The Impacts of Food Safety Certification on Producers' Safety Outcomes

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Abstract: We investigate the impacts of private food safety certification on producer's safety outcomes. We use the U.S. Department of Agriculture (USDA) Food Safety Inspection Service (FSIS) pathogen sampling results as the measurement of food safety outcomes. We obtain a unique panel dataset by combining this governmental data and private food safety certification data. By applying penalized maximum likelihood approach, we find that there is a weak link between private food safety certification and *Salmonella* and *Campylobacter* test results.

Introduction

Food safety has been and is still a serious matter in the United States. Centers for Disease Control and Prevention (CDC) estimates 48 million people get sick, 128,000 are hospitalized, and 3,000 die from foodborne diseases each year in the United States. Additionally, one of CDC's surveillance systems, Foodborne Disease Outbreak Surveillance System (FDOSS) identified 841 foodborne disease outbreaks, resulting in 14,481 illnesses, 827 hospitalizations, and 20 deaths in 2017(Centers for Disease Control and Prevention, 2019). Among these outbreaks, *Salmonella* is the second most common cause (113 cases), followed by Shiga toxin-producing *Escherichia coli* (19 cases). Furthermore, the United States Department of Agriculture, Economic Research Service (ERS) estimates the total economic cost[1] of major foodborne illness being $15.5 billion in 2013 and increasing to $17.6 billion in 2018.

While consumers have always demanded safe food, supply chains have become increasingly complex and of a global nature. At the same time, the ability to identify factors related to food safety-as well as the ability to communicate these metrics-has increased. Improving food safety system needs the joint efforts of government, industry, individuals, and private sector. Over the past two decades, there has been a proliferation of private food safety standards (also known as private food safety management system to the industry) and private entities that certify producers, processors, and manufacturers as having met these standards. Though this new phenomenon has been receiving increasing attention, in general, there is a lack of empirical studies especially certification's food safety effect on firm or farm. Only one study has investigated the effect of private sector on food safety outcomes (Adalja et al., 2021). The authors find that adoption

[1] Economic cost is calculated by medical care cost, the value of lost earnings, and a monetary measure of death linked to how much people are willing to pay to reduce risk of dying from foodborne illness.

of food safety guidelines by government-backed organizations (e.g., trade association and product commissions) results in improvements in some food safety outcomes. This study aims to fill the gap in the literature of private food safety certification market.

We use a unique panel dataset to examine whether private food safety certification makes food systems safer with a focus on the meat, poultry, and egg products industry. We merge multiple datasets, both private and government datasets, to study the effects of private food safety certification on food safety performances. We use the United States Department of Agriculture, Food Safety and Inspection Service (FSIS) sampling program results as the measurement for food safety performances.

Investigating the role of the private certification in food safety is particularly informative to policy makers and producers, helping them better allocating. From a business perspective, our research will quantify the benefits of certification and therefore help especially small-scale producers make informed decisions on the certification decision. From the regulatory perspective, we can provide policymakers with insights into the complementarity of private food safety certification and mandatory government monitoring. For USDA, our results address a fundamental question regarding the use of a private mechanism in government inspection. How much can private food safety certification be trusted? If private food safety certification indeed improves the food safety outcomes, then the government might utilize certification to optimize the use of budgeted resources. For example, one implication is that the government might benefit from the cost perspective by allocating more inspections to those without food safety certification.

In this study, we adopt the penalized maximum likelihood due to our rare event data and separation issue. When the number of observations for one class of the binary response is much smaller than the number of observations for the other class of the binary response, we have rare events data, also called imbalanced data. One of the consequences of rare events data is separation issue, where one or more of a model's covariates perfectly predict the outcome variable (Zorn, 2005) .When separation issue exists, traditional maximum likelihood estimates in logistic regression are biased away from zero (Zorn, 2005; Gao & Shen, 2007). Rare events data and separations issues have attracted a lot of attention in fields like political science (King & Zeng, 2001; Muchlinski et al., 2016; Rainey, 2016; Cook et al., 2020), health and medical science (Zare et al., 2013; Lane, 2013; Haem et al., 2015; Böhning et al., 2015; Shuster et al., 2007; Mansournia et al., 2018; Hunter, 2015), natural hazards (Guns & Vanacker, 2012; Nosrati et al., 2018; Van Den Eeckhaut et al., 2006; Bai et al., 2011; Kim et al., 2014), Geoscience (Xiong & Zuo, 2018; Vanwalleghem et al., 2008; Veazey et al., 2016), and other low risk accidents studies such as windshear occurrence (Chen et al., 2020), red-light running (Ren et al., 2016), and school shooting (Westphal, 2013). Based on the literature, penalized maximum likelihood approach is suggested for rare events data to solve separation issues (Puhr et al., 2017; Kim et al., 2014; Lee, 2020; Mansournia et al., 2018; Cook et al., 2020; Heinze & Schemper, 2002). The theoretical basis of panelized maximum likelihood method is that a penalty term is placed on the standard maximum likelihood function. It has the advantage of producing unbiased estimates, even with small samples. Therefore, we apply panelized maximum likelihood method to investigate the impact of private food safety certification on FSIS sampling program results.

We contribute to the literature in three ways. First, to our knowledge, this is the first study that examines whether the private food safety certification help improve food safety outcomes. Second, this study tries untangles the interaction between private sector (private food safety certification) and public sector (FSIS sampling) with our unique dataset that combines private and government dataset. Third, this study adds to the literature that adopt penalized maximum likelihood method for rare events data and separation issue.

