Foodborne Outbreaks, Product Recalls, and Firm Learning*

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Abstract

Firms in the food industry may experience more than one contamination incident over time. In a food safety context, increasing the time between foodborne outbreaks represents a key objective for the food industry and public health officials. We demonstrate a systematic way of analyzing repeated recalls, specifically to evaluate factors that influence time to next recall and, more importantly, to identify the extent of firm learning from inter-event time. Analysis of meat/poultry recalls issued by publicly traded firms in the United States for the period 1994-2015 indicates that more diversified firms incur a smaller risk of repeat recall as firm size expands compared to firms producing primarily meat/poultry products. The hazard of a recall incident decreases with the severity of the past recall incident. Some evidence of firm learning is found, but there is no definitive evidence indicating that a firm's ability to prevent recalls grows with the number of foodborne outbreaks it has experienced. Our findings highlight the need for the design of policies that incetivize food industry to reflect more effectively on food safety incidents.

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 an issue of shared responsibility across the food supply chain. Public health officials, policy makers, food firms and consumers all play an important role in minimizing the risk of a foodborne outbreak.[1] Food firms, in particular, invest in the implementation of food safety technologies and protocols to prevent the occurrence of these incidents (Henson and Reardon, 2005). Despite such efforts, both the frequency and severity of foodborne outbreaks reported in the United States, particularly those related to meat/poultry products, have been on the rise. 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, which represents almost 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 amount of time. For example, Tyson Foods, one of the largest processors and marketers of chicken, beef, and pork products, has issued 36 different meat and poultry recalls from 1994 through 2015 (FSIS, 2017). The case of Tyson Foods is not unique in the food industry, thus raising the question of what factors determine time to next recall for firms producing meat and poultry products, and to what extent (if any) these firms learn from previous 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, both firm- and recall-specific factors are evaluated. Second, and importantly, we investigate whether firms that have issued a recall in the past learn from that experience in the context of *increased* time to next recall, and how this learning is influenced by firm- and recall-specific characteristics. If firms learn from a previous recall incident, they should in theory be able to *lengthen* the amount of time until the next recall event by, for instance, implementing more effective quality control monitoring systems, thereby increasing the likelihood of their survivorship (i.e., not experiencing a recall event). Acting otherwise would contradict profit-maximization motives of the firm since food contamination incidents may cause substantial economic losses (Sockett, 1993). As a result, *inter-event* time

[1] Consumers may prevent foodborne illnesses by following appropriate food handling practices and guidelines from the moment they purchase food products until their consumption.

can plausibly proxy organizational learning as it reflects the extent of efforts taken by the firm upon a food contamination incident to prevent or reduce the occurrence of future incidents.[2]

We implement a recurrent event survival analysis framework to identify the extent of firm learning from inter-event time. Unlike the methods used in previous literature, which are either inefficient or inappropriate as discussed below, our approach is opportune for the analysis of repeated recall incidents as it (i) incorporates information provided by subsequent failures times (i.e., recalls), (ii) accommodates the order of recurring events, and (iii) accounts for intra-firm correlation arising from these events. As such, differences in recall dynamics between first, second, third, etc. recall events can be directly examined under this methodology, which allows for the 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 occurrence of acute lower respiratory infections (Kelly and Lim, 2000; Amorim and Cai, 2015), and hospital readmission of the elderly (Kennedy et al., 2001), among others. Given that a significant percentage of food firms analyzed in this study has issued more than one recall, a recurrent event survival analysis is more appropriate than methods considering only the duration to first failure event. To the best of our knowledge, our paper is the first to implement this methodology to food recalls as well as product recalls in general.

The results from our analysis show that firm-specific factors, including firm size and diversification, play a role in the likelihood of occurrence of recall events. In particular, firms producing only meat and poultry products are at higher risk of issuing a repeat recall compared to more diversified ones. In addition, firms with a more diversified product line incur smaller risk of recall with the expansion of firm size, as measured by market capitalization, relative to their primarily meat producing counterparts. Our analysis also reveals that past recall attributes have a significant effect on future recall occurrences. Specifically, the hazard of recall incident decreases with the amount of product recalled in the past recall event. Furthermore, the risk of a future recall is smaller for firms whose previous recall was of Class I, the most severe class of recalls, 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 a future foodborne outbreak. While there is no conclusive evidence indicating that a firm's ability to prevent recalls grows

[2]We realize there are other ways to capture the extent of firm learning upon a recall event, such as through direct or indirect costs of recalls, penalty amounts, investment in food safety and sanitation protocols, food processing safety certificates, etc. While the analysis of these other dimensions of organizational learning is desirable, it is crucially precluded by data availability. Our measure of organizational learning (inter-event time) is readily available and, importantly, it 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).

with the number of recalls it has experienced, we do find some evidence of firm learning between a firm's first and second recall, and third and fourth recall.

Our findings have managerial and policy implications. In a food safety context, increasing the time between recall events represents a key driver of success to food firms. Therefore, understanding the factors that influence time to next recall event provides managers with an important tool to improve both private food safety protocols and quality management systems (e.g., acceptance sampling and statistical process control), which in turn enhance food quality standards. For any given amount of recall prevention and handling experience gains, firms potentially avoid economic costs of recalls and consumers ultimately benefit from healthier food products (Foster and Just, 1989; Elbasha and Riggs, 2003). From a policy perspective, although it appears the food industry is targeting its resources appropriately to address those recalls that pose the greatest risks to human health (i.e., Class I), overall firms' ability to prevent recalls does not consistently grow with past recall experience. Therefore, public health officials and policy makers perhaps need to re-visit their inspection programs and design appropriate policies that would incentivize food firms to reflect more effectively on their previous food safety incidents.

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, while this process is overseen by federal or state officials (FDA, 2017).[4] In 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 recall class), and the number of pounds recalled. The FSIS classifies food recalls into three broad categories. Class I is the most severe category of recalls, which can cause adverse health consequences or death. Class II has a remote probability of adverse health effects. Class III is the least severe class of recalls and it does not cause any adverse health impacts.

[3]Common contaminants include Salmonela, E. coli, and Lesteria (CDC, 2020).

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

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 from the market, but also because of the associated litigation expenses, damage in reputation, and decrease in stakeholders confidence (Jarrell 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). A bulk 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 indicating that the negative economic effects of repeated recalls on firm value were less substantial than first recalls.

While measuring and understanding the economic footprint of food recalls are crucial for the food industry to conduct cost-benefit analyses and to develop food safety strategies, determining 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, are also of interest from policy standpoint. The organizational learning literature defines learning or knowledge creation as systematic change in 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 in terms of, for instance, searching for alternatives (Sitkin, 1992). At the same time, the broader product recall literature has showed that experience does not always translate to positive learning outcomes. This then presents a testable hypothesis as to 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) showed that firms that experienced a recall event in the past discovered food safety problems later compared to those that experienced their first recall. This suggests that firms did not learn from past recall events in terms of time taken to identify a subsequent recall. Importantly, the statistical approach adopted by this study is appropriate for modelling the time to a single failure event (e.g., first recall event) and is ill-fitted for the analysis of *repeated* recall incidents, which needs consideration of the 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

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

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, and concluded that conformance quality failures represent an important motivation for organizational learning or knowledge transfer. The nature of the empirical strategy employed by Hall and Johnson-Hall (2017) allows the authors to uncover factors influencing the number of recalls (i.e., recall counts), which are informative to policy and practice in their own right. To depict a more complete picture of how learning-by-doing dynamically evolves over time (i.e., after each incident), one needs 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 aims to fill this gap in the literature by proposing to implement a recurrent event survival analysis framework that is well-suited for the analysis of repeated recall incidents.

Aside from food safety and public health, our study relates and contributes to two bodies of research. First, 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 through empirical examination of repeated recalls in the U.S. food industry, which is essential to 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. With regard to organizational learning upon recall events, the evidence is rather mixed, with some reporting a fall in the likelihood of future recalls (Haunschild and Rhee, 2004; Thirumalai and Sinha, 2011; Kalaignanam et al., 2013), while others a jump (Haunschild and Rhee, 2004; Steven et al., 2014). Important to the present study, these studies also treat 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

[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.

experience by taking necessary preventative measures so as to extend time until their next recall event.

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 regarding the name of the firm issuing a recall, recall date, quantity of product recalled, and recall classification.[7] Table 1 presents the number of recalls and total quantity of product recalled by 31 publicly traded firms included in our study. Our data includes many major processors and marketers of meat/poultry. These firms range from very 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 based on their 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. Given that the event of interest can occur more than once, these events are called recurrent events. We consider a firm's "entry" into the study as either January 1, 1994, the date when the recall data started being collected by the FSIS, or the date of the firm's initial public offering (IPO), whichever came later. The end of the study period is December 2015. Firms that went bankrupt or were acquired prior to 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 acknowledge 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 is the time between first and second recall; stratum 3 is the time between second and third recall; and so on. Given that the largest number of recalls issued by a firm in the data is 36, the last stratum (stratum 37) measures time elapsed between 36th recall and the end of the study period.

[7] In line with the literature, we consider recalls by publicly traded firms because the 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 many privately held ones are smaller firms (Hall and Johnson-Hall, 2017). Besides, small firms tend to go out of business as the result of a product recall, thus offering a limited insight about organizational learning.

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

The firm-specific factors considered in the analysis include firm size, level of diversification, and firm age. The information needed to build these variables was obtained from companies' annual and 10-K reports. *Firm Size* is measured in terms of market capitalization (in million U.S.$) and is constructed 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 varies over time based on the growth of the company. We adjust this value against inflation using the Consumer Price Index (CPI) provided by the U.S. Bureau of Labor Statistics.[9] *Diversification* is a binary variable that is equal to 1 if meat or poultry products represent the firm's main output, and 0 otherwise. In essence, this variable distinguishes meat processors from multi-product food producers and retailers. *Firm Age*, which is also time-variant, represents the age of the firm since its establishment and is measured in years.

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*, do partially absorb information about production levels and food safety practices and protocols. According to the Economic Research Service (ERS) reports, larger food firms tend to have better sanitation and process controls and laboratory capabilities (Ollinger and Mueller, 2003) and invest more on 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 the practice seen in the empirical literature related to 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 (pounds recalled). The information used to build these variables was obtained from the USDA FSIS Recall Case Archive. We create three binary variables for the three recall classes. *Class I* is specified as a binary variable that is equal to 1 if a recall is of Class I, and 0 otherwise. *Class II* and *Class III* binary variables are defined in an analogous manner. Furthermore, *Recall Size* captures the total amount of product recalled during a recall event and is measured in thousand pounds.

[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 therefore, information regarding production level of a specific product (e.g., sausage) or product segment (e.g., red meats) matching the date when the recall occurred is not available. In addition, firms do not generally disclose their investment in food safety technologies or protocols.

Table 2 reports descriptive statistics of 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 (Tyson Foods) experienced 36 recalls (figure 1(a)). The majority of recalls per firm tends to be of Class I, followed by Class II and then Class III (figure 1(b)). While diversified firms account for a greater portion of recalls within each stratum (figure 1(c)), primarily meat producing firms that represent 38% of all firms experience more recalls compared to their diversified counterparts. Comparing empirical distributions of duration times for different strata (portrayed by boxplots in figure 1(d)), it becomes apparent that it generally takes the longest until recall event for stratum 1, with stratum 2 coming close behind. For stratum 3 we see a sizable dip in time relative to stratum 2, and then a jump 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 for which meat is the main output relative to those for which meat is not the primary output. This suggests that the risk of foodborne outbreak is greater for firms that handle primarily meat products compared to those whose product line is more diversified. The relationships between duration times and firm size and firm age (figure 1(f-h)) are less obvious, although it seems duration shrinks with firm size (figure 1(g)). These observations will be examined formally using a recurrent event survival analysis framework.

3.2 Statistical Analysis

There are several statistical methods proposed in the literature that can be used to analyze recurrent time-to-event data (Kelly and Lim, 2000; Amorim and Cai, 2015). The choice between these models largely depends on assumptions about the events of interest (particularly, dependence structure between events) as well as 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), hence referred to as the Andersen-Gill or AG model. This approach assumes that recurrent events within subject are conditionally uncorrelated, given the covariates, and are considered identical. When a firm issues a recall, there is close monitoring by the FSIS throughout the process. If at any point during the process it is determined that more product was affected than initially thought, a recall extension will be issued. Thus, if there was a subsisting problem related to the initial recall event, a subsequent recall would not be issued, it would be addressed with a recall extension (FSIS, 2013). Because of this, it is reasonable to treat each recall event within each firm as an independent event.

This model also assumes that covariates are time independent, i.e., variables do not differ depending on whether they are observed for first recall or last recall. This assumption, which is commonly known as the proportional hazard (PH) assumption, is tested using a proportionality test (Grambsch and Therneau, 1994). If one or more covariates did 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 time to next recall (or the rate at which recalls occur) for food firms?*

Let T denote the random variable for duration or event time and the outcome t is time measured in months. The standard Cox PH model (Cox, 1972) is used to carry out the counting process approach. In particular, the hazard function of this model has the functional form of:

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

where $\mathbf{x} = (x_1, \dots, x_p)'$ is a vector of covariates (firm-specific and/or recall-specific factors) 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, several time intervals on 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 having failed (i.e., experiencing a recall event) or censored. If subjects display multiple failure times (recall events), they remain in the risk set until last interval is completed; that is, their last failure time or censorship. Hence the partial likelihood function (L) used to fit the Cox PH model is formulated as the product of individual likelihoods (L_j, $j = 1, \dots, J$) for each ordered unique failure time as follows:

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

where J is the total number of unique failure times for all subjects (Kleinbaum and Klein, 2005). For a single failure at the jth ordered failure time $t_{(j)}$, L_j takes the following form:

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

where $R(t_{(j)})$ is the risk set for 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 on the same subject, robust standard errors are used for model inference as described by Lin and Wei

(1989).

3.2.2 Stratified Cox PH Model

The main advantage of the stratified Cox PH model is that we do not have to assume independence between recurrent events of the same subject. Thus, unlike the counting process model, this method conveniently accommodates the order of the events, which in turn allows the effect of covariates to vary from event to event. Estimating this model helps us answer 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 different versions of the stratified Cox PH model developed by Prentice et al. (1981), hence referred to as PWP models. The first version is called conditional 1 or the PWP Total Time (PWP-TT) model. This model uses time to events from study entry of each subject. The second version, which uses survival from a 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 next recall after a previous recall, as opposed to the time to first, second, third, etc. recall from study entry (Kleinbaum and Klein, 2005). Besides, 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 stratified PWP-GT model is specified as:

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

where $g = 1,2,3,...$ is the stratum of interest and z_l, for $l = \{2,3,...\}$, is a dummy variable for l'th stratum, with stratum 1 dropped out as the base group (Kleinbaum and Klein, 2005). The same set of covariates are included in $\mathbf{x}$ as those for the counting process model. Further, interacting each covariate with dummies for each stratum allows to control for the differential effects of firm characteristics on each stratum. Again, we use the Breslow approximation method (Breslow, 1974) to handle tied survival times, and robust standard errors to control 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 different strata. Comparison of 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, *Diversification* does not satisfy the PH assumption in specifications (1) and (3), while *Firm Size* in specification (1). As discussed before, the failure of the PH assumption implies time-dependence, with a 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 does not necessarily have an immunity to food safety incidents. From specifications (1) and (2) in table 3, estimates for *Diversification* 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 product is about 2.6 times the rate of firms that are more diversified. This may be because meat and poultry naturally contain a larger 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 the size of a firm, the log risk of recall increases by 0.0023 percentage points. In other words, as the size of a firm 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 firm's diversification. To answer this question, the joint effect of *Firm Size* and *Diversification* on firms' *Duration till Recall* is investigated in specifications (3) and (4) in table 3. When the interaction term for *Firm Size* and *Diversification* is included along with 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 primarily meat/poultry producing firm. The parameter estimate on the interaction term indicates that for every one-million-dollar increase in the size of primarily meat producing firms (*Diversification* $= 1$), 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 (*Diversification* $= 0$). This shows that firms with a more diversified output line incur smaller risk of recall with the expansion of firm size relative to those producing mainly meat products.

Moving on to recall-specific factors, it is crucial to note that the amount of meat recalled as well as recall class for a given recall event are not determinants of that recall but its consequences. Hence it would be erroneous to include these variables directly in the covariates list. Such variables must be lagged—meaning the loss of a first recall event per firm—in order to study their effects on a subsequent recall event. We provide this analysis in specifications (5) and (6) in table 3. The effects of firm-specific factors (*Firm Size* and *Diversification*) 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 of firms that experienced a Class III recall (a 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 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 when they face 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 shows that the hazard of a future recall incident decreases with the quantity of meat recalled in the past 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 is also suggestive of 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 conveys the probability of surviving (i.e., no recall event) longer than 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 >60 months, which indicates 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 since either the beginning of business or 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 all recall events (panel (c)). Clearly, the shape of the estimated survival curve for each event stratum is distinct. For instance, in figure 2(b), strata 1 and 2 look somewhat similar, so do strata 3 and 4, but strata 1 and 2 are different from strata 3 and 4. Visually, this is an indication that the Andersen-Gill model, which treats all strata as identical, may not be adequate to model the repeated recall data, and that firms' duration times to next recall behave differently depending on where they fall in time compared to other recall events.

If firms learned from a previous recall event, and were able to *lengthen* the amount of time until next recall, we would generally expect a survivorship curve for the later stratum to be above that of the past stratum, so that the probability of survivorship longer than t periods would be higher for the later stratum. Examining the survival curve for stratum 1 in figure 2(b), we see that all observations in the sample issued a recall by 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, which is evident from the flat-lining of the estimated survival curve for stratum 2 at probability 0.25. Comparing survivorship curves for strata 1 and 2, it is apparent that the curves largely overlap for the first ≈50 months, and after that the survival curve for stratum 2 diverges and lies above that of stratum 1. This implies the likelihood of survivorship (i.e., no recall event) in the first and second recall events appears similar for the first ≈50 months, and after that the probability of survivorship increases in case of the second recall event relative to the first. This prolonged time-to-event in case of 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 previous two incidents, we would expect a survivorship curve for stratum 3 to be above that of the past strata. From the survivorship curve for stratum 3 in figure 2(b), we find no evidence for that to be the case: the survival time from second to third recall (stratum 3) is lower than that from first to second recall (stratum 2), which is in line with observations from figure 1(d). Therefore, this result does not support 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 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 ≈50 months, with the bulk piling up within the first ≈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 that we find is between strata 1 and 2, and particularly, strata 3 and 4, as discussed above. In section 5, we review possible mechanisms underlying our findings here.

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 the Kaplan-Meier (KM) survivorship curves (Kaplan and Meier, 1958). To ensure adequate sample size for estimation and inferences for each strata (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:

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

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, $\text{Prob}(T > t)$, where T is the random variable for duration and the outcome t is time measured in months.

Figure 3(a) illustrates the stratified KM survivorship curves decomposed by *Diversification*. This variable describes 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, which indicates firms producing meat/poultry as their main output have 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 it takes longer (in months) for a firm to issue a subsequent recall after it faces a Class I recall compared to a Class II recall. Consequently, firms seem to learn and reflect more effectively upon experiencing the most severe type of recalls. This observation is in line with our findings from table 3 as well as with the broader literature on the organization learning that suggest 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)), the inferences for 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. That is, whether decreasing or increasing the number of strata in the analysis, which is essentially 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), has any impact on the estimation results. Towards this end, we carry out the analysis similar to that in table 3 with different sets of strata; specifically, stratum 1 only; strata 1 and 2; strata 1, 2, and 3; and so on. Strata 1-37 analysis corresponds to that presented in table 3.

The results from this sensitivity analysis are portrayed in figure 4, which is organized similar to table 3, with a focus on main regressors in each specification. Couple of observations are in order. First, the effect of individual regressors on the hazard of a (next) recall event remain remarkably stable across different sets of strata, particularly after stratum 5. A somewhat higher variability in the estimates and their confidence bounds in the first few strata are explained by 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 estimates of reported regressors are consistent with our main findings, which speaks for their robustness against 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 next recall (e.g., between a firm's first and second recall, and third and fourth recall), there is a lack of evidence indicating that the firm's ability to prevent recalls grows consistently with the number of recalls it has experienced. Why is this? What explains apparent stagnation, and decline, in learning after the first few recall events? In what follows, we briefly discuss several mechanisms that may potentially rationalize the observed findings. Further research is warranted to formally verify these mechanisms.

First, trade-offs between investment costs in more effective food safety and sanitation protocols and economic costs of recalls play a vital role in shaping firm's incentives to adopt any given level of precaution. Firms have an incentive to enhance food safety management efforts when expected benefits exceed costs of prevention (Holleran et al., 1999; Elbasha and Riggs, 2003). Underinvestment in safety and sanitation programs may be optimal to a firm if the savings from under-investing in more sophisticated programs outweigh the economic costs of handling a recall event. Although such incentive may emerge in isolated cases, such as upon 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 economic costs of recalls, and thus incentives, change with each subsequent recall event. That is, costs of the first recall event might be more consequential, but less so with each subsequent event. Complimentary to our paper, the evidence in the existing literature has showed that the negative economic effects of repeated recalls on firm value were less severe than first recalls (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 a decline in the economic impact of repeated recalls on firm's value may conceivably provide a perverse incentive to 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 really making conscious decisions and/or innovations (Alchian, 1950). Such imitation consequently shields the firms against negative publicity or judgments of their actions upon failure (Devenow and Welch, 1996), leading to survival and inefficient outcome.

Third, rareness of conformance quality failures and major recalls is posited as another impediment to organizational learning and incentives thereof (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 of time 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 until another incident, 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 the amount of 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 blemish. 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 end up going 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 attributable to changing production styles and broader systemic issues. For instance, meat and poultry production operations have become increasingly consolidated, with production facilities processing larger and larger quantities of products, which naturally increases the chance of a pathogen spread in animals passing through these facilities (Ducharme, 2019).

In terms of policy recommendations, improvements in the U.S. food safety system are needed and that requires a collective action of public health officials, policy makers, food firms and consumers. First, improving access to information is essential for decision making on any level. Producers and consumers often have imperfect information (Marino, 1997; Elbasha and Riggs, 2003), which can lead to suboptimal levels of precautions. Therefore, the provision of information can improve social welfare. Towards this end, the government perhaps needs to play a more active advisory and information broker role. For markets to work smoothly, information must be accessible to both consumers and producers. Second, the broader industrial organization literature has shown that firms exhibit a greater willingness to reflect on the information provided from a rare event when a causal link can be established to the event (Starbuck, 2009; Weiner, 1995). This points to the increased importance of robust statistical quality control programs as well as empirical research rigorously examining causes and consequences of recall events. Last but not least, recall insurance products can be an alternative to regulation (Skees et al., 2001), as they provide incentives to food firms to achieve greater food safety standards and improve the information flows in the industry.

6 Conclusion

This study demonstrated a systematic way of 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 is targeting its resources appropriately to address those recalls that pose the greatest risks to human health (i.e., Class I), overall firms' ability to prevent recalls does not consistently grow with past recall experience. Therefore, public health officials and policy makers perhaps need to re-visit their inspection programs and/or design appropriate policies that would incentivize food firms to reflect more effectively on their previous food safety incidents.

Our work makes several noteworthy contributions to the extant literature on product recalls, organizational learning, and food safety. First, we propose to identify the extent of firm learning using *inter-event* time between recalls. This variable is readily available and offers a well-rounded measure of firm learning as it reflects the effect of all efforts taken by food firms upon a food safety incident. Second, we demonstrate a novel, and creative, application of a *recurrent* event survival analysis methodology to the applied economics audience. Although this method has been around for a while, and been used widely in epidemiology and biostatistics, it has surprisingly evaded the mainstream economics practice. Third, armed with the above empirical strategy, the article sheds light on the behavior of the food industry in face of repeated food safety incidents, which is important for policy and public safety. On a final note, while this study focused exclusively on foodborne outbreaks to demonstrate a new empirical framework to inferring firm learning from inter-event time, there are many promising applications of this approach elsewhere. For instance, repeated recall events in other industries (e.g., automotive, pharmaceutical, and medical device), repeated health violations, repeated and environmental violations, among others.[11]

References

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.

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.

[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.

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.

Lin, D. Y. and Wei, L. J. (1989). The robust inference for the Cox proportional hazards model. *Journal of the American Statistical Association*, 84(408):1074–1078.

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.

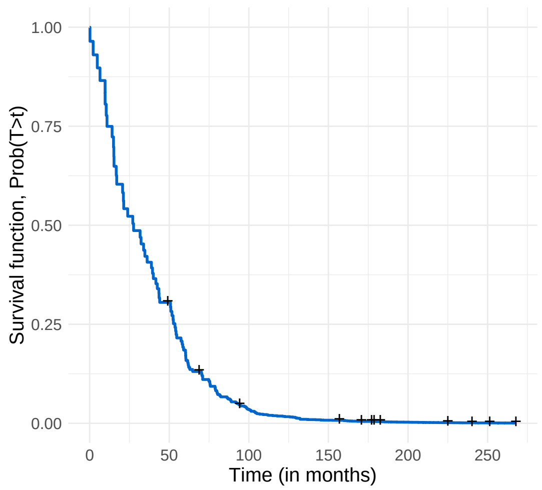
Tucker, A. L. (2004). The impact of operational failures on hospital nurses and their patients. *Journal of Operations Management*, 22(2):151–169.

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

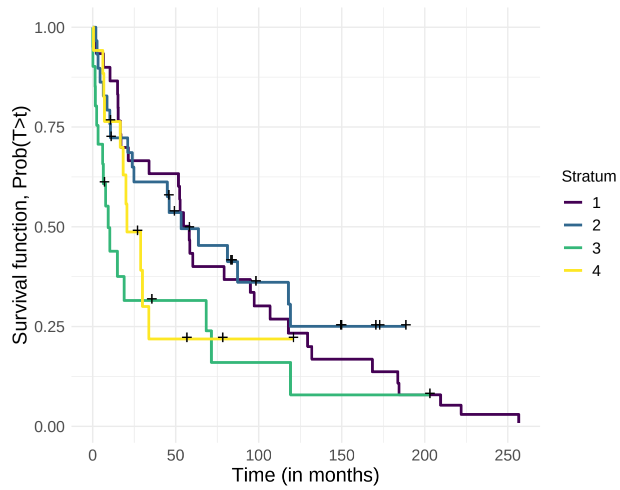
Welling, L. (1991). A theory of voluntary recalls and product liability. *Southern Economic Journal*, 57(4):1092–1111.

Figures and Tables

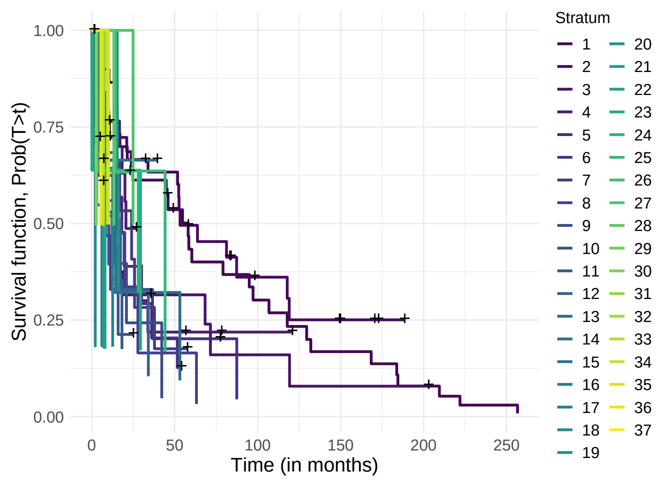
Figure 1: Characteristics of the study recalls and firms issuing them.



(a) The Andersen-Gill model fit

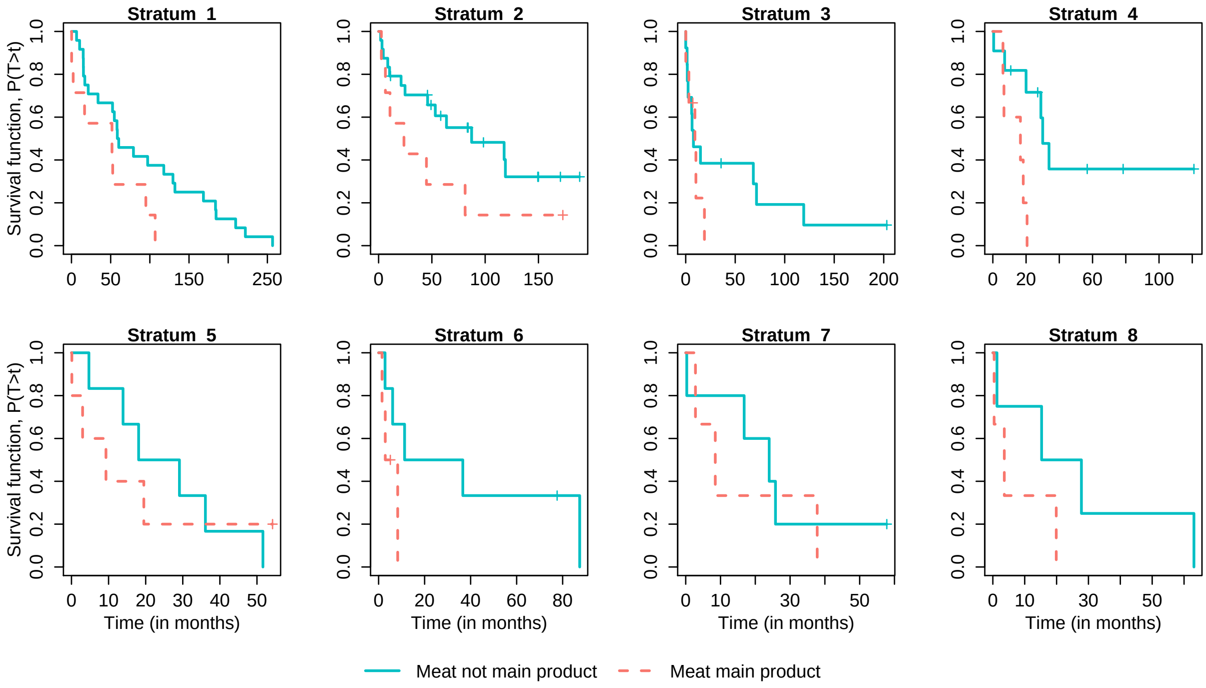


(b) The PWP-GT model fit (first four recalls)

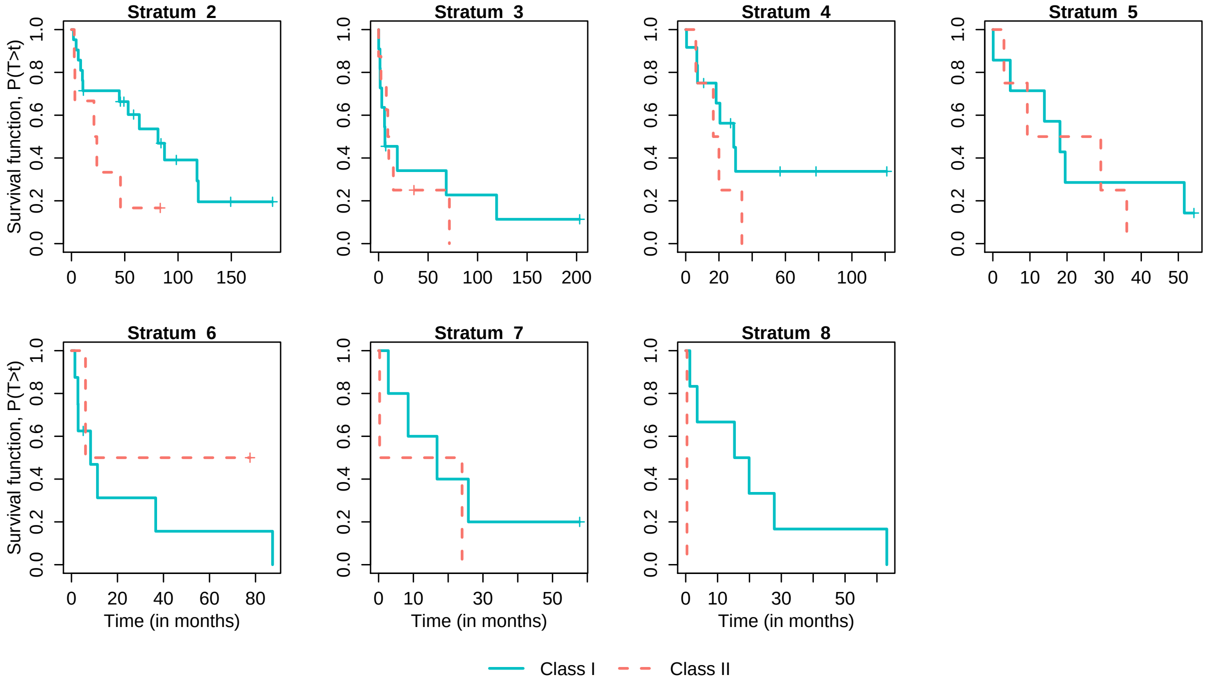


(c) The PWP-GT model fit (all recalls)

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 on the plots denote individual firms whose survival times have been right-censored (i.e., they have not demonstrated the event of interest).



(a) Conditional on diversification



(b) Conditional on lag of recall class

Figure 3: Estimated Kaplan-Meier survival functions for the first eight strata.
Notes: The estimated survival function shows the probability of surviving (i.e., no recall event) longer than t periods, Prob($T > t$). Small "+" marks on the plots denote individual firms whose survival times have been right-censored (i.e., they have not demonstrated the event of interest).

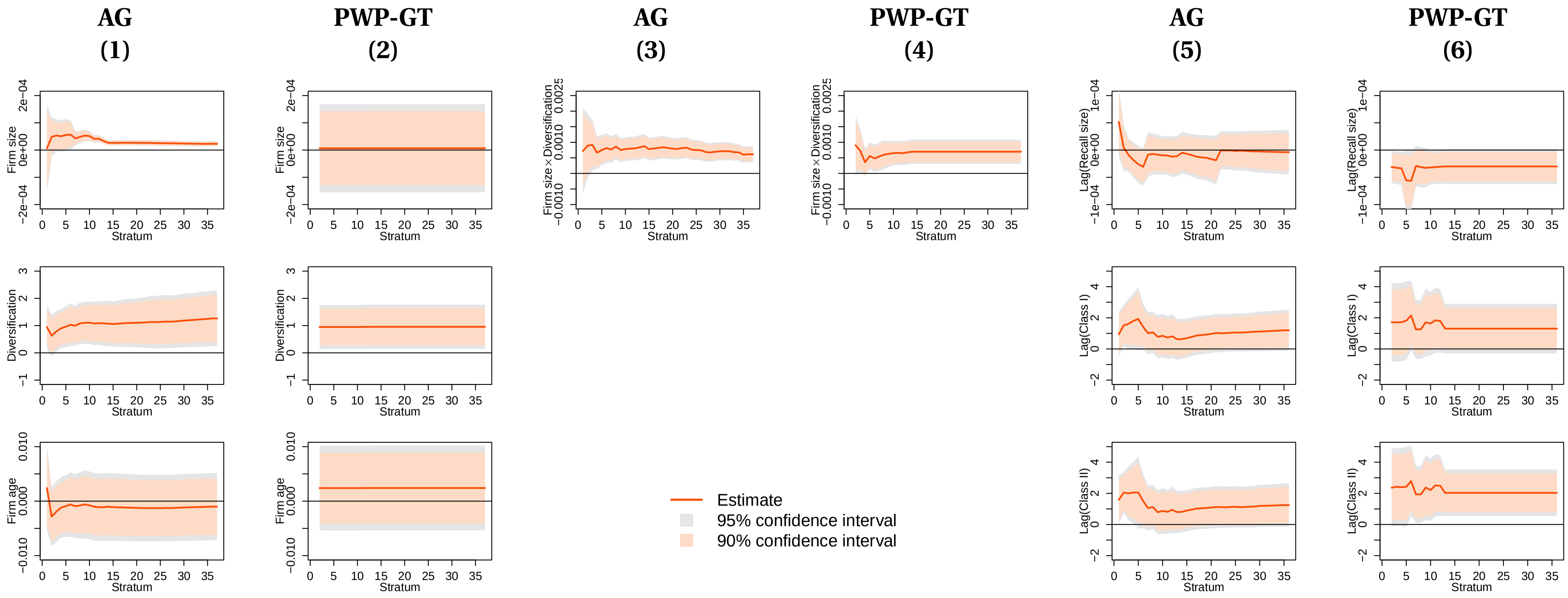


Figure 4: Recurrent event survival analysis estimation with different sets of strata.

Notes: Reported are $\hat{\beta}_i$ and the 95% and 90% confidence intervals obtained using robust-standard errors for the Anderson-Gill (AG) model and the PWP-GT model. Specification of control variables corresponds to that in Table 3. Firm size is measured in million U.S.$. Firm age is measured in years. Diversification is equal 1 if meat is main product, and 0 otherwise. Recall size is measured in thousand pounds.

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
Diversification (1=meat main)	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	170	0.71	0.46	0	0	1	1
Class II	170	0.24	0.43	0	0	0	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]
Diversification	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×Diversification			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		✓		✓		✓
Diversification×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
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 estimation results, including $\hat{\beta}_i$, robust-standard error of $\hat{\beta}_i$ (in parenthesis), and $\exp(\hat{\beta}_i)$ (in brackets), for the Anderson-Gill (AG) model and the PWP-GT model using the full sample (all recalls). Firm size is measured in million U.S.$. Firm age is measured in years. Diversification is equal 1 if meat is main product, and 0 otherwise. Recall size is measured in thousand pounds. 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
Diversification	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
Diversification	0.12	0.73
Firm age	0.17	0.68
Firm size×Diversification	0.01	0.95
Global	1.36	0.85
Specification (5) in Table 3		
Firm size	3.19	0.07
Diversification	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.