Foodborne Outbreaks, Product Recalls, and Firm Learning*

Sherzod B. Akhundjanov
Corresponding author
Department of Applied Economics
Utah State University
sherzod.akhundjanov@usu.edu
ORCID: 0000-0003-3372-3574

Veronica F. Pozo
Department of Applied Economics
Utah State University

Briana Thomas
Department of Applied Economics
Utah State University

*We would like to acknowledge the comments and feedback we received from audiences at various venues, including the AEA/ASSA, AAEA, AARES, CAES, and the Asian Meeting of the Econometric Society. This study was funded by the UAES projects 1198 and 1577. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Foodborne Outbreaks, Product Recalls, and Firm Learning

Abstract

Firms in the food industry may experience more than one contamination incident over time. In the context of food safety, increasing the interval between foodborne outbreaks represents a key objective for both the food industry and public health officials. We demonstrate a systematic approach to analyzing repeated recalls, specifically to evaluate factors influencing the time until the next recall and, more importantly, to identify the extent of organizational learning from inter-event times. An analysis of meat and poultry recalls issued by publicly traded firms in the United States between 1994-2015 indicates that more diversified firms face a lower risk of repeat recalls as firm size expands, compared to firms primarily producing meat and poultry products. The hazard of a recall incident decreases with the severity of the previous recall. Some evidence of firm learning is found, but there is no definitive evidence indicating that a firm's ability to prevent recalls improves with the number of foodborne outbreaks it has experienced.

Keywords: Foodborne outbreaks; Food recalls; Food safety; Public health; Recurrent event survival analysis.
JEL: L66; D22; Q18.

Learning is the product of experience. Learning can only take place through the attempt to solve a problem and therefore only takes place during activity. (Arrow, 1962)

"Practice makes perfect"; that is, through repetition of an activity one gains proficiency. This is the phenomenon of "learning-by-doing". (Fudenberg and Tirole, 1983)

1 Introduction

Food safety is a shared responsibility across the entire food supply chain. Public health officials, policymakers, food firms, and consumers all play important roles in minimizing the risk of foodborne disease outbreaks.[1] Food firms, in particular, invest in implementing food safety technologies and protocols to prevent these incidents (Henson and Reardon, 2005). Despite such efforts, both the frequency and severity of foodborne outbreaks reported in the United States, especially those related to meat and poultry products, have been rising. In 2015, the U.S. Department of Agriculture's (USDA's) Food Safety and Inspection Service (FSIS), an agency tasked with monitoring the safety of the U.S. supply of meat, poultry, and egg products, reported 150 recalls—a nearly threefold increase from the number of recalls issued in 2005 (FSIS, 2017). Surprisingly, some firms have experienced more than one food safety incident within a relatively short period. For example, Tyson Foods, one of the largest processors and marketers of chicken, beef, and pork products, issued 36 separate meat and poultry recalls between 1994 and 2015 (FSIS, 2017). The case of Tyson Foods is not unique in the food industry, raising the question of what factors determine the time to the next recall for firms producing meat and poultry products, and to what extent (if any) these firms learn from past food safety incidents.

In this study, our main objective is twofold. First, we aim to determine key factors that influence a firm's risk of repeated recall occurrence at any given time. Towards this end, we evaluate both firm-specific and recall-specific factors. Second, and importantly, we investigate whether firms that have issued a recall in the past learn from that experience, particularly in the context of an *increased* time to the next recall, and how this learning is influenced by firm-specific and recall-specific characteristics. Conceptually, if a firm learns from a past recall incident, it should be able to *lengthen* the amount of time until the next recall event by, for instance, adopting a more effective quality control monitoring system that increases the likelihood of its survivorship (i.e., not experiencing a recall event). Acting otherwise would contradict the firm's profit-maximization motives, as food contamination incidents can result in substantial economic losses (Sockett, 1993). Consequently, *inter-event* time can plausibly serve as a proxy for organizational learning, as it

[1] We use "foodborne disease outbreak" and "foodborne outbreak" interchangeably throughout this paper.

reflects the extent of efforts undertaken by the firm upon a food contamination incident to prevent or reduce future occurrences.[2]

We implement a recurrent event survival analysis framework to identify the extent of organizational learning from inter-event time (Akhundjanov et al., 2024). Unlike the methods used in previous literature, which are either inefficient or inappropriate (as discussed below), our approach is well-suited for the analysis of repeated recall incidents as it (i) incorporates information from subsequent failure times (i.e., recalls), (ii) accommodates the order of recurring events, and (iii) accounts for intra-firm correlation arising from these events. As such, this methodology allows for direct examination of differences in recall dynamics between the first, second, third, and subsequent recall events, enabling analysis of a firm's ability to prevent recalls over time. Recurrent event survival analysis has been commonly used in epidemiology and biostatistics for applications where events occur more than once, such as bladder tumor recurrence (Amorim and Cai, 2015), repeated occurrences of acute lower respiratory infections (Kelly and Lim, 2000; Amorim and Cai, 2015), and hospital readmissions of the elderly (Kennedy et al., 2001), among others. Given that a significant percentage of food firms in this study have issued more than one recall, recurrent event survival analysis is clearly more appropriate than methods that consider only the duration to the first failure event.

The results of our analysis show that firm-specific factors, including firm size and diversification, influence the likelihood of recall events. Specifically, firms that produce only meat and poultry products are at a higher risk of issuing repeat recalls compared to more diversified firms. In addition, firms with a more diversified product line incur a lower risk of recalls as firm size expands, as measured by market capitalization, relative to their primarily meat-producing counterparts. Our analysis also reveals that past recall attributes significantly affect future recall occurrences. In particular, the hazard of a recall decreases with the volume of the product recalled in previous incidents. Furthermore, the risk of a future recall is lower for firms whose previous recall was of Class I, the most severe category, compared to those whose past recall was of Class II. This suggests that firms appear to learn from their losses in past recall events and implement necessary measures to reduce the likelihood of future foodborne disease outbreaks. While there is no conclusive evidence indicating that a firm's ability to prevent recalls grows with the total number of recalls it has experienced, we do find some evidence of firm learning between firms' first and second recall, as well as between their third and fourth recall.

[2]We acknowledge that there are other ways to measure the extent of firm learning upon a recall event, such as through direct or indirect costs of recalls, penalty amounts, investments in food safety and sanitation protocols, or food processing safety certifications. While analyzing these other dimensions of organizational learning would be desirable, it is crucially precluded by data availability. Our measure of organizational learning (inter-event time) is readily available and, importantly, reflects the effects of all efforts taken by the firm upon a food safety incident, thus offering a well-rounded measure of firm learning and "the most fundamental dimension of experience" (Argote and Miron-Spektor, 2011).

Our findings have managerial and policy implications. In the context of food safety, increasing the time between recall events represents a key success factor for food firms. Therefore, understanding the factors that influence the time to the next recall event provides managers with valuable insights to improve private food safety protocols and quality management systems (e.g., acceptance sampling and statistical process control), which in turn enhance food quality standards. By gaining recall prevention and handling experience, firms can potentially avoid the economic costs associated with recalls, while consumers benefit from healthier food products (Foster and Just, 1989; Elbasha and Riggs, 2003). From a policy perspective, while it appears the food industry is allocating its resources appropriately to address recalls that pose the greatest risks to human health (i.e., Class I), firms' overall ability to prevent recalls does not consistently improve with past recall experience.

The remainder of the paper is organized as follows. In the following section, we provide some background information and review of the existing literature. In section 3.1, we present the data, while in section 3.2 we discuss the empirical methodology used to analyze recurrent product recalls. The main results are provided in section 4, with discussions following in section 5. Finally, section 6 offers some concluding remarks.

2 Background and Literature

Food recalls occur when a contaminated food product is distributed to the market, which, depending on the severity of contamination, may pose serious health hazards.[3] In the United States, it is the firm's responsibility to retrieve the tainted product from the marketplace, with the process overseen by federal or state officials (FDA, 2017).[4] In the case of meat and poultry products, when a firm issues a recall, the FSIS sends out a recall announcement to the public, indicating the type of product recalled by a specific firm, the reason for the recall, the severity of the threat (also known as the recall class), and the number of pounds recalled. The FSIS classifies food recalls into three broad categories: Class I is the most severe, involving recalls that can cause adverse health consequences or death; Class II recalls have a remote probability of adverse health effects; and Class III recalls are the least severe, with no associated adverse health impacts.

The process of recalling a product from the market can be very costly to firms, not only because of the direct costs of removing the product, but also due to the associated litigation expenses, damage in reputation, and decreased stakeholders confidence (Jar-

[3]Common contaminants include Salmonella, E. coli, and Listeria, Campylobacter, Clostridium perfringens, and Yersinia (CDC, 2020).

[4]Not all slaughter establishments are inspected directly by the FSIS; some are inspected by state agencies. However, state-federal cooperative inspection programs are required by law to be "at least equal to" federal inspection in terms of regulatory rigor, as mandated by the 1967 Federal Meat Inspection Act and the 1968 Wholesome Poultry Products Act.

rell and Peltzman, 1985; Pruitt and Peterson, 1986; Welling, 1991; Sockett, 1993; Ollinger and Ballenger, 2003; Rhee and Haunschild, 2006; Chen et al., 2009; Hua, 2011). Much of the previous literature has focused on estimating direct and/or indirect economic costs of food recalls (Henson and Mazzocchi, 2002; Lusk and Schroeder, 2002; Marsh et al., 2004; Piggott and Marsh, 2004; McCluskey et al., 2005; Mazzocchi, 2006; Thomsen et al., 2006; Schroeder et al., 2007; Shang and Tonsor, 2017; Spalding et al., 2023). For example, Thomsen and McKenzie (2001) and Pozo and Schroeder (2016) conducted event study analyses to estimate the economic impact of meat and poultry recalls issued by publicly traded firms. Both studies found significant losses in firm value immediately after a Class I recall. Moreover, both studies found evidence suggesting that the negative economic effects of repeated recalls on firm value were less substantial than those of first recalls.