This paper proceeds as follows: section 2.2 discusses the datasets we exploit and the data structure. Section 2.3 provides a look at some of the empirical tools used to analyze panel data with binary outcome variable, justifies our choice of methodology. Section 2.4 discusses the results. Section 2.5 concludes the findings and provides suggestions for future research.

Data

We construct a unique dataset that combines private food safety certification data, ReferenceUSA data, FSIS inspection directory, FSIS sampling data, and FSIS Quarterly Enforcement Data for the year 2015 to 2018. We merge FSIS inspection directory, FSIS sampling data, and FSIS Quarterly Enforcement Data using establishment number assigned by FSIS. Then we merge FSIS-related data with private food safety certification data and ReferenceUSA data using address matching. Unfortunately, a large portion of establishments from different sources cannot be matched together. Match failures occur for two reasons: (1) FSIS inspection directory is from the year 2019, while our ReferenceUSA data is from 2015 to 2018. Many establishments that were active from 2015 to 2018 may not be active or exist in 2019, thus do not appear on the 2019 inspection directory. (2) ReferenceUSA does not collect information from all the establishments. (3) We could not merge the establishments if they change name or address and do not report it on either ReferenceUSA or FSIS. We compare the establishments in our dataset and in FSIS dataset, and we find that both datasets have a similar composition in terms of establishment size (mostly small establishments). Therefore, we believe that the unmatched establishments are not systematically missing from our datasets. The data merge yields a data set with a total of 215,744 observations for which the establishment's certification status, scope, sales volume, FSIS enforcement action information, FSIS sampling results, and the product and pathogen tested are known.

Private Food Safety Certification Data

As mentioned in chapter one, there are seven internationally accepted collective standards, including Global Good Agricultural Practices (GLOBALG.A.P.), British Retail Consortium Food (BRC), Food Safety System Certification (FSSC 22000), International Featured Standards (IFS), International Organization for Standardization 22000 (ISO 22000), PrimusGFS, and Safe Quality Food (SQF). The purpose of private food safety standards is to harmonize food safety standards across the supply chain and build confidence in the food supply chain. Of the seven standards, BRC, FSSC 22000, and SQF offer food safety certifications to meat, poultry, and egg establishments[2]. The Global Food Safety Initiative (GFSI) was founded in May 2000 to benchmark food safety schemes. BRC, FSSC 22000, and SQF are all recognized standards by the Global Food Safety Initiative (GFSI) and offer certification to all sectors of the food supply chain.

BRC was founded in the United Kingdom in 1996. FSSC 22000 is based in the Netherlands and has representatives in North America, South America, India, Japan, and a liaison in China. GFSI has given FSSC 22000 full recognition since 2010. SQF was first developed in Australia in 1994 and then was recognized by GFSI in 2004. SQF is a US-based standard now, while BRC and FSSC 22000 are Europe-based. Table 1 shows the number of meat, poultry, and egg products establishments certified with BRC, FSSC 22000, and SQF. SQF and BRC are two significant players in the private food safety certification market in the United States. SQF alone takes around

[2] Currently, we do not have access to IFS data.

58% of the market share, and it has an increasing trend. BRC takes approximately 37% of the market share, while FSSC 22000 only takes 4%.

ReferenceUSA Data

ReferenceUSA provides establishment-level characteristics annual data, such as sales volume. Annual sales volume is classified into eleven ranges (as a multiple of $1,000): 1 - 499,999; 500,000 - 999,999; 1,000,000 - 2,499,999; 2,500,000 - 4,999,999; 5,000,000 - 9,999,999; 10,000,000 - 19,999,999; 20,000,000 - 49,999,999; 50,000,000 - 99,999,999; 100,000,000 - 499,999,999; 500,000,000 - 999,999,999; over 1 billion[3]. Table 2 shows the number of establishments by annual sales volume and year. On average, 10% of establishments have annual sales volume less than 500 dollars, 50% of establishments have annual sales volume less than 10,000 dollars, and 80% have annual sales volume less than 50,000 dollars.

Annual sales volume data for an establishment vary on a small scale from year to year. We calculate the mean and standard deviation and display them in Table 3. Over 98% of variation comes from between variation rather than within variation, demonstrating that annual sales volume at the establishment level does not vary significantly from 2015 to 2018.

Meat, Poultry, and Egg Product Inspection Directory

The Meat, Poultry, and Egg Product Inspection (MPI) Directory provides a list of official establishments regulated by FSIS that produce meat, poultry, and/or egg products. An official establishment, determined by USDA's Secretary or FSIS's Administrator, is where inspection is maintained following regulations for the slaughter of meat or poultry animals or processing of

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[3] Annual sales volume is always modeled.

meat or poultry food products (Food Safety Inspection and Service, 1992). The Directory is updated monthly; we used the version from April 2019.

In addition, this Directory provides establishment scope information, whether the establishment is involved in meat, poultry, egg, import, and/or export activities. We summarize establishment's scope in Table 4. The number of egg and import establishments stays relatively stable, while the number of establishments in meat, poultry, and export industries increases gradually throughout the years.

