AN ABSTRACT OF THE DISSERTATION OF

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Title: Essays on the Effect of Product Recalls and Mergers on Firm Performance

Abstract approved:

Victor J. Tremblay

This dissertation investigates the effect of endogenous and exogenous events on firm behavior and performance. These are fundamental questions in economics. The contribution of this study is threefold. First, it provides estimates of the impact of mergers on railroad efficiency, which has important antitrust implications. Second, it provides new estimates of the effect of negative events on the market value of Johnson & Johnson, Bridgestone, and Toyota, which is important to the understanding of how markets punish corporate errors. Third, it develops better ways to estimate these effects.

Chapter 2 uses the event study approach to determine how product recalls due to exogenous and endogenous shocks affect the value of the firm. Three recalls

from Johnson & Johnson, Bridgestone, and Toyota have been studied in this chapter. The traditional event study method assumes that markets are efficient, a questionable assumption in the short run. Thus, the current stock value of a firm may not reflect its true market value. To address this potential problem, frontier based methods are used, including data envelopment analysis, corrected ordinary least squares, and stochastic frontier regression analysis. Stochastic frontier methods are shown to be more appropriate when market behavior is not fully rational. The evidence shows that endogenous events due to firm errors are more detrimental to firm value than exogenous negative events that are beyond the control of the firm. That is, the market is more forgiving of negative shocks that the company cannot control.

Chapter 3 studies the effects of merger activity on the efficiency and productivity growth of U.S. Class I railroads from 1983 to 2008. In this chapter, I assess the effects of merger activity on efficiency, and identify the major factors associated with productivity growth. Unlike previous research, I use data envelopment analysis with an attribute-incorporated Malmquist productivity index. This approach allows firm specific measures of efficiency and productivity to be calculated for firms with differences in technology. The approach allows a decomposition of the attribute-incorporated Malmquist productivity index into technical, efficient and attribute components, the impacts of railroads mergers, and the real source and change of productivity. I find that (1) the technology efficiency performance of the seven survivor firms has grown through time; (2) mergers overall do not lead significant technology and scale efficiency gains, but there are differences across mergers; (3) mergers in the 1980s do not have significant different effect on efficiency change compared to those in the 1990s; and (4) the productivity gains are mostly attributed to the network and operation attributes change and industry technology improvement. Overall, the mergers have no direct impact on the efficiency gains or losses during our study period.

The application of these techniques to product recalls and railroad merger models demonstrates how they can provide superior estimates over traditional estimation techniques. It is hoped that these applications will motivate the use of these techniques in other settings.

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APPROVED:

Major Professor, representing Economics

Director of the Applied Economics Graduate Program

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Wenfeng Yan, Author

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CONTRIBUTION OF AUTHORS

Dr. Victor J. Tremblay provided ideas and assistance in all aspects of this dissertation. Dr. Wesley Wilson and Dr. Rolf Färe helped with Chapter 3. Jayendra Gokhale helped with generation idea and methodology in Chapter 2.

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Chapter 1

General Introduction

Understanding firm performance is fundamental to the analysis of a market economy. This dissertation addresses one of the major economics research issues— how to evaluate the effect of a major event on firm behavior and performance. I investigate two major firm activities: product recalls and mergers. I am also concerned with research methodology, including the exploration of more suitable methodologies to address the economic effect of a particular event. I conducted comparative studies of traditional and alternative approaches. The goal is to investigate the relationship between the origins of a major event and its influence on the magnitude of a change in the value and performance of a firm.

In Chapter 2, I analyze the economic effect of three negative events: the1982 Tylenol capsule recall, the 2000 Firestone tire recall, and the 2010 Toyota gas pedal recall. Several methods are used. First, I use the traditional market model event study method and compare it to results that use three alternative methods: data envelopment analysis, corrected ordinary least squares, and stochastic frontier analysis. I estimate the short run and the middle run impact of the three events on the value of firms. In order to prevent the influence of overvalue or undervalue, I investigate two types of stochastic frontier methods: the upper and lower stochastic frontier models to control for the problem of misevaluation (e.g., traders overvalue or undervalue the price of a stock).

