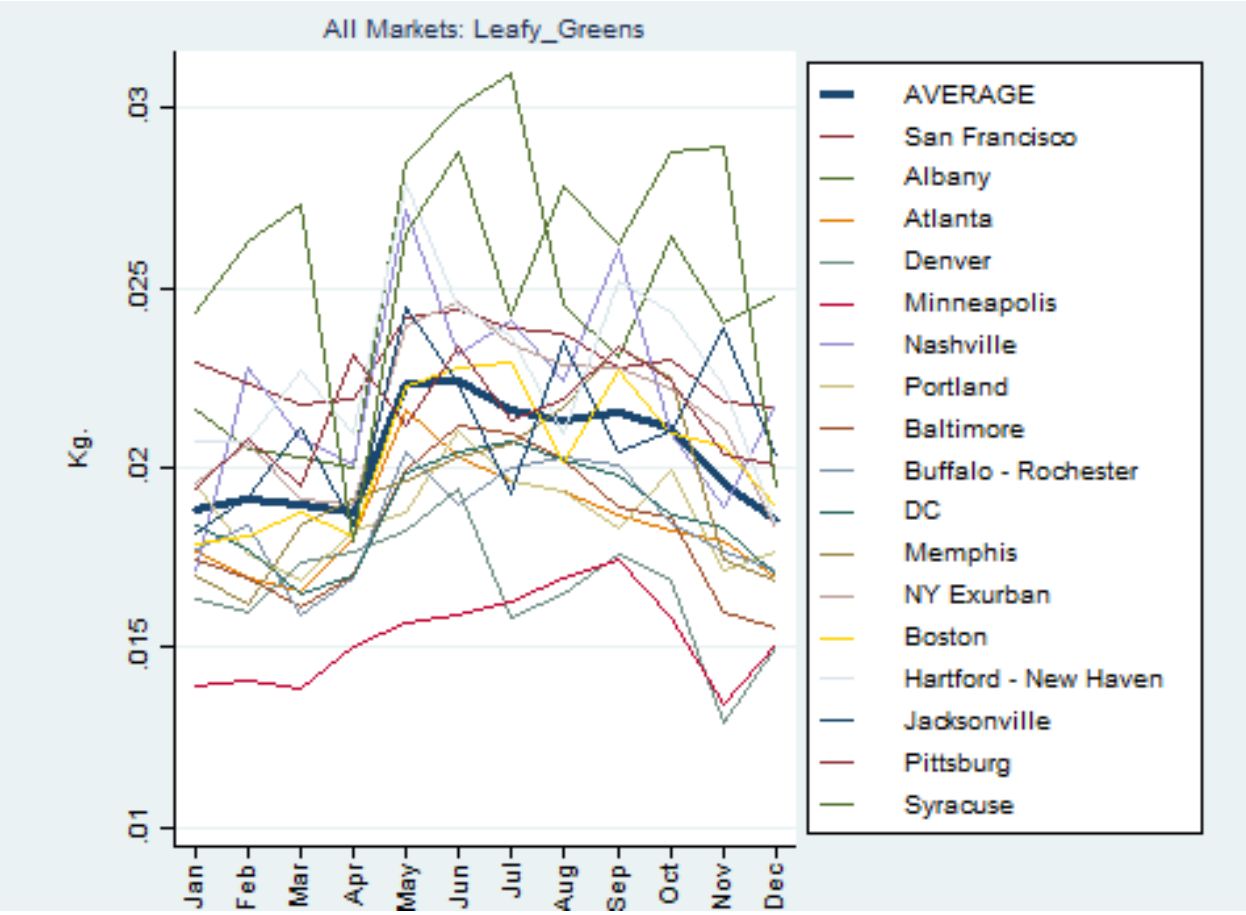
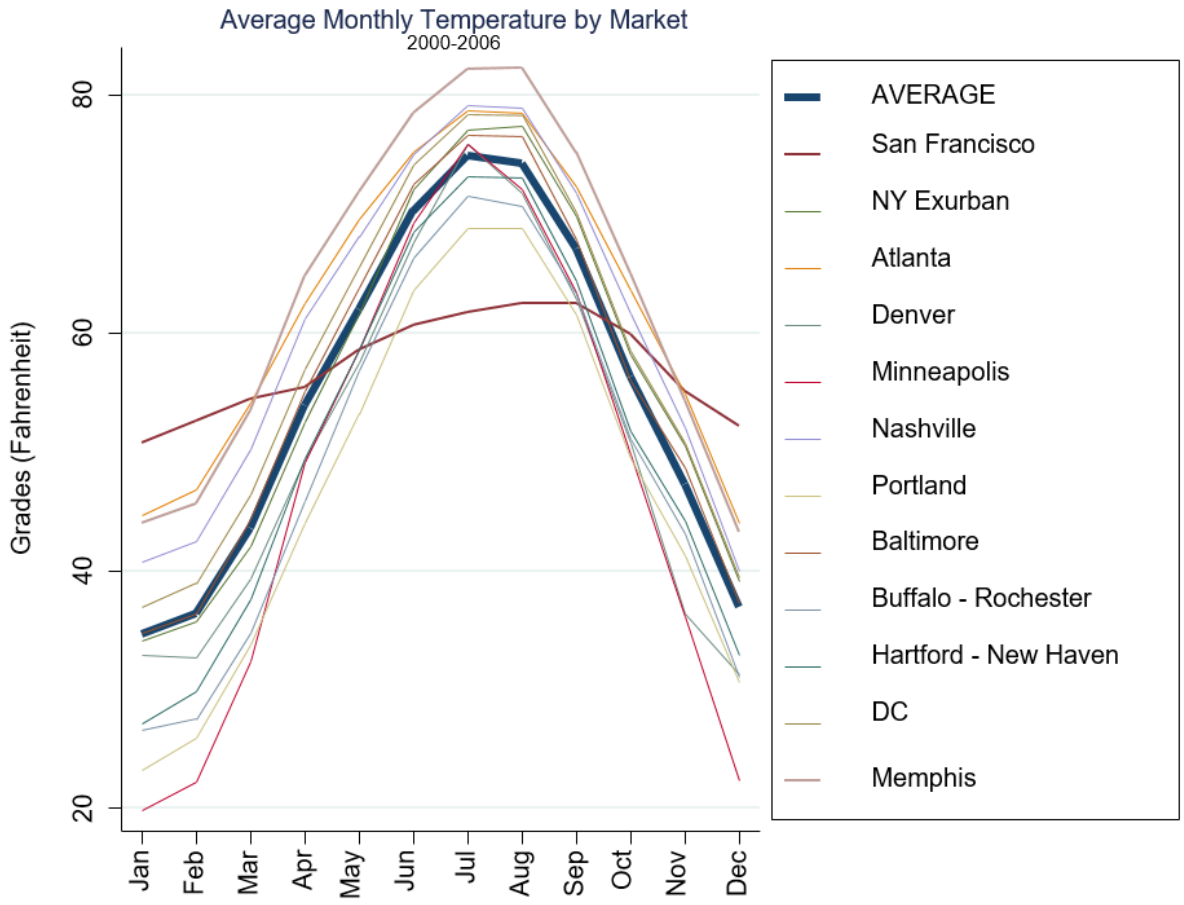


Figure 6. Weakly average temperature by market



Appendix 1. Other Regression Results

Table A1.1. *Campylobacter*. Omitting Low Overlap Markets

VARIABLES	(1) All Areas	(2) omit <15%	(3) omit <50%
beef_ground	1.441***	1.393***	1.393***
	-0.166	(0.168)	(0.173)
berries	2.122***	1.790**	1.936***
	-0.45	(0.437)	(0.486)
canned	1.018	1.006	0.984
	-0.0462	(0.0482)	(0.0494)
cereal	0.936	1.191	1.112
	-0.237	(0.324)	(0.315)
chicken_frozen	0.626**	0.571**	0.670*
	-0.126	(0.126)	(0.158)
chicken_nt_frozen	1.007	1.014	1.066
	-0.0809	(0.0841)	(0.0903)
dairy	0.945**	0.959	0.943**
	-0.0239	(0.0270)	(0.0280)
deli	1.139*	1.198**	1.195*
	-0.0862	(0.108)	(0.110)
eggs	1.214	1.281	1.309
	-0.264	(0.291)	(0.312)
frozen_fv	1.187	1.422**	1.208
	-0.201	(0.255)	(0.232)
fruits_nt_peeled	0.848	0.899	0.999
	-0.117	(0.131)	(0.151)
ruits_peeled	0.748***	0.726***	0.712***
	-0.0623	(0.0674)	(0.0689)
juice	0.899*	0.855**	0.854**
	-0.0574	(0.0586)	(0.0616)
leafy	0.714*	0.681**	0.734
	-0.132	(0.133)	(0.146)
meat_ground_nb	0.0742*	0.0685*	0.0666*
	-0.107	(0.101)	(0.104)
meat_whole	1.138*	1.065	1.138
	-0.083	(0.0838)	(0.0917)
nuts	1.245	0.854	0.687
	-0.303	(0.227)	(0.192)
seafood	0.543	0.419	0.441
	-0.254	(0.229)	(0.250)
turkey	0.952	0.951	0.946
	-0.0719	(0.0757)	(0.0785)
upc_snacks	0.939	0.978	0.846
	-0.12	(0.133)	(0.124)

veggie_fresh	1.254***	1.282***	1.216***
	-0.0717	(0.0772)	(0.0760)