While measuring and understanding the economic footprint of food recalls is crucial for the food industry to conduct cost-benefit analyses and develop food safety strategies, determining the factors that make firms more or less prone to repeated food safety incidents, and how prior experience with recalls affects firms' ability to prevent future incidents, is also of interest from policy standpoint. The organizational learning literature defines learning or knowledge creation as a systematic change in a firm's behavior or routines due to direct or indirect experience (Argote and Miron-Spektor, 2011). Firms generally learn more from their failures compared to their successes, such as in the search for alternatives (Sitkin, 1992). At the same time, the broader product recall literature has shown that experience does not always translate to positive learning outcomes. This presents a testable hypothesis regarding whether and to what extent food firms learn from their previous conformance quality failures.

There is a paucity of research on firms' risk of food product recalls and organizational learning through food recall experience. Using standard survival analysis techniques, Teratanavat et al. (2005) found that firms that experienced a recall event in the past discovered food safety problems later compared to those that encountered their first recall. This suggests that firms did not learn from past recall events in terms of the time taken to identify a subsequent recall. Importantly, the statistical approach used in this study is suitable for modelling the time to a single failure event (e.g., first recall) but is ill-fitted for analyzing *repeated* recall incidents, which requires consideration of information between recall events and the order of these events (Kleinbaum and Klein, 2005).[5]

In investigating food product recalls announced in the United States by publicly traded firms, Hall and Johnson-Hall (2017) used a panel generalized linear model framework with a negative binomial link function to show that prior recall experience was negatively associated with recall counts. They concluded that conformance quality failures represent

[5]In fact, statistical methods that ignore the intra-subject correlation in recurrent time-to-event data have been shown to reject the null hypothesis more often than they should, leading to spurious inferences (Amorim and Cai, 2015).

an important motivation for organizational learning or knowledge transfer. In a similar vein, Johnson-Hall (2017) employed a logistic regression model to identify determinants of whether firms take corrective action (e.g., amended testing and inspection plans) following a recall. The nature of the empirical strategies employed by Hall and Johnson-Hall (2017) and Johnson-Hall (2017) allow the authors to uncover factors influencing the number of recalls (i.e., recall counts) and whether firms report corrective actions, respectively. These insights are informative for policy and practice in their own right. To provide a more granular picture of how learning-by-doing evolves over time (i.e., after each incident), it is necessary to obtain and investigate hazard and/or survivorship curves for *each* ordered recall event. Drawing on the above and the broader organizational learning literature, our study addresses this gap in the literature.

Aside from food safety and public health, our study relates and contributes to two bodies of research. First, the economics and management of product recalls. Recalls are not unique to the food industry; examples from other industries include automobiles (Crafton et al., 1981; Reilly and Hoffer, 1983; Jarrell and Peltzman, 1985; Hoffer et al., 1988; Barber and Darrough, 1996; Haunschild and Rhee, 2004; Rupp, 2004; Rhee and Haunschild, 2006; Kalaignanam et al., 2013; Shah et al., 2017), toys (Hora et al., 2011; Freedman et al., 2012), pharmaceuticals (Jarrell and Peltzman, 1985; Hoffer et al., 1988; Dranove and Olsen, 1994; Cawley and Rizzo, 2008), and medical equipments (Thirumalai and Sinha, 2011), among others.[6] Our work adds to this line of research by empirically examining repeated recalls in the U.S. food industry, which is essential for both firm performance and public safety.

Second, learning and learning-by-doing. Previous studies have explored theoretically and/or empirically the effects of learning and learning-by-doing on technical change and productivity (Arrow, 1962; Levhari, 1966; Levitt et al., 2013), firm dynamics (Tian, 2022), market conduct and performance (Fudenberg and Tirole, 1983; Goldbaum and Panchenko, 2010), and product innovation and diffusion (Stokey, 1988; Jovanovic and Lach, 1989; Kutsoati and Zábojnik, 2005), among others. Regarding organizational learning upon recall events, the evidence is rather mixed. Some studies report a decrease in the likelihood of future recalls (Haunschild and Rhee, 2004; Thirumalai and Sinha, 2011; Kalaignanam et al., 2013), while others report an increase (Haunschild and Rhee, 2004; Steven et al., 2014). Important for the present study, these studies also use the likelihood of future recalls as a proxy for firm learning. Our study contributes to this line of work—specifically, learning from recalls (Haunschild and Rhee, 2004; Kalaignanam et al., 2013; Thirumalai and Sinha, 2011; Tucker, 2004)—by empirically verifying whether food firms learn from their previous recall experience and take necessary preventative measures to extend the time until their next recall event.

[6] In contrast to recalls in these industries, which may stem from both product design flaws and conformance quality issues, food industry recalls are solely due to conformance quality failures (Hall and Johnson-Hall, 2017). This differentiation is significant because it involves distinct organizational processes and functional areas dedicated to enhancing product design compared to ensuring conformance quality.

3 Methods

3.1 Data

The data used in this study is obtained from the USDA FSIS Recall Case Archive and corresponds to meat and poultry recalls issued by publicly traded firms in the United States between 1994-2015. The FSIS provides information on the firm issuing the recall, the recall date, the quantity of product recalled, and the recall classification.[7] Table 1 presents the number of recalls and the total quantity of product recalled by the 31 publicly traded firms included in our study. Our data includes many major processors and marketers of meat and poultry. These firms range from highly specialized, such as Sanderson Farms, which produces raw chicken products, to highly diversified, such as Kraft. In addition, these firms range from small to large in terms of market value.

In the context of a recurrent event survival analysis framework, each firm represents a subject and each recall issued by a firm represents an event. Since the event of interest can occur more than once, these events are termed recurrent events. We define a firm's "entry" into the study as either January 1, 1994 (the date when the FSIS began collecting recall data) or the date of the firm's initial public offering (IPO), whichever is later. The study period ends in December 2015. Firms that went bankrupt or were acquired before the end of the study period are considered to have "dropped out" of the study and are right-censored at the date of the firm's acquisition or bankruptcy filing. Our sample consists of 201 observations and 170 events.[8]

The variable of interest in this study, *Duration till Recall*, is measured in months and represents the time until a recall event (or censoring). To account for the order of recurrent recall events, we classify *Duration till Recall* by stratum. Specifically, stratum 1 represents the time until the first recall event; stratum 2 represents the time between the first and second recall; stratum 3 represents the time between the second and third recall; and so on. Since the largest number of recalls issued by a firm in the data is 36, the last stratum (stratum 37) measures the time elapsed between the 36th recall and the end of the study period.

The firm-specific factors considered in the analysis include firm size, whether meat and poultry is firm's main output, and firm age. The information needed to construct these variables was obtained from companies' annual and 10-K reports. *Firm Size* is measured

[7] In line with the literature, we focus on recalls by publicly traded firms because financial and accounting information is not publicly available for privately held companies. Besides, many major processors and marketers of meat and poultry are publicly traded firms, while privately held ones tend to be smaller (Hall and Johnson-Hall, 2017). Small firms also often go out of business as a result of a product recall, limiting insight into organizational learning.

[8] The difference between the number of observations and recall events is due to right-censored observations (i.e., observations that either dropped out of the study before the end of the study period or experienced no event by the end of the study period), which are still informative for survival analysis (Kleinbaum and Klein, 2005; Hosmer et al., 2011).

in terms of market capitalization (in million U.S. dollars) and is calculated by multiplying the number of shares outstanding by the stock price quoted 10 days before the recall announcement (Fama and French, 1992). Therefore, this value fluctuates over time based on the firm's growth. We adjust for inflation using the Consumer Price Index (CPI) provided by the U.S. Bureau of Labor Statistics.[9] *Meat Main* is a binary variable that is equal to 1 if meat or poultry products represent the firm's primary output and 0 otherwise. Essentially, this variable differentiates meat processors from multi-product food producers and retailers. *Firm Age*, which is also time-variant, represents the number of years since the firm's establishment.

While controlling for other firm-specific characteristics, such as production level and food safety investment, is admittedly desirable, such data is either limited or unavailable.[10] The firm-level controls included in our analysis, such as *Firm Size*, partially account for information related to production levels, food safety practices, and protocols. According to reports from the Economic Research Service (ERS), larger food firms tend to have better sanitation, process controls, and laboratory capabilities (Ollinger and Mueller, 2003) and invest more in sanitation equipment and testing technologies (Ollinger et al., 2004) than smaller firms. Similarly, *Firm Age* can serve as a proxy for firm experience. Nevertheless, the quantity and quality of firm-specific controls included in our analysis are comparable to those used in the empirical literature on food product recalls (e.g., Henson and Mazzocchi, 2002; Lusk and Schroeder, 2002; Teratanavat and Hooker, 2004; Teratanavat et al., 2005; Shang and Tonsor, 2017; Spalding et al., 2023), other consumer and durable product recalls (e.g., Jarrell and Peltzman, 1985; Hoffer et al., 1988; Dranove and Olsen, 1994; Barber and Darrough, 1996; Rupp, 2004; Freedman et al., 2012), and learning-by-doing (e.g., Sheshinski, 1967; Hora et al., 2011; Thirumalai and Sinha, 2011).

The recall-specific factors considered in the analysis include recall class and recall size (measured in pounds recalled). The information used to construct these variables was obtained from the USDA FSIS Recall Case Archive. We create three binary variables corresponding for the three recall classes. *Class I* is a binary variable set to 1 if the recall is classified as Class I, and 0 otherwise. *Class II* and *Class III* are defined analogously. Furthermore, *Recall Size* represents the total amount of product recalled during an event and is measured in thousands of pounds.

Table 2 reports descriptive statistics for the study variables, while figure 1 provides data visualizations. All 31 firms experienced at least one recall event during the study period: about half experienced three recalls, five experienced 13 recalls, two experienced 25 recalls, and one firm (Tyson Foods) experienced 36 recalls (figure 1(a)). The majority of recalls per

[9] Available at `https://data.bls.gov/cgi-bin/surveymost?cu`.