FSIS Sampling Data

The U.S. Department of Agriculture has a long, rich history of improving and protecting public health's food supply. The USDA inspection services began in 1890 to inspect salted pork and bacon for exportation and expanded to all live cattle and beef products the following year. In 1906, the Federal Meat Inspection Act (FMIA) became law and prohibited the sale of adulterated or misbranded meat products and ensured that meat products were slaughtered and processed under sanitary conditions. Inspection services evolved over time, especially with the passing of the Federal Meat Inspection Act (FMIA) and the growth of meat industry. Before 1993, FSIS inspection mainly relied on sight, touch, and smell. However, an outbreak of *E. coli* (*Escherichia coli*) O157:H7 in raw ground beef occurred in the Pacific Northwest, causing 400 illnesses and four deaths. It caused the most significant change in U.S. food inspection history. In response to the public's demand for safer products, FSIS issued Pathogen Reduction/HACCP systems, starting a microbiological testing program to detect E. coli *(Escherichia coli)* O157: H7 in 1996.

Nowadays, FSIS tests for five pathogens, including *E. coli*, *Campylobacter*, *Listeria Monocytogenes*, *Salmonella*, and non-O157 STECs[4] on various FSIS-regulated products.

To fulfill the goal of protecting the public from foodborne illnesses associated with the consumption of meat and poultry products, FSIS routinely collects sampling and conducts microbiological testing from regulated establishments to verify that establishments maintain control of their production processes and adhere to regulations, policies, and performance standards. In addition to sampling on regulated establishments, FSIS posts these data on the FSIS website, including establishment-specific data and sampling results data. We collect sampling data and establishment data from the FSIS website.

Descriptive data for sampling are summarized in Table 5. In our dataset, sampled products include raw beef (raw beef components, raw-ground-beef or otherwise RGB, beef trim), raw chicken (chicken carcass, chicken parts, comminuted or otherwise nonintact chicken), raw turkey (turkey carcass), processed egg, and ready-to-eat (RTE) products. A testing program to detect Escherichia coli O157:H7 in raw beef products started in October 1994. In addition to *E. coli* O157:H7, FSIS considers raw beef products with six other Shiga toxin-producing *Escherichia coli* (STEC) to be adulterated. These six non-O157 STECs are O26, O45, O103, O111, O121, and O145. FSIS began testing for these non-O157 STECs on beef manufacturing trimmings in June 2012. FSIS has conducted a regulatory *Listeria* testing program in RTE products since 1983 and started random testing in the 1990 (Food Safety Inspection and Service, 2022). Currently, FSIS samples randomly to detect *Listeria* on all RTE and processed egg products. Further, FSIS collects *Salmonella* samples in all raw beef, raw turkey, raw chicken, RTE, and egg products and collects

[4] FSIS tests six Shiga toxin-producing Escherichia coli (STEC) in raw, non-intact beef products or the components of these products. These six non-O157 STECs are O26, O45, O103, O111, O121, and O145.

Campylobacter samples in all raw turkey and raw chicken products. In fact, all samples collected for raw chicken and raw turkey are both analyzed for both *Campylobacter* and *Salmonella*.

From 2015 to 2018, 43,103 samples were taken for *E. coli* testing, 89,916 samples were taken for *Salmonella*, 33,518 samples were taken for *Listeria*, and 40,246 samples were taken for *Campylobacter*, and 8,961 samples were taken for non-O157STECs, resulting in a total of 215,744 samples. Overall, *Salmonella* and *Campylobacter* have high positive rates, 5.06% and 3.65%, while *E. coli*, *Listeria*, and non-O157STECs have relatively low positive rates.

We summarize the number of establishments by annual sampling frequency and year in Table 6. The annual sampling frequency includes sampling for all types of pathogens. The four columns under 2015, 2016, 2017, and 2018 represent the number of establishments by the range of annual sampling frequency each year. For instance, there are 733 establishments were sampled between 1 and 10 times in the year 2015. The range for annual sampling frequency is between 1 and 355. The following column after the year 2018 is the number of establishments responding to each annual sampling frequency range, summed over the year 2015 to the year 2018. The last column of this table is the cumulative percentage of the number of establishments according to the increasing annual sampling frequency. It reveals that most of the establishments, 70% of them, were sampled less than 20 times, and 90% of them were sampled less than 50 times. The numbers differ from year to year. The bottom row of this table for columns 2015 to 2018 indicates the total number of establishments sampled each year. The number of establishments in this dataset stays relatively stable, around 2000 each year. The number of establishments by total sampling frequency over four years is listed in Table 7. Similarly, over 90% of establishments were sampled between 2015 and 2018 less than 200 times. Assuming that all the establishments were sampled during the observed period, about 90% of the establishments were sampled below 50 times on average.

As mentioned earlier, production volume is one key factor determining sampling frequency. We do not have data on production volume; however, we have sales volume data from ReferenceUSA. We illustrate the number of establishments by sales volume and by sampling frequency for the year 2018 in Table 8. When the annual sampling frequency is between one to ten, the number of establishments decreases as sales volume increases. However, when the annual sampling frequency is between 101-355, the number of establishments increases as sales volume increases. Therefore, we find evidence supporting that sampling frequency is likely to increase as sales volume (production volume) increases.

Quarterly Enforcement Data

An establishment needs to have a validated food safety system to operate in a sanitary manner that aligns with regulations. The food safety system required for meat, poultry, or/and egg product establishment is the Hazard Analysis and Critical Control (HACCP) system. The HACCP system consists of the establishment's plans, programs, measures, and procedures to prevent, eliminate, or otherwise control identified food safety hazards. This system lays the foundation of the establishment's food safety system. The regulations also require that the establishment maintain Sanitation SOPs and meet the SPS requirements. Sanitation SOPs are a prerequisite to the HACCP plan and cover procedures that the establishment take daily before and during operations to prevent products from being contaminated and adulterated. The SPS regulations cover all the other aspects of establishment sanitation that can affect food safety, for example, pest control and ventilation. Establishment activities that are covered by Sanitation SOPs and SPS overlap sometimes. HACCP system, Sanitation SOPs, and SPS are three essential elements that form an establishment's food safety system to prevent contaminated products from entering commerce. IPP file a non-compliance if an establishment fails to meet any regulatory requirements[5]. When there are two or more non-compliances filed on an establishment, enforcement actions will take place. Enforcement actions refer to regulatory control action, withholding, or suspension.

FSIS Quarterly Enforcement Report provides a summary of the enforcement actions at the establishment. Enforcement actions may be due to HACCP non-compliance, Sanitation SOPs non-compliance, SPS non-compliance, inhumane treatment/slaughter, and/or interference/assault. We focus on enforcement actions that affect an establishment's food safety system, that is, enforcement actions caused by HACCP non-compliance, Sanitation SOP non-compliance, and/or SPS non-compliance.

Table 9 demonstrates the number of enforcement actions taken at the establishment by year and quarter. In this study, quarter one is defined as January, February, and March; quarter two includes April, May, and June; Quarter three includes July, August, and September. Quarter four includes October, November, and December. The number of enforcement actions display a seasonal pattern, where fewer enforcement actions were taken in quarter four each year. We use this data to measure an establishment's food safety system.

Model and Results

The general form of the model we would like to estimate is as followed:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon_i = x_i' \beta + \varepsilon_i \quad (1)$$

[5] The establishment's generic E. coli testing results cannot, by themselves support a finding of non-compliance.

Equation (1) specifies that the dependent variable Y is a function of k explanatory variables. Given that the dependent variable is a binary variable, we will start will a basic logit model. With logit model, we have:

$$P(y_i = 1|x_i, \beta) = \pi_i = \mathrm{F}\ (x_i'\beta) = \frac{1}{1+e^{-x_i'\beta}} \quad (2)$$

Where $F(\cdot)$ is the cumulative distribution function of μ_i for a logit model. This equation indicates that the probability of having $y_i = 1$ depends on the vector x containing individual characteristics. The parameters are estimated by maximum likelihood, with the likelihood function formed as:

$$\ln L(\beta|y) = \sum_{y_i=1} \ln (\pi_i) + \sum_{y_i=0} \ln (1 - \pi_i) = -\sum_{i=1}^{n} \ln (1 + e^{(1-2y_i)x_i\beta}) \ (3)$$

The first derivative vector, or score vector, is given by:

$$U(\beta) = \frac{\partial \ln L(\beta|y)}{\partial \beta} = \sum_{i=1}^{n} \frac{\partial \ln f(y_i|\beta)}{\partial \beta} = \sum_{i=1}^{n} (y_i - \pi_i)x_i = 0 \quad (4)$$

We can obtain the information matrix as minus the expected value of the second derivatives of the loglikelihood:

$$I\ (\beta) = -E[\frac{\partial^2 \ln L(\beta|y)}{\partial\beta\partial\beta'}] \quad (5)$$

When analyzing panel data with binary dependent variables, researchers often select between pooling, random effects (RE), and fixed effects (FE) models. Pooled logit model does not recognize panel structure of data; thus, the pooled logit model is the usual cross-section model. And it assumes no unobserved unit heterogeneity. The logit FE and RE models recognizes panel structure, thus, includes individual effects. The logit individual-effects model specifies that:

$$P(y_i = 1|x_i, \beta, \alpha_i) = F\ (x_i'\beta + \alpha_i) \quad (6)$$

where α_i represents individual effects and it may be a fixed effect or random effect. The logit RE model specifies that $\alpha_i \sim N(0, \sigma_\alpha^2)$, which means that random effect model requires that any unit heterogeneity is orthogonal to the explanatory or unrelated to the explanatory variables. The logit FE model relaxes this assumption, allowing for unobserved time-invariant individual heterogeneity with an arbitrary distribution. Besides, The FE model has the advantage of controlling unobserved time-invariant individual characteristics that may influence the dependent variable. The strong assumption by logit RE model is hard to achieve. However, researchers still either pooled logit or logit RE model and avoid FE models (Cook et al., 2020). FE estimator suffers from the incidental parameters problem when T is small, resulting in biased estimates even for conditional FE models.

Based on our data structure, we have a rare events issue, which makes pooled, RE, or FE less ideal for this analysis. Rare events issue is the situation where the number of events is significantly smaller than the number of no-events. In this study, the event refers to the positive test result, and no-event refer to the negative results. The percentage of positive rate in our datasets vary by pathogen, ranging from 0.06% to 5.06%. Even with the highest percentage, 5.06% for *Salmonella*, the probability of positive results is still very low.

One consequence of rare events is separation. With rare events, the maximum likelihood estimation of the logit model suffers from small-sample bias. Separation occurs when one or more of a model's covariates always or never occur with the outcome variable event. It implies that there is a subsector $x_s \subseteq x$ by which all N observations can be categorized as either $y_i = 0$ or $y_i = 1$. Consequently, the units that do not experience the event do not enter the log-likelihood. That is, parameter estimates are produced using only the data from the event-experiencing set of units. With rare events and separation, maximum likelihood estimation of the logit model suffers from small-sample bias. Several studies demonstrate maximum likelihood estimates are biased away from zero using Monte Carlo simulations thus, the probability of $y_i = 1$ tends to be underestimated.

The literature has provided a comprehensive comparison of options to address separation or rare events issues (Zorn, 2005; Heinze & Schemper, 2002). Evidence suggests that the Firth method is superior to its alternatives in the presence of separation., Penalized maximum likelihood, also called Firth Method, has the advantage of producing a finite, consistent estimate of regression parameters when separation issue occurs. In 1993, Firth proposed a modification of the score equation in order to mitigate small sample bias in generalized models, also called the penalized maximum likelihood method. Subsequently, this method was shown as an effective tool for solving the separation issue in logistic regression (Heinze & Schemper, 2002). The intuition of penalized maximum likelihood approach is to introduce a bias term into the standard likelihood function. Following Zorn (2015) and Heinze and Schemper (2002), the penalized likelihood function is given by:

$$L(\beta|y)^* = L(\beta|y)||I(\beta)|^{\frac{1}{2}} \quad (7)$$

The penalty function $|I(\beta)|^{\frac{1}{2}}$ is known as the Jeffreys invariant prior. With corresponding log-likelihood:

$$\mathrm{lnL}(\beta|\mathrm{y})^* = lnL(\beta|y) + 0.5ln|I(\beta)| \quad (8)$$

where $|I(\beta)|$ is the information matrix; the score function is then replaced with:

$$U(\beta) = \sum_{i=1}^{n}(y_i - \pi_i)\,x_i\left(1 + \frac{h_i}{2}\right) + \sum_{i=1}^{n}(1 - y_i - \pi_i)x_i(\frac{h_i}{2}) = 0 \quad (9)$$

Where the h_i are the diagonal elements of the penalized-likelihood version of the standard "hat" matric H:

$$H = w^{\frac{1}{2}}x(x'wx)^{-1}x'w^{\frac{1}{2}} \quad (10)$$

The Firth method split the observations i into two new observations with response values y_i and $1 - y_i$ and updated weights $1 + \frac{h_i}{2}$ and $\frac{h_i}{2}$, thus eliminating the problem of separation (Heinze & Schemper, 2002). It guarantees the existence of estimates by removing the first-order bias at each iteration step (Gao & Shen, 2007). With penalized estimation, we are able to maintain the full sample. At the same time, as the number of observations goes to infinite, the penalty term converges towards zero, and the results return to the usual maximum likelihood estimates. As a result, the parameter estimates and standard errors from penalized likelihood approach are smaller in absolute value.

We conduct pooled logit, logit RE, logit FE, and PML models to five pathogens sampling results and illustrate the results in Table 10. We conduct pooled logit, logit RE, logit FE to illustrate the separation issue caused by rare events.

In this study, the dependent variable is the pathogen test result. There are multiple samples taken for many establishments, which yields repeated observations in our panel. We transform the data to one observation each day for an establishment, where one represents there is at least one positive testing result on that day, and zero represents no positive testing results that day. Explanatory variables include certification status, sales volume, lag of enforcement actions taken, establishment scopes (whether the establishment is involved in meat, poultry, egg products, import, or export activities). The variable enforcement action is a measurement of an establishment's "quality". The establishment's "quality" can be correlated with both certification status and sampling results. Intuitively, an establishment with lower "quality" is more difficult to obtain a private certification and is more likely to get tested positive for a pathogen test. Without controlling for "quality", it causes the endogeneity issue. Enforcement action is an enforced action taken by FSIS, and it happens when there are reasons for IPP to believe that the establishment's food safety system is compromised. It is a much more comprehensive indicator than a single accident of positive results for a pathogen. Additionally, many types of pathogenic microorganisms exhibit seasonal patterns. For example, an FSIS analysis in 2008 found that *E. coli* O157:H7 in cattle products displayed positive seasonal effects during warmer months. We include month and year as control. Furthermore, we add state control to examine the demographic pattern.

Results

Regression results for *Salmonella, Campylobacter, E. coli*, non-O157 STECs, and *Listeria* are presented in Table 10, 11, 12, 13, and 14, respectively. For each pathogen, we conduct pooled logit regression, RE logit, FE logit, and penalized maximum likelihood approach.

We begin by analyzing the existence of separation. The bottom row of the five tables shows the number of observations in the regression. As we notice, the number of observations is not consistent across different approaches. In general, fewer observations entered the regressions for pooled logit model, RE logit model, and much fewer for FE logit model. In fact, many observations drop due to the failure of imperfect prediction. Taking regression results for *Salmonella* as an example, the row for the number of observations indicates that 61,464 observations were used for pooled logit and RE model and only 34,443 observations for FE model. However, we have 64,679 observations in total for the analysis of *Salmonella*. The difference in the number of observations between FE model and Firth approach is substantial. This pattern stays valid for all the regression results of the five pathogens. It is noted that this is how some software packages (e.g., Stata) deals with separation, automatically omitting variable and dropping observations from the analysis (Zorn, 2005). In the case of non-O157 STECs, SQF and FSSC 22000 are omitted for pooled, RE, and FE models; they successfully enter the regression for the Firth method.

Another indication of separation is the magnitude of the estimates and standard errors. Traditional maximum likelihood estimates are biased away from zero with separation. From Table 10, 12 and 13, we find that the estimates for our key variables, BRC, SQF, and FSSC 22000, are smaller in absolute value for pooled logit, RE, and FE models than the one for Firth models. In addition, the standard errors using Firth method is much smaller than the other three approaches. Comparing results from Firth method and other methods, we find that Pooled logit yields similar results with Firth method. For RE and FE models, we find cases where they have opposite signs with Firth estimates. For example, The RE and FE estimates for BRC are positive for *Salmonella*, while the Firth estimates is negative. Even though Pooled logit and Firth method yield similar results, they show different significant levels and standard errors. For *Campylobacter,* the coefficient of SQF from pooled logit is not significant, but it is significant from the Firth method. Therefore, we find evidence that we have separation issues in our data resulting from rare events. From this point, we will analyze the results from the Firth method.

For *Salmonella*, we find that BRC certification, sales volume, and the establishments involved in exporting activities are negatively associated with test results, while tested products like turkey, chicken, and beef are positively associated with test results compared to RTE products. For *Campylobacter*, BRC, SQF certification, last year's enforcement action taken by FSIS, and turkey products are found to be negatively associated with test results. For *E. coli* and *non-O157 STECs,* we do not find significant relationship between private food safety certification and test results; only establishment scope, such as whether the establishment is involved in export activity or egg products, is found to be significant.

Our key variables are BRC, SQF, and FSSC 22000, the three variables that represent private food safety certification status. In Table 15, we present the estimated average marginal effects of Firth method for five pathogens. We expect that establishments with private food safety certifications will be less likely to be tested positive for the FSIS pathogen test. Intuitively, private food safety standards are supposed to be stricter than the public regulations, HACCP in this case; thus, establishments with private food safety certifications will have a better food safety system and perform better in the FSIS pathogen sampling programs. Consistent with our prediction, we find that BRC is negatively associated with *Salmonella and Campylobacter* test results, though the magnitude of average marginal effect is small. For instance, the probability of being tested positive for *Salmonella* decreases by 0.03 percent if establishments are certified with BRC.

To check for the robustness of our results, we replace BRC, SQF, and FSSC 22000 status with last year's BRC, SQF, and FSSC 22000 status. Table 16 displays the average marginal effects of our key variables. BRC is still significant and negatively associated with *Salmonella*, *Campylobacter*, and *Listeria* test results. SQF is also significant at 10% level and negatively associated with *Campylobacter* test results.

Conclusion

In this study, we empirically explore the effects of private food safety certification on food safety performance in the meat, poultry, and egg products industry using FSIS pathogen sampling results as the measurement. This is the first try in the literature to reveal how the private food safety certification market interacts with the government-regulated food safety system. Our conceptual framework examines the effects of private food safety certification status, annual sales volume, establishment scope, and product types on FSIS pathogen test results. Since we have rare events data and separation issues, we apply penalized maximum likelihood approach to address the problems. First, we illustrate the presence of separation by comparing results from pooled logit, RE logit, FE logit, and penalized maximum likelihood models; and we find evidence to support that the estimates from the traditional maximum likelihood approach are biased from zero. In another word, we show that maximum likelihood estimates are underestimated with the presence of separation, which is consistent with previous studies. Therefore, we prefer the results from penalized maximum likelihood approach.

Second, we have mixed findings regarding the effects of private food safety certifications; the results differ across pathogen and certification types. Adoption of BRC certification results in food safety improvements in *Salmonella*, *Campylobacter*, and *Listeria* tests, and adoption of SQF certification results in food safety performance in *Campylobacter* tests. The results are robust to changes where we replace certification status with last year's certification status. Though the marginal effect is small, the finding itself is not trivial. Given the complexity of an establishment's food safety system and the food supply chain, the weak linkage between private foods safety certification and food safety outcomes has huge implications for both establishments and the government.

Our results create incentives for establishments to adopt a private food safety certification, preferably BRC or SQF, to improve food safety outcomes and eventually help reduce economic costs caused by food safety incidents if the products go into commerce. From the establishment's point of view, the benefits of adopting a private food safety certification outweigh the costs. Whenever a food safety incident occurs, an establishment faces expenses from conducting recalls and the costs caused by reputation damage. From society's point of view, adopting a private food safety certification help guarantee the safety of the food supply chain, thus the health of the public. This study also provides meaningful insights into how the private food safety market works along with the government food safety system. We have partial evidence that the private food safety certification sector operates as complementary to the government's food safety regulations.

In future work, we plan to expand on this analysis in two ways. First, even though we include a measurement for the establishment's "quality", we still have concerns about endogeneity. We will work on an instrumental variable for certification as a robust check for our results presented in this study. Second, we will extend our analysis to explore other industries, such as fresh fruit and vegetables, where food safety incidences frequently happen.

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Tables

Table 1 Number of Establishments certified with BRC, SQF, FSSC 22000 by Year

Certification	2015	2016	2017	2018
SQF	496	557	513	686
BRC	335	373	378	342
FSSC 22000	33	38	40	44
Total	864	968	931	1072

Table 2 Number of Establishments by Annual Sales Volume (As a Multiple of $1,000) and Year

	Year				
Annual Sales Volume	2015	2016	2017	2018	Total
1	114	144	217	227	702
2	162	163	195	210	730
3	256	270	285	308	1,119
4	247	259	265	256	1,027
5	267	274	312	314	1,167
6	303	304	260	274	1,141
7	293	306	256	268	1,123
8	144	156	169	160	629
9	253	262	229	223	967
10	31	30	24	31	116
11	20	18	21	18	77
Total	2,090	2,186	2,233	2,289	8,798

Note: Annual sales volume represents a range of estimated annual sales volume at that location. 1: 1 - 499,999; 2: 500,000 - 999,999; 3: 1,000,000 - 2,499,999; 4: 2,500,000 - 4,999,999; 5: 5,000,000 - 9,999,999; 6: 10,000,000 - 19,999,999; 7: 20,000,000 - 49,999,999; 8: 50,000,000 - 99,999,999; 9: 100,000,000 - 499,999,999; 10: 500,000,000 - 999,999,999; 11: Over 1 billion.

Table 3 Standard Deviation by Variables and Pathogen

Variables		*Salmonella*	*Campylobacter*	*Listeria*	*E. coli*	non-O157 STECs
Test Results	overall	0.22	0.18	0.05	0.02	0.08
	between	0.09	0.11	0.02	0.00	0.03
	within	0.20	0.17	0.05	0.02	0.07
Sales Volume	overall	2.76	2.50	2.47	2.72	3.18
	between	2.49	2.52	2.42	2.25	2.25
	within	0.57	0.59	0.54	0.55	0.50
Certification	overall	0.50	0.48	0.48	0.45	0.48
	between	0.42	0.46	0.43	0.33	0.25
	within	0.18	0.20	0.17	0.14	0.17
BRC	overall	0.45	0.50	0.29	0.39	0.44
	between	0.30	0.43	0.27	0.23	0.23
	within	0.13	0.17	0.07	0.11	0.14
SQF	overall	0.39	0.37	0.43	0.29	0.22
	between	0.34	0.32	0.37	0.24	0.11
	within	0.13	0.12	0.15	0.09	0.09
FSSC 22000	overall	0.10	0.06	0.10	0.11	0.16
	between	0.09	0.08	0.09	0.08	0.07
	within	0.02	0.00	0.02	0.03	0.04

Table 4 Number of Establishments by Scope and Year

Establishment Scope	Year 2015	2016	2017	2018	Total
Meat	1,930	2,020	2,061	2,112	8,123
Poultry	1,742	1,820	1,844	1,909	7,315
Egg	34	35	35	34	138
Export	445	472	494	496	1,907
Import	3	3	3	4	13

Note: One establishment can be involved in more than one of the above activities. For example, an establishment can do both meat and poultry processing.

Table 5 Descriptive Data for Sampling Programs by Pathogen

Pathogen	Species	Number of Establishments	Number of samples	Number of positive	Positive Rate
E. coli	Raw beef	1,094	43,103	27	0.06%
Salmonella	Raw beef, raw turkey, raw chicken, egg, RTE	2,539	89,916	4,550	5.06%
Listeria	RTE, egg	1,534	33,518	83	0.25%
Campylobacter	Raw turkey, raw chicken	423	40,246	1,470	3.65%
Non-O157STECs	Raw beef	371	8,961	53	0.59%

Table 6 Number of Establishments by Annual Sampling Frequency and by Year

Annual Sampling Frequency	Year					Cumulative Percentage (%)
	2015	2016	2017	2018	Total	
1-10	733	716	721	968	3,138	35.67
11-20	774	828	695	853	3,150	71.47
21-30	275	264	411	166	1,116	84.16
31-40	84	82	101	64	331	87.92
41-50	41	51	60	32	184	90.01
51-60	36	33	38	21	128	91.46
61-70	20	36	25	17	98	92.58
71-80	23	19	19	16	77	93.45
81-90	31	13	12	21	77	94.33
91-100	22	9	12	13	56	94.96
101-200	51	103	97	113	364	99.10
201-355	0	32	42	5	79	100.00
Total	2,090	2,186	2,233	2,289	8,798	100.00

Table 7 Number of Establishments by Total Sampling Frequency

Total Sampling Frequency	Number of Establishments	Percentage (%)	Cumulative Percentage (%)
1-10	45	5.46	5.46
11-20	52	6.31	11.77
21-30	82	9.95	21.72
31-40	88	10.68	32.4
41-50	77	9.35	41.75
51-60	102	12.38	54.13
61-70	105	12.74	66.87
71-80	50	6.07	72.94
81-90	36	4.37	77.31
91-100	27	3.27	80.58
101-200	82	9.95	90.53
201-827	78	9.47	100
Total	824	100	

Note: We dropped three sites because they only have one sampling from 2015 to 2018.

Table 8 Number of Establishments by Annual Sampling Frequency and Annual Sales Volume in 2018

Annual Sampling Frequency	Annual Sales Volume											Total
	1	2	3	4	5	6	7	8	9	10	11	
1-10	127	117	154	127	155	107	105	42	29	5	0	968
11-20	75	59	122	89	110	126	110	75	83	4	0	853
21-30	10	22	18	26	26	17	23	9	13	0	2	166
31-40	4	3	6	3	11	4	11	8	12	2	0	64
41-50	4	1	2	3	2	5	2	5	6	1	1	32
51-60	0	3	1	2	1	2	3	3	5	1	0	21
61-70	0	1	2	2	3	2	1	1	4	0	1	17
71-80	0	0	0	1	0	4	5	1	5	0	0	16
81-90	1	0	1	0	1	3	0	6	7	2	0	21
91-100	0	1	0	0	2	1	1	0	6	1	1	13
101-355	6	3	2	3	3	3	7	10	53	15	13	118
Total	227	210	308	256	314	274	268	160	223	31	18	2289

Note: Annual sales volume represents a range of estimated annual sales volume at that location. 1: 1 - 499,999; 2: 500,000 - 999,999; 3: 1,000,000 - 2,499,999; 4: 2,500,000 - 4,999,999; 5: 5,000,000 - 9,999,999; 6: 10,000,000 - 19,999,999; 7: 20,000,000 - 49,999,999; 8: 50,000,000 - 99,999,999; 9: 100,000,000 - 499,999,999; 10: 500,000,000 - 999,999,999; 11: Over 1 billion.

Table 9 Number of Enforcement Actions by Year and Quarter

	Year				
Quarter	2015	2016	2017	2018	Total
1	7	13	16	18	54
2	21	24	20	10	75
3	18	14	11	9	52
4	12	11	6	0	29
Total	58	62	53	37	210

Table 10 Regression Results for *Salmonella*

Variables	Pooled	Random	Fixed	Firth
BRC	-0.08	0.13	0.31***	-0.08*
	(0.14)	(0.15)	(0.12)	(0.05)
SQF	-0.04	-0.17	-0.12	-0.04
	(0.12)	(0.15)	(0.15)	(0.06)
FSSC	-0.59*	-0.67		-0.50
	(0.36)	(0.46)		(0.44)
Lagged Enforcement Action	0.13	0.13	0.01	0.14
	(0.17)	(0.18)	(0.14)	(0.11)
Sales Volume	-0.03	0.05*	-0.04	-0.03***
	(0.03)	(0.02)	(0.05)	(0.01)
Constant	-7.31***	-7.26***		-6.75***
	(0.33)	(0.63)		(1.44)
State Control	Yes	Yes	Yes	Yes
Year Control	Yes	Yes	Yes	Yes
Month Control	Yes	Yes	Yes	Yes
Observations	61,464	61,464	34,443	64,679

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11 Regression Results for *Campylobacter*

Variables	Pooled	Random	Fixed	Firth
BRC	-0.57***	-0.44**	-0.12	-0.57***
	(0.20)	(0.17)	(0.24)	(0.09)
SQF	-0.23	-0.31	-0.38	-0.23*
	(0.20)	(0.19)	(0.30)	(0.12)
FSSC	0.36	0.44		0.70
	(0.54)	(0.63)		(0.90)
Lagged Enforcement Action	-0.49	-0.69*	-0.75**	-0.47*
	(0.32)	(0.35)	(0.32)	(0.27)
Sales Volume	-0.03	-0.01	0.04	-0.03*
	(0.04)	(0.04)	(0.08)	(0.02)
Constant	-2.69***	-3.201***		-2.68***
	(0.42)	(0.46)		(0.21)
State Control	Yes	Yes	Yes	Yes
Year Control	Yes	Yes	Yes	Yes
Month Control	Yes	Yes	Yes	Yes
Observations	29,188	29,188	22,954	29,704

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12 Regression Results for *E.coli*

Variables	Pooled	Random	Fixed	Firth
BRC	-0.80	-0.80		-0.63
	(0.72)	(0.72)		(0.77)
SQF	-0.08	-0.08		0.22
	(1.04)	(1.03)		(0.92)
Lagged Enforcement Action	-0.08	-0.08	0.28	0.18
	(1.10)	(1.10)	(1.29)	(0.90)
Sales Volume	-0.13	-0.13	1.51	-0.13
	(0.11)	(0.11)	(1.15)	(0.09)
Constant	-5.37***	-5.367***		-6.52***
	(1.23)	(1.44)		(2.11)
State Control	Yes	Yes	Yes	Yes
Year Control	Yes	Yes	Yes	Yes
Month Control	Yes	Yes	Yes	Yes
Observations	12,249	12,249	1,087	29,308

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: For fixed-effect model, BRC, SQF, and FSSC does not enter the regression.

Table 13 Regression Results for Non-O157 STECs

Variables	Pooled	Random	Fixed	Firth
BRC	-1.18	-1.18	-12.96	-1.02
	(0.85)	(0.85)	(1,38)	(0.79)
SQF	Omitted	Omitted	Omitted	-0.33
				(2.31)
FSSC	Omitted	Omitted	Omitted	-1.02
				(1.58)
Lag Enforcement Action	0.70	0.70	0.72	0.73
	(0.75)	(0.88)	(0.68)	(0.48)
Sales Volume	-0.11	-0.11	0.23	-0.10
	(0.11)	(0.11)	(0.55)	(0.09)
State Control	Yes	Yes	Yes	Yes
Year Control	Yes	Yes	Yes	Yes
Month Control	Yes	Yes	Yes	Yes
Observations	3,613	3,613	873	6,446

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 14 Average Marginal Effects for Certification Status

Average Marginal Effects	*Salmonella*	*Campylobacter*	*E. coli*	non-O157 STECs	*Listeria*
BRC	-0.003*	-0.02***	-0.001	-0.01	
	(0.00)	(0.00)	(0.00)	(0.01)	
SQF	-0.001	-0.01*	0.000	-0.003	
	(0.00)	(0.00)	(0.00)	(0.02)	
FSSC	-0.02	0.02	0.002	-0.01	
	(0.02)	(0.03)	(0.00)	(0.02)	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 15 Average Marginal Effects for Lagged Certification Status

Average Marginal Effects	*Salmonella*	*Campylobacter*	*E. coli*	non-O157 STECs	*Listeria*
Lagged BRC	-0.01***	-0.02***	-0.001	-0.01	
	(0.00)	(0.00)	(0.00)	(0.01)	
Lagged SQF	-0.002	-0.01*	0.000	-0.001	
	(0.00）	(0.00)	(0.00)	(0.02)	
Lagged FSSC	-0.03	0.02	0.002	-0.01	
	(0.02）	(0.03)	(0.00)	(0.02)	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1