The results show that the market value of Johnson & Johnson, Bridgestone, and Toyota are significantly influenced by the product recall events in the short and middle run. The traditional market model produces similar results to the upper stochastic frontier approaches for the three recall events. However, the traditional event study is not appropriate when markets are not fully rational. Researchers may need to carefully select one type of stochastic frontier model to offset the influence of overvaluation and undervaluation. I also investigate whether an endogenous negative event is more damaging to the firm than an exogenous negative event. The results show that this is the case.

In Chapter 3, I examine evolution of the level of efficiency and productivity for U.S. Class I railroads during the past three decades, a period when the number of railroad companies dropped from 40 to 7 through mergers and acquisitions. I develop full specific efficiency measures and estimate the effects of mergers on efficiency and productivity performance as well as the real sources of the productivity growth. Different from other studies, I used an AMPI (attribute-incorporated Malmquist productivity index) version data envelopment analysis method, which allows one to measure changes in firm efficiency over time and to decompose the changes into technical, efficient and attribute components by the decomposition of the attribute-incorporated Malmquist productivity index. The analysis helps us to understand the impacts of railroads mergers and the real source and change of productivity.

A few findings emerge from this study. (1) The technology efficiency of the seven survivor firms grows gradually throughout time. (2) The mergers overall do not lead to significant technology and scale efficiency gains. (3) The mergers that occurred in the 1980s did not have significantly different effects on efficiency compared to those in the 1990s. (4) The productivity gains were mostly contributed by the network and operation attributes changes and technology improvement during the study period. Overall, mergers had no direct impact on the efficiency gains or losses over the study period.

This dissertation analyzes the evaluation of the impact of events on a firm’s value and efficiency/productivity performance after a product recall and after a merger. The research provides a better understanding of traditional evaluation methods and proposes alternative stochastic frontier techniques to analyze the economic effect when markets are not fully rational. In addition, this research develops a new index decomposition approach used to evaluate the change of the level of efficiency/productivity and to locate the sources of changes in efficiency/productivity.

Chapter 2

The Effect of Product Recalls on the Value of the Firm: Event Study and Frontier Estimation Techniques

2.1. Introduction

A product recall is a request to return some or all of a product to the maker due to some defect in the product. Product recall occurred when a firm's product fails to comply with a mandatory safety standard, contains a defect that could create a substantial product hazard, creates an unreasonable risk, or fails to comply with a voluntary standard adopted by the specific industry (Mullan 2004). According to the Consumer Product Safety Commission (CPSC), more than 1000 consumer products were recalled in 2010 and 2011 because of safety concerns.[1]

This study has two main objectives. One is to investigate the relationship between the origins of a product recall event and its influence on the magnitude of a change in the value of the firm. Another goal is to propose an alternative way to analyze the economic effect of a negative event when there is overvaluation in the market.

In order to evaluate the impact of a product recall in the short and the middle run, researchers usually use the event study approach. However, the traditional research method is valid only when markets are efficient.

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[1] U.S. Consumer Product Safety Commission, "Recalls and Product Safety News," http://www.cpsc.gov/cpscpub/prerel/prerel.html, accessed January 8, 2012.

In this study, I first use the traditional event study method and three frontier based methods to estimate the short run and middle run impact of three product events. Second, I investigate two types of stochastic frontier methods (upper and lower stochastic frontiers) to control for the misevaluation.

I choose three product recall events (i.e., the 1982 Tylenol capsule recall, the 2000 Firestone tire recall, and the 2010 Toyota gas pedal recall) based on the following considerations. First, all three recall events resulted in disastrous outcomes and brought damage to the companies. Second, the three recall events cover multiple industries and have gone through distinctive courses over the last three decades. Third, each company reacted differently to its negative event.[2]

2.1.1. Product Recalls and Consequences on the Stock Market

A product recall could distort the product's established favorable reputation among the public. The action of a product recall also tarnishes a firm's image and causes major revenue and market-share losses, which can devastate brand equity.