[10] For example, depending on their level of diversification, food firms may produce many different products, and thus information regarding the production level of a specific product (e.g., sausage) or product segment (e.g., red meats) at the time of the recall is not available. Moreover, firms do not generally disclose their investments in food safety technologies or protocols.

firm tend to be Class I, followed by Class II, and then Class III (figure 1(b)). While diversified firms account for a larger portion of recalls within each stratum (figure 1(c)), primarily meat and poultry producing firms, which represent 38% of all firms, experience more recalls compared to their diversified counterparts. Comparing empirical distributions of duration times across different strata (as shown in the boxplots in figure 1(d)), it becomes apparent that the time until the first recall event (stratum 1) is generally the longest, followed closely by stratum 2. For stratum 3, there is a noticeable dip in duration relative to stratum 2, followed by an increase in stratum 4, with a mostly stable pattern thereafter. Conditional on diversification (figure 1(e)), we observe that duration times across different strata are shorter for firms whose main output is meat and poultry, compared to those whose product line is more diversified. This suggests that the risk of a foodborne disease outbreak is greater for firms that primarily handle meat products than for more diversified firms. The relationships between duration times and firm size and firm age (figure 1(f-h)) are less obvious, though it seems duration shrinks with firm size (figure 1(g)). These observations will be formally examined using a recurrent event survival analysis framework.

3.2 Statistical Analysis

There are several statistical methods proposed in the literature for analyzing recurrent time-to-event data (Kelly and Lim, 2000; Kleinbaum and Klein, 2005; Amorim and Cai, 2015; Akhundjanov et al., 2024). The choice between these models largely depends on the assumptions about the events of interest (particularly the dependence structure between events) and the nature of the research question. In what follows, we discuss two such models and elaborate on their suitability for our purposes.

3.2.1 Counting Process Model

The counting process model used in our analysis was developed by Andersen and Gill (1982) and is referred to as the Andersen-Gill (AG) model. This approach assumes that recurrent events within a subject are conditionally uncorrelated, given the covariates, and are considered identical. When a firm issues a recall, the FSIS closely monitors the process. If, at any point, it is determined that more product was affected than initially thought, a recall extension will be issued. Thus, if there is a subsisting problem related to the initial recall event, a subsequent recall will not be issued; instead, it will be addressed with a recall extension (FSIS, 2013). Therefore, it is reasonable to treat each recall event within a firm as an independent event.

This model also assumes that covariates are time-independent, i.e., the variables do not differ depending on whether they are observed for first recall or last recall. This assumption, commonly known as the proportional hazard (PH) assumption, is tested using a proportionality test (Grambsch and Therneau, 1994). If one or more covariates do not

satisfy the PH assumption, a stratified Cox PH model, discussed in the next section, would be a more appropriate approach (Kleinbaum and Klein, 2005). Fitting the Andersen-Gill model allows us to answer the first question of interest: *What factors affect the time to next recall (or the rate at which recalls occur) for food firms?*

Assume T is the random variable representing the duration—time till an event or censoring—with t as its outcome. The standard Cox PH model (Cox, 1972) is used to carry out the counting process approach. In particular, the hazard function of this model takes the following form:

$$h(t,\mathbf{x}) = h_0(t)\exp\left(\sum_{i=1}^{p}\beta_i x_i\right) \tag{1}$$

where $\mathbf{x} = (x_1,\ldots,x_p)'$ is a vector of covariates (firm-specific and/or recall-specific) and $h_0(t)$ is the baseline hazard function that describes the risk when $\mathbf{x} = \mathbf{0}$.

When using a Cox PH model with recurrent event data, multiple time intervals for the same subject must be included in the formulation of the likelihood function used to estimate $h(t,\mathbf{x})$. Importantly, unlike in the standard Cox PH model, subjects do not drop out of the risk set after experiencing a failure (i.e., a recall event) or being censored. If subjects display multiple failure times (recall events), they remain in the risk set until the final interval is completed—either their last failure time or censoring. Hence, the partial likelihood function (L) used to fit the Cox PH model is formulated as the product of individual likelihoods (L_j, $j = 1,\ldots,J$) for each ordered unique failure time:

$$L = L_1 \times L_2 \times \cdots \times L_J \tag{2}$$

where J is the total number of unique failure times for all subjects. For a single failure at the jth ordered failure time $t_{(j)}$, L_j is specified as:

$$L_j = \text{Prob}(\text{failing at time } t_{(j)} | \text{survival up to } t_{(j)}) = \frac{\exp\left(\sum_{i=1}^{p}\beta_i x_{i(j)}\right)}{\sum_{s\in R(t_{(j)})}\exp\left(\sum_{i=1}^{p}\beta_i x_{is(j)}\right)} \tag{3}$$

where $R(t_{(j)})$ is the risk set for the time period $t_{(j)}$ and $x_{i(j)}$ is the value of the variable x_i for subject failing at period $t_{(j)}$.

To handle tied survival times, we use the Breslow approximation method (Breslow, 1974). Further, to account for possible correlation among recurrent events within the same subject, robust standard errors are used for model inference.

3.2.2 Stratified Cox PH Model

The main advantage of the stratified Cox PH model is that it does not require assuming independence between recurrent events within the same subject. Unlike the counting pro-

cess model, this method conveniently accommodates the order of the events, allowing the effect of covariates to vary from event to event. Estimating this model helps us address our second question of interest: *Do we see evidence of firm learning after a recall, and if so, how does firm learning differ between various types of firms (as identified by covariates)?*

There are two versions of the stratified Cox PH model developed by Prentice et al. (1981), commonly referred to as PWP models. The first version is called conditional 1, or the PWP Total Time (PWP-TT) model, which uses time to events from study entry of each subject. The second version, which uses survival time from the previous recall, is called conditional 2, or the PWP Gap Time (PWP-GT) model. In the present study, the PWP-GT stratified Cox PH model is used, as we are interested in the time to the next recall after a previous recall, rather than the time to the first, second, third, etc., recall from study entry (Kleinbaum and Klein, 2005). Besides, in comparing the performance of different survival models, including AG, PWP-TT, and PWP-GT, Kelly and Lim (2000) conclude that PWP-GT model is "useful for analyzing recurrent event data".

The hazard function of the stratified PWP-GT model is given by:

$$h_g(t,\mathbf{x}) = h_{0g}(t)\exp\left(\sum_{i=1}^{p}\left(\beta_i x_i + \sum_l \delta_{il} z_l x_i\right)\right) \tag{4}$$

where $h_{0g}(t)$ is the baseline hazard function for stratum g, and z_l, for $l = \{2,3,...\}$, is a dummy variable for the l'th stratum, with stratum 1 omitted as the base group (Kleinbaum and Klein, 2005). The same set of covariates included in $\mathbf{x}$ are used as those in the counting process model. Further, interacting each covariate with dummies for each stratum allows for controlling the differential effects of firm characteristics across strata. As before, we use the Breslow approximation method (Breslow, 1974) to handle tied survival times and robust standard errors to account for potential within-subject correlation.

This model is similar to the specification of the Andersen-Gill model, but note that in (4), a different baseline hazard is estimated for each stratum, unlike in the Andersen-Gill model. This crucially allows us to obtain different hazard and survival functions for each stratum. Comparing the survivorship functions corresponding to different strata reveals whether firms learn after each recall event.

4 Results

4.1 What Factors Affect Time to Next Recall for Food Firms?

Table 3 reports estimation results for the Andersen-Gill counting process model and the PWP-GT stratified Cox PH model. The diagnostic tests in table 4 indicate the PH assumption holds globally for the Andersen-Gill model in specifications (1) and (3), but fails to hold in specification (5). At the individual variable level, *Meat Main* does not satisfy the

PH assumption in specifications (1) and (3), while *Firm Size* does not satisfy it in specification (1). As discussed earlier, the failure of the PH assumption implies time-dependence, with the PWP-GT stratified Cox PH model offering a more appropriate framework for inferences.

Our results suggest that *Firm Age* is not a statistically significant factor influencing the risk of recall occurrence. So, firms that have been in business for a longer period do not necessarily have immunity to food safety incidents. From specifications (1) and (2) in table 3, estimates for *Meat Main* are significant at the 5 percent level across both models, and the sign of the parameter estimate matches expectations and findings from the literature (Haunschild and Rhee, 2004; Hall and Johnson-Hall, 2017). According to the preferred model, the hazard of recall for firms whose main output is meat and/or poultry products is about 2.6 times the rate for firms that are more diversified. This may be because meat and poultry naturally contain a higher number of pathogenic bacteria than other products. Further, the coefficient of *Firm Size* is statistically significant at the 1 percent level for the Andersen-Gill model. In particular, for every one-million-dollar increase in firm size, the log risk of recall increases by 0.0023 percentage points. In other words, as a firm's size expands, so does the likelihood of a recall event, which is consistent with the pattern from figure 1(g) as well as the literature (Thirumalai and Sinha, 2011; Hall and Johnson-Hall, 2017).

A natural question is whether the risk of recall associated with the growth of firm size varies by a firm's diversification. To answer this question, the joint effect of *Firm Size* and *Meat Main* on firms' *Duration till Recall* is investigated in specifications (3) and (4) in table 3. When the interaction term for *Firm Size* and *Meat Main* is included along with the main effects for these variables, the interaction term comes out to be highly statistically significant for both the Andersen-Gill and the PWP-GT models. This suggests that what raises the likelihood of a meat/poultry product recall is not just being a large firm, but being a large firm that primarily produces meat/poultry products. The parameter estimate on the interaction term indicates that for every one-million-dollar increase in the size of primarily meat-producing firms (*Meat Main* = 1), the log risk of recall increases by an additional 0.0615 (Andersen-Gill) or 0.0697 (PWP-GT) percent relative to multi-product food producers and retailers (*Meat Main* = 0). This shows that firms with a more diversified output incur a smaller risk of recall with the expansion of firm size compared to those producing mainly meat products.

Moving on to recall-specific factors, it is crucial to note that the amount of meat recalled and recall class for a given recall event are not determinants of that recall but rather its consequences. Hence, it would be erroneous to include these variables directly in the list of covariates. Such variables must be lagged—meaning the loss of a first recall event per firm—to study their effects on subsequent recall events. We provide this analysis in specifications (5) and (6) in table 3. The effects of firm-specific factors (*Firm Size* and *Meat*

Main) remain qualitatively unaltered when compared to specifications (1) and (2).

We can observe that the lag of *Class I* is statistically significant at the 10 percent level across the two models, while the lag of *Class II* is significant at the 10 percent level for the Anderson-Gill model and at the 1 percent level for the PWP-GT model. Our results from the preferred (PWP-GT) specification suggest that the hazard of recall for firms that experienced a Class II recall in the past is about 7.6 times the rate for firms that experienced a Class III recall (the reference category) previously. In contrast, the hazard for firms that suffered a Class I recall in the past is approximately 3.7 times the hazard for firms that reported a Class III recall in the past. Comparing the risks for firms that experienced Class I and Class II recalls in the past, it is evident that firms that dealt with the latter have about twice the risk of those that dealt with the former. This suggests that firms seem to learn more after facing a Class I recall, the most severe category, than after a Class II recall event.

Additionally, the lag of *Recall Size* is statistically significant at the 10 percent level for the PWP-GT model. The parameter estimate for this variable indicates that the hazard of a future recall incident decreases with the quantity of meat recalled in the previous recall event. Specifically, for every one million pounds of meat recalled in the past, the log risk of a firm's next recall decreases by 3.01 percent, which also suggests potential firm learning.

4.2 Do Firms Learn from Previous Food Safety Incidents?

Figure 2 depicts the estimated survival functions for the Andersen-Gill counting process model (panel (a)) and the PWP-GT stratified Cox PH model (panels (b)-(c)). In this context, the estimated survival function represent the probability of surviving (i.e., not experiencing a recall event) beyond t periods, i.e., Prob($T > t$). Since the Andersen-Gill model treats recall events within firms as independent, we obtain a single survivorship curve, as demonstrated in figure 2(a). The slope of this survival curve is relatively steep between 0-60 months compared to that for period greater than 60 months, indicating that the likelihood of survivorship declines rapidly between 0-60 months and slows down considerably thereafter. In other words, firms are generally most prone to issuing a recall within 60 months of operation, whether since the beginning of business or since the last recall event.

To illustrate survivorship curves for each stratum while acknowledging the order of recurring events, figure 2(b-c) plots the results from the PWP-GT stratified Cox PH model for the first four (panel (b)) and for all recall events (panel (c)). Clearly, the shape of the estimated survival curve varies by event stratum. For instance, in figure 2(b), strata 1 and 2 appear somewhat similar, as do strata 3 and 4, but strata 1 and 2 differ from strata 3 and 4. Visually, this suggests that the Andersen-Gill model, which treats all strata as identical, may not adequately model the repeated recall data, and that firms' duration times to the next recall differ depending on their position in the sequence of recall events.

If firms learned from a previous recall event and were able to *lengthen* the amount of time until the next recall, we would generally expect the survivorship curve for the later stratum to be above that of the past stratum, indicating that the probability of surviving longer than t periods would be higher for the later stratum. Examining the survivorship curve for stratum 1 in figure 2(b), we see that all observations in the sample issued a recall by approximately the 250th month, when the probability of survivorship converges to zero. From the survivorship curve for stratum 2, we observe that not all firms in the sample issued a second recall event, as evidenced by the flat-lining of the estimated survival curve for stratum 2 at a probability of 0.25. Comparing the survivorship curves for strata 1 and 2, it is apparent that the curves largely overlap for the first approximately 50 months. After that, the survival curve for stratum 2 diverges and lies above that of stratum 1. This implies that the likelihood of surviving (i.e., no recall event) is similar for the first approximately 50 months for both recall events, but after that, the probability of survivorship increases in case of the second recall event relative to the first. This prolonged time-to-event for the second recall is suggestive of firm learning after the first recall event.

The survival curve for stratum 3 is similar to that of stratum 2 in that not all firms experienced a third recall event. If firms learned how to avoid a subsequent recall after handling the previous two incidents, we would expect the survivorship curve for stratum 3 to be above that of the earlier strata. However, from the survivorship curve for stratum 3 in figure 2(b), we find no evidence to support this: the survival time from the second to the third recall (stratum 3) is shorted than that from the first to the second recall (stratum 2), which aligns with observations from figure 1(d). Therefore, this result does not support the notion of firm learning in this particular case. Finally, the evidence of firm learning between strata 3 and 4 is more substantial, as the survivorship curve for stratum 4 is almost always above that for stratum 3.

Figure 2(c) plots the survivorship curves corresponding to all strata examined in the study. Upon careful examination, two salient facts come to light. First, recalls after stratum 4 occur within approximately 50 months, with the majority occuring within the first approximately 25 months. Second, no definitive evidence of learning, as a clear and consistent pattern of increasing survivorship after each recall incident, emerges. The only evidence of learning we find is between strata 1 and 2, and particularly, between strata 3 and 4, as discussed above. In section 5, we review possible mechanisms underlying our findings.

4.3 Decomposing Survivorship by Firm and Recall Characteristics

To illuminate the effects of firm- and recall-specific factors on the likelihood of survivorship, we next decompose survivorship curves for each stratum by measurable covariates, specifically those found to be statistically significant in table 3, using Kaplan-Meier (KM) survivorship curves (Kaplan and Meier, 1958). To ensure an adequate sample size for esti-

mation and inferences for each stratum (Kelly and Lim, 2000; Amorim and Cai, 2015), this portion of our analysis focuses on the first eight recall events, which is the average number of recalls per firm (see table 2).

The KM curves non-parametrically estimate the survival function for each stratum as:

$$S(t) = \text{Prob}(T > t) = \prod_{j|t_j \leq t} \frac{n_j - d_j}{n_j} \tag{5}$$

where n_j is number of observations at risk just prior to time t_j and d_j is the number of events (recalls) at time t_j. Time in months is plotted against the estimated probability that a recall event will occur in the next immediate time frame, Prob($T > t$), where T is the random variable for duration and t represents its outcome measured in months.

Figure 3(a) illustrates the stratified KM survivorship curves decomposed by *Meat Main*. This variable indicates whether a firm's main output line is meat/poultry or if they have more diversified output. As can be seen, the estimated KM curves for firms whose main output is meat/poultry consistently lie below those of diversified firms across all strata. This indicates that firms producing meat/poultry as their main output have a lower probability of surviving (i.e., not experiencing a recall event) at any given time compared to their multi-product rivals. This observation corroborates our findings from both the Andersen-Gill and PWP-GT models in table 3 at a more granular level.

In figure 3(b), we decompose survival functions by recall class. Evidently, the survival functions for firms that experienced a Class I recall in the past are almost always higher than those for firms that dealt with a Class II recall previously. This implies that it takes longer (in months) for a firm to issue a subsequent recall after experiencing a Class I recall compared to a Class II recall. Consequently, firms seem to learn and adapt more effectively in the aftermath of the most severe type of recalls. This observation is in line with our findings from table 3 and with the broader literature on organization learning, which suggests that learning may depend on the type of quality failure (e.g., Hall and Johnson-Hall, 2017). Given that Class III recalls were observed only a few times in the data (see figure 1(b)), inferences about Class III recall cannot be made robustly and are thus excluded.

4.4 Robustness to the Number of Strata

A natural question is how robust the study findings are to the number of strata (recall events) considered in the analysis. Specifically, whether decreasing or increasing the number of strata, which is equivalent to changing the end of the study period to an earlier time (i.e., fewer strata) or a later time (i.e., more strata), affects the estimation results. Towards this end, we perform an analysis similar to that presented in table 3 with various sets of strata: stratum 1 only; strata 1 and 2; strata 1, 2, and 3; and so on. The analysis for strata 1-37 corresponds to that presented in table 3.

The results from this sensitivity analysis are depicted in figure 4, which is organized similarly to table 3, focusing on the main regressors in each specification. A few observations are in order. First, the effect of individual regressors on the hazard of a (next) recall event remains remarkably stable across different sets of strata, particularly after stratum 5. The somewhat higher variability in the estimates and their confidence bounds in the first few strata can be attributed to sample size. Other than that, it is obvious that increasing the number of strata contributes to the stability of the estimates. Second, and importantly, the magnitude and significance of the estimates for the reported regressors are consistent with our main findings, indicating their robustness against variations in both the number of strata and the sample size.

5 Discussion

While we find some evidence of firm learning in the context of extended time to the next recall (e.g., between a firm's first and second recall, and third and fourth recall), there is a lack of evidence suggesting that a firm's ability to prevent recalls consistently improves with the number of recalls it has experienced. Why is this? What explains the apparent stagnation and decline in learning after the first few recall events? In what follows, we briefly discuss several mechanisms that might rationalize the observed findings. Further research is warranted to formally verify these mechanisms.

First, trade-offs between the investment costs in more effective food safety and sanitation protocols and the economic costs of recalls play a vital role in shaping firm's incentives to adopt any given level of precaution. Firms are motivated to enhance food safety management efforts when the expected benefits exceed the costs of prevention (Holleran et al., 1999; Elbasha and Riggs, 2003). Underinvestment in safety and sanitation programs may be optimal for a firm if the savings from under-investing in more sophisticated programs outweigh the economic costs of handling a recall event. While such an incentive may emerge in isolated cases—such as after experiencing a relatively benign food contamination incident, where recall handling costs are relatively low—in more serious instances, it may not be optimal, as the direct and indirect economic costs of recalls can be substantial (Sockett, 1993), thus incentivizing firms to adopt more effective preventative measures.

It may also be that the economic costs of recalls, and thus incentives, change with each subsequent recall event. In particular, the costs of the first recall event might be more consequential, but less so with each subsequent event. Complimentary to our paper, existing literature shows that the negative economic effects of repeated recalls on firm value are less severe than those of the first recall (Thomsen and McKenzie, 2001; Pozo and Schroeder, 2016) and that firms that experienced a recall event in the past discovered food safety problems later compared to those that experienced their first recall (Teratanavat et al., 2005). Therefore, it appears that a decline in the economic impact of repeated recalls on a firm's

value may conceivably provide a perverse incentive for continuous learning to avoid foodborne outbreaks.

Second, ambiguity and uncertainty surrounding an adverse event can induce the "hide in the herd" behavior, whereby organizations engage in imitating observed successful or acceptable practices without making conscious decisions and/or innovations (Alchian, 1950). Such imitation consequently shields firms from negative publicity or judgments of their actions upon failure (Devenow and Welch, 1996), leading to survival but resulting in inefficient outcomes.

Third, the rareness of conformance quality failures and major recalls is posited as another impediment to organizational learning (Baumard and Starbuck, 2005; Starbuck, 2009). Managers may perceive organizational failures as exceptionally idiosyncratic, which in turn reduces incentives for organizational action. It is also possible that, after an extended period since a recall event, the perceived threat of a future recall by managers may become less imminent. If new safety procedures were put in place after a recall event and some time passes before another incident occurs, the firm's operations and employees may naturally grow laxer in their adherence to these quality control procedures.

Fourth, while considerable government attention and initiatives have been directed to enhancing food safety by increasing protective actions taken by consumers and producers—such as through the implementation of the Hazard Analysis Critical Control Point (HACCP) system—food safety regulation is not without its flaws. In fact, the legal system has frequently been argued to provide limited incentives to the meat and poultry industry when it comes to food safety investment (Ollinger and Ballenger, 2003; Johnson-Hall, 2017), thus contributing to the problem (Skees et al., 2001). Under the HACCP, for instance, firms are required to perform necessary tasks to meet the minimum standards for food safety. This, combined with the fact that few lawsuits related to foodborne outbreaks actually go to trial (Buzby et al., 2003), further distorts the food industry's incentives to properly reflect on past incidents.

Finally, part of the reason for the absence of conclusive evidence for the growth in firms' ability to prevent recalls with the number of previous incidents can be attributed to changing production styles and broader systemic issues. For instance, meat and poultry production operations have become increasingly consolidated, with facilities processing larger and larger quantities of products. This naturally increases the likelihood of pathogen spread among animals passing through these facilities (Ducharme, 2019).

6 Conclusion

This study demonstrated a systematic approach to analyzing repeated food recalls with the main goal of identifying the extent of firm learning after each recall event. Although our results suggest that the food industry targets its resources appropriately to address recalls

that pose the greatest risks to human health (i.e., Class I), overall, firms' ability to prevent recalls does not consistently improve with past recall experience. Therefore, public health officials and policymakers may need to revisit their inspection programs and/or design policies that incentivize food firms to reflect more effectively on their previous food safety incidents.

On a final note, while this study focused exclusively on foodborne disease outbreaks to demonstrate a new empirical framework for inferring firm learning from inter-event time, there are many promising applications of this approach in other contexts. For instance, repeated recall events in other industries (e.g., automotive, pharmaceutical, and medical devices), repeated health violations, and repeated environmental violations, among others.[11]

References

Akhundjanov, S. B., Pozo, V. F., and Thomas, B. (2024). Inference on learning upon repeated compliance issues. *Economics Letters*, 242:111871.

Alchian, A. A. (1950). Uncertainty, evolution, and economic theory. *Journal of Political Economy*, 58(3):211–221.

Amorim, L. D. A. F. and Cai, J. (2015). Modelling recurrent events: A tutorial for analysis in epidemiology. *International Journal of Epidemiology*, 44(1):324–333.

Andersen, P. K. and Gill, R. D. (1982). Cox's regression model for counting processes: A large sample study. *The Annals of Statistics*, 10(4):1100–1120.

Argote, L. and Miron-Spektor, E. (2011). Organizational learning: From experience to knowledge. *Organization Science*, 22(5):1123–1137.

Arrow, K. J. (1962). The economic implications of learning by doing. *Review of Economic Studies*, 29(3):155–173.

Barber, B. M. and Darrough, M. N. (1996). Product reliability and firm value: The experience of American and Japanese automakers, 1973-1992. *Journal of Political Economy*, 104(5):1084–1099.

Baumard, P. and Starbuck, W. H. (2005). Learning from failures: Why it may not happen. *Long Range Planning*, 38(3):281–298.

Breslow, N. (1974). Covariance analysis of censored survival data. *Biometrics*, 30(1):89–99.

Buzby, J. C., Frenzen, P. D., and Rasco, B. (2003). Product liability and microbial foodborne illness. Agricultural Economics Report No. 799. Washington DC: Economic Research Service.

[11] For further information and data, see the Consumer Product Safety Commission (CPSC), the National Highway Traffic Safety Administration (NHTSA), and the Good Jobs First violation tracker.

Cawley, J. and Rizzo, J. A. (2008). Spillover effects of prescription drug withdrawals. In Helmchen, L., Kaestner, R., and Lo Sasso, A., editors, *Beyond Health Insurance: Public Policy to Improve Health (Advances in Health Economics and Health Services Research)*, volume 19, pages 119–143. Emerald Group Publishing Limited.

CDC (2020). Foods that can cause food poisoning. Retrieved from: https://www.cdc.gov/foodsafety/foods-linked-illness.html.

Chen, Y., Ganesan, S., and Liu, Y. (2009). Does a firm's product-recall strategy affect its financial value? An examination of strategic alternatives during product-harm crises. *Journal of Marketing*, 73(6):214–226.

Cox, D. R. (1972). Regression models and life tables. *Journal of the Royal Statistical Society: Series B*, 34(2):187–220.

Crafton, S. M., Hoffer, G. E., and Reilly, R. J. (1981). Testing the impact of recalls on the demand for automobiles. *Economic Inquiry*, 19(4):694.

Devenow, A. and Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40(3-5):603–615.

Dranove, D. and Olsen, C. (1994). The economic side effects of dangerous drug announcements. *Journal of Law and Economics*, 37(2):323–348.

Ducharme, J. (2019). You're not imagining it: Food recalls are getting more common. Here's why. *Time*. Retrieved from: https://time.com/5504355/food-recalls-more-common/.

Elbasha, E. H. and Riggs, T. L. (2003). The effects of information on producer and consumer incentives to undertake food safety efforts: A theoretical model and policy implications. *Agribusiness*, 19(1):29–42.

Fama, E. and French, K. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

FDA (2017). Recalls of foods and dietary supplements. Retrieved from: https://www.fda.gov/Food/RecallsOutbreaksEmergencies/Recalls/default.htm.

Foster, W. and Just, R. E. (1989). Measuring welfare effects of product contamination with consumer uncertainty. *Journal of Environmental Economics and Management*, 17(3):266–283.

Freedman, S., Kearney, M., and Lederman, M. (2012). Product recalls, imperfect information, and spillover effects: Lessons from the consumer response to the 2007 toy recalls. *Review of Economics and Statistics*, 94(2):499–516.

FSIS (2013). Recall of meat and poultry products. FSIS Directive 8080.1, Washington DC.

FSIS (2017). Recall case archive. Retrieved from: https://www.fsis.usda.gov/wps/portal/fsis/topics/recalls-and-public-health-alerts/recall-case-archive.

Fudenberg, D. and Tirole, J. (1983). Learning-by-doing and market performance. *The Bell Journal of Economics*, 14(2):522–530.

Goldbaum, D. and Panchenko, V. (2010). Learning and adaptation's impact on market efficiency. *Journal of Economic Behavior and Organization*, 76:635–653.

Grambsch, P. M. and Therneau, T. M. (1994). Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika*, 81(3):515–526.

Hall, D. C. and Johnson-Hall, T. D. (2017). Learning from conformance quality failures that triggered product recalls: The role of direct and indirect experience. *Journal of Supply Chain Management*, 53(4):13–36.

Haunschild, P. R. and Rhee, M. (2004). The role of volition in organizational learning: The case of automotive product recalls. *Management Science*, 50(11):1545–1560.

Henson, S. and Mazzocchi, M. (2002). Impact of bovine spongiform encephalopathy on agribusiness in the United Kingdom: Results of an event study of equity prices. *American Journal of Agricultural Economics*, 84(2):370–386.

Henson, S. and Reardon, T. (2005). Private agri-food standards: Implications for food policy and the agri-food system. *Food Policy*, 30(3):241–253.

Hoffer, G. E., Pruitt, S. W., and Reilly, R. J. (1988). The impact of product recalls on the wealth of sellers: A reexamination. *Journal of Political Economy*, 96(3):663–670.

Holleran, E., Bredahl, M. E., and Zaibet, L. (1999). Private incentives for adopting food safety and quality assurance. *Food Policy*, 24(6):669–683.

Hora, M., Bapuji, H., and Roth, A. V. (2011). Safety hazard and time to recall: The role of recall strategy, product defect type, and supply chain player in the US toy industry. *Journal of Operations Management*, 29(7-8):766–777.

Hosmer, D. W., Lemeshow, S., and May, S. (2011). *Applied survival analysis: Regression modeling of time-to-event data*. John Wiley & Sons, New York.

Hua, X. (2011). Product recall and liability. *Journal of Law, Economics, & Organization*, 27(1):113–136.

Jarrell, G. and Peltzman, S. (1985). The impact of product recalls on the wealth of sellers. *Journal of Political Economy*, 93(3):512–536.

Johnson-Hall, T. D. (2017). Ensuring food safety by preventing food recalls: The impact of locus of failure, regulatory agency discovery, breadth, and firm size on corrective action. *Journal of Marketing Channels*, 24(3-4):115–135.

Jovanovic, B. and Lach, S. (1989). Entry, exit, and diffusion with learning by doing. *American Economic Review*, 79(4):690–699.

Kalaignanam, K., Kushwaha, T., and Eilert, M. (2013). The impact of product recalls on future product reliability and future accidents: Evidence from the automobile industry. *Journal of Marketing*, 77(2):41–57.

Kaplan, E. L. and Meier, P. (1958). Nonparametric estimation from incomplete observations. *Journal of the American Statistical Association*, 53(282):457–481.

Kelly, P. J. and Lim, L. L.-Y. (2000). Survival analysis for recurrent event data: An application to childhood infectious diseases. *Statistics in Medicine*, 19(1):13–33.

Kennedy, B., Kasl, S., and Vaccarino, V. (2001). Repeated hospitalizations and self-rated health among the elderly: A multivariate failure time analysis. *American Journal of Epidemiology*, 153(3):232–241.

Kleinbaum, D. G. and Klein, M. (2005). *Survival analysis: A self-learning text*. Springer, New York, 2 edition.

Kutsoati, E. and Zábojnik, J. (2005). The effects of learning-by-doing on product innovation by a durable good monopolist. *International Journal of Industrial Organization*, 23(1):83–108.

Levhari, D. (1966). Extensions of Arrow's "learning by doing". *Review of Economic Studies*, 33(2):117–131.

Levitt, S. D., List, J. A., and Syverson, C. (2013). Toward an understanding of learning by doing: Evidence from an automobile assembly plant. *Journal of Political Economy*, 121(4):643–681.

Lusk, J. L. and Schroeder, T. C. (2002). Effects of meat recalls on futures market prices. *Agricultural and Resource Economics Review*, 31(1):47–58.

Marino, A. M. (1997). A model of product recalls with asymmetric information. *Journal of Regulatory Economics*, 12:245–265.

Marsh, T. L., Schroeder, T. C., and Mintert, J. (2004). Impacts of meat product recalls on consumer demand in the USA. *Applied Economics*, 36(9):897–909.

Mazzocchi, M. (2006). No news is good news: Stochastic parameters versus media coverage indices in demand models after food scares. *American Journal of Agricultural Economics*, 88(3):727–741.

McCluskey, J. J., Grimsrud, K. M., Ouchi, H., and Wahl, T. I. (2005). Bovine spongiform encephalopathy in Japan: Consumers' food safety perceptions and willingness to pay for tested beef. *Australian Journal of Agricultural and Resource Economics*, 49(2):197–209.

Ollinger, M. and Ballenger, N. (2003). Weighing incentives for food safety in meat and poultry. *Amber Waves*, pages 35–41.

Ollinger, M., Moore, D. L., and Chandran, R. (2004). Meat and poultry plants' food safety investments: Survey findings. Technical Bulletin No. 1911. Washington DC: Economic Research Service.

Ollinger, M. and Mueller, V. (2003). Managing for safer food: The economics of sanitation and process controls in meat and poultry establishments. Agricultural Economics Report No. 817. Washington DC: Economic Research Service.

Piggott, N. E. and Marsh, T. L. (2004). Does food safety information impact US meat demand? *American Journal of Agricultural Economics*, 86(1):154–174.

Pozo, V. and Schroeder, T. (2016). Evaluating the costs of meat and poultry recalls to food firms using stock returns. *Food Policy*, 59:66–77.

Prentice, R. L., Williams, B. J., and Peterson, A. V. (1981). On the regression analysis of multivariate failure time data. *Biometrika*, 68(2):373–379.

Pruitt, S. W. and Peterson, D. R. (1986). Security price reactions around product recall announcements. *Journal of Financial Research*, 9(2):113–122.

Reilly, R. J. and Hoffer, G. E. (1983). Will retarding the information flow on automobile recalls affect consumer demand? *Economic Inquiry*, 21(3):444–447.

Rhee, M. and Haunschild, P. R. (2006). The liability of good reputation: A study of product recalls in the US automobile industry. *Organization Science*, 17(1):101–117.

Rupp, N. G. (2004). The attributes of a costly recall: Evidence from the automotive industry. *Review of Industrial Organization*, 25:21–44.

Schroeder, T. C., Tonsor, G. T., Pennings, J. M. E., and Mintert, J. (2007). Consumer food safety risk perceptions and attitudes: Impacts on beef consumption across countries. *The B.E. Journal of Economic Analysis & Policy*, 7(1).

Shah, R., Ball, G. P., and Netessine, S. (2017). Plant operations and product recalls in the automotive industry: An empirical investigation. *Management Science*, 63(8):2439–2459.

Shang, X. and Tonsor, G. T. (2017). Food safety recall effects across meat products and regions. *Food Policy*, 69:145–153.

Sheshinski, E. (1967). Tests of the "learning by doing" hypothesis. *Review of Economics and Statistics*, 49(4):568–578.

Sitkin, S. B. (1992). Learning through failure: The strategy of small losses. *Research in Organizational Behavior*, 14:231–266.

Skees, J. R., Botts, A., and Zeuli, K. A. (2001). The potential for recall insurance to improve food safety. *International Food and Agribusiness Management Review*, 4(1):99–111.

Sockett, P. (1993). Social and economic aspects of food-borne disease. *Food Policy*, 18(2):110–119.

Spalding, A., Goodhue, R. E., Kiesel, K., and Sexton, R. J. (2023). Economic impacts of food safety incidents in a modern supply chain: E. coli in the romaine lettuce industry. *American Journal of Agricultural Economics*, 105(2):597–623.

Starbuck, W. H. (2009). Cognitive reactions to rare events: Perceptions, uncertainty, and learning. *Organization Science*, 20(5):925–937.

Steven, A. B., Dong, Y., and Corsi, T. (2014). Global sourcing and quality recalls: An empirical study of outsourcing-supplier concentration-product recalls linkages. *Journal of Operations Management*, 32(5):241–253.

Stokey, N. L. (1988). Learning by doing and the introduction of new goods. *Journal of Political Economy*, 96(4):701–717.

Teratanavat, R. and Hooker, N. H. (2004). Understanding the characteristics of US meat and poultry recalls: 1994–2002. *Food Control*, 15(5):359–367.

Teratanavat, R., Salin, V., and Hooker, N. (2005). Recall event timing: Measures of managerial performance in U.S. meat and poultry plants. *Agribusiness*, 21(3):351–373.

Thirumalai, S. and Sinha, K. K. (2011). Product recalls in the medical device industry: An empirical exploration of the sources and financial consequences. *Management Science*, 57(2):376–392.

Thomsen, M. R. and McKenzie, A. (2001). Market incentives for safe foods: An examination of shareholder losses from meat and poultry recalls. *American Journal of Agricultural Economics*, 82:526–538.

Thomsen, M. R., Shiptsova, R., and Hamm, S. J. (2006). Sales responses to recalls for listeria monocytogenes: Evidence from branded ready-to-eat meats. *Applied Economic Perspectives and Policy*, 28(4):482–493.

Tian, C. (2022). Learning and firm dynamics in a stochastic equilibrium. *Journal of Economic Theory*, 203:105486.

Tucker, A. L. (2004). The impact of operational failures on hospital nurses and their patients. *Journal of Operations Management*, 22(2):151–169.

Weiner, B. (1995). *Judgments of responsibility: A foundation for a theory of social conduct*. Guilford Press, New York.

Welling, L. (1991). A theory of voluntary recalls and product liability. *Southern Economic Journal*, 57(4):1092–1111.

Figures and Tables

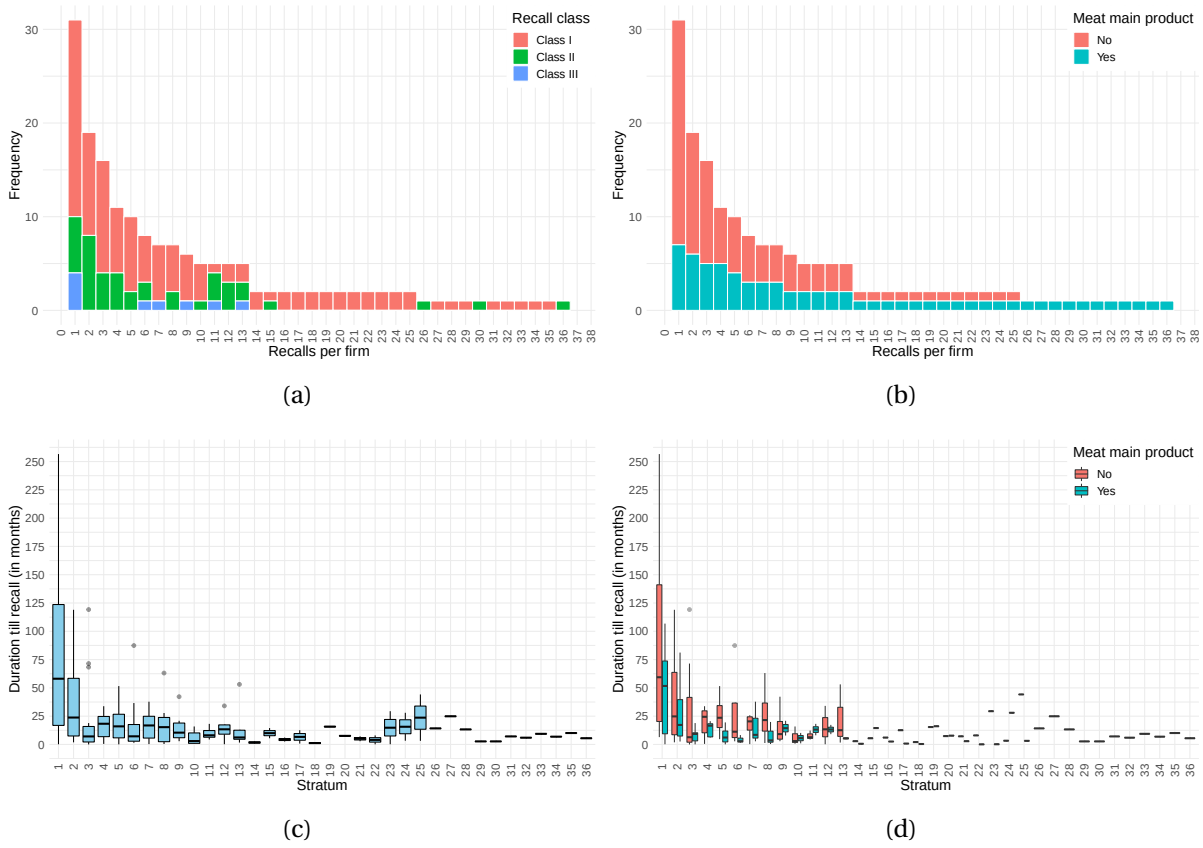
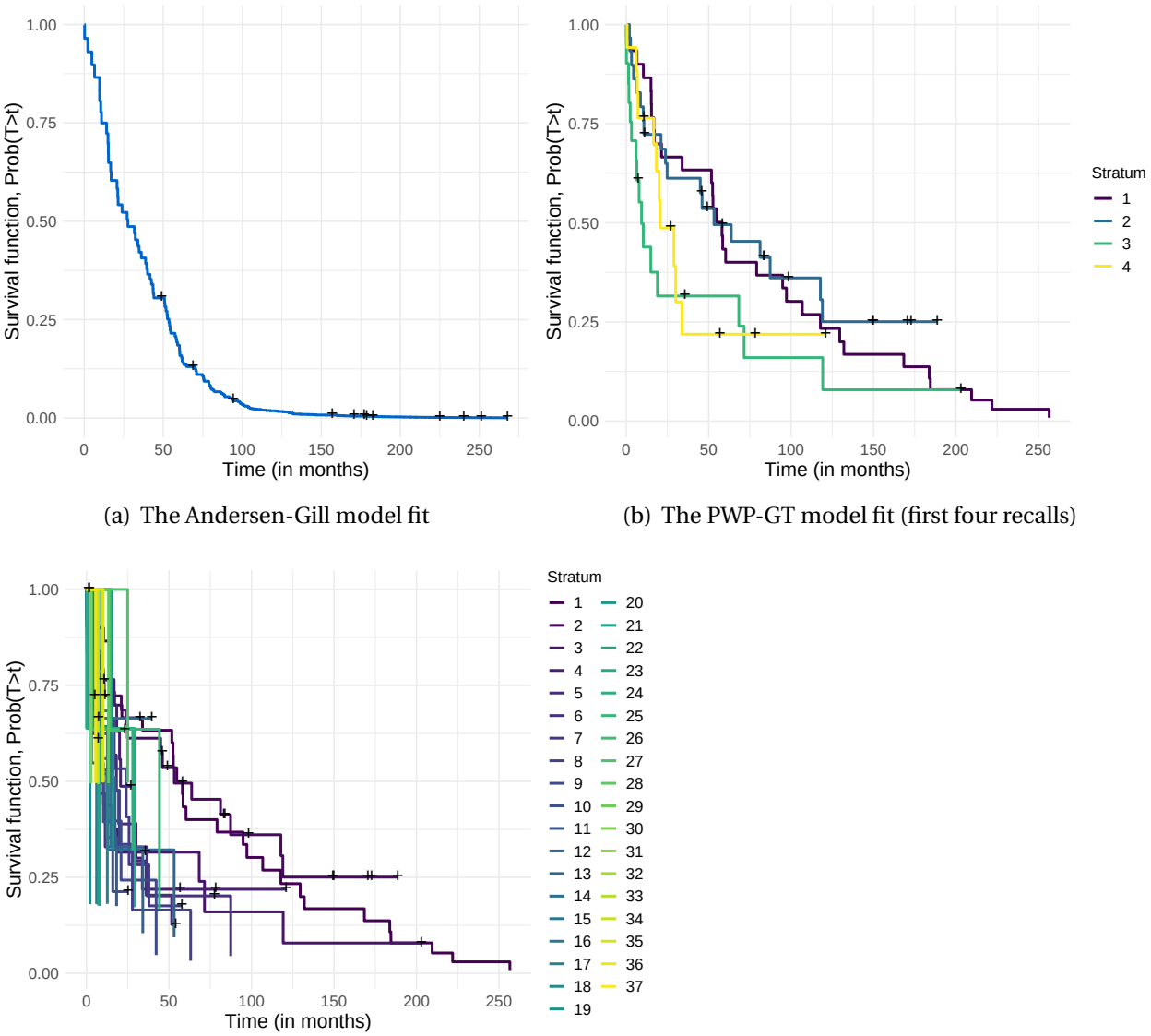


Figure 1: Characteristics of the study recalls and firms issuing them.

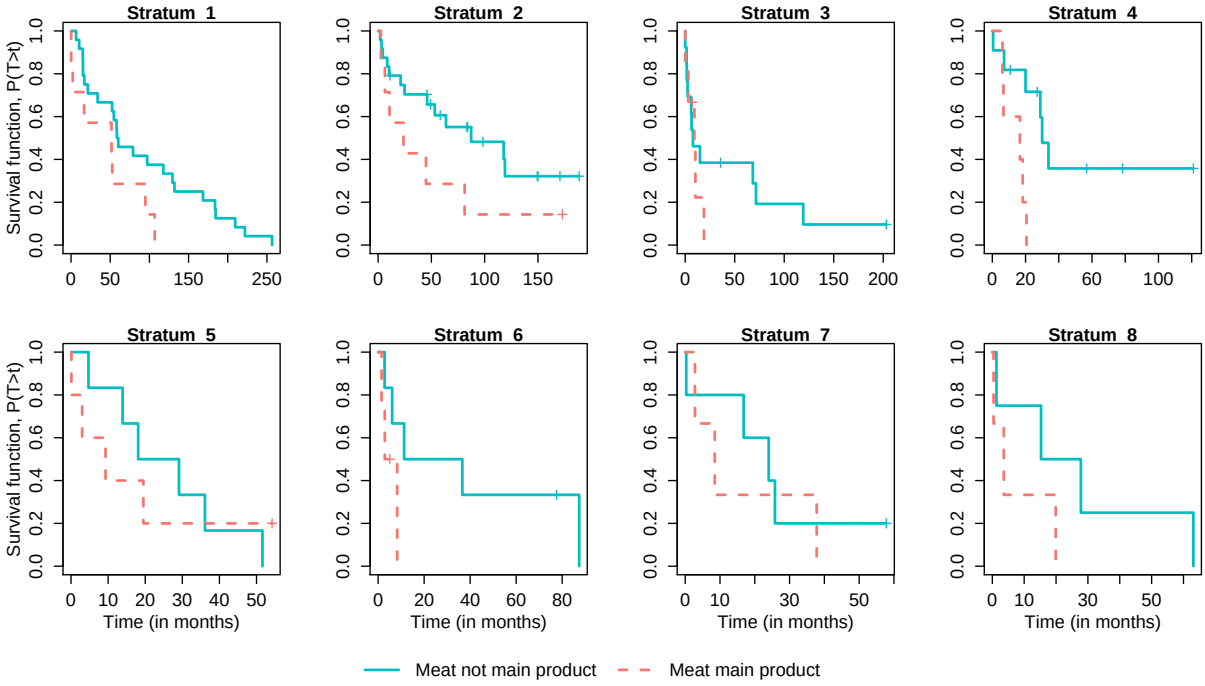


(a) The Andersen-Gill model fit

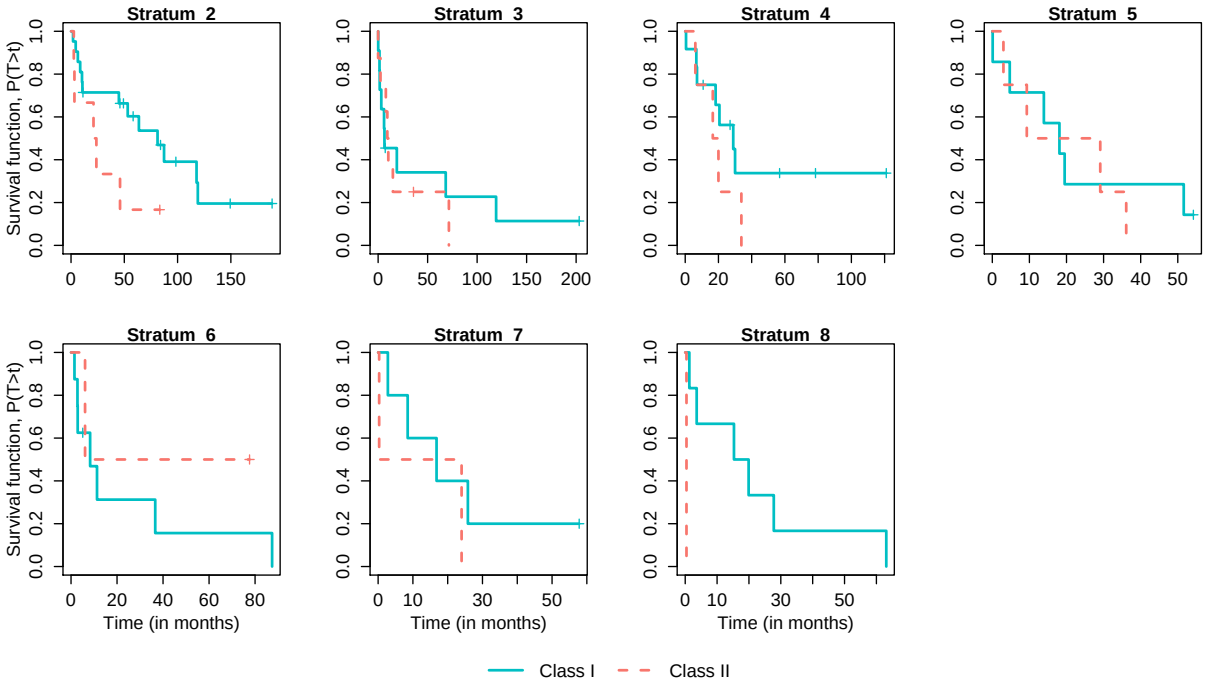
(b) The PWP-GT model fit (first four recalls)

(c) The PWP-GT model fit (all recalls)

Figure 2: Estimated survival functions.
Notes: The estimated survival function shows the probability of surviving (i.e., no recall event) longer than t periods, Prob($T > t$). Small "+" marks denote individual firms whose survival times have been right-censored.



(a) Conditional on diversification



(b) Conditional on lag of recall class

Figure 3: Estimated Kaplan-Meier survival functions for the first eight strata.
The estimated survival function shows the probability of surviving (i.e., no recall event) longer than t periods, Prob($T > t$). Small "+" marks denote individual firms whose survival times have been right-censored.

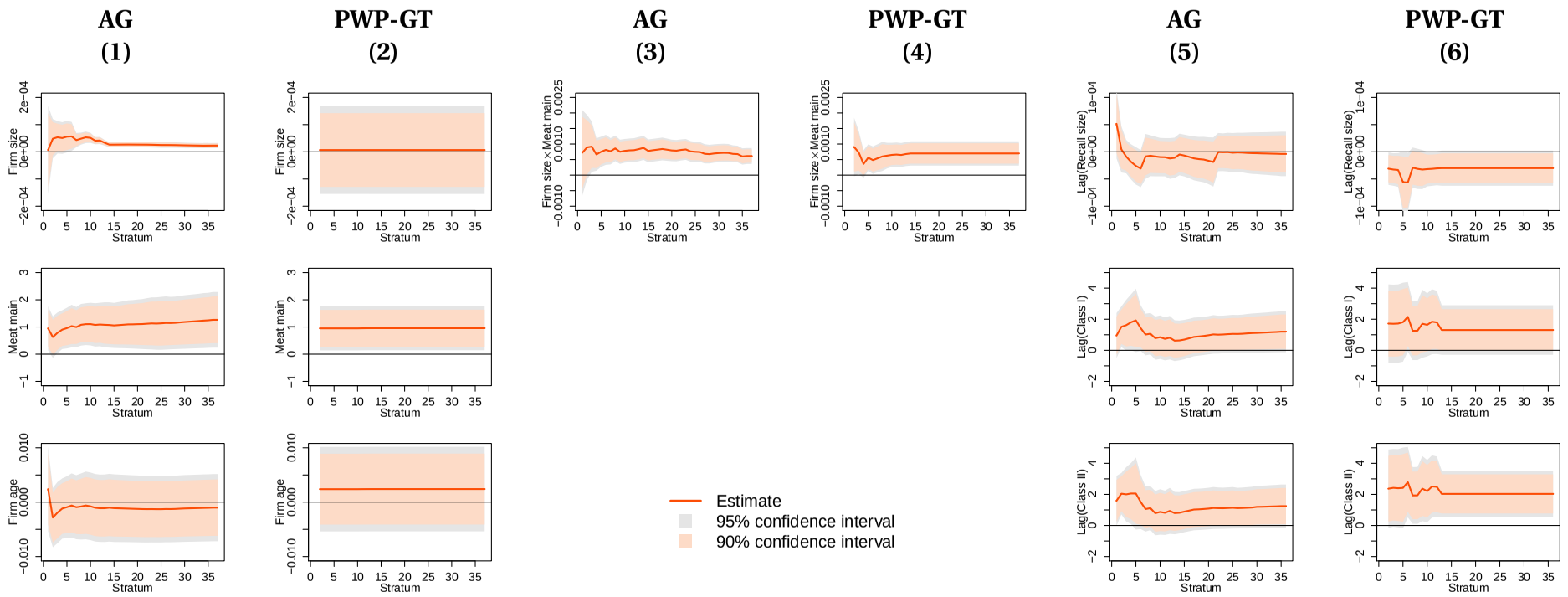


Figure 4: Recurrent event survival analysis estimation with different sets of strata.
Notes: Reported are the coefficients (β's), and the 95% and 90% confidence intervals obtained using the robust-standard errors. Specification of control variables corresponds to that in Table 3.

Table 1: Number of recalls and total quantity of meat/poultry recalled by publicly traded firms in the United States between 1994-2015.

Stock	Firm	Recalls	Pounds
AHP	American Home Products Corp.	1	150,000
BOBE	Bob Evans Farms Inc.	1	8,500
CAG	ConAgra Inc.	25	115,316,548
COST	Costco Wholesale Corp.	3	222,123
CPB	Campbell Soup Co.	9	16,322,137
DEG	The Delhaize Group	1	112,230
GIS	General Mills Inc.	2	3,442,445
HAIN	The Hain Celestial Group Inc.	1	983,700
HFI	Hudson Foods Inc.	5	28,313,959
HNZ	Heinz H. J. Co.	3	94,886
HRL	Hormel Foods Corp.	6	234,946
HWKN	Hawkins Inc.	1	529
IBP	Iowa Beef Processors, Inc.	8	1,938,155
K	Kellogg Co.	1	2,790
KFT	Kraft Foods Inc.	5	28,508
KR	Kroger Co.	3	490,131
NSRGY	Nestle SA	13	1,689,393
PPC	Pilgrims Pride Corp.	4	28,806,600
SAFM	Sanderson Farms Inc.	1	10,000
SFD	Smithfield Foods Inc.	13	1,007,821
SJM	Smucker J. M. Co.	1	3,000
SLE	Sara Lee Corp.	13	37,723,229
SVU	Supervalu Inc.	2	962
SYY	Sysco Corp.	1	16,800
TAVI	Thorn Apple Valley Inc.	2	35,009,936
THS	TreeHouse Foods Inc.	3	214,957
TSN	Tyson Foods Inc.	36	4,285,559
UVV	Universal Corp.	1	578,000
WFM	Whole Foods Market Inc.	3	34,834
WIN	Winn Dixie Stores Inc.	1	1,734,002
WMK	Weis Markets Inc.	1	2,852
Total		170	278,779,532

Notes: The data is obtained from the USDA FSIS Recall Case Archive.

Table 2: Summary statistics of study variables.

	Sample	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Strata	201	8.24	8.49	1	2	11	37
Duration till recall (in month)	201	35.58	49.34	0.01	5.50	46	256.60
Firm size (in million US$)	201	6,253.06	14,224.67	11.20	974	4,875.30	92,539.20
Meat main (1=Yes)	201	0.38	0.49	0	0	1	1
Firm age (in years)	201	82.66	36.77	4.69	63.44	106.63	185.98
Class I (1=Class I)	170	0.71	0.46	0	0	1	1
Class II (1=Class II)	170	0.24	0.43	0	0	0	1
Class III (1=Class III)	170	0.05	0.23	0	0	0	1
Recall size (in thousand lbs)	167	1,669.34	8,181.06	0.07	8	161	83,900

Table 3: Estimation results from recurrent event survival analysis.

	AG (1)	PWP-GT (2)	AG (3)	PWP-GT (4)	AG (5)	PWP-GT (6)
Firm size	2.30×10^{-5}***	6.65×10^{-6}	2.41×10^{-5}***	2.66×10^{-6}	2.86×10^{-5}***	6.74×10^{-5}
	(4.78×10^{-6})	(8.24×10^{-5})	(4.61×10^{-6})	(8.39×10^{-5})	(5.46×10^{-6})	(7.64×10^{-5})
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
Meat main	1.26**	0.96**	0.44	0.69*	1.32**	1.41*
	(0.52)	(0.41)	(0.45)	(0.40)	(0.54)	(0.77)
	[3.54]	[2.60]	[1.56]	[2.00]	[3.76]	[4.12]
Firm age	-1.01×10^{-3}	2.41×10^{-3}	-1.81×10^{-3}	2.71×10^{-3}	-1.41×10^{-3}	-3.54×10^{-3}
	(3.15×10^{-3})	(3.96×10^{-3})	(3.10×10^{-3})	(3.99×10^{-3})	(3.79×10^{-3})	(6.27×10^{-3})
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
Firm size×Meat main			6.15×10^{-4}***	6.97×10^{-4}***		
			(1.31×10^{-4})	(1.99×10^{-4})		
			[1.00]	[1.00]		
Lag(Recall size)					-3.90×10^{-6}	-3.01×10^{-5}*
					(2.08×10^{-5})	(1.65×10^{-5})
					[1.00]	[1.00]
Lag(Class I)					1.20*	1.31
					(0.67)	(0.81)
					[3.32]	[3.69]
Lag(Class II)					1.25*	2.03***
					(0.70)	(0.76)
					[3.47]	[7.62]
Firm size×Strata		✓		✓		✓
Meat main×Strata		✓		✓		✓
Firm age×Strata		✓		✓		✓
Observations	201	201	201	201	167	167
AIC	1068.79	595.07	1033.69	591.35	704.88	418.05
BIC	1078.70	773.45	1046.91	773.04	723.59	586.42
Pseudo R^2	0.27	0.31	0.39	0.33	0.32	0.39
Likelihood ratio test	62.78***	74.72**	99.88***	80.43***	65.30***	82.10***
Wald test	29.71***	48,041***	70.50***	707,017***	40.80***	1,155,625***

Notes: Reported are the coefficients (β's), the exponentials of the coefficients (in brackets), and the robust-standard errors (in parenthesis). Pseudo R^2 is based on the Cox and Snell approach and has an upper bound that is less than 1.0. The likelihood-ratio test and Wald test are used to check the overall significance of the models, with the null hypothesis of $\beta_1 = \beta_2 = ... = \beta_p = 0$. Statistical significance is denoted according to the following convention: *p<0.1; **p<0.05; ***p<0.01.

Table 4: Test of the proportional hazard assumption for the Andersen-Gill model.

	χ^2	p-value
Specification (1) in Table 3		
Firm size	4.28	0.04
Meat main	3.00	0.08
Firm age	1.05	0.31
Global	5.42	0.14
Specification (3) in Table 3		
Firm size	1.29	0.25
Meat main	0.12	0.73
Firm age	0.17	0.68
Firm size×Meat main	0.01	0.95
Global	1.36	0.85
Specification (5) in Table 3		
Firm size	3.19	0.07
Meat main	14.15	0.00
Firm age	0.38	0.54
Lag(Meat recalled)	0.12	0.72
Lag(Class I)	1.57	0.21
Lag(Class II)	1.42	0.23
Global	15.72	0.02

Notes: Reported are the chi-square (χ^2) statistics and associated p-values from testing the proportional hazards assumption of the Andersen-Gill model fits (Grambsch and Therneau, 1994). Under the null hypothesis, the proportional hazards assumption is satisfied.