THE EFFECT OF BRANDING AND FIRM SIZE ON THE RECURRENCE OF FOOD

RECALL EVENTS ASSOCIATED WITH PATHOGENIC CONTAMINATION IN

THE UNITED STATES

A Thesis

by

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The Effect of Branding and Firm Size on the Recurrence of Food Recall Events

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ABSTRACT

The Effect of Branding and Firm Size on the Recurrence of Food Recall Events

Associated with Pathogenic Contamination in the United States.

(May 2012)

Montalee Kapilakanchana, B.S., Kasetsart University

Chair of Advisory Committee: Dr. Victoria Salin

Food recalls caused by pathogens receive considerable public attention due to health risk and the potential loss to the companies involved. There are very few studies analyzing the relationship between food recalls and characteristics of the companies involved. Because of the significance of the problem and lack of available research, the association between food recalls caused by pathogen and characteristics of the companies involved is examined in this thesis.

To address the problem, data on food product recalls in the United States from January 2000 to October 2009 are used. Only the events caused by pathogens are analyzed in the thesis. The firms that have multiple recall incidents are the units of analysis. The study employs an econometric model with discrete choice modeling approaches: logit and probit.

There are two main hypotheses. Firstly, it is hypothesized that branding decreases the likelihood of the occurrence of the repeated recall event. Secondly, size of the firm is hypothesized to be associated with higher likelihood of recurrence. The major finding is that branding and firm size are associated with higher probability of the

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recurrence of food recall events associated with pathogenic contamination. A firm that produces branded products is around 15 percent more likely to have a recurrence of food recall events than a firm producing unbranded product. This finding points out the interesting and unexpected issue that branding is not associated with improved performance in food safety. Additionally, an increase in firm size has a minute but significant association with rising likelihood to have a recurrence of a food recall event. This study is the first concerning the firm level factors that can influence risk of the recurrence of food recall incidents involving pathogens. Thus, its results are distinctive and can benefit both government and private sectors with respect to food safety policy or food safety standards.

DEDICATION

I dedicate my dissertation to my beloved parents, Sarinya and Vudtechai Kapilakanchana and brother, Piyawat Kapilakanchana. I also dedicate my work to my grandparents, Somsong and Harn Haritavorn, and Pairoh and Aumphorn Kapilakanchana.

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Finally, I would like to express my most grateful thanks to my mother, father, and brother who have inspired and encouraged me to pursue higher study. I am truly grateful for their love and continuous support.

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CHAPTER I

INTRODUCTION

While the food supply in the United States is often claimed to be one of the safest in the world, the Centers for Disease Control and Prevention (CDC) estimates that each year there are approximately 48 million episodes of foodborne illness-causing sickness to 1 in 6 Americans annually. The consequence is roughly 128,000 hospitalizations and 3,000 deaths (Scallan et al. 2011a; 2011b). The CDC 2011 estimates highlight the fact that foodborne illnesses caused by pathogens are the leading reason for foodborne illnesses in the U.S.

Foodborne illnesses due to pathogen contamination can be closely linked to food product recall events. For example, in 2009 a severe salmonellosis outbreak in peanut butter caused approximately 9 deaths and 714 cases of illnesses (CDC 2009). This incident brought about a vast recall of 3,918 peanut butter related products from 361 brand names across 43 states of the U.S. (FDA 2009b). The latest serious foodborne illness outbreak in the U.S. is the listeriosis outbreak of whole cantaloupes distributed from Jensen Farms. As of November 1, 2011, 29 deaths and 139 cases of illnesses have reportedly been linked to the outbreak (CDC 2011).

It is obvious that food recalls caused by pathogenic contamination are associated

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with public health problems and even consumers' deaths. Moreover, the manufacturers that announce the food recalls also risk financial damage or even a failure that drives the firms out of business. For example, Peanut Corporation of America (PCA) that announced a large recall of peanut butter in September, 2011 is undergoing bankruptcy (FDA 2009b). Due to the possible great loss of consumers, companies and trading partners, the public and the private sectors pay increasing attention to the recall events caused by pathogens.

Recently, the food recalls associated with pathogenic contamination have been growing in a number of events. Furthermore, there are increasingly widespread concerns for all the agents involved. This has also raised the question about what factors influence the food recall events associated with pathogenic contamination. The answer to this question is very helpful for both public and private sectors in order to have a better understanding on this important problem. Since, food recall problems often result from the deficiencies of companies themselves, it is important to focus on the private sectors or companies that produce food products more than the public sectors or the government. Hence, this thesis will examine firm-level factors that influence the food recalls caused by pathogens.

A food recall is an undesirable and harmful incident for the food companies because it implies that firms fail to provide safe and quality foods to consumers. The firm will not announce the recall unless it needs to. Once a recall occurs, the firm should try to improve its food safety performance in order to not let the recall happens again. Thus, the recurrence of a recall event implies that the firm lacks of an ability to provide a

sufficient performance in food safety. That is why we decided to use the recurrence of a recall event as an indicator of food safety performance for the firm.

There are very few research studies about the link between companies and food recall events. The thesis by Joy (2010) is the most similar research to our main focus. However, the major difference is that his study used all of the food recall events over 2000 through 2009, but in this thesis we will use only the food recalls caused by pathogenic contamination. Joy's findings were that branding and firm size had significant effects on the hazard of the recurrence of a recall. According to his interesting findings, the thesis question we will investigate is the effect of branding and firm size on the food recall recurrence associated with pathogenic contamination.

Objectives

This thesis will pursue two objectives:

- To examine how branding and firm size affect the likelihood of the firm's recurrence of a recall event caused by pathogenic contamination; and

- To estimate the size of the effects of branding and firm size on the probability of a firm that has the recurrence of a recall event.

To pursue the main objectives, this thesis consists of the next six chapters. The next chapter (the second chapter), we will provide literature focus on the economic concept and food safety issues. The third chapter, we will discuss about the data utilized in this study. The fourth chapter, we will then present the suitable econometric models

employed in the study and also the expectations based on the economic and management frameworks. Next, in the fifth chapter, we will show the major findings and the additional interesting findings including the discussion from our examination. Finally, the conclusions including implications, limitations and further research will be presented in the last chapter.

CHAPTER II

LITERATURE REVIEW

This chapter presents information and past research related to food companies and food recall events in the first two sections: economies of scale and food safety. Additionally, the last section of the chapter, discrete choice models, also discusses about the theoretical basis of the econometric models employed in this study.

Economies of Scale

In defining economies of scale and scope, we rely on the explanation of the theory from Besanko (2010) in chapter 2. Besanko (2010) as well as other microeconomic textbooks defines economies of scale as the cost advantage when the average cost of production becomes lower as the producer expands its output. On the other side, when the average cost of production rises as output increases we say that a firm experiences diseconomies of scale.

The relation between average costs and output can be represented by an average cost curve. Typically economists describe average cost curve as U-shaped, as shown in figure 1. An average cost curve begins with the descent of average costs because of the spreading of fixed costs over extra units of output. As production grows, average costs increase as production encounter some difficulties such as capacity constraints, complexity, and transaction costs. This average cost curve which has a U-shape can be implied that over the range of different firm sizes, there is a possible for large firms to

not have economies of scale or the inefficiency in firm operation can happen due to a large size.
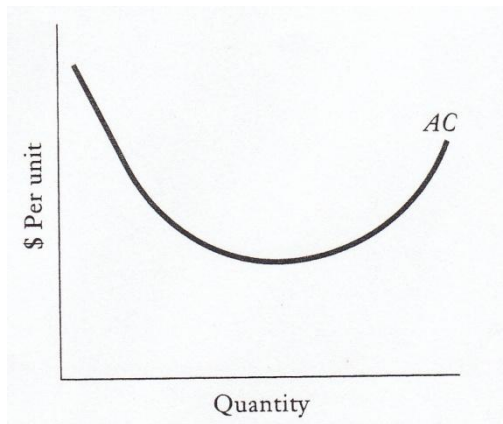
Figure 1. A U-shaped average cost curve
Source: Besanko (2010, p.42)

However, Besanko (2010) states that in reality, large firms infrequently seem to have huge cost disadvantages compared to smaller competitors. This was based on the finding from the examination of production costs in many industries by the famous econometrician Johnston. Johnston determined that, in reality, the cost curves were more similar to L-shaped curves than to U-shaped curves. An L-shaped cost curve depicted in figure 2 shows that average costs fall until they meet the minimum efficient scale (MES) of production. When output goes beyond MES, average costs are the same across production levels.

Consider a single firm, an average cost curve can be a U-shaped or L-shaped curve depending on a different time frame of the production. In the short run, production

occasionally exhibits U-shaped average cost curve since the firm spread over the same fixed assets or overheads in the first stage and then face with its capacity limitation in the second stage. The firm cannot expand its capacity in the short term. While, in the long run, by constructing new facilities the firm can enlarge its capacity to reach a production level that keeps its average costs low. Hence, the average cost curve in the long run is an L shape.
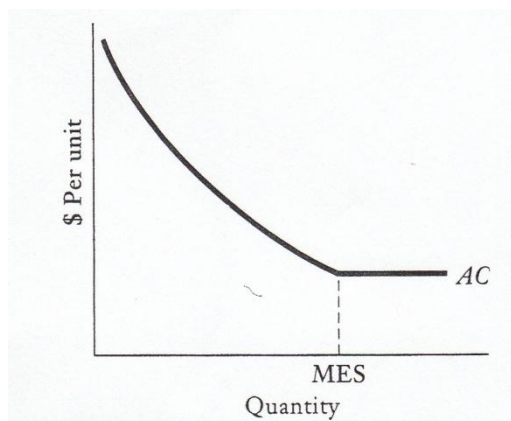
Figure 2. An L-shaped average cost curve
Source: Besanko (2010, p.43)

Economies of scale is an important issue in food industries. For example, in meat and poultry industries, economies of scale is a crucial key to determine a plant cost structure. This statement is supported by Duewer and Nelson (1991), MacDonald et al. (2000), and Ward (1993) in cattle slaughter, MacDonald and Ollinger (2000) in hog slaughter, and Ollinger, MacDonald, and Madison (2000) in poultry slaughter. Each study is elaborated in the following.

MacDonald et al. (2000) found the moderate but widespread existence of economies of scale in hog and cattle slaughter plants. The cost advantages for the largest plants were only 1 to 3 percent more than smaller plants; however, the scale economies existed in all plant sizes in 1992. Moreover, they suggested that the modest economies of scope might exist in cattle slaughter plants.

Furthermore, for the study of cattle slaughter, Ward (1993) compared the results from two past studies; the study of Sersland (1985) and the study of Duewer and Nelson (1991), in the same subject of economies of size of cattle slaughtering and fabrication. He found that even though the two studies used different data and methods, the results from both studies were similar. The results show that estimated average cost of both slaughter and fabrication plants declined as plant size became larger. In other words, the economies of scale existed in both slaughter and fabrication plants. Ward (1993) also asserted that firms that were in the beef packing industry had an economic motivation to operate at a larger plant size in order to keep plants functioning near full-capacity utilization.

In hog slaughter industry, MacDonald and Ollinger (2000) found the moderate but widespread existence of economies of scale. In poultry slaughter industry, Ollinger, MacDonald, and Madison (2000) found the existence of economies of scale as well. Their results indicated that there is a 15-percent decrease in plant average costs for chicken slaughter plants that produce at four times greater than the sample mean volume. Likewise, turkey slaughter plants that manufacture at four times of the sample mean volume have a 17 percent reduction in average costs compare to turkey plants that

produce at the sample mean volume. Ollinger, MacDonald, and Madison (2000) also stated that poultry plants exploited economies of scale by producing at the larger volume. This is supported by the fact that in 1992 and 1967, the number of poultry plants was approximately the same even though the poultry production amount in 1992 was three times larger than in 1967.

Economies of Scale and Safety

In considering food safety control, we expect to have an existing of economies of scale. For example, the cost of hiring quality assurance (QA) and quality control (QC) personnel is an indivisible fixed cost, which is one of main sources of scale economies. "Fixed costs arise when there are indivisibilities in the production process. Indivisibility simply means that an input cannot be scaled down below a certain minimum size, even when the level of output is very small" (Besanko 2010, p.45). Thus, if each plant requires at least one QA and one QC to examine products, the firm can get the financial benefit from reducing average cost per unit, when it expands its output or we say that the firm can enjoy economies of scale.

Our expectation is supported by the new standard in food safety management systems in the food packaging industry that requires each plant that makes food packaging has to employ one practitioner. This new standard is one of the standards in the Safe Quality Food (SQF) certification. SQF is one of the leading private-sector global food safety and quality certifications and is recognized by the Global Food Safety Initiative (GFSI) as a standard that satisfies its benchmark requirements. The standard is

for at least one professional called an SQF practitioner to be employed. An SQF practitioner is a permanent full time company employee and has training in hazard analysis and critical control points (HACCP) systems and the SQF auditing standard. The responsibilities of an SQF practitioner is developing, implementing and maintaining the safety assurance system of the company. According to the new rule having one practitioner per plant, the packaging company could have economies of scale in the food safety control department as described in the previous paragraph.

In addition, another example of economies of scale in food safety control happens when the machines used for safety control processes such as heating or steaming are capital-intensive. These machines are viewed as an indivisible fixed cost and function with scale economies.

In spite of the potential for scale economies, Ollinger and Mueller (2003) found that the sanitation and process control effort exhibits diseconomies of scale since cost of sanitation and process control rises as output increases. They argued that however, it appears to have a diseconomies of scale in food safety process control effort but overall, the larger plants still benefit from scale economies by lowering total cost of producing an additional product. This conflicting evidence calls into question whether firms can achieve the scale economies from food safety control process.

Food Safety

Since, food safety issues are becoming more important worldwide, governments from many countries including the United States of America (USA) are increasing their

attempts to enhance food safety. These attempts are due to an increasing level of consumer concerns and food safety problems.

In the USA, food safety concerns have considerably increased as meat products contamination events occurred in the past ten years (Piggott and Marsh 2004). Recently, the concerns have intensified because of the outbreak of *Salmonella* spp. in peanut butter in 2009 and the listeriosis outbreak from cantaloupes in 2011. The concerns result from many hospitalizations or even deaths of consumers caused by contaminated food products.

According to Scallan et al. (2011a; 2011b), the estimated number of foodborne illnesseses that occur each year in the USA is 47.8 million cases of illness, resulting in 127,839 hospitalizations and 3,037 deaths. Among these cases of foodborne illnesses, the 31 highest risk foodborne pathogens in the USA accounted for 9.4 million illnesses, leading to 55,961 hospitalizations, and 1,351 deaths for each year. Among the 31 most important pathogens, leading causes of foodborne illnesses were norovirus (58 percent), followed by nontyphoidal *Salmonella* spp. (11 percent), and *Campylobacter* spp. (9 percent). Most hospitalizations (35 percent) were caused by nontyphoidal *Salmonella* spp., followed by norovirus (26 percent), and *Campylobacter* spp. (15 percent). Most deaths (28 percent) were caused by nontyphoidal *Salmonella* spp., followed by *Toxoplasma gondii* (24 percent), and *Listeria monocytogenes* (19 percent).

Food Recalls

An important measure in the USA used to prevent the public from consuming contaminated product is a food recall. Before 2011, the food recall was a voluntary action implemented by a firm under the provisions of the government agencies. The intention of a recall is to take away food products that are reasonably believed to be misbranded or adulterated from commerce to prevent consumers from health problems or even deaths (FSIS 2011).

Recalls of contaminated food products are increasing in the rate of occurrences and severity (Skees, Botts, and Zeuli 2001). Meat products had been the major cause of food product recalls for a decade. However, recently, nut products have been added as a major cause of food product recalls during the 2000's as problems occurred in almonds and peanut products. The consequences of the food recalls not only effect consumers but also the responsible company.

A large food recall can cause a massive economic loss to a responsible firm. In the meat and poultry industries, there is a clear evidence of the significant loss for the processor companies. For example, Hudson Foods, a large beef processor, recalled a total of 25 million pounds of ground beef in 1997 (Skees, Botts, and Zeuli 2001). The recall was implemented because of the suspected contamination of *E. coli* O157:H7 and the lack of a clear lotting system to clearly separate processing days. The severe consequence of this recall is that Hudson Foods shut down its plant and exited the industry. Additionally, Thorn Apple Valley Inc., which was a meat and poultry

processor, went bankrupt in 1999 due to the recall of 30 million pounds of its products contaminated with *Listeria* (Skees, Botts, and Zeuli 2001).

While Hudson Foods and Thorn Apple Valley Inc. could not deal with the large expenses from their recalls, some companies are able to overcome the difficulties of recalls and still move on with their businesses. For example, Sara Lee Corporation recalled their meat products due to a *Listeria* contamination at the Bil Mar Foods subsidiary in 1998 (Skees, Botts, and Zeuli 2001). The company lost approximately $76 million from removing their contaminated products and closing the production lines during the outbreak (Dwyer 1999 as cited by Skees, Botts, and Zeuli 2001). Even though, this was a great loss to the company at that time, it still exists in business.

Firm Product-Recall Strategies

The two main strategies that firms apply to manage recall events are proactive and passive strategies. These strategies are categorized by firms' reactions to a recall event (Siomkos and Kurzbard 1994). The firm implementing the proactive or responsible strategy tends to announce a voluntary recall when the firm realizes a potentially unsafe product by inspections inside the firm and before any public safety incidents are reported. Conversely, the firm adopting passive or defensive strategy is more likely to delay or avoid a product recall. The passive recalls are frequently issued after severe incidents happen to consumers such as injuries or death (Chen, Ganesan and Liu 2009).

Several researchers have shown that a proactive strategy results in positive consumer perceptions of firms. Firms are perceived to have a greater quality, if they act responsibly to the general public (Siegel and Vitaliano 2007). Consumers perceive that a firm is more responsible if it takes action before required by a government agency (Jolly and Mowen 1984; Shrivastava and Siomkos 1989). In addition, the negative effect of product-harm crisis on consumers' future purchases and their perceptions will be mitigated if a firm actively responds to a recall (Siomkos and Kurzbard 1994). Furthermore, a proactive strategy can be perceived as a signal for firm's reliability and care of consumers. In general, consumers are likely to interpret these two strategic alternatives as an indication of firm's trustworthiness and quality of firm's products and services (Chen, Ganesan and Liu 2009).

Even though, some studies showed a firm gets benefits or the positive feedbacks from consumers by adopting a proactive strategy, Chen, Ganesan and Liu (2009) proposed that unlike consumers, investors and the stock market might have negative feedbacks on the proactive approach. Their finding indicated that a firm that uses a proactive strategy to a recall event has more damage on their financial value than a firm that uses a passive approach. The explanation is that the investors and the stock market tend to view firm's proactive action as an indicator of large financial loss and severe product danger. Salin and Hooker (2001) studied about the responses of shareholders returns resulting from food recalls. They found that the returns to shareholders of the smallest firm, Odwalla, dropped instantaneously after the recall event. This result is consistent with the findings from Chen, Ganesan and Liu (2009).

Because of some advantages and some drawbacks on both product-recall strategies, firms may choose a different strategy depending on their priority concerns (consumers or investors) and the severity degree of the food contamination incidents.

Discrete Choice Models

In describing the discrete choice models, the explanation of the models is heavily based on four books: Greene (2003), Gujarati (1995), Train (2009), and Wooldridge (2009). Greene's (2003), Gujarati's (1995), and Wooldridge's (2009) books are general econometric reference works, while, Train's (2009) is the leading book especially in the area of the discrete choice models. They defined discrete choice models as the qualitative response models in which the economic outcome is a discrete choice. The discrete choice is chosen by a decision maker among a finite set of options. In other words, the dependent variables in the discrete models are discrete values representing some qualitative outcome. For example, a yes decision equals one and a no decision equals zero. The general approach used to analyze the relation between the decision or the outcome and a set of factors is the probability model (Greene 2003, p.664):

(1)   Prob (event j occurs) = Prob ($Y=j$) = F [relevant effect, parameters].

Discrete choice models can be classified by the number of alternatives. If there are two available alternatives, the models were called binomial or binary choice models. For three or more alternatives, the models were known as multinomial choice models.

Binary Choice Models

The model for binary choice contains a binary response variable that can only be either zero or one. For example, suppose we want to study the factors that influence whether a Ph.D. student passes the qualifying exam. The binary outcome for this example is that a student passes or fails the exam. The binary dependent variable can be defined as one for passing and zero for failing.

Two common approaches used to analyze binary choice models are the logit model and the probit model.

Logit and Probit Models

To explain the logit and probit models, we consider the simple probability model (1). The outcome is either an event occurs (Y=1) or does not (Y=0). The relevant effects are represented by a vector **x** or a set of explanatory variables and the set of parameters are presented as $\boldsymbol{\beta}$. Thus, we obtained the following probability models (Greene 2003).

(2)   Prob ($Y = 1 \mid$ **x**) $= F$ (**x**, $\boldsymbol{\beta}$)

Prob ($Y = 0 \mid$ **x**) $= 1 - F$ (**x**, $\boldsymbol{\beta}$)

The two features needed in the probability models: the probability or response variable lies between zero and one, and the probability varies nonlinearly with **x** (Gujarati 1995). The model for a probability is shown in figure 3. Hence, the cumulative distribution function (CDF) which has the sigmoid or S-shaped curve is suitable to use in the probability models.
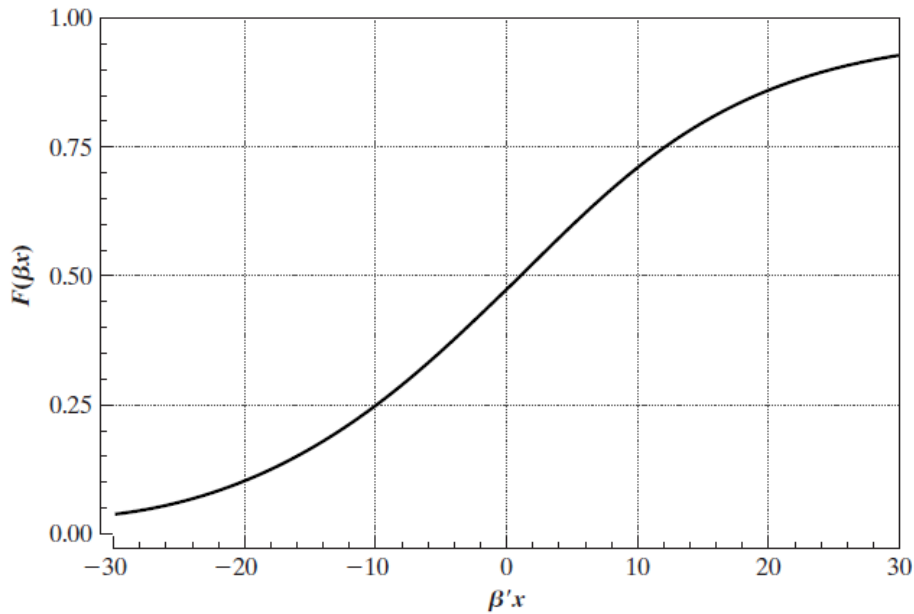
Figure 3. Model for a probability
Source: Greene (2003, p.666)

The two CDFs commonly chosen to represent the binary choice models are the logistic and the standard normal CDFs. The logistic CDF gives rise to the logit model, while, the standard normal CDF underlies the probit model (Gujarati 1995). The important point is that these two models are suitable to analyze binary responses, because they can satisfy the two requirements in the probability model considered earlier.

Pertaining to Wooldridge (2009), the function in the logit model is a logistic function, $\Lambda(z)$:

(3) $$\Lambda(z) = \exp(z)/[1 + \exp(z)].$$

z is latent, or unobserved variable, derived from

(4) $$z = \mathbf{x}'\boldsymbol{\beta} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon,$$

where ε is the error or disturbance term.

ε has the standard logistic distribution which is symmetrically distributed (Wooldridge 2009). In other words, we would say that the logistic disturbances generate the logit model (Greene 2003).

Hence, according to Greene (2003), the logit model can be written as

(5) $$\text{Prob } (Y = 1|\mathbf{x}) = e^{\mathbf{x}'\boldsymbol{\beta}}/[1 + e^{\mathbf{x}'\boldsymbol{\beta}}] = \Lambda(\mathbf{x}'\boldsymbol{\beta}),$$

$\Lambda(.)$ is the notation for the logistic cumulative distribution function. The logit model is one of the appropriate models suitable used to analyze binary choice models. For all real numbers z, the logistic function, Λ (z), is between zero and one (Wooldridge 2009). Hence, it is assured that the probabilities from this model constrained to the 0-1 interval which is the key point of the model for a probability.

The other approach that is widely used for studying binary choice is the probit model. In the probit model, the cumulative distribution function (cdf) is the standard normal cumulative distribution function, $\Phi(.)$, rather than the logistic function, Λ (.), in the logit model. According to Greene (2003), the probit model is presented as:

(6) $$\text{Prob } (Y = 1|\mathbf{x}) = \int_{-\infty}^{\mathbf{x}'\alpha} \phi (t)dt = \Phi(\mathbf{x}'\boldsymbol{\alpha}),$$

where $\phi(.)$ is the standard normal density.

$\mathbf{x}'\boldsymbol{\alpha}$ or z* is an latent variable, derived from

(7) $$\mathbf{x}'\boldsymbol{\alpha} = \alpha_0 + \alpha_1 x_1 + \alpha\beta_2 x_2 + \cdots + \alpha\beta_k x_k + u = z^*,$$

where $\boldsymbol{\alpha}$ represents a set of estimated parameters; u is the error or disturbance term.

This is the same concept as presented in the logit model. However, the main difference from the logit model is that in the probit model, *u* has the standard normal distribution. Thus, normally distributed disturbances produce the probit model (Greene 2003).

The probit model as well as the logit model guarantees that the estimated probabilities lie between zero and one. As, $\Phi(z^*)$ is a function giving values strictly in the range between zero and one: $0< \Phi(z^*) <1$, for all real number z^*.

Comparing between Logit and Probit Models

The CDFs of logit and probit models are quite similar, however; the main difference is that the logistic has slightly flatter tails than the normal or probit. In other words, the logistic curve comes near the axes more slowly than the normal or probit curve as shown in figure 4 (Gujarati 1995).
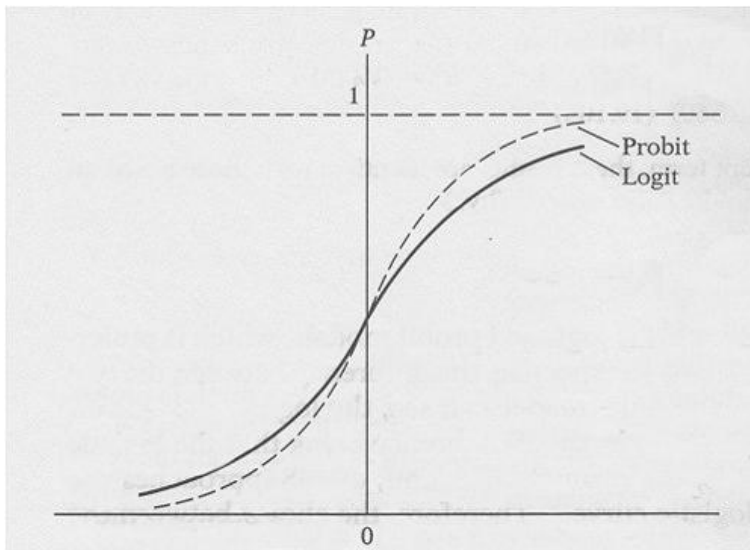
Figure 4. Logit and probit CDFs
Source: Gujarati (1995, p.568)

Because of this similarity of the logit and probit distributions, it is difficult to choose between these two models. There are many discussions about this issue. Amemiya (1981) stated that the probit and logit models generally provide similar results and therefore statistically distinguishing between them is not easy. This discussion is also supported by Greene (2003) that there does not seem to make much difference of the selection between the two models.

Although, the preference between logit and probit models is still unclear, Wooldridge (2009) concluded that in econometrics, the probit model is preferred to logit because of the popularity of the normal distribution. In the opposite way, Train (2009, p.34) argued that "By far the easiest and most widely used discrete choice model is logit. Its popularity is due to the fact that the formula for the choice probabilities takes a closed

form and is readily interpretable." Because of this contradiction, we should look at the advantages and disadvantages of these two models.

As stated earlier, one of the advantages of the logit model is its convenient form for the discrete choice probability. Furthermore, the logistic CDF is simpler than the normal CDF, which is related to an unevaluated integral. For the interpretability, when one transforms the logit model in to the linear model: $Z = a + b \, X$, Z has a direct interpretation as a log-odds. While, in case of the probit, Z has no direct interpretation. Besides the log-odds, an odds ratio can be derived from the logit model, while the probit cannot. Hence, the logit model is better than the probit in the aspect of simplicity, the mathematical convenience, and the interpretability.

Despite these advantages, the logit model still has disadvantages. The main disadvantage is that the logit model cannot deal with random taste variation and the correlations over time (Train 2009). This limitation in the logit model due to its assumption becomes the important advantage for probit model. The probit model is flexible to deal with this limitation. Thus, in the aspect of the flexibility in handling specific problems, the probit model is better.

The probit models are used in many economic studies. In food safety economics, Ollinger and Mueller (2003) also employed the probit model to study about meat and poultry plant exits and the food safety control.

In this chapter, we provided major literature involved in the thesis, which are the economic concept of economies of scale, food safety issues, and the theoretical basis of discrete choice models. Next chapter, we will discuss about the data utilized in the study.

CHAPTER III

DATA

The data used in this thesis are well organized and also obtained from credible sources. Most of the information in the data sets we used is acquired from Joy (2010); however, we updated and made some adjustments to the information in order to make it more suited to our study. In order to acquire the valid outcome from the data, appropriate software was utilized.

This chapter is separated in to four parts. The first part is the information of food product recall events caused by pathogens. The second part provided the information of the companies related to the recall events. The main issues of company are brand information, the number of employees and sales. The third part is the analysis of selected variables. In the last part, we will describe for only the observations that are going to be analyzed in the model in the next chapter.

Food Product Recall Event Information

The study is based on the information of food product recall events in the U.S. from January 2000 through October 2009. The information of recall events was obtained from the Food and Drug Administration (FDA) and the Food Safety Inspection Service (FSIS). Press releases issued by the FDA and the FSIS were collected from Recalls, Market Withdrawals and Safety Alerts website (FSIS 2009) and Recall Case Archive website (FDA 2009a) respectively. Each recall event provides the following information:

firm name, location of the firm (city and state), recall event date, type of recall product, recall problem, and firm contact information.

The recall event information were selected only the recall events caused by pathogens such as *Salmonella* spp., *Listeria* spp. We considerably focus on this group of recall events, since recently there are substantially high concerns on the product recall resulting in foodborne illnesses in the U.S.

During 2000 to 2009, the total number of recall events caused by pathogens was 1,394. Most product recalls were caused by *Salmonella* spp. (56.06 percent), followed by *Listeria* spp. (27.46 percent), *E. coli* (10.82 percent), and other bacteria (5.66 percent). The figures are shown in table 1. Looking at types of product recalls in table 2, we observe that the most high- risk product for recall events is meat products (32.14 percent), followed by nut products (23.60 percent), and confectionary and bakery products (16.93 percent). In this case, we defined meat products as the product which includes at least one of these types of products: beef, poultry, pork, seafood and others meats. The meat product is also the most high-risk product for all of each type of pathogen stated above except *Salmonella* spp. The percentages of meat product recalls caused by *Listeria* spp., *E. coli*, and other bacteria are 66.06 percent, 94.04 percent, and 37.97 percent respectively as given in table 3 to table 6. While, the product recall events caused by *Salmonella* spp. were found mostly in the nut products (41.94 percent).

Types of food products have different risk characteristics and profiles. For example, raw products such as meat has to be cooked before consume. Thus, if a consumer properly cooks them, foodborne illness problem will not occur even though

the raw products may be less safe or low quality products. In the opposite way, the processed or ready-to-eat products are those that are safe to eat without cooking. Since the processed products do not need any preparation before consume, any mistake in food safety of the products can easily cause foodborne illness problem. Table 2 shows that in the food recall data, the processed products account for 9.47 percent of recall events. However, the product type is not the main interest in this study so we do not categorize recall by product type in the analysis.

Table 1. Numbers and Percentages of Product Recalls Classified by Types of Pathogens from the Recall Event Information during 2000-2009

Pathogen	Number	Percent
Salmonella spp.	782	56.06
Listeria spp.	383	27.46
E. coli	151	10.82
Others Bacteria	79	5.66
Total	1395	100.00

Source: Data from FSIS 2009; FDA 2009a

Note: 1) The total number is 1395 because we have one observation that has both of *Listeria* spp. and *Salmonella* spp.

    2) The total number of observations is 1394.

Table 2. Numbers and Percentages of Product Recalls Classified by Types of Products from the Recall Event Information during 2000-2009

Product	Number	Percent
Meat	448	32.14
Nut	329	23.60
Confectionary-Bakery	236	16.93
Dairy	165	11.84
Others (Not Meats)	88	6.31
Other Fruit- Vegetables	69	4.95
Fresh Fruit	28	2.01
Fresh Vegetables	26	1.87
Beverage	4	0.29
Juice	1	0.07
Total	1394	100.00
Processed	132	9.47

Source: Data from FSIS 2009; FDA 2009a

Table 3. Numbers and Percentages of Product Recalls Caused by *Listeria* spp. and Classified by Types of Products from the Recall Event Information during 2000-2009

Product	Number	Percent
Meat	253	66.06
Dairy	70	18.28
Other Fruit- Vegetables	22	5.74
Others (Not Meats)	20	5.22
Confectionary-Bakery	11	2.87
Fresh Vegetables	4	1.04
Fresh Fruit	2	0.52
Nut	1	0.26
Total	383	100.00

Source: Data from FSIS 2009; FDA 2009a

Table 4. Numbers and Percentages of Product Recalls Caused by *E. coli* and Classified by Types of Products from the Recall Event Information during 2000-2009

Product	Number	Percent
Meat	142	94.04
Fresh Fruit	3	1.99
Dairy	2	1.32
Other Fruit- Vegetables	2	0.85
Confectionary-Bakery	1	0.66
Others (Not Meats)	1	0.66
Total	151	100.00

Source: Data from FSIS 2009; FDA 2009a

Table 5. Numbers and Percentages of Product Recalls Caused by *Salmonella* spp. and Classified by Types of Products from the Recall Event Information during 2000-2009

Product	Number	Percent
Nut	328	41.94
Confectionary-Bakery	222	28.39
Dairy	90	11.51
Others (Not Meats)	47	6.01
Meat	24	3.07
Other Fruit-Vegetables	26	3.32
Fresh Fruit	22	2.81
Fresh Vegetables	21	2.69
Juice	1	0.13
Beverage	1	0.13
Total	782	100.00

Source: Data from FSIS 2009; FDA 2009a

Table 6. Numbers and Percentages of Product Recalls Caused by Other Bacteria and Classified by Types of Products from the Recall Event Information during 2000-2009

Product	Number	Percent
Subtotal Meat	30	37.97
Others (Not Meats)	20	25.32
Other Fruit- Vegetables	19	24.05
Dairy	3	3.80
Beverage	3	3.80
Confectionary-Bakery	2	2.53
Fresh Fruit	1	1.27
Fresh Vegetables	1	1.27
Total	79	100.00

Source: Data from FSIS 2009; FDA 2009a

The data collected are the recall events from 2000 to 2009. Since most of the recall occurrences took place in 2009, the number of recall occurrences is thus high in this year compared to other years (see table 7). Also, the graph (shown in figure 5) has been generated to illustrate the trend of product recall events during 2000 to 2009. It is noticed that the fluctuation of the recall event numbers in the year of 2000 to 2008 has caused the wavy pattern in the graph; yet, the number of recall events for each year is not much different from the others. However, in 2009, the numbers of recall occurrences spiked dramatically thus, an extremely sharp slope is produced. This rising of product recall events occurrence in the recent years should, therefore, be given attention.

Table 7. Occurrences of Product Recall Events by Year from 2000 to 2009

Year	Number of recall events	Percent
2000	82	5.88
2001	73	5.24
2002	98	7.03
2003	60	4.30
2004	99	7.10
2005	77	5.52
2006	51	3.66
2007	93	6.67
2008	89	6.38
2009	672	48.21
Total	1394	100.00

Source: Data from FSIS 2009; FDA 2009a
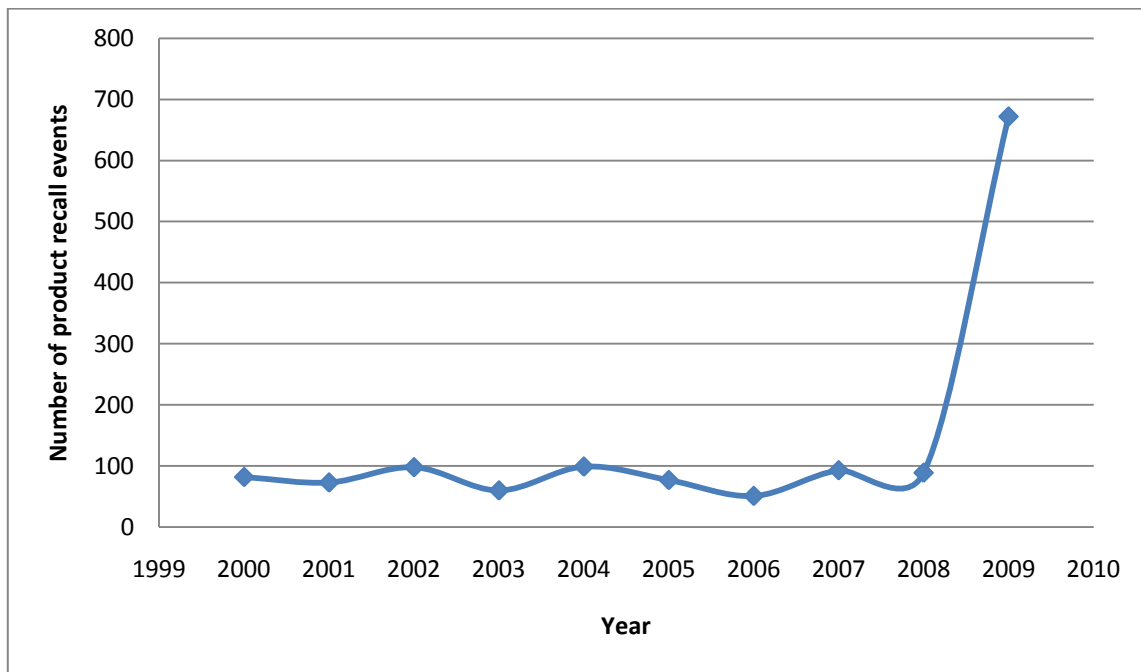
Figure 5. Trend of number of recall events by year from 2000 to 2009
Source: Data from FSIS 2009; FDA 2009a

Company Information

In the study, we defined a company as a corporate parent company. Since, we would like to see the overall image of the company. Thus, subsidiary companies that have the same parent company will be presented as the same company.

The company information includes two parts. In the first part, the information was acquired from Hoover's Company information Database (2009). This company information includes financial detailed information of the corporate parent company: company name, amount of sales in million dollars, number of employees, and type of company. Sales and employee figures are collected from the newest available information on the website. Type of company is separated as a manufacturer, retailer, or food service supplier.

The second part is company information on brand. Numerous individuals put a lot of effort into the work on the brand information in this study. Thus, the brand information is very valuable and unique information in this study. The information on company's brand includes whether a company has a brand or not represented by brand binary variable and the number of brands per company for the branded company. Hence, we created a brand binary variable (BRAND). If a company has a brand, the brand binary variable equals one, otherwise zero.

We have the company information of a total of 1,005 companies that were reported on the recall events caused by pathogens during 2000 to 2009. A problem exists because some company information cannot be obtained. Hence, some companies are lacking some information such as sales figure or employee figure. According to table 8,

all of the companies have information on brand (whether they have their brand or not). However, only 974 companies have the information on the number of brands. Sales (million dollars) and the number of employees are two major figures used for company size grouping. There are only 334 and 310 companies having employee and sales figures respectively. The reason behind this missing information is that some companies, such as non-public or very small companies do not expose their financial information to public. So the information on the number of brands, sales or employees is very difficult to be obtained. In the next part, we will closely describe the company information on sales, number of employees, and brand.

Table 8. Company Information

Information	Mean	Standard deviation	Number of companies with available information
Brand	0.10	0.30	1005
Number of brands	0.53	3.73	974
Number of employees	12,169.66	40,860.22	334
Sales (million dollars)	4,202.54	14,586.27	310
Total number of companies			1005
Total number of recall events			1394

Source: Data from Hoover's Inc. 2009

Sales

We were able to collect the sales (million dollars) of 310 companies from the total of 1,005 companies. The distribution of sales data is a right-skewed distribution shown in figure 6. This means we have many more companies having small sales figures

and relatively few companies having high sales values. Actually, the representation in figure 6 is difficult to comprehend because, on the left of the figure, we have numerous companies containing small amount of sales figures. These companies pile up so densely on the left side that the plot seems to have many y-intercepts. However, in fact there is no y-intercept at all because a company has to have at least a small amount of sales.

This difficulty we faced also results from the characteristics of this sales data as in the following. First characteristic, as stated earlier, is the data having loads of companies with small sales figures. Second characteristic is a very broad range of sales figure (presented in table 9) with a minimum of $200,000 and a maximum of $120.44 billion. That is why it is not easy to make all of the sales levels clearly display in one graph. Hence, we transformed the figure 6 to a histogram, shown in figure 7 which is a better graphical form for understand sales distribution.
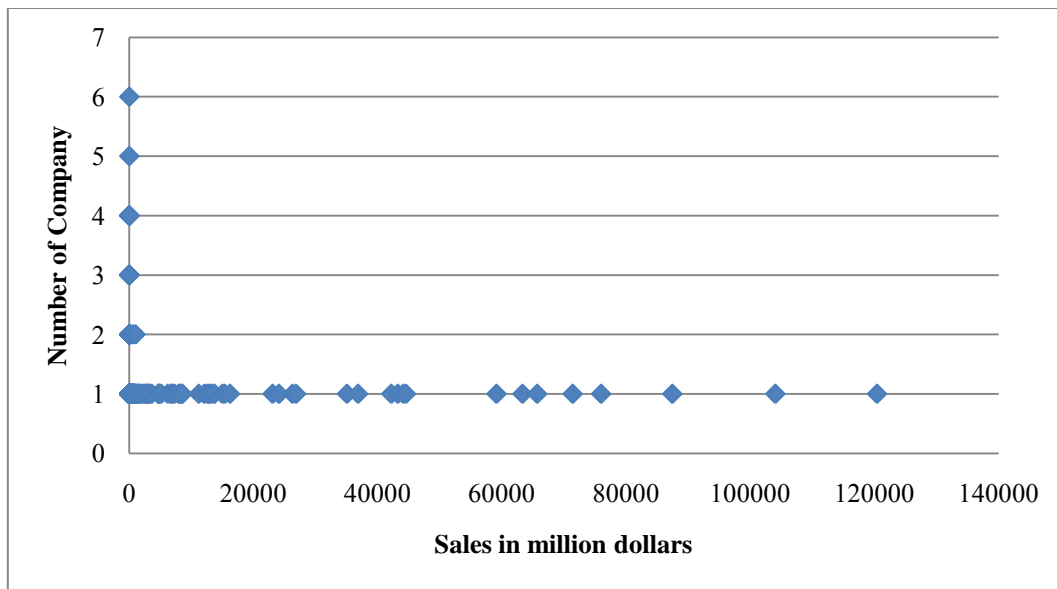
Figure 6. The frequency distribution of sales figures (million dollars) presented by a scatter plot
Source: Data from Hoover's Inc. 2009
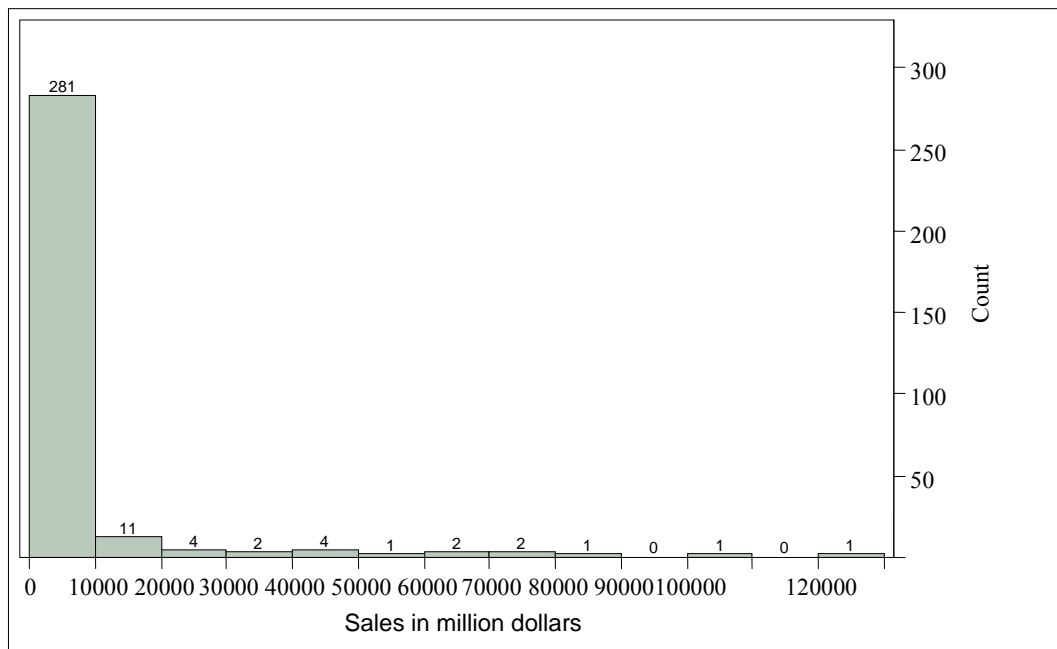
Figure 7. A histogram of sales in million dollars distribution
Source: Data from Hoover's Inc. 2009

Table 9. Descriptive Statistics of Sales Figures

Statistics	Values
Number of observations	310
Mean	$4.20 Billion
Standard deviation	$14.59 Billion
Minimum value	$200,000
Maximum value	$120.44 Billion
25th Percentile	$4 Million
Median	$14.95 Million
75th Percentile	$600 Million

Source: Data from Hoover's Inc. 2009

Number of Employees

As stated earlier, there are 334 companies from the total 1,005 companies having employee figures. Consider the distribution on the number of employees; the distribution provided in figure 8 is also skewed to the right because there is a large share of companies having a small number of employees. The plot in figure 8 has the same problem, as in figure 6. So we created a histogram, shown in figure 9, making the data easier to comprehend.

The range of the number of employees begins with a minimum of 3 employees to a maximum of 326,000 employees. The values are presented in table 10. Due to the wide range of the data and many companies having small employees figures, the employee data set is a right-skewed distribution with most observations compact to the left side.
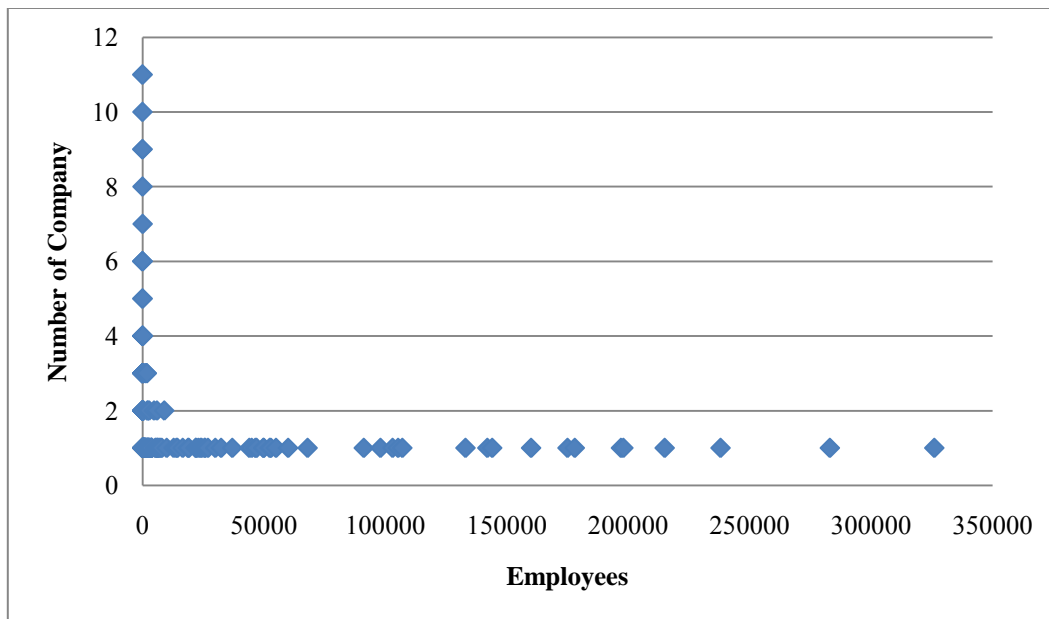
Figure 8. The frequency distribution of the number of employees presented by a scatter plot
Source: Data from Hoover's Inc. 2009
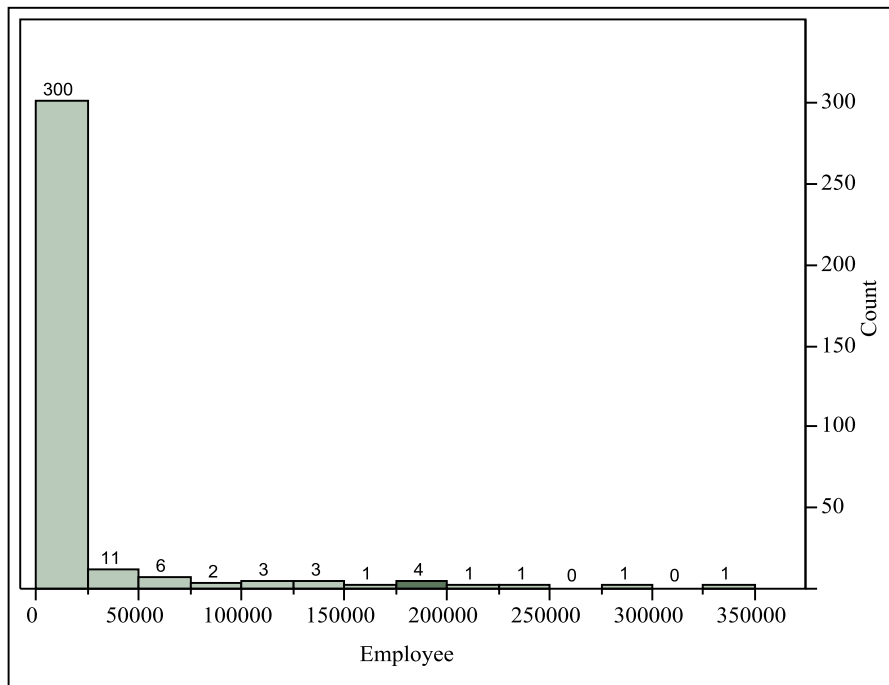
Figure 9. A histogram of the number of employees distribution
Source: Data from Hoover's Inc. 2009

Table 10. Descriptive Statistics of Employee Figures

Statistics	Values
Number of observations	334
Mean	12,169.66
Standard deviation	40,860.22
Minimum value	3
Maximum value	326,000
25th Percentile	25
Median	90
75th Percentile	1,800

Source: Data from Hoover's Inc. 2009

Brand

The information available on brand is provided in table 11. 100 companies from a total of 1,005 companies have their own brands. In other words, they comprise about 10 percent of all the branded companies. Among all branded companies, 68 companies released information regarding the number of brands.

Table 11. Descriptive Information on Brand

Information	Number of companies	Percent
Have a brand	100	9.95
Have a number of brands	68	6.77
Total number of companies	1005	100

Source: Data from Hoover's Inc. 2009

Analysis of Selected Variables

In this part, some important variables are selected to be analyzed. The purpose is to have more understanding on the variables and get the variables ready to be used in the model in the next step.

Recall Frequency Variables

From a total of 1,005 companies, most companies (78.91 percent) had only one recall events (see table 12). Nevertheless, there are 21.09 percent of companies that had a repeated recall event. The number of recall events for each company ranges from a minimum of 1 recall to a maximum of 13 recalls. Nevertheless, 13 recalls caused by one company is an extreme case of recall events and, does not commonly occur. In the data,

there is only one company that had 13 recall events. Additionally, the average of the number of recall events is 1.39 (see table 13) and only 7.16 percent of companies were reported on the recalls three times or more (see table 12). We also provided a list of 39 company names ranked from the most to the least number of recall events in table 22 in Appendix A.

Table 12. Number of Companies by Number of Recall Events

Number of recall events	Number of companies	Percent
1	793	78.91
2	140	13.93
3	33	3.28
4	15	1.49
5	10	1.00
6	5	0.50
7	4	0.40
8	1	0.10
9	1	0.10
12	2	0.20
13	1	0.10
Total	1,005	100.00
≥ 2	212	21.09
≥ 3	72	7.16

Source: Data from FSIS 2009; FDA 2009a; Hoover's Inc. 2009

Table 13. Descriptive Statistics of Recall Frequency

Statistics	Values
Number of observations	1,005
Mean	1.39
Standard deviation	1.09
Minimum value	1
Maximum value	13
25th Percentile	1
Median	1
75th Percentile	1

Source: Data from FSIS 2009; FDA 2009a

Since about one-fifth companies were reported to have a recall event more than once, we created two main variables for representing the frequency of recalls: REPEATED and GREPEAT variables

REPEATED is a binary variable indicating whether a company had a repeated recall event or not. If a company had a repeated recall event (more than one recall event), this binary variable is equal to one, otherwise zero.

GREPEAT is a categorical variable of the occurrence of recall events. This variable is created by grouping the number of the recall events into three groups; non-repeated recall event (one recall event), one repeated recall event (two recall events), and more than one repeated recall events (more than two recall events). In other words, we can look at these three levels as low, medium, and high categories of the occurrence of recall events by frequency order. We assigned the numbers for these three levels as zero, one, and two, respectively.

Size Categories

In order to obtain an accurate interpretation of the outcome, it is important to be extremely careful of how firms are divided. In this section, the selection of size measure and method used will be discussed, followed by a description of the firm size grouping result.

In the U.S., a United States government agency called the Small Business Administration (SBA) has an authority to define small business. According to the Size Standards Division Office of Government Contracting & Business Development (2009), "For the ongoing comprehensive size standards review, SBA has established three "base" or "anchor" size standards: (1) 500 employees for manufacturing, mining and other industries with employee based size standards (except for Wholesale Trade); (2) $7.0 million in average annual receipts for most nonmanufacturing industries with receipts based size standards; and (3) 100 employees for all Wholesale Trade industries."

SBA principally uses two criteria for classification on business size, i.e., receipts and the number of employees. Receipts (average annual receipts) are normally used as a standard-size measure by SBA since it estimates business's output value and can be proved easily. While the number of employees has been mainly utilized for the manufacturing sector and widely applied by the government such as the Small War Plants Corporation and the Small Defense Plants Administration. In general, the 500-employee size standard has gotten recognition in the government (Size Standards Division Office of Government Contracting & Business Development 2009).

According to SBA, we adopted those size standards for determining firm size in our data. However, we need only one standard-size measure in the study. The number of employees is preferred because of two main reasons. First, the number of employees has used as a size standard for the manufacturing industries and also the types of company in the data mostly are food manufacturers. Second, the number of observations containing employee data, 334, is larger than the number of observation containing sales data, 310. Hence, for the size classification analysis, we selected the number of employees as a standard-size measure.

In selecting the method used for grouping, first we have to understand the characteristics of our data set. As mentioned in the company information, the employee data has distinct characteristics that are its non-normal distribution and skewness to the right. Furthermore, the employee data has a dramatically wide range of value. The range of number of employees begins with a minimum of 3 employees to a maximum of 326,000 employees (see table 10).

Because of those reasons, we need to find an informative technique to describe our non-normal distributed data. The two main alternative methods we have considered are the Jenks natural breaks and the Quantile.

The Jenks natural breaks classification method is a data classification method that separates the data based on its natural groupings inherent in the data. The criterion for grouping by this method is minimizing the variance within classes while maximizing the variance between classes (Jenks 1967). After applying this method to the data, we will obtain the best similar values in each group and the best relatively different values

between groups. Alternatively, the Quantile method groups the data by dividing an equal number of observations in each category. Thus, class breaks can be considerably different in range's size.

Because of the uniqueness of these two classification methods, we utilized both the Jenks natural breaks and the Quintile methods to group firms by the number of employees. Thus, we can capture the feasible or appropriate ways to represent the size of a company. Moreover, we decided to group all of the observations into five sizes from the smallest-sized firm to the largest-sized firm in an ascending order; size 1, size 2, size 3, size 4, and size 5 respectively.

Within the same size measure, the number of employees, the difference between methods used for size grouping causes a substantially diverse in the number of companies for each size class (see table 14). It is clearly that when using the Jenks natural breaks method, many companies around 87 percent are put in a very small size (size 1). While, applying the Quantile method gave only about 21 percent of the companies put in the same size. Furthermore, the number of companies in each group using the Jenks natural breaks method is getting smaller as the company size is growing (shown in figure 10). The Quantile method provided an approximately equal number of firms in each group (66-69).

Table 14. Firm Size Classification by the Number of Employees Using the Jenks Natural Breaks and the Quantile Classification Method

Method	Firm Size	Range	Average value	Frequency	Percent
Jenks natural breaks	1	0-10,000	733.22	289	86.5
	2	10,001-37,000	22,872.65	17	5.1
	3	37,001-91,125	55,139.17	12	3.6
	4	91,126-178,000	134,526.10	10	3.0
	5	178,001-326,000	242,833.33	6	1.8
Total				334	100
Quantile	1	0-20	13.13	69	20.66
	2	21-54	35.04	67	20.06
	3	55-178	100.76	66	19.76
	4	179-2,986	1,190.85	66	19.76
	5	2,987-326,000	60,244.97	66	19.76
Total				334	100
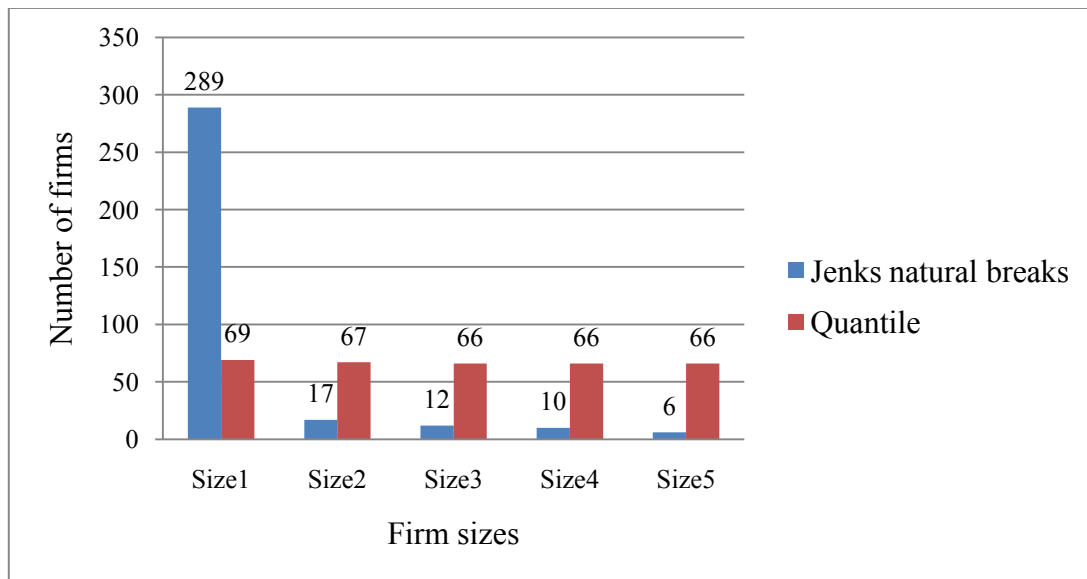
Figure 10. A histogram of the number of firms in each size group categorized by employee data using several classification methods

These dissimilarities stemmed from different ranges of dividing by various methods and the skewness to the right of the employee data. For example, firm size 1 grouped by the Jenks natural breaks method has a very wide range from 0 to 10,000 employees when compared to the Quantile method which has a narrower range from 0 to 20 employees (see table 14). This example shows that the range in the two methods used to group the data are unique from each other. While the Jenks natural breaks method is designed to divide the data into its inherent break based on the skewness, Quantile method, on the other hand, is intended to provide each group with an equal number of observations.

The diagrams shown in figure 11 and figure 12 are provided to clarify the different of range and number of firms in each size group by applying the the Jenks natural breaks and the Quantile method, respectively. Each figure is a diagram of each firm's employee values to illustrate the range, particularly among small firms. The bins according to the method categories are shown with numbers at the bottom of a diagram. As shown in the diagrams, there is a large number of very small firms, in other words, there is a large number of firms with a small number of employees. The diagrams also demonstrate that the Quantile method separates more groups among small firms while the Jenks natural breaks method combines all the small firms in to one group. For example, if we use the 500-employee size standard from SBA, a small business can be placed in size1 to size 4 for the Quantile method but it is only classified in size 1 for the Jenks natural breaks method.

In conclusion, we decided to use the number of employees as the size measure and keep both of the firm size classifications by the Jenks natural breaks and the Quantile methods. Since, there is no universally classification method of firm size.
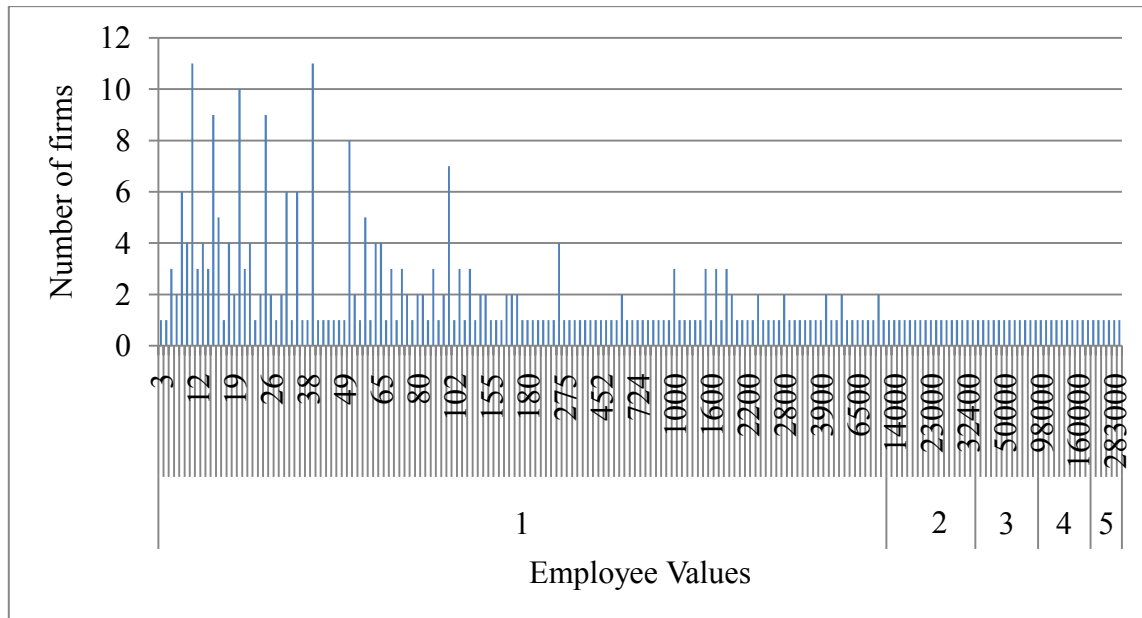
Figure 11. Range of employee values categorized by the Jenks natural breaks method
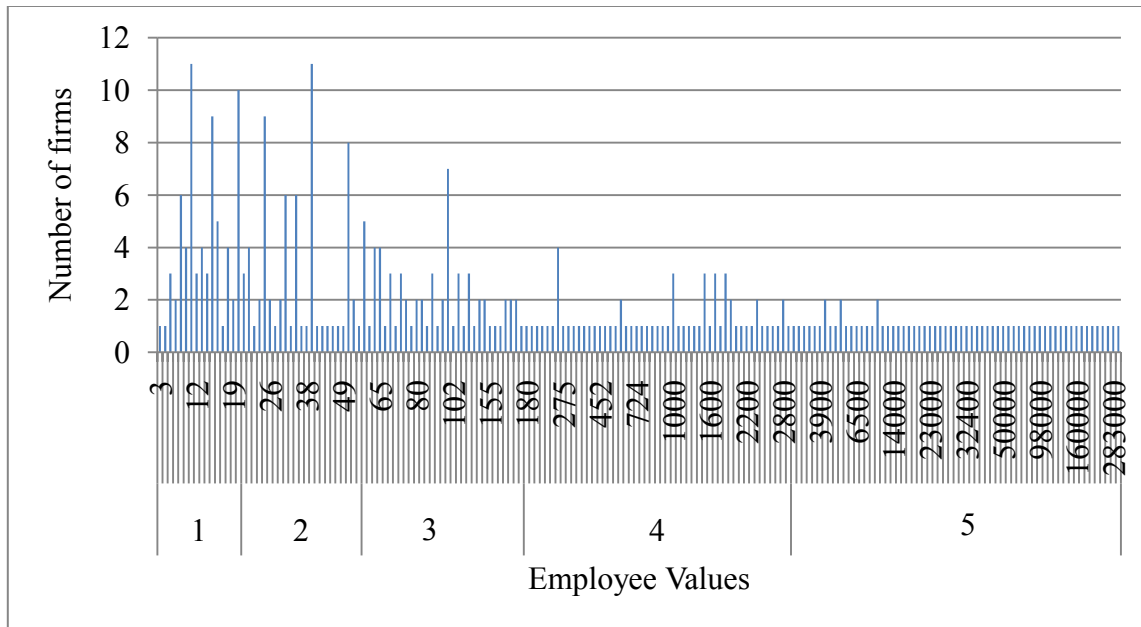
Figure 12. Range of employee values categorized by the Quantile method

Correlation between Brands and Firm Size

Since, we are interested in both of the brand binary variable and the firm size variables, we have to consider the possible correlation between the two variables. The firm size variables that we used are the number of employees and we named it as EMPLOYEES variable and the size category variables: SIZE 1, SIZE 2, SIZE 3, SIZE 4, and SIZE 5 (the smallest-sized firm to the largest-sized). Each size category variable is a binary variable. For example, SIZE 1 equals to one, SIZE 2, SIZE 3, SIZE 4, and SIZE 5 equal to zero, if a company is in the size 1 category. Additionally, the brand binary variable is named BRAND variable.

According to Devore (2004), we define the correlation (ρ) as follows:

     1. A weak correlation: $0 \leq |\rho| \leq 0.5$

2. A moderate correlation: $0.5 \leq |\rho| \leq 0.8$

3. A strong correlation: $0.8 \leq |\rho| \leq 1$.

As show in table 15, there is a significantly weak positive correlation between BRAND and EMPLOYEES (ρ=0.342). For both of the size classification methods, the correlation between BRAND and each size variable shows the same general result which is a weak positive correlation (see table 16 and table 17). Thus, the low correlation would not generate a problem if we include the brand binary variable and the firm size variables as independent variables in the same model.

Furthermore, consider the sales (million dollars) figure or SALES variable, EMPLOYEES and SALES are highly correlated (ρ=0.880). This supports the idea that we should keep only one variable for size measure.

Table 15. Correlation Coefficients between Three Variables: Brand, Employees and Sales (million dollars)

Variable	Correlation Coefficient	Significant Value	Number of Observations
BRAND and EMPLOYEES	0.342	<0.0001	334
EMPLOYEES and SALES	0.880	<0.0001	308

Table 16. Correlation Coefficients between Brand and Sizes by the Quantile Method based on Employee Data

Variable	Correlation Coefficient	Significant Value
BRAND and SIZE 1	-0.284	<0.0001
BRAND and SIZE 2	-0.226	<0.0001
BRAND and SIZE 3	-0.152	0.0053
BRAND and SIZE 4	0.237	<0.0001
BRAND and SIZE 5	0.432	<0.0001

Note: The total observation number is 334.

Table 17. Correlation Coefficients between Brand and Sizes by the Jenks Natural Breaks Method based on Employee Data

Variable	Correlation Coefficient	Significant Value
BRAND and SIZE 1	-0.461	<0.0001
BRAND and SIZE 2	0.352	<0.0001
BRAND and SIZE 3	0.158	0.0039
BRAND and SIZE 4	0.150	0.0059
BRAND and SIZE 5	0.190	0.0005

Note: The total observation number is 334.

Association of Repeated Recalls with Brand

As shown in table 18, we observed that the proportion of corporate companies with a brand compared to those with no brand grows with the number of recall occurrences. For example, the percentages of the number of branded companies had one recall, two recalls, and three recalls are 6.31, 15.71, and 24.24 respectively. The average number of brands also increases with the number of the recall events. The average numbers of brand are 0.17 for the branded companies with one recall, 1.99 for the branded companies with more than one recall, and 3.98 for the branded companies with more than two recalls.

Table 18. Number of Companies with Brand or No Brand and Statistical Values of the Number of Brands for Branded Companies for Each Number of the Recall Occurrences

Number of the recall occurrences	Number of companies			Number of brands			
	Have Brand	No Brand	Total	Average	Standard deviation	Min	Max
1	50(6.31)	743(93.69)	793	0.17	1.36	0	30
2	22(15.71)	118(84.29)	140	1.04	5.76	0	50
3	8(24.24)	25(75.76)	33	2.32	7.00	0	32
4	4(26.67)	11(73.33)	15	2.08	7.19	0	26
5	5(50.00)	5(50.00)	10	9.44	16.73	0	50
6	3(60.00)	2(40.00)	5	14.00	24.17	0	50
7	3(75.00)	1(25.00)	4	0.67	0.58	0	1
8	1(100)	0(0)	1	-	-	-	-
9	1(100)	0(0)	1	-	-	-	-
12	2(100)	0(0)	2	5	-	5	5
13	1(100)	0(0)	1	-	-	-	-
≥ 2	50(23.58)	162(76.42)	212	1.99	7.79	0	50
≥ 3	28(38.89)	44(61.11)	72	3.98	10.66	0	50

Source: Data from FSIS 2009; FDA 2009a; Hoover's Inc. 2009
Note: 1) Numbers in parentheses are row percentage numbers.
 2) The total observation number is 1,005.

Summary of Observations Used in the Models

Even though we have a total of 1,005 companies or 1,005 observations to examine in the study, the number of observations used in the models we are going to analyze is 334. The reason is that we decided to use the number of employees as a firm size measure and there were only 334 companies that we were able to obtain the numbers of employees. Thus, before we move to the methodology chapter, we summarize the descriptive information on the selected variables of only the observations used in the analyzed models in table 19.

Table 19. Descriptive Information on Brand and Number of Recalls of Only the Observations Used in the Models

Variable	Mean	Std. Dev.	Min	Max	Information	Number of Companies
Brand	0.237	0.426	0	1	Have a brand	79 (23.65)
					Have no brand	255 (76.35)
Number of brands	1.480	6.291	0	50	Have one brand	15(4.49)
					Have more than one brand	32(9.58)
Number of recalls	1.763	1.635	1	13	Have one recall	221 (66.17)
					Have more than one recall	113 (33.83)
					Have more than two recalls	51 (15.27)
Total number of recalls						589
Total number of observations						334

Source: Data from FSIS 2009; FDA 2009a; Hoover's Inc. 2009

Note: 1) Numbers in parentheses are company percentage numbers.

2) There are 32 companies that have no information on a number of brands.

3) Std. Dev is a standard deviation.

According to table 19, the companies that have no brand (255) number greater than the companies that have a brand (79). Hence, we can say that this data is unbalanced between the branded companies and unbranded companies. Furthermore, we also noticed that the numbers of observations are unbalanced between the number of observations that has one recall event (221) and the number of observations that has a recurrence of a recall event or more than one recall event (113). Most of the companies, around 66 percent, have only one recall event. These observations should be considered when we analyze the data in the next step. Additional, there are only 51 companies or 15 percent of companies that have more than two recall events. We provided a list of 31 company names from all of these 334 companies ranked from the most to the least number of recall events in table 23 in Appendix A.

The description of the data used in the study and the analysis of selected variables were presented in this chapter. Additionally, we summarized the descriptive information for only observations that are going to be analyzed by the methodology explained in the next chapter.

CHAPTER IV

METHODOLOGY

The logit and probit models were employed to estimate the effect of company's factors: branding and size on the occurrence of a repeated recall event. Thus, we will have the model with a binary dependent variable and the logit and probit models are commonly models used when a dependent variable is binary. Moreover, the two models are suited to predict probabilities since they constrain the response variable to lie between zero and one.

In order to estimate the logit and probit models, which are nonlinear binary response models, a maximum likelihood estimation (MLE) is indispensable (Wooldridge 2009). "MLE has some desirable efficiency properties: it is generally the most efficient estimation procedure in the class of estimators that use information on the distribution of the endogenous variables given the exogenous variables" (Wooldridge 2002, p.385). Hence, the estimation method used in this study is MLE.

Models Specification

The models used in the study examine whether the probability that a company has a repeated recall event, P_i, depends on factors or explanatory variables (X_{ij}) associated with the company i.

Logit Model

First, we provide the main model in the logit approach:

(8)　　$P_i = P_i (\text{REPEATED}_i = 1) = \Lambda(\mathbf{x_i \beta}) = \Lambda(\mathbf{z_i}) = \exp(\mathbf{z_i})/[1 + \exp(\mathbf{z_i})],$

where

P_i　　　　　　　　　= the probability that a company i has a repeated recall event,

given a set of independent variables($\mathbf{x_i}$) and a set of estimated

parameters $(\mathbf{\beta})$;

$\Lambda(.)$　　　　　　　　= the logistic CDF;

REPEATED_i　　　= the binary variable equals one if company i has a repeated recall

event, otherwise zero;

$\mathbf{z_i}$　　　　　　　　= a logit latent or logit unobserved variable or the log odds for

company i;

i　　　　　　　　　= the index for companies.

$\mathbf{z_i}$ is attained from the underlying latent variable model:

(9)　　　　　　$\mathbf{z_i} = ln\left[\frac{P_i}{1-P_i}\right] = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \varepsilon_i = \mathbf{x_i \beta},$

where

β_j　　　　　　　　　= logit parameter to be estimated for variable x_{ij};

x_{ij}　　　　　　　　= j^{th} attribute of company i; j = 1, 2, …, k;

ε_i　　　　　　　　= the error or disturbance term that has a standard logistic

distribution.

Probit Model

The second main model we apply in the probit approach:

(10) $\qquad P_i = P_i \, (\text{REPEATED}_i = 1) = \boldsymbol{\Phi}(\mathbf{x_i}\boldsymbol{\alpha}) = \boldsymbol{\Phi}(z_i^*),$

where

P_i $\qquad$ = the probability that a company *i* has a repeated recall event,

$\qquad$ given a set of independent variables($\mathbf{x_i}$) and a set of estimated

$\qquad$ parameters $(\boldsymbol{\alpha})$;

$\boldsymbol{\Phi}(.)$ $\qquad$ = the standard normal CDF;

REPEATED_i $\qquad$ = the binary variable equals one if company *i* has a repeated recall

$\qquad$ event, otherwise zero;

z_i^* $\qquad$ = a probit latent or probit unobserved variable for company *i*;

i $\qquad$ = the index for companies.

z_i^* is obtained from the latent variable model:

(11) $\qquad z_i^* = \boldsymbol{\Phi}^{-1}(P_i) = \alpha_0 + \alpha_1 x_{i1} + \alpha_2 x_{i2} + \ldots + \alpha_k x_{ik} + u_i = \mathbf{x_i}\boldsymbol{\alpha},$

where

$\boldsymbol{\Phi}^{-1}(.)$ $\qquad$ = the inverse of the CDF of the standard normal distribution;

α_j $\qquad$ = probit parameter to be estimated for variable x_{ij};

x_{ij} $\qquad$ = j^{th} attribute of company i; j = 1, 2, …, k;

u_i $\qquad$ = the error or disturbance term that has a standard normal

$\qquad$ distribution.

Interpreting the Logit and Probit Estimates

The estimated parameters from logit model in equation (8) and probit model in equation (10) are not directly the marginal effects of the explanatory variables on the probability that a company has a repeated recall event (P_i). In order to compute the marginal effects, we have to consider the characteristic of the explanatory variables.

For a continuous variable like the number of employees (EMPLOYEES), the marginal effects can be estimated by using the first derivative of the response probability with respect to the independent variable of interest which is continuous. Thus, in the logit model, the marginal effect of continuous variable (x_{ij}) on the probability P_i would be

(12)
$$\frac{\partial P_i}{\partial x_{ij}} = \frac{\beta_j exp(z_i)}{[1+exp(z_i)]^2},$$

For the probit model, the marginal effect of x_{ij} would be

(13)
$$\frac{\partial P_i}{\partial x_{ij}} = (\alpha_j)\phi(z_i^*),$$

where $\phi(.)$ is the standard normal density.

For both models, the marginal effect of x_{ij} on the probability P_i is evaluated at the means of the other independent variables in the model.

In case that the explanatory variables are dummy variables such as the BRAND variable, it is not appropriate to obtain the marginal effects by using the first derivative like we applied with the continuous variables. In this case, the marginal effect of a binary explanatory variable is acquired by estimating Pi at the two values of the dummy variable: 0 and 1 while using all of the other variables in the model at the means (Greene

2003). The marginal effect of the binary explanatory variable, denoted d, is determined as:

(14) $\quad P_i\big[\text{REPEATED}_i = 1\big|\bar{\mathbf{x}}_{(d)}, d = 1\big] - P_i\big[\text{REPEATED}_i = 1\big|\bar{\mathbf{x}}_{(d)}, d = 0\big],$

where $\bar{\mathbf{x}}_{(d)}$ represents the means for all of the other independent variables in the model.

Discussion of Variables

In this section, we identify several factors that we thought might be associated with food recall events. To explain our thought, we applied economic and management framework that can link between the factors and the possibility of having a repeated recall event.

According to the research by Joy (2010), he suggested that branding and firm size significantly affect the risk of a food recall event by the firm. Hence, branding and firm size are the two major firm-level factors that we suspect to have an effect on the recurrence of a recall event associated with pathogenic contamination. We first discuss about branding and then move to the firm size issue.

Branding is one of the important issues when we discuss about product quality and safety. Next we will explain about the relation between branding and food quality and food safety based on the principal-agent theory.

Weiss (1995 p.71) explained about the principal-agent theory as follows, "A principal-agent relationship is said to hold between two individuals when one (the principal) provides compensation to the other (the agent) to perform services desired by the principal but whose successful completion cannot be directly verified by the

principal." In the food safety sector, we can view consumers as principals and producers as agents. Consumers provide money at the purchased price to producers to supply safe and wholesome food products; however, consumers cannot directly know whether the food products are safe and wholesome or not. This principal-agent problem is cause by the asymmetric information between the producers and consumers and makes it impossible for consumers to distinguish between low quality or less safe products and high quality or safe products. Thus firms that produce high quality or safe products will try to separate themselves from the others with low quality or less safe products by using branding as a signaling device to their consumers.

Firms also use brand advertising to obtain a positive reputation from consumers. Nelson (1970 and 1974) suggested that brand advertising could be a signaling device of high quality products to consumers, even though the advertisements did not carry much informative content. Milgrom and Roberts (1986) confirmed Nelson's idea and also noted that companies invest in brand advertising in the long run to gain a reputation that they produce quality products. Hence, we would say that branding and brand advertising are practical signaling devices of high quality products to customers.

Lawrence, Schroeder, and Hayenga (2001) and Ollinger and Mueller (2003) also support the idea that branding is linked to high product quality. They stated that in the poultry and meat processing industry, plants usually manufacture branded products the sources of which can be easily revealed. Hence, the manufacturers must be very active to maintain product quality.

Since branding is an important signal of high quality or safe products, we expect that a firm that has a brand will have less likelihood of a recurrence of a recall event than a firm without a brand. However, we have to keep in mind that a firm that has a brand or more than one brand will have more complexities within the firm rather than a firm without a brand. Thus, a bounded rationality problem may occur in a firm that has a brand or an umbrella brand and can lead to an increasing likelihood of having a recurrence of a recall event.

Besides branding, firm size is also one of the key factors that can be linked to the quality and safety of products. We will first examine firm size by looking at firm's nature. Coase (1937) studied about this issue and he stated that "A firm becomes larger as additional transactions (which could be exchange transactions co-ordinated through the price mechanism) are organized by the entrepreneur" (p.393). In the study, Coase (1937) interpreted the size of firm as employees and sales or volume.

As the additional transactions increases, the transactions would be likely to have an increase in the dissimilarity and the spatial distribution. This can result in the rising of the costs of organizing extra transactions and the increasing losses through mistakes by failing to use the factors of production at their greatest value. At this point, Coase (1937) argues that the firm becomes less efficient as the firm size gets larger. In other words, he also stated that the point can be matched with the economic concept of the "diminishing returns to management."

In summary, this concept suggests that as a firm becomes larger, it will experience increasing costs of organizing and the higher losses from mistakes, due to

differences in places and in kinds of extra transactions. This is a reason why firm's efficiency may decline as the firm increases its size.

Coase's (1937) argument is also consistent with Williamson's (1981) assertion. He stated that when a plant increases in size, its bureaucratic structure becomes more complex and difficult to be managed. This leads to the higher transaction costs that finally overcome benefits from economies of scale due to further growth.

The other idea that supports the lower efficiency of a larger firm is based on the bounded rationality concept. Bounded rationality has been described as a human or an agent behavior that is "intendedly rational, but only limitedly so" (Simon 1961 as cited by Williamson 1981, p. 571). In complex environments, boundedly rational agents are limited by abilities to manage problems and to process information (Williamson 1981). Even though they attempt to make a rational decision, they only have a second-best possible solution constrained with the limitations such as available information they have. Therefore, more complexities within a larger firm make it become less effective in management.

Since firm management drives quality control, less effective management due to the growing of firm size may cause problem to the safety of food products. For example, if the larger firm still uses the same number of employees to work as a quality assurance (QA) or quality control (QC) personnel, the constraints of their ability to supervise and examine products in more complex environment such as a variety of products and processes may lead to difficulty in maintaining product process control. The consequence is that the less safe products are produced to the market.

Furthermore, Ollinger and Mueller (2003) studied about the economics of food safety in meat and poultry plants. In the study, they used percent critically deficient of sanitation and process controls practices (SPCPs) to measure for food safety control effort. "A critical deficiency is a failure to adequately perform an operation that FSIS deems essential to plant sanitation and process control" (Ollinger and Mueller 2003, p.21). There are many interesting findings associated with firm size in the study as in the following. The first finding is that plants with smaller size had a smaller share of critically deficient SPCPs when comparing to the larger plants. The second finding is that all processing plants and large slaughter plants in high deficient SPCPs level have a greater likelihood to exit the industry than other plants. Moreover, the closest study by Joy (2010) also found that an expansion of firm size will make the risk of the firm that has a recurrence of a food recall event increase.

In contrast, we have to consider that the larger firms can get more benefits from economies of scale that lead to more efficiency in production process than smaller ones. This may assume that the products of large firms will be safe and have a good quality due to the efficient production process. However, it is not assured that the large firm can enjoy economies of scale, unless we have the information to calculate average cost of the firm. Hence, we cannot conclude that the large firms in this study are more efficient than the smaller firms.

According to the economics concepts and the research findings stated above, thus, we suspect that as firm size increases, so does firm complexity, and the probability of the firm has a recurrence of a recall event will also increase. However, another

important perspective on the large firms is that the large firms are often linked to more automation in production that typically makes a safer and more controlled product with less chance for human error (G. Acuff, personal communication). Due to the contradiction of these two viewpoints, the two tailed test will be used as the hypothesis test on the coefficient of firm size variable explained in the Hypothesis Tests section.

Consideration on Missing Variables

Consider multiple variables that are the underlying causal factors in observed phenomenon. Even if these causal factors are difficult to measure, it is important to consider them to avoid omitted variable bias in the results. Therefore, in this study, one needs to understand what causes branding and what causes firm size. It might be the case that another latent variable that we did not include in the model could have a correlation with the independent variables in the model (Bessler 2009). This latent variable might have an effect on either branding or firm size or both of these firm-level factors. The effects are important to specification of the econometric model. Furthermore, if the food safety policy has a significant association with the occurrence of a repeated recall event, the variable that measures this policy must be included in the model to prevent biased estimation of parameters in the model (Wooldridge 2009).

The food safety policy or standard set by government agencies might be the factor that should be considered as the latent variable that could manipulate branding and firm size. If the food safety policy or standard is not very stringent to inspect food products, with infrequent sampling and testing, the government agencies may not find

many problems on the products. When a firm finds no problem with its products such as no recall, it may want to expand its production to generate more profits. In this example, it might be possible that the policy can have an influence on firm size.

It is difficult to find the appropriate measure of food safety policy and also the correlations between food safety policy and the occurrences of a repeated recall event. Further, the correlation between food safety policy and firm size or branding has been unclear. Additionally, this study's unit of analysis is a company and all companies are subjected to the same policy. Hence, policy is constant across firms. Also, the effect of policy on firm size needs to be assessed through temporal scale. Since this study does not include temporal variation in the model, the potential bias of excluding policy as a variable might not be a problem. Therefore, the variable of food safety policy is not included in the model.

It is important to consider and be aware of other possible factors that may become a hidden variable and may cause the bias problem to the model unless they are included in the model. The bias direction depends on the sign of the estimated parameter of the interested variable in the model and the sign of the correlation between this variable and the omitted variable. If the sign of the estimated parameter and the sign of the correlation are the same, the bias is positive, otherwise negative (Wooldridge 2009).

Hypothesis Tests

According to the study by Joy (2010) that is the most similar research to this study, he found that branding and firm size significantly affect the risk of food recall

event. Thus, in this study, we contend that these two factors: branding and firm size have an effect on the recurrence of a recall event associated with pathogenic contamination. Therefore, the first hypothesis we will test is that the estimated coefficient of branding variable (β_B) in the model that controls for the effect of firm size will not be equal to zero. The proposed hypothesis is:

(1) H_0: $\beta_B = 0$

        H_1: $\beta_B \neq 0$

In the first hypothesis test, the null hypothesis is that the coefficient of branding variable equals zero. As the expectation stated above, we would like to reject the null hypothesis by obtaining the small p-value ($p < 0.01$) in order to conclude that branding has a significant effect on the recurrence of a recall event.

The second hypothesis we will test is that the estimated coefficient of firm size variable (β_{FS}) in the model that controls for the effect of branding will not be equal to zero. This hypothesis is presented as:

(2) H_0: $\beta_{FS} = 0$

        H_1: $\beta_{FS} \neq 0$

In the second hypothesis test, the null hypothesis is that the coefficient of firm size variable equals zero. Using the same concept as discussion in the first hypothesis test, we would like to reject the null hypothesis by obtaining the small p-value ($p < 0.01$) in order to conclude that firm size has significantly effect on the recurrence of a recall event.

Variable Specification

The dependent variable is REPEATED. This binary variable sets at one if a company has a repeated recall event, otherwise zero.

The independent variables (x_{ij}) are the attributes of company that we are interested. The first attribute is whether a company has a brand or not. Thus, one of the independent variable is a brand binary variable or BRAND. BRAND was set to one if a company has a brand, otherwise zero.

The second attribute is the size of a firm that can be determined by size categorical variables, the number of employees, or the transformation variables of the number of employees. The size categorical variables are SIZE 1, SIZE 2, SIZE 3, SIZE 4, and SIZE 5, which are all the binary variables. If a company is put in the size 1 category, SIZE 1 equals to one, SIZE 2, SIZE 3, SIZE 4, and SIZE 5 equal to zero. The variable representing the number of employees in the company is EMPLOYEES. The transformation variables of the number of employees can be in many forms. One form is the number of employees in thousands (EMPLOYEES_TH). The form of firm size variable that we selected is the natural log of the number of employees of the company and Ln(EMPLOYEES) represents this variable. Due to some limitations from the size categorical and EMPLOYEES variables, we used only Ln(EMPLOYEES) variable for representing firm size variable. The limitation issue will be discussed in the next chapter.

Empirical Model of Repeated Recall Occurrence

Model 1

The first model, we employed the following logit model:

$$(15) \quad \text{Logit}(P_i) = z_i = ln\left[\frac{P_i}{1-P_i}\right] = \beta_0 + \beta_1 \text{ BRAND}_i + \beta_2 \text{ Ln(EMPLOYEES}_i) + \varepsilon_i,$$

where

i = the index for companies;

P_i = the probability that a company i has repeated recalls or

P_i (REPEATED$_i$=1), given the independent variables: BRAND$_i$

and EMPLOYEES$_i$;

z_i = a logit latent or logit unobserved variable or the log odds for

company i;

BRAND$_i$ = the brand binary variable equals one if company i has a brand,

otherwise zero;

Ln(EMPLOYEES$_i$)   = the natural log of the number of employees of company i;

β = parameters to be estimated;

ε_i = the error or disturbance term.

The estimated probability can be calculated by substitute z_i from equation (15) into equation (8).

Model 2

In the second model applied the probit model in the model 1 instead of the logit

model. This second model is given as:

(16) $\text{Probit}(P_i) = z_i^* = \Phi^{-1}(P_i) = \alpha_0 + \alpha_1 \, \text{BRAND}_i + \alpha_2 \, \text{Ln}(\text{EMPLOYEES}_i) + u_i,$

where

i	= the index for companies;
$\Phi^{-1}(.)$	= the inverse of the CDF of the standard normal distribution;
P_i	= the probability that a company i has repeated recalls or
	P_i (REPEATED$_i$=1), given the independent variables: BRAND$_i$
	and EMPLOYEES$_i$;
z_i^*	= a probit latent or probit unobserved variable for company i;
BRAND$_i$	= the brand binary variable equals one if company i has a brand,
	otherwise zero;
Ln(EMPLOYEES$_i$)	= the natural log of the number of employees of company i;
α	= parameters to be estimated;
u_i	= the error or disturbance term.

The estimated probability can be calculated by substitute z_i^* from equation (16)

into equation (10).

In summary, the appropriate models employed to examine the effect of firm's

factors: branding and firm size on the recurrence of a food recall event associated with

pathogenic contamination are logit and probit probability models. According to

economic and management frameworks and the research involved with a firm and food

safety, we make assumptions that larger firm size is associated with greater likelihood of

a recurrence of a recall event and branding is associated with lower likelihood. Then, the

assumptions will be examined and the results will be discussed in the next chapter.

CHAPTER V

ANALYSIS & RESULTS

The content in this chapter is separated into three parts. The first part provides the main results from the estimation of the logit and probit models frameworks that were shown in the prior chapter. The second part presents the additional results from other models we tested. The last part is the results discussion and the possible reasons for the results.

Main Results

The two models: logit and probit models are estimated to clarify and predict how an occurrence of a repeated recall event varies by branding and company size. The results for logit and probit regressions illustrated in table 20 and table 21 respectively contain the estimated coefficients, the associated standard errors, and the marginal effects of the independent variables. Additionally, the table provides various measures of goodness of fit for the model including the Likelihood Ratio (LR), the pseudo R-squared (Pseudo R^2), the Akaike information criterion (AIC), and the percent correctly predicted.

The results from the logit regression are consistent with the results derived from the probit regression. First, look at the main hypothesis tests, for both variables: branding and firm size (table 20). The null hypothesis that the coefficient of the variables equals zero was significantly rejected. This indicates that both branding and firm size have significant effects on the recurrence of a recall event associated with pathogenic

contamination. Second, the results indicate how these two factors influence the recurrence of a recall event. The results suggest that companies having a brand or branded companies are more likely to have a repeated recall event caused by pathogens than companies with no brand. Furthermore, the results also suggest that larger companies are more likely to experience a repeated recall event than the smaller ones.

Table 20. Effect of Brand and Firm Size on the Occurrence of the Repeated Recall Event Using the Logit Model

Variable	Coefficient		Marginal Effect	Mean
	Estimate	Standard error		
Intercept***	-1.859	0.287	-	-
BRAND**	0.645	0.323	0.148	0.237
Ln(EMPLOYEES)***	0.179	0.051	$3.919*10^{-4}$	5.4748
Likelihood Ratio***	36.313			
Pseudo R^2	0.085			
AIC	397.152			
Observations	334			
	Correct Prediction	Actual		
Have repeated recalls	43 (38.05)	113		
No repeated recalls	195 (88.24)	221		
Total	238 (71.26)	334		

Note: 1) ***, **are significant at the 1 and 5 percent level, respectively.
    2) Numbers in parentheses are row percents correctly predicted

Table 21. Effect of Brand and Firm Size on the Occurrence of the Repeated Recall Event Using the Probit Model

Variable	Coefficient		Marginal Effect	Mean
	Estimate	Standard error		
Intercept***	-1.132	0.170	-	-
BRAND**	0.399	0.201	0.149	0.237
Ln(EMPLOYEES)***	0.109	0.031	$3.932*10^{-4}$	5.4748
Likelihood Ratio***	36.197			
Pseudo R^2	0.085			
AIC	397.267			
Observations	334			
	Correct Prediction	Actual		
Have repeated recalls	44 (38.94)	113		
No repeated recalls	195 (88.24)	221		
Total	239 (71.56)	334		

Note: 1) ***, **are significant at the 1 and 5 percent level, respectively.
     2) Numbers in parentheses are row percents correctly predicted

As shown in table 20 and table 21, the estimated coefficients of BRAND and Ln(EMPLOYEES) are positive and statistically significant at the 5 percent level or the lower level. Hence, these coefficients suggest that a firm having a brand and firm size have a positive relationship to the probability of the occurrence of the repeated recall event by the firm. A sign of an effect of an independent variable on a dependent variable is determined by the sign of the estimated parameter of the independent variable (Wooldridge 2002). Furthermore, in this study, the positive sign of the estimated coefficient can be interpreted that the variable is associated with worse performance in terms of food safety. Although, the sign of the estimated parameter is adequate to define whether the independent variable has a positive or negative effect on the dependent

variable, the magnitude of the parameter is not meaningful to explain about the magnitude of the effect (Wooldridge 2009).

The estimated marginal effects are especially important for determining the magnitude of the effects of the explanatory variables on the dependent variable. The marginal effects indicate how much the probability of the event changes when changing a given independent variable by one unit and holding the other variables constant. The results from both probit and logit approaches provided approximately the same values of the marginal effect of branding and firm size. The marginal effect of BRAND suggests that companies with a brand or branded companies are around 15 percent more likely to have a recurrence of a recall event compared to those with no brand.

The estimated marginal effect of Ln(EMPLOYEES) is difficult to interpret. By definition the marginal effect estimate indicates that a 1-percent increase in company size or the number of employees increases the likelihood of the occurrence of the repeated recall event by about 0.04 percent. Even though, the effect of the number of employees seems to be very small, 0.04 percent, it is still meaningful because it is statistically significant. For example, consider a single company that doubles employee number because of double shift or operating a new plant, the 100 percent growth in size is associated with a 4-percent rise in probability of the recurrence of the recall event. There are many small firms (around 30 firms) in the dataset for which it is feasible to double employee number by only hiring 3 to 10 more people.

The goodness of fit for the model can be measured by various statistics; likelihood ratio (LR), pseudo R^2, and AIC. Both of the two approaches: logit and probit

have similar values of the statistics for all the goodness of fit measures. The LR statistic indicates the overall model significance. In the logit and probit model, the LR statistics are 36.313 and 36.197 respectively. Furthermore, the LR statistics are both significant at the 1 percent level. This suggests that these two models have a very significant explanatory power. The pseudo R^2 for the two approaches is 0.085. This pseudo R^2 is suggested by McFadden (1974) and also called the likelihood ratio index (LRI). The LRI indicates a perfect fit. The more LRI increases, the better the model fits (Greene 2003). The AIC values of the logit and probit models are 397.152 and 397.267, respectively. The AIC is also a fit measure of the model and can be used as a criterion of a model selection. Among different models, the smallest AIC value is represented the best.

The last goodness-of-fit measure provided is the percent correctly predicted. The logit and probit models have the similar percents correctly predicted as well. The overall percents correctly predicted of the logit and probit models are 71.26 and 71.56 percent, respectively. These values indicate that the overall models predict well.

However, some questions about correct prediction are remaining. For each of the outcome, the percents correctly predicted are different within the same model but similar between the logit and probit models. Both models are more successful in the prediction of the event that the repeated recall does not occur with 88 percent correctly predicted than the event that occurs. The percents correctly predicted for the event that the repeated recall occurs are 38 percent for the logit model and 39 percent for the probit model. The less correctly predicted for the event that the repeated recall occurs may be caused by the threshold value of 0.5 that we chose. Greene (2003) asserted that even

though the value of 0.5 is a common threshold, it may not always be the good choice to select in all cases such as the unbalanced data. If the data has many more observations that the event occurs ($y_i = 1$), or vice versa ($y_i = 0$), by using the threshold value of 0.5 the model is hardly to predict the zero outcomes, or vice versa (the one outcomes). While our data are not perfectly balanced, the 34-percent ones are sufficient to lead us to conclude that imbalance is not a severe problem in assessing goodness of fit.

Additional Results

Before we decided to choose the Ln(EMPLOYEES) variables to be a firm size variable in the model 1 and the model 2, we tested many different forms of size variables; size categorical variables by the Jenks natural breaks method, size categorical variables by the Quantile method, the number of employees (EMPLOYEES), and the number of employees in thousand units (EMPLOYEES_TH). Since the results from logit regressions and probit regressions are very similar, only the results from logit regressions are included in this study. The results are shown in table 24 through table 27 in Appendix B.

For all of the models using different forms of firm size variables, the results on branding are consistent with the results from Model 1 and Model 2 (table 20 and table 21). That is, branded companies are positively and statistically significantly associated with recurrence of a recall event. In other words, companies with a brand are more likely to have a recurrence of a recall event compared to those with no brand. The likelihoods

are around 18 to 25 percent greater for branded companies than nonbranded, depending on forms of firm size variables used.

For studying the effect of firm size, first we used the size categorical variables. The size categorical variables are SIZE 1, SIZE 2, SIZE 3, SIZE 4, and SIZE 5 which are each binary variables. In the model, since we have 5 categories of firm size, we put only 4 categorical variables; SIZE 1, SIZE 2, SIZE 3, and SIZE 4 and leave 1 categorical variable, SIZE 5, out of the model to prevent the perfect multicollinearity problem. Hence, the interpretation of each size categorical variable is each firm size compared to firm size of 5 which is the reference size. For example, SIZE 1 represents firm size 1 compare to firm size 5.

Two options of categorizing companies to the 5 size groups were studied: Jenks natural breaks method and Quantile method. In the model using size categorical variables by the Jenks natural breaks method, all 4 size categorical variables are not statistically significant. However, we noticed that SIZE 1, SIZE 2, and SIZE 3 have negatively nonsignificant effects on the probability that a firm has a recurrence of a recall event, while SIZE 4 has a positive nonsignificant effect on the probability. Even though, the firm size categorical variables by the Jenks natural breaks method are not statistically significant, the coefficient sign indicates that a firm that has a smaller size compared size of 5 is less likely to have a repeated recall event than a firm of size of 5 .

For the model using the Quantile size categorical variables, the estimated coefficients of SIZE 1, SIZE 2, and SIZE 3 are negative and statistically significant at the 5 percent level or the higher level. Nevertheless, the estimated coefficient of SIZE4

is negative but not statistically significant. Since, marginal effects are more meaningful than the estimated coefficients, we must interpret effects of variables from marginal effects. The marginal effect of SIZE 1 suggests that size 1 companies are about 23 percent less likely to have a recurrence of a recall event compared to size 5 companies. Similarly, the marginal effect of SIZE 2 and SIZE 3 suggest that compared to size 5 companies, the size 2 and size 3 companies are less likely to have a recurrence of a recall event by 26 and 23 percent, respectively.

In general, by using size categorical variables to represent firm size, we may conclude that the smaller firm sizes are less likely to have a repeated recall event than the largest firm size (size 5). The limitation for using size categorical variables is that the estimated marginal effects only show a tendency of a probability of smaller firm sizes comparing to the largest firm size. Hence, it is difficult to find the explanation of a marginal increasing in firm size. Moreover, since we determined firm size categories by a range of a number of employees, some size categories have very wide ranges of the number of employees so they become very difficult to interpret or to find the best number of employees for representing each size category. Also it is not clear that the two categorical methods that we used would create the firm size categories that can be the good representation of firm size.

These are the reasons why we turn back to the raw number of employees in order to determine firm size. For the model using the number of employees as a firm size variable, the coefficient of EMPLOYEES variable is positive and statistically significant. The result of the marginal effect suggests that a one employee increase in

firm size raises the probability that the firm has a recurrence of a recall event by about $2*10^{-6}$. Because of a very small value of the marginal effect of EMPLOYEES variable, we tried other transformations of the number of employees variables.

For the model using the number of employees in thousands (EMPLOYEES_TH), the results are consistent with the model using EMPLOYEES variable. The marginal effect of EMPLOYEES_TH variable indicates that a one thousand employee increase in firm size raises the likelihood that the firm has a recurrence of a recall event by about 0.002 percent. In this model, a limitation still exists because an increasing of one thousand employees in small firms may not be practical. For example, in the data, the smallest firm has only three employees. An expansion of the firm by one thousand employees is difficult to be possible. Thus, for small firms, the interpretation of the marginal effect of EMPLOYEES_TH is not quite useful.

At last we decided to use the natural log of the number of employees to represent the firm size. This is because the log form allows for possible diminishing marginal effects. Consider a very small firm in the data set that has only three employees, if the firm hires one more person, this can lead to a substantial effect on the production or the complexity within the firm. While considering a very large firm in the data set with a hundred thousand of employees, hiring one more person will have much less impact to the firm comparative to the very small firm. Hence, the good way to capture the possible diminishing effect of additional employee is to use the log transformation of the number of employees.

In summary, even though, there are some limitations exist in the models using these different forms of size variables, the results of branding and firm size are always consistent with the models we selected (model 1 and model 2). That is, a firm that has a brand is more likely to have a repeated recall event than a firm that has no brand. And the probability that a firm has a recurrence of a recall event increases as firm size increases.

Discussion

In this part, the two major finding associated with branding and firm size will be discussed and also the reasonable plausible explanations will be provided.

Branding

The first major finding is that a company that has a brand is more likely to have a recurrence of a food recall event associated with pathogenic contamination than a company without a brand. This finding is consistent with the results from Joy (2010). Joy (2010) found that branding by the firm raises the risk of recurrence of food recall incidences. However, the finding contradicts to what we expected based on other literature. Branding is often viewed as a key signal of high quality or safe products (Lawrence, Schroeder, and Hayenga 2001; Milgrom and Roberts 1986; Ollinger and Mueller 2003). Thus, the belief that branded products have higher quality and are safer than non-branded products may be wrong. Several plausible explanations for this result are provided in the following.

The first plausible explanation is that a branded company may have substantial concern about its brand and reputation, thus the company may adopt a proactive-recall strategy in order to protect them. The firm may want to accept the recall costs of the proactive action rather than losing its reputation. "The expenses required to remove the product from the market may be minor compared to the lost consumer confidence, damaged brand strength, and reduced sales that follow the bad publicity" (Dwyer 1999 as cited by Skees, Botts, and Zeuli 2001, p. 100).

Furthermore, a support statement why a firm would like to make a proactive recall is that it can lessen the negative effect from the recall incident by getting positive perceptions from consumers such as firm's trustworthiness (Chen, Ganesan and Liu 2009; Siomkos and Kurzbard 1994).

The reason why a firm is very concerned about its reputation is that a positive reputation can be interpreted as an insurance against problematic incidents. Several researchers also pointed out that the effect of product-harm crisis is relatively small on a firm that is well-known and has a positive image when comparing to an unknown firm. The study by Siomkos and Kurzbard (1994) found that in a product-harm crisis, a well known and high-reputation firm receives less negative effect from consumers' future purchases and their perceptions than a low-reputation firm. Hence, damaging a reputation can be very costly. It would damage the firm more to delay or avoid a recall and later be implicated.

Especially, in our study we focused solely on microbiological contamination recall events that can cause severe health problems to consumers and gain lots of

attention in public. Thus, it is possible that if a branded firm suspect contaminated products, even before any consumers' health problems have been reported, the firm will step forward and act responsibly by making a recall in order to minimize the negative effect from the recall incident and maintain positive consumers' perceptions and its positive reputation.

The second plausible explanation is that a firm that produces branded products can be tracked and identified more easily than a firm that produces unbranded products. This is caused by the imperfect linkage between the cause of foodborne sickness and the product. For example, meat and poultry processing plants usually produces branded products, so the processor is more easily revealed and linked to contaminated products than meat and poultry slaughter plants. On the other hand, slaughter products are often unbranded and can be co-mingled with identical products from others suppliers by a buyer. Hence, the producer's identity is obscure and difficult to identify by a buyer or consumer (Lawrence, Schroeder, and Hayenga 2001; Ollinger and Mueller 2003). Thus, the firm with a brand may have more probability of being reported by consumers for causing foodborne illness than the firm with no brand.

For the third plausible explanation, if a firm that produces branded products has more than one brand, the negative effect from a recurrence of a recall event may be lessened by a broad range of product lines under several brand names. Consumers may not be aware that the products with different brand names are manufactured by the same company. Since, the company name is not recognized by customers consuming its products under several brand names, the negative effect from a recall event from one

brand will not affect the other brands within the same company. For example, few customers recognize that Bisquick, Gold Medal and Betty Crocker are produced by General Mills. If Gold Medal products have a problem, both products from Bisquick and Betty Crocker will not have a negative effect associated with Gold Medal's problem. This will be possible unless the media brings up the issue about the connection between these three brand names. Additionally, if the company produces products with different brand names but in the same product area, customers may think that the different brand names are competitors (Siomkos and Kurzbard 1994). The result is that a product recall may not hurt the company because consumers switch to buy the other brands within the same company.

The final plausible explanation is that the firm may create new additional brand names in order to offset the negative effect that is caused by the recall problem of the previous brand name. It may be possible that every time a firm has a recall it may created a new brand name with a little investment. Hence, a firm with multiple brands may have more likelihood to have a repeated recall event. This plausible explanation is also linked to the previous explanation that most of the consumers cannot link between the difference brand names which are created by the same company. Moreover, the loss from a product-harm crisis is specific to one brand and does not affects the other brands within the same company.

Firm Size

The second major finding is that a growing of firm size increases the probability of a recurrence of a food recall event caused by pathogenic contamination. This finding is consistent with our expectation and Joy (2010). Furthermore, the finding is also in line with the economic concepts suggested by Coase (1937) and Williamson (1981) and the bounded rationality concept proposed by Simon (1961). The larger firm size is, the more inefficient the firm becomes. The greater inefficient stemming from the limitations of the management's ability may reduce product safety.

Furthermore, it is more difficult for the larger firm to improve the food safety control practices compared with the smaller one due to complexities within the larger firm. Hence, the costs of improvement on the food safety control sector may very expensive for the larger firm than the smaller one. For example, a large company that had one recall event may want to improve its performance on food safety control. However, it may be difficult to achieve the goal. Therefore, a recall event may happen again. This idea is supported by Ollinger and Mueller (2003) who stated that "larger plants will find it more costly to reduce percent-deficient of SPCPs than smaller plants" (p.26). They also asserted that, to comply with quality standards, larger plants may face a comparatively higher cost than smaller ones. Next, we will propose other feasible explanations for this major finding in the following.

For the first feasible explanation, since the economies of scale within the firm is important in food industries, the larger firm may attempt to generate economies of scale in the food safety process control sector. By not realizing the potential limits of bounded

rationality, the firm may face with the food safety problem. For example, if the firm increases its size but does not hire more QA or QC personnel in order to get benefits from economies of scale, increasing the amount of products or expanding with differentiated in product types can limit the worker's ability toward maintaining safety of the products. The result is that the less safe products may be produced to the market. Additionally, the firm succeeds in achieving economies of scale in production operation through fast or mechanized operation. This produces more at lower average cost but is more complex to monitor.

The second feasible explanation for risk of recall to increase with size is that large firms produce very large volumes of products. Hence, the likelihood of an incident that a consumer gets sick from foodborne illnesses leading to an announcement of a product recall is a lot greater, holding everything else equal. Therefore, larger firms producing larger volume of products tend to have more chance to make recalls than smaller ones.

The final feasible explanation is connected with the previous explanation. That is, smaller firms produce at a smaller volume of products and the products are consumed by fewer consumers. Even though, the firms realize that the products are contaminated, they may not announce a recall if the problem has not been noticed in the public. There are many possible reasons for small firms to avoid making a recall.

The first reason is that the recall costs including announcing the recall, removing, and replacing the products are very high. The small firm may unable to handle these costs, thus they end up with not implementing a recall. The second reason is that there is

small likelihood of a consumer to get sick from the contaminated products because small firms produce a small amount of products which are consumed by a few consumers. Thus, the small firm may risk on a little chance that food safety problem will occur yet not be discovered. The third reason is that the small firm may fear to have a large reduction of returns to shareholders after a recall event. For example, in the study of Salin and Hooker (2001), they found that the returns to shareholders of the smallest firm, Odwalla, dropped instantaneously after the recall event.

However, the decision to announce a product recall depends on the severity of the food contamination problem. If the contamination problem is severe, a firm may choose to announce a product recall. It will damage the firms' reputation badly and create tremendous losses later due to the bad publicity, if they do not take a responsibility by making a recall.

In the opposite view, an alternative plausible explanation is that smaller firms may have more safety process control than the larger ones. The reason is that the smaller firms may have a greater fear to have a recall event so they try the best to prevent or at least have less of the recurrence of a recall event. The greater fear might be the fear for the large recall costs that may cause the firm hardly to survive or the fear of a large reduction of returns to shareholders due to a recall event. This explanation is also consistent with the finding from Ollinger and Mueller (2003) that the smaller meat and poultry plants had a lower proportion of critical deficient SPCPs than the larger plants.

CHAPTER VI

CONCLUSIONS

This study examined the effect of branding and firm size on the probability that a firm has a recurrence of a recall event associated with microbiological contamination, in the U.S. from January, 2000 through October, 2009. The total food recall events involved with pathogenic contamination in this period is 1,394 recall events that were issued by 1,005 companies. The number of food recall events associated with pathogenic contamination has been growing recently. This has resulted in extensive concerns for consumers, government and food companies.

The first major finding is that firms that produce branded products are associated with worse performance in terms of food safety. The firms with brand are around 15 percent more likely to have a recurrence of a recall event than firms producing unbranded product. This finding opposes to what we expected, that branded firm would perform better than a firm without brand. Branding has been commonly inferred as a key signal of high quality or safe products (Lawrence, Schroeder, and Hayenga 2001; Milgrom and Roberts 1986; Ollinger and Mueller 2003). Thus, the confidence that branded products have higher quality and are safer than nonbranded products may be mistaken. We provide several possible explanations in the following.

Branded companies may try to protect their brands and positive reputations by adopting the proactive-recall strategy. Since they depend more on consumers' perceptions, the brand owner publicly issues a recall to apologize and warn consumers.

By quickly responding to the problem the company expects to protect its brands and return to normal sales more quickly than if the problem is not acknowledged publicly.

Moreover, firms that produce branded products may be more easily tracked and identified than firms with unbranded products.

Furthermore, firms with more than one brand name may have less negative effect from a recurrence of a recall event, because of compensation from other branded products they have. The loss for a product recall event is specific only to that troubled brand and some consumers cannot link between brand names and the company creating the brand names. Thus, it will not have a negative effect on other brand names within the same company and the firm is able to withstand one or more product recalls. In addition, the firm may create new brand names in order to offset the negative effect due to the recall incidence of the previous brand name.

Finally, it is possible that branding strategies are more common for the types of foods at risk for product recall.

The second major finding is that larger firms are associated with worse performance in terms of food safety comparative to smaller firms. A 1-percent increase in firm size as measured by the number of employees increases the likelihood of firm to have the recurrence of a recall event by about 0.04 percent. This worse performance due to the size of firm is consistent to the expectation based on the bounded rationality concept. Large firms may face limitations of the management's ability and more complexities within the firms. Thus, after a first recall event, improving the food safety

control efforts in larger firms may have more difficulties than in the smaller ones. We proposed several possible explanations for this finding.

The larger firm may attempt to create economies of scale in the overall production process, but is not able to assure benefits in safety and quality along with the increased production.

Moreover, very large amount of products are produced by larger firms. For example, in meat and poultry processing industry, many manufacturers such as Tyson Foods, Inc. have slaughtering and processing plants that produce products in millions of pounds. Hence, the likelihood of a consumer getting sick from foodborne illnesses that lead the firms to announce a product recall is greater. On the other hand, due to the small volume of products produced by smaller firm, the smaller firm may have an incentive to not announce a recall if the problem has not been noticed in the public.

The findings from this study can have implications for policy makers and also managers of private sectors, food companies. The policy makers should not take branding as an indicator of food safety performance. Since the large company or branded company tend to have more risk of making a repeated recall event caused by pathogens, policy makers should pay extra attentions to these types of companies. They may carefully observe the food safety control efforts of these types of firms by using more strict regulations or providing alternative standards in order to prevent severe foodborne illnesses that may happen with their food.

In case of the private sectors or food companies, they should view product recall as one of many management tools. In addition, if they are large firms or branded firms,

the implication may be that they should take the results as guidelines for their food safety control standards. For example, they may take more precautions or put more efforts on their safety in the process control sectors since the high comparative probability of having a recurrence of recall event.

The study also has a limitation on the data resource. We used the data of food recall events as an inference of food safety quality. Although, this is the best data that we could obtain, someone may view the food recall events data as inadequate data. The main weakness is that FSIS or FDA only takes a random sample of food products and does not examine all products. FDA also rarely samples and tests products. Hence, we cannot infer that all of the product that has no recall will be safe. Thus, the further research we suggested is that we may use alternative measure for food quality control effort.

In addition, further possible research is the developing of the same model used in this study by including other factors which may be significantly associated with product recalls such as the product types. Furthermore, future research may employ more complex models as the alternative model approaches such as ordered logit, ordered probit, multinomial logit, or multinomial probit. These methods are examples that might be helpful to understanding about food safety problems.

REFERENCES

Amemiya, T. 1981. Qualitative Response Models: A Survey. *Journal of Economic Literature* 19 (4) (Dec.): 1483-1536.

Besanko, D. 2010. *Economics of Strategy*. Hoboken, NJ: John Wiley & Sons.

Bessler, D. A. 2009. Directed Acyclic Graphs and Algorithms of Inductive Causation. Lecture presented at Texas A&M University, College Station.

Centers for Disease Control and Prevention (CDC). 2011. *Investigation Update: Multistate Outbreak of Listeriosis Linked to Whole Cantaloupes from Jensen Farms, Colorado*. http://www.cdc.gov/listeria/outbreaks/cantaloupes-jensen-farms/110211/index.html (accessed Nov. 20, 2011).

———. 2009. *Investigation Update: Outbreak of Salmonella Typhimurium Infections, 2008–2009.* http://www.cdc.gov/salmonella/typhimurium/update.html (accessed Nov. 20, 2011).

Chen, Y., S. Ganesan, and Y. Liu. 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) (Nov.): 214-26.

Coase, R. H. 1937. The Nature of the Firm. *Economica* 4 (16) (Nov.): 386-405.

Duewer, L. A. and K. E. Nelson. 1991. *Beefpacking and Processing Plants: Computer-Assisted Cost Analysis*. Washington, D.C.: U.S. Department of Agriculture, Economic Research Service, Staff report AGES 9115.

Dwyer, S. 1999. Is Your Brand Bullet Proof? *Prepared Foods*. June.

Greene, W. H. 2003. *Econometric Analysis*. Upper Saddle River, N.J.: Prentice Hall.

Gujarati, D. N. 1995. *Basic Econometrics*. New York: McGraw-Hill.

Hoover's Inc. 2009. *Business Solutions from Hoovers*. 2009. www.hoovers.com (accessed 2009).

Jenks, G. F. 1967. The Data Model Concept in Statistical Mapping. *International Yearbook of Cartography* 7: 186−190.

Jolly, D.W. and J.C. Mowen. 1984. Product Recall Communications: The Effects of Source, Media, and Social Responsibility Information. *Advances in Consumer Research* 12: 471-475.

Joy, N. A. 2010. A Duration Analysis of Food Safety Recall Events in the United States: January, 2000 to October, 2009. Master's thesis, Texas A&M University.

Lawrence, J. D., T. C. Schroeder, and M. L. Hayenga. 2001. Evolving Producer-Packer-Customer Linkages in the Beef and Pork Industries. *Review of Agricultural Economics* 23 (2) (Autumn - Winter): 370-385.

MacDonald, J., M. Ollinger, K. Nelson, and C. Handy. 2000. *Consolidation in U.S. Meatpacking*. Washington, D.C.: U.S. Department of Agriculture, Economic Research Service, Agricultural Economic, Report No. 785.

MacDonald, J. M. and M. E. Ollinger. 2000. Scale Economies and Consolidation in Hog Slaughter. *American Journal of Agricultural Economics* 82 (2) (May): 334-346.

McFadden, D. 1974. The Measurement of Urban Travel Demand. *Journal of Public Economics* 3: 303-328

Milgrom, P. and J. Roberts. 1986. Price and Advertising Signals of Product Quality. *Journal of Political Economy* 94 (4) (Aug.): 796-821.

Nelson, Phillip. 1974. Advertising As Information. *Journal of Political Economy* 82 (4) (Jul. - Aug.): 729-754.

———. 1970. Information and Consumer Behavior. *Journal of Political Economy* 78 (2) (Mar. - Apr.): 311-329.

Ollinger, M., J. M. MacDonald, and M. Madison. 2000. *Structural Change in U.S. Chicken and Turkey Slaughter*. Washington, D.C.: U.S. Department of Agriculture, Economic Research Service, Report No. 787.

Ollinger, M. and V. Mueller. 2003. *Managing for Safer Food: The Economics of Sanitation and Process Controls in Meat and Poultry Plants.* Washington, D.C.: U.S. Dept. of Agriculture, Economic Research Service, Report No. 817.

Piggott, N. E. and T. L. Marsh. 2004. Does Food Safety Information Impact U.S. Meat Demand? *American Journal of Agricultural Economics* 86 (1) (Feb.): 154-174.

Salin, V. and N. H. Hooker. 2001. Stock Market Reaction to Food Recalls. *Review of Agricultural Economics* 23 (1) (Spring - Summer): 33-46.

Scallan, E., P. M. Griffin, F. J. Angulo, R. V. Tauxe, and R. M. Hoekstra. 2011a. Foodborne Illness Acquired in the United States--Unspecified Agents. *Emerging Infectious Diseases* 17 (1) (Jan): 16-22.

Scallan, E., R. M. Hoekstra, F. J. Angulo, R. V. Tauxe, M. A. Widdowson, S. L. Roy, J. L. Jones, and P. M. Griffin. 2011b. Foodborne Illness Acquired in the United States--Major Pathogens. *Emerging Infectious Diseases* 17 (1) (Jan): 7-15.

Sersland, C. J. 1985. *Cost Analysis of the Steer and Heifer Processing Industry and Implications on Long-Run Industry Structure.* Ph.D. Dissertation, Oklahoma State University, Stillwater, OK.

Shrivastava, P. and G. J. Siomkos. Disaster Containment Strategies. 1989. *Journal of Business Strategy* 10 (5): 26-30.

Siegel, D. S. and D. F. Vitaliano. 2007. An Empirical Analysis of the Strategic Use of Corporate Social Responsibility. *Journal of Economics & Management Strategy* 16 (3): 773-92.

Simon, H. A. 1955. A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics* 69 (1) (Feb.): 99-118.

Siomkos, G. and G. Kurzbard. 1994. The Hidden Crisis in Product-Harm Crisis Management. *European Journal of Marketing* 28 (2): 30-41.

Size Standards Division Office of Government Contracting & Business Development. 2009. *SBA Size Standards Methodology.* http://www.sba.gov/sites/default/files/size_standards_methodology.pdf (accessed Jul., 2011).

Skees, J. R., A. Botts, and K. A. Zeuli. 2001. The Potential for Recall Insurance to Improve Food Safety. *The International Food and Agribusiness Management Review* 4 (1): 99-111.

Train, K. 2009. *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press.

United States Department of Agriculture: Food Safety and Inspection Service (FSIS). 2009. *Recall Case Archive.*

http://www.fsis.usda.gov/Fsis_Recalls/Recall_Case_Archive/index.asp
(accessed 2009).

———. 2011. *FSIS Food Recalls.*
http://www.fsis.usda.gov/Fact_Sheets/FSIS_Food_Recalls/index.asp (accessed
2011).

United States Food and Drug Administration (FDA). 2009a. *Archive for Recalls, Market
Withdrawals & Safety Alerts*.
http://www.fda.gov/Safety/Recalls/ArchiveRecalls/default.htm (accessed
2009).

———. 2009b. *Peanut Butter and Other Peanut Containing Products Recall List*.
http://www.accessdata.fda.gov/scripts/peanutbutterrecall/index.cfm (accessed
Nov. 20, 2011).

Ward, C. E. 1993. Comparative Analysis of Cattle Slaughtering and Fabricating Costs.
Agribusiness 9 (5): 441-51.

Weiss, M. D. 1995. Information Issues for Principals and Agents in the "Market" for
Food Safety and Nutrition. In J. Caswell (Ed.), *Valuing Food Safety and
Nutrition.,* 69-79. Boulder, CO: Westview Press.

Williamson, O. E. 1981. The Economics of Organization: The Transaction Cost
Approach. *American Journal of Sociology* 87 (3) (Nov.): 548-577.

Wooldridge, J. M. 2009. *Introductory Econometrics : A Modern Approach*. Mason,

    Ohio: South-Western Cengage Learning.

———. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge,

    Mass.: MIT Press.

APPENDIX A

ADDITIONAL TABLES

Table 22. Top 39 Companies from All of 1,005 Companies in the Food Recall Event Data Ranked by Number of Recalls

Rank	Company Name	Number of Recalls	Product Type of Recalls	Brand Binary	Employees	Sales (Million Dollars)
1	The Kroger Co.	13	Dairy(5), Nut(3), Meat(2), Others(1), Fruit-Vegetables(1), Confectionary-Bakery(1)	1	32,6000	76,000.0
2	Cargill, Incorporated	12	Meat(12)	1	160,000	120,439.0
2	Whole Foods Market, Inc.	12	Nut(7), Meat(2), Confectionary-Bakery (2), Others(1)	1	52,900	7,953.9
3	Kellogg Company	9	Confectionary-Bakery (6), Nut(3)	1	32,400	12,822.0
4	Supervalu Inc.	8	Meat(4), Dairy(2), Confectionary-Bakery(1), Nut(1)	1	178,000	44,564.0
5	Giant Food Inc.	7	Dairy(5), Meat(1), Nut(1)	1	27,000	N/A
5	Tyson Food, Inc.	7	Meat(7)	1	107,000	26,862.0
5	Harry & David Holdings, Inc.	7	Meat(3), Confectionary-Bakery(1)	1	1,321	545.1
5	Peregrina Cheese Corporation	7	Dairy(7)	0	N/A	N/A
6	Kraft Foods Inc.	6	Nut(2), Confectionary-Bakery(1), Dairy(1), Others(1), Meat(1)	1	98,000	42,201.0
6	Smithfield Foods, Inc.	6	Meat(6)	1	52,400	11,200.0
6	ALDI Group	6	Confectionary-Bakery (3), Fruit-Vegetables(1), Nut(1), Meat(1)	1	885	65,700.0
6	John B. Sanfilippo & Son, Inc	6	Nut(6)	0	1,350	553.8
6	New Era Canning Company	6	Fruit-Vegetables(6)	0	250	34.1
7	Dean Foods Company	5	Dairy(5)	1	25,820	12,454.6
7	General Mills, Inc.	5	Confectionary-Bakery (2), Fruit-Vegetables(1), Nut(1), Meat(1)	1	30,000	13,652.1

Table 22. Continued

Rank	Company Name	Number of Recalls	Product Type of Recalls	Brand Binary	Employees	Sales (Million Dollars)
7	Hanover Foods Corporation	5	Meat(2), Others(2)	1	2,205	290.3
7	Swiss-American, Inc.	5	Dairy(5)	1	100	N/A
7	Betty Lou's, Inc.	5	Confectionary-Bakery (4), Nut(1)	0	75	7.3
7	Palmer Candy Company	5	Nut(4), Confectionary-Bakery(1)	0	130	18.6
7	Ralcorp Holdings, Inc.	5	Confectionary-Bakery (4), Nut(1)	1	9,000	2,824.4
7	Eilleen's Candies, Inc.	5	Confectionary-Bakery(5)	0	N/A	N/A
7	GKI Foods Inc.	5	Nut(5)	0	N/A	N/A
7	Union International Food Company	5	Fruit-Vegetables(5)	0	N/A	N/A
8	Rosen's Diversified, Inc.	4	Meat(4)	0	8,000	N/A
8	Clearly Canadian Beverage Corporation	4	Confectionary-Bakery (2), Nut(2)	1	36	10.6
8	Kerry Group plc	4	Nut(3), Confectionary-Bakery(1)	1	22,008	6,752.6
8	Publix Super Markets, Inc.	4	Nut(3), Confectionary-Bakery(1)	0	144,000	24,109.6
8	Golden Taste, Inc.	4	Meat(3), Confectionary-Bakery(1)	0	13	1.0
8	Lance, Inc.	4	Confectionary-Bakery(4)	1	4,800	825.5
8	Meijer, Inc.	4	Dairy(2), Meat(1), Confectionary-Bakery(1)	0	60,000	13,700
8	Nebraska Beef, Ltd	4	Meat(4)	0	1,000	96.3
8	PRG Packing Corp	4	Meat(4)	0	96	15.5
8	Rich Ice Cream Co.	4	Dairy(3), Confectionary-Bakery(1)	0	134	11.6
8	Walgreen Co.	4	Confectionary-Bakery (2), Nut(2)	1	238,000	63,335
8	House of Flavors Ice Cream Company	4	Dairy(4)	0	N/A	N/A
8	Mountain Man Nut & Fruit Co.	4	Nut(4)	0	N/A	N/A
8	Peanut Corporation of America	4	Nut(4)	0	N/A	N/A
8	Setton International Foods, Inc.	4	Nut(4)	0	N/A	N/A

Source: Data from FSIS 2009; FDA 2009a; Hoover's Inc. 2009
Note: 1) If a company has a brand, Brand Binary equals one, otherwise zero.
    2) Numbers in parentheses are numbers of recalls for each product type.

Table 23. Top 31 Companies from All of 334 Companies Used in the Models Ranked by Number of Recalls

Rank	Company Name	Number of Recalls	Product Type of Recalls	Brand Binary	Employees	Sales (Million Dollars)
1	The Kroger Co.	13	Dairy(5),Nut(3), Meat(2),Others(1), Fruit-Vegetables(1), Confectionary-Bakery(1)	1	326,000	76,000.0
2	Cargill, Incorporated	12	Meat(12)	1	160,000	120,439.0
2	Whole Foods Market, Inc.	12	Nut(7), Meat(2), Confectionary-Bakery (2), Others(1)	1	52,900	7,953.9
3	Kellogg Company	9	Confectionary-Bakery (6), Nut(3)	1	32,400	12,822.0
4	Supervalu Inc.	8	Meat(4), Dairy(2), Nut(1), Confectionary-Bakery (1)	1	178,000	44,564.0
5	Giant Food Inc.	7	Dairy(5), Meat(1), Nut(1)	1	27,000	N/A
5	Tyson Foods, Inc.	7	Meats(7)	1	107,000	26,862.0
5	Harry & David Holdings, Inc.	7	Meat(3), Confectionary-Bakery(4)	1	1,321	545.1
6	Kraft Foods Inc	6	Nut(2), Dairy(1), Others(1), Meat(1), Confectionary-Bakery(1),	1	98,000	42,201.0
6	Smithfield Foods, Inc.	6	Meat(6)	1	52,400	11,200.0
6	ALDI Group	6	Confectionary-Bakery (3), Fruit-Vegetables(1), Nut(1), Meat(1)	1	885	65,700.0
6	John B. Sanfilippo & Son, Inc.	6	Nut(6)	0	1,350	553.8
6	New Era Canning Company	6	Fruit-Vegetables (6)	0	250	34.1
7	Dean Foods Company	5	Dairy(5)	1	25,820	12,454.6
7	General Mills, Inc	5	Confectionary-Bakery (2), Fruit-Vegetables(1), Nut(1), Meat(1)	1	30,000	13,652.1
7	Hanover Foods Corporation	5	Meat(2), Others(3)	1	2,205	290.3
7	Swiss-American, Inc.	5	Dairy(5)	1	100	N/A
7	Betty Lou's, Inc.	5	Confectionary-Bakery (4), Nut(1)	0	75	7.3
7	Palmer Candy Company	5	Nut(4), Confectionary-Bakery(1)	0	130	18.6

Table 23. Continued

Rank	Company Name	Number of Recalls	Product Type of Recalls	Brand Binary	Employees	Sales (Million Dollars)
7	Ralcorp Holdings, Inc.	5	Confectionary-Bakery (4), Nut(1)	1	9,000	2,824.4
8	Rosen's Diversified, Inc.	4	Meats(4)	0	8,000	N/A
8	Clearly Canadian Beverage Corporation	4	Confectionary-Bakery (2), Nut(2)	1	36	10.6
8	Kerry Group plc	4	Nut(3), Confectionary-Bakery(1)	1	22,008	6,752.6
8	Publix Super Markets, Inc.	4	Nut(3), Confectionary-Bakery(1)	0	144,000	24,109.6
8	Golden Taste, Inc.	4	Meat(3), Confectionary-Bakery(1)	0	13	1.0
8	Lance, Inc.	4	Confectionary-Bakery(4)	1	4,800	825.5
8	Meijer, Inc.	4	Dairy(2), Meat(1), Confectionary-Bakery(1)	0	60,000	13,700
8	Nebraska Beef, Ltd	4	Meat(4)	0	1,000	96.3
8	PRG Packing Corp	4	Meat(4)	0	96	15.5
8	Rich Ice Cream Co.	4	Dairy(3), Confectionary-Bakery(1)	0	134	11.6
8	Walgreen Co.	4	Confectionary-Bakery (2), Nut(2)	1	238,000	63,335

Source: Data from FSIS 2009; FDA 2009a; Hoover's Inc. 2009

Note: 1) If a company has a brand, Brand Binary equals one, otherwise zero.

2) Numbers in parentheses are numbers of recalls for each product type.

APPENDIX B

ADDITIONAL RESULTS

Table 24. Effect of Brand and Firm Size on the Occurrence of the Repeated Recall Event Using Size Categorical Variables by the Jenks Natural Breaks Method

Variable	Coefficient		Marginal Effect	Mean
	Estimate	Standard error		
Intercept	-0.080	0.913	-	-
BRAND**	0.946	0.303	0.224	0.237
SIZE 1	-1.001	0.909	-0.227	0.865
SIZE 2	-0.140	1.019	-0.035	0.051
SIZE 3	-0.120	1.069	-0.030	0.036
SIZE 4	0.963	1.197	0.227	0.030
Likelihood Ratio***	34.388			
Pseudo R^2	0.080			
AIC	405.077			
Observations	334			
	Correct Prediction	Actual		
Have repeated recalls	26 (23.01)	113		
No repeated recalls	210 (95.02)	221		
Total	236 (70.66)	334		

Note: 1) ***, **are significant at the 1 and 5 percent level, respectively.
2) Numbers in parentheses are row percents correctly predicted

Table 25. Effect of Brand and Firm Size on the Occurrence of the Repeated Recall Event Using Size Categorical Variables by the Quantile Method

Variable	Coefficient		Marginal Effect	Mean
	Estimate	Standard error		
Intercept	-0.139	0.315	-	-
BRAND**	0.747	0.320	0.182	0.237
SIZE 1**	-1.059	0.425	-0.234	0.207
SIZE 2***	-1.233	0.428	-0.263	0.201
SIZE 3**	-1.011	0.406	-0.225	0.198
SIZE 4	-0.504	0.360	-0.121	0.198
Likelihood Ratio***	34.219			
Pseudo R^2	0.080			
AIC	405.245			
Observations	334			
	Correct Prediction	Actual		
Have repeated recalls	43 (38.05)	113		
No repeated recalls	195 (88.24)	221		
Total	238 (71.26)	334		

Note: 1) ***, **are significant at the 1 and 5 percent level, respectively.
2) Numbers in parentheses are row percents correctly predicted

Table 26. Effect of Brand and Firm Size on the Occurrence of the Repeated Recall Event Using the Raw Number of Employees

Variable	Coefficient		Marginal Effect	Mean
	Estimate	Standard error		
Intercept***	-1.061	0.144	-	-
BRAND***	1.043	0.283	0.245	0.237
EMPLOYEES**	$9.733*10^{-6}$	$3.92*10^{-6}$	$1.967*10^{-6}$	12,169.665
Likelihood Ratio***	31.706			
Pseudo R^2	0.074			
AIC	401.759			
Observations	334			
	Correct Prediction	Actual		
Have repeated recalls	34 (30.09)	113		
No repeated recalls	203 (91.86)	221		
Total	237 (70.96)	334		

Note: 1) ***, **are significant at the 1 and 5 percent level, respectively.
2) Numbers in parentheses are row percents correctly predicted

Table 27. Effect of Brand and Firm Size on the Occurrence of the Repeated Recall Event Using the Number of Employees in Thousand Unit

Variable	Coefficient		Marginal Effect	Mean
	Estimate	Standard error		
Intercept***	-1.061	0.144	-	-
BRAND***	1.043	0.283	0.245	0.237
EMPLOYEES_TH**	0.010	0.004	0.002	12.170
Likelihood Ratio***	31.706			
Pseudo R^2	0.074			
AIC	401.759			
Observations	334			
	Correct Prediction	Actual		
Have repeated recalls	34 (30.09)	113		
No repeated recalls	203 (91.86)	221		
Total	237 (70.96)	334		

Note: 1) ***, **are significant at the 1 and 5 percent level, respectively.
2) Numbers in parentheses are row percents correctly predicted

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