To illustrate, consider the following examples. In 1982, Johnson & Johnson recalled Tylenol capsules nationwide with market retail revenue of over US$100 million after seven people died by taking cyanide-laced Extra-Strength Tylenol capsules (Moore, 1982). In 1999, Coca-Cola was forced to withdraw 30 million cans and bottles in northern Europe following a tainting scare in Belgium.[3] In 2000,

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[2] Johnson & Johnson successfully addressed the problem within one month. Toyota issued a no-electronic-(or mechanic)-wrong investigative report within 10 months. Bridgestone could not eliminate its negative reputation for a lengthy period.
[3] Stephen Bates, "Coke is Banned After Safety Scare," *The Guardian*, June 15, 1999 at http://www.guardian.co.uk/news/1999/jun/16/food.foodanddrink, accessed September 8, 2011.

Bridgestone recalled 6.5 million Firestone tires after news broke that more than a hundred people had died in accidents involving defective tires.[4] More recently, on January 21, 2010, Toyota announced a voluntary recall of approximately 2.3 million vehicles to correct "sticking accelerator pedals" on eight specific Toyota models.[5]

Generally, a product recall brings severe damage to a company's stock market performance due to expected decreases in brand value and future profits. Occasionally, a product recall can occur due to non-product or non-factory related reasons. The extent of damage varies depending not only on the scale of a recall event, but also on the valuation type of the company and the origins of the recall event. The magnitude and length of a shock impact stock market performance.[6] The effect on a firm's stock market performance can be reflected in the short run, the middle run, and the long run.

In the stock market, to value the securities of a company, traders look at a variety of financial data, such as earnings, revenues, and cash flow. Some companies gain a better performance than average market gain, due to a better reputation, financial return, and management team. According to traditional finance theory, efficiency and rationality are the two essential points for a firm's valuation. However, researchers in behavioral finance claim that not all traders are fully rational and thus misevaluation (i.e. overvaluation and undervaluation of stock price) may exist.

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[4] Mark Dodosh, "Firestone Woes Create Opportunity," *Advertising Age*. September 18, 2000 at http://adage.com/article/news/firestone-woes-create-opportunity/56974/, accessed September 8, 2011.
[5] Peter Valdes-Dapena, "Toyota recall: 2.3 million cars," *CNNMoney.com*. January 22, 2010 at http://money.cnn.com/2010/01/21/autos/toyota_recall/, accessed September 8, 2011.
[6] Shocks include endogenous shocks and exogenous shocks.

Barberis, Shleifer and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1997) argue that judgment biases of investors can produce overreaction to the performance news of a company. The empirical findings from Barber, Odean and Zhu (2009) confirm that individual investors are more likely to buy stocks with strong past returns.

Usually, if a company was successful in the past, it will make investors behave more optimistically in the future regarding the company's stocks. Thus, overvaluation is expected in this situation. For example, in our previous examples, Johnson & Johnson, Bridgestone and Toyota are all leading companies in their specialized fields with good market positions and stock market performance prior to the negative event. Thus, behavioral finance theory suggests that it is highly possible that the stocks of these companies will be overvalued.

2.1.2. Introduction of the Event Study Method

In order to evaluate the impact of a product recall in the short run and the middle run, researchers usually use the event study approach. The event study method has been widely used to study economic effects of a positive or negative event, including the impact of an unanticipated product recall on a company's stock return.[7] The event study method focuses on developing estimates of abnormal stock returns attributed to a recall event and measures of post-event period loss in shareholder

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[7] MacKinlay (1997) and Dolley (1933) examined the price effect of stock splits and conducted the first published event study. The seminal articles were published in the late 1960s by Ball and Brown (1967), Fama, Fisher, Jensen, and Roll (1969) and established the foundation for modern event study methodology. The papers by Brown and Warner (1980, 1985) contributed to performance evaluation of different stock data and models using the event study method.

value.[8] Traditionally, to use the event study method to evaluate the impact of a product recall in the short and middle run, researchers employ ordinary least square (OLS) estimates to set up a forecast model and measure the impact of an unanticipated product recall on a company's stock return.

An advantage of the event study method is that researchers do not need to analyze accounting-based measures of profit, which may not reflect true economic profit. Instead, researchers investigate stock price data that is expected to reflect a firm's true market value. The stock price of a firm reflects the discounted value of all expected future profits and incorporates all relevant market information. Due to this reason, the event study is an effective method of estimating the economic impact of a positive or negative unexpected event.

On the other hand, the event study method has certain limitations. For example, it relies on the assumption that markets are efficient, which requires that there is no misevaluation of the stock price in the market. If overvaluation or undervaluation is present, then the stock price does not reflect the true market value of a firm and the event study approach will be invalid.

To address this problem, I explore new methods to evaluate the financial effect of a positive or negative event. In this research, after comparing the results from several frontier-based methods with the conventional setting, I will pick two types of stochastic frontier techniques to explore the evaluation question under the existing of misevaluation problem.

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[8] Abnormal return, the gap between normal stock returns (the percentage change in the value of the security) and the forecasted stock returns, usually assume no company related event has happened.

2.1.3. Introduction of Frontier Estimation Techniques

Frontier analysis is an economic modeling method, which usually includes construction of a best or worst practice frontier against which to evaluate the performance of individual producers or service providers. There are three major frontier estimation approaches: data envelopment analysis (DEA), corrected ordinary least squares (COLS), and stochastic frontier analysis (SFA). A frontier can be classified as upper frontier or lower frontier, depending on the direction of the systematic drift.[9] Two different types of frontier models can be used in different settings based on the questions we are studying. In this study, I discuss how these methods can be used to estimate the economic effect of a positive or a negative event. Additional, if financial markets are efficient, then stock prices constitute the best possible estimate of the net present value of discounted cash flows of a firm (Fama, 1970). When this is true, the event study method provides reliable estimates of an event's impact on a company's value. However, this is not true when some traders are not fully rational.[10] To remedy the misevaluation problem, I use frontier estimation approaches, including the COLS, SFA, and DEA methods. To date, no study in the field of finance has employed all these frontier estimation methods on the issue of the economic impact of a product recall.

Specifically, DEA is a non-parametric mathematical approach that constructs a frontier and measures distance relative to the constructed frontier. In this study,

[9] The systematic drift is another way to express the best or the worst practice frontier. In productivity economics, the upper frontier model is called production frontier model, and the lower frontier model is called cost frontier model.
[10] See, for example, Fama (1998).

DEA is used to measure the relative performance of a firm’s stock return and market return. It is also used to measure frontier shifts before and after a product recall event. In the application of the valuation of a firm’s stock market performance, the market return, (i.e., defined as the average return across all stocks in a stock market), and the stock return are used to construct the frontiers. Regarding the type of DEA frontier model, the upper frontier DEA model focuses on the construction of the best relative performance frontier, whereas the lower frontier DEA model focuses on building the least relative performance frontier.

COLS methodology is another approach that is used to estimate a frontier. COLS involves two steps: obtain the estimated value of an error term from an ordinary least squares (OLS) equation, and shift an estimated OLS equation so that no errors are positive or negative (i.e., if we keep the errors all positive, this is a lower frontier COLS model, whereas if all errors are negative, it is a upper frontier COLS model). In this paper, I will use the COLS technique to examine the distance between market return and stock return.

SFA estimates a frontier by incorporating the possibility of systematic drift and random factors into the estimation. Similar to the other frontier approaches, a stochastic frontier can be classified as upper stochastic frontier or lower stochastic frontier, depending on the direction of the systematic drift. With misevaluation, the upper stochastic frontier can be used when there is undervaluation and the lower stochastic frontier model can be used when there is overvaluation.

In the traditional event study approach, a firm's stock market returns is regressed on market returns. OLS is the underlying statistical approach for the traditional market model. However, if stocks are overvalued or undervalued, the OLS approach will produce misleading results. In this situation, employing the frontier-based approach (DEA, COLS, and SFA) makes it possible to solve the problem. Furthermore, the stochastic frontier method provides a more accurate estimate when there is over or under valuation.

2.1.4. Introduction of the Study

Four results emerge from this study. (1) The market value and stock returns of Johnson & Johnson, Bridgestone, and Toyota are significantly influenced by the product recall events in the short run. (2) The traditional market model produces similar results to the upper stochastic frontier approach, an indication of robustness of the traditional event study method. (3) The traditional event study approach may not be appropriate when markets are not fully rational. A carefully selected stochastic frontier model can effectively offset the influence from pre-event misevaluation (e.g., traders overvalue or undervalue the price of stocks). (4) Endogenous events are significantly different from exogenous events in terms of their impact on a firm's economic value when we are using the traditional event study method. However, the differences are not always significant when we use the stochastic frontier method.

The rest of the paper is divided into four sections. Section 2 presents a literature review covering the event study method, frontier estimation techniques, and research on product recalls. Section 3 introduces the methodologies that are used to examine the data and test the hypotheses. Section 4 describes the data and discusses the results and is followed by the conclusions in Section 5.

2.2. Literature Review

In this section, I first summarize the literature on the event study technique and research on the market reaction to a product recall. Specifically, I review the traditional event study method, which uses ordinary least squares (OLS), and three frontier methods, data envelopment analysis (DEA), corrected ordinary least squares (COLS), and stochastic frontier analysis (SFA). Next, I review the literature on frontier estimation, followed by a literature review on empirical studies regarding the endogenous versus exogenous events.

2.2.1. Theory of the Event Study Method

The event study method is a popular and powerful tool used to measure a change in a company's expected future earnings associated with a given event. After the seminal studies by Ball and Brown (1967) and Fama et al. (1969), Brown and Warner (1980, 1985) studied data implementation issues for the traditional event study approach using monthly and daily data. MacKinlay (1997) provided a comprehensive review of key considerations and methodological issues in event studies. Campbell, Lo and MacKinlay (1997) studied event study analysis from implementation procedures, model selection, power evaluation analysis, and test design. Kothari and Warner (2004) pointed out that the event study method is a reliable short-horizon method.[11] However, they argued that the method has serious

[11] Kothari and Warner (2004) define short-horizon as an event window less than 12 months.

limitations when the time period is long-horizon. In addition, the properties of the event study method vary by time period and depend on a firm's characteristics such as volatility of individual firm returns (where return is defined as the percentage change in the value of the security, which is a firm's stock price) and volatility is measured by variance (or standard deviation).

The event study method has several important advantages. Stock price is a suitable measure of market value of a firm, assuming efficient markets. McWillians and Siegel (1997, p. 626) pointed out that "stock prices are not as subject to manipulation by insiders and reflect the true value of a firm, because they are assumed to reflect the discounted value of all expected future cash flows and incorporate all relevant information." Another advantage of the event study method is that it is relatively easy to implement because it requires data that only include the name of a publicly traded firm, date of an event, and stock price. However, Lunney (2008) pointed out that an event study does not provide an unbiased measure of an event's impact on a firm's future earnings. Rather, estimates from an event study measure the loss that a firm's shareholders have experienced over the event window.

The event study methodology relies on several assumptions. First, the equity market is efficient.[12] Second, the event is unanticipated by traders. Third, during the post-event window, there are no other confounding events (McWillians and Siegel,

[12] According to Schwert (1981), efficiency means that at any given time, stock prices reflect all publicly available information regarding a company and its prospects. In addition, I assume that stock prices react very quickly to new information. Taken together, these assumptions suggest that firm-specific stock price movements are due to newly available information. This allows researchers to infer a causal role when it is possible to identify an abnormal stock price movement contemporaneous with newly available information, at least in the absence of any other material information available.

1997). Meeting the requirement of these assumptions is critical in an event study. For example, researchers need to identify the investigation period during which no confounding events could obscure the effects associated with the event under investigation (MacKinlay 1997; McWilliams and Siegel 1997). Issues related to research design and implementation, such as sample size, abnormal returns, and test design, also need to meet these assumption requirements.

Misuse or ignorance of the event study assumptions will result in unreliable results. For example, regarding the assumption of market efficiency, Lunney (2008) stated that the gap between the event study estimation and a traditional measure of an event's costs would be too large to reflect real costs if traders overreacted to a negative event. Davidson and Worrell (1992) conducted a study of the effects of firms that were found guilty of illegal acts during a 181-day post-event window without justifying the length. They found that the effects from a product recall were vague because of the lengthy post-event window.

Researchers also pointed out that future research should focus on detailed classification of product recalls because recall events are not necessarily homogeneous (Hilliard and Savickas 2003). In fact, the effects on unsystematic volatility of the stock market may vary considerably with different types of recalls.

2.2.2. Applications of the Event Study Method

Over the past three decades, the event study methodology has been widely used in finance, accounting, marketing and economics. The firm-specific events covered by these studies include product recalls, mergers, acquisitions, earnings announcements, and new debt or equity (MacKinley, 1997; Kothari and Warner, 2004).[13] Researchers in law, economics, and management, have also embraced this methodology.[14]

Many of the event study applications deal with the impact of product recalls in the automobile, drug, food, and pharmaceutical industries.[15] For example, Jarrell and Peltzman (1985) laid the foundation of this approach by examining the impact of product recalls on shareholders in the drug and automobile industries. They found that shareholders of a firm that issued a product recall bore greater personal financial loss than the costs directly associated with the recall itself. In addition, the firm's competitors also experienced a substantial negative effect although not as great as the firm issuing the recall.

Davidson and Worrell (1992) examined the impact of product recalls in a broad range of consumer products, such as toys, electronics, and household products. Announcements of these recalls had received a great amount of public attention but few had been formally investigated. Their results showed that although the stock market had a significantly negative reaction to a recall announcement, most of the negative abnormal returns were found in reaction to an announcement of product

[13] For example, in the marketing field, event studies have been used to examine the impact of various marketing strategies on stock returns. Examples include the addition of internet distribution channels (Geyskens, Gielens, and Dekimpe, 2002), celebrity endorsement (Agrawal and Kamakura, 1995), brand extension announcements (Lane and Jacobson, 1995), and the change of company names (Horsky and Swyngedouw, 1987).
[14] See, for example, Mitchell and Netter (1994) about legal liability.
[15] See, for example, Jarrell and Peltzman (1985), Pruitt and Peterson (1986), Hoffer, Pruitt and Reilly (1988), Davidson and Worrell (1992), and Thomsen and McKenzie (2001).

replacing or returning. Davidson and Worrell argued that a product recall ordered by a government agency produced greater loss than a voluntary recall by a firm.

Chen, Ganesan and Liu (2009) examined product recalls resulting from harmful product crises (i.e. a product defect that could harm consumers). They found that the product recalls had significant impacts on a firm's reputation, sales performance, and market value. They investigated recalls from the Consumer Product Safety Commission over a 12-year period from 1996 to 2007. They found that regardless of characteristics of the firms and products, a proactive recall strategy generated more negative effects on a firm's value than a passive recall strategy.[16]

Researchers have also investigated the degree of the stock market's reaction to a product recall announcement. For example, Pruitt and Peterson (1986) found significantly negative financial impacts of product recalls on stockholder equity. However, they found no significant relationship between the magnitude of the market reaction and direct costs of the recalls. Chu, Lin and Prather (2005) conducted a cross-industry event study and examined the impact of security price reactions over a time period different from that in the study by Pruitt and Peterson (1986).[17] They found that the drug and cosmetics industries had more losses than the rubber and automotive industries. In another study, Thomsen and McKenzie (2001) examined shareholders' losses in the meat and poultry industries at different hazard levels of

[16] Proactive or passive strategy is one way to categorize a product recall strategy. According to Chen, Ganesan and Liu (2009), a proactive recall is a recall initiated by the firm which initially finds the potential defective problem itself and takes recall action without receiving any complaints from consumers or orders from a related government agency. This kind of proactive recall is a signal of a firm's diligence in attending to quality issues. Otherwise, the recall strategy is passive.

[17] The data of the study by Chu, Lin and Prather (2005) covers the period from January 1984 to December 2003, and the study by Pruitt and Peterson (1986) covers the period from 1968 to 1983.

product recalls. They found that the more serious a recall, the more negative the loss a company suffered.

There are several studies of the effect of the 1982 Tylenol poisonings recall and the 2000 Firestone tire recall (i.e., Mitchell, 1989; Dowdell, Govindaraj and Jain, 1992; Pearsall, 2002; Govindaraj, Jaggi and Lin, 2004; Khansa and Liginlal, 2011).[18] Mitchell (1989) studied the impact of the 1982 Tylenol poisonings on the stocks of Johnson & Johnson. He found that the losses far exceeded those of other pain-reliever producers. The study provided support for Klein and Leffler's (1981) theory that brand names should be considered as quality-assuring mechanisms. Prior to the 1982 and 1986 Tylenol poisonings, Tylenol had been the top brand of non-aspirin pain reliever. In his later studies, Mitchel (1989) found that the 1982 Tylenol poisonings was associated with significant stock market losses. Other pain relievers with similar problems actually had a much lower level of brand-name capital to lose.

Dowdell, Govindaraj and Jain (1992) assessed the wealth effects of the 1982 Tylenol incident and subsequent regulations in the industry.[19] The market value of common stocks of Johnson & Johnson declined approximately 29%, an equivalent of $2.31 billion. Although other firms in the industry also suffered significantly during that period, the decline of their share prices did not occur until the subsequent packaging regulation proceedings. On average, 28 other pharmaceutical firms

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[18] Because the 2010 Toyota "sticking accelerator pedals" event happened no more than one year ago, I could not find any studies on this recall event using event study methodology or frontier estimation methodology.

[19] Nov. 5, 1982, the federal government announced the packaging regulations specifying new over-the-counter drug packaging requirements. (The announcement about regulation was released on November 4, 1982, by the FDA and was reported the next day by The *Wall Street Journal*).

analyzed in the study experienced an average decline of $310 million per firm, a total of about $8.68 billion. The researchers suggested that regulations had a significantly negative effect on the common stock prices of firms in the pharmaceutical industry.

Pearsall (2002) explored several alternatives to Mitchell's approach. These include the incremental values associated with the Tylenol brand name, cost to develop the brand, alternative market factors, and changes in income streams. Pearsall compared the changes in brand value to Mitchell's estimation of the brand name capital depreciation. The results showed that Pearsall's study provided different estimates of the loss in brand value associated with the 1982 poisonings.[20]

Govindaraj, Jaggi and Lin (2004) studied the market reaction of the Firestone tire recall that was linked to rollover accidents of the Ford Explorer SUVs. The results indicated that initial losses in the market value for both Bridgestone Corporation and Ford Motor Company was far in excess of direct costs associated with the recall. The market loss was approximately equal to the near worst-case estimate of other costs, such as direct and indirect costs, litigation costs, regulation compliance costs, and costs associated with future loss in sales. Both firms recovered their market value when more credible information on actual costs became available. Govindaraj et al. argued that initially the market overreacted negatively to the recall announcement based on potential losses associated with the recall. This reaction was corrected when information on actual costs became available.

[20] Mitchel (1989) found that the total loss in Johnson & Johnson's shareholder value attributed to the poisonings is $1.24 billion, whereas Pearsall (2002) concluded that the estimation is $0.32 based on a cost approach, and $0.48 based on an income approach.

No studies to date have been done that deal with endogenous and exogenous sources. Neither have researchers examined the problem of overvaluation and undervaluation, although these factors have partially caused some controversial results in studies. Maddala (1992) pointed out that in most standard event studies, the events were treated as exogenous when in fact they were often endogenous. He argued that financially motivated managers can control the timing, type and magnitude of a recall announcement in a voluntary product recall event.

2.2.3. Literature Review of the DEA, COLS, and SFA Methodologies

Stock market price is a common measure of a company's performance. The relationship between stock return and the market average return is fundamental to the event study method. However, the traditional event study is not appropriate when markets are not fully efficient and traders are not fully rational. To offset the influence of overvaluation and undervaluation, an alternative approach is to use frontier methods. A frontier method can measure a company's performance by examining the distance between the event performances to the frontier. Among the frontier analysis approaches, the most commonly used parametric methods are stochastic frontier analysis (SFA) and corrected ordinary least squares (COLS); the most commonly used nonparametric method is the data envelopment analysis (DEA) method. In the following sections, I briefly review each of these techniques, in terms of their applications in product recalls.

The DEA approach was initially proposed by Charnes, Cooper and Rhodes (1978). It uses linear programming to construct a non-parametric piece-wise surface or frontier against which efficiency is measured. Charnes, Cooper and Rhodes (1978) generalized Farrell (1957)'s single-input/single-output efficiency measures into the multiple-input/multiple-output case by constructing a relative efficiency score as the ratio of a single virtual output to a single virtual input.[21] Their approach was extended by Färe, Grosskopf and Lovell (1994) who incorporated non-constant returns to scale and allowed the possibility of input congestion. An important advantage of the DEA approach is that is does not assume specific parametric functional forms for the production frontiers. Neither does it use distributional assumptions on the noise and inefficiency components. The DEA approach can easily accommodate multiple inputs and outputs simultaneously. A disadvantage of the DEA method is that it is subject to distortions introduced by data outliers, random shocks, and measurement errors.

The COLS approach was first suggested by Winsten (1957) in his discussion of Farrel's original paper (1957). Winsten suggested that the deterministic production frontier model could be estimated by two steps. Later, Aigner, Lovell, and Schmidt (1977) extended the COLS method to the estimation of a standard cost function. A lengthy application with an extension to panel data appeared in a study by Simar (1992). Generally, the COLS approach assumes that the frontier is deterministic and all variation in an output is attributed to inefficiencies. The COLS method is based on the assumptions that (1) the OLS estimator of the slope parameter is consistent and

[21] The pioneering work on the efficiency and productivity literatures is by Farrell (1957), which drew upon the work of Debreu (1951) and Koopmans (1951). Their studies stated that efficiency of a production unit is defined as the ratio of observed to optimal values of its output and input. Productive efficiency of a firm consists of two components: technical efficiency, which reflects the ability of a firm to obtain maximal output from a given set of inputs, and allocative efficiency, which reflects the ability of a firm to combine the inputs and the outputs in optimal proportions, given their respective prices.

unbiased, and (2) the OLS residuals are point-wise and consistent estimators of linear translations of the original error terms. As a result, the COLS approach is convenient in implementation and explanation. However, a weakness of OLS is that the regression results are sensitive to the functional form. If a researcher selects a wrong functional form, the error term will be incorrect. According to Greene (2006), the COLS results are especially sensitive to outliers because the “best” performer along any dimension serves as the anchor for the estimate. Thus, the performance scores are very sensitive to outliers.

The SFA method is an econometric methodology for the measurement of distance from a frontier function. The SFA model was first developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) to estimate firm inefficiency. This approach attributes part of the deviations from the frontier to inefficiency and part to random noise. In other words, the SFA model takes both inefficiency and random noise into account. Based on different assumptions regarding the distribution of random shocks and random inefficiency components, the SFA model can be categorized as an the upper frontier model or a lower frontier model. Kumbhakar and Lovell (2000) classified the SFA into normal-half-normal model, the normal-exponential model, and the normal-truncated-normal model.[22] A few comprehensive reviews of this literature are Førsund, Lovell and Schmidt (1980), Bauer (1990) and Greene (1993).

[22] Another widely accepted classification is that SFA models include the stochastic production frontier model, stochastic cost frontier model, and stochastic distance function model.

Comparing SFA with DEA, Greene (2006) provided three reasons that the SFA was an attractive alternative to the DEA approach. First, the "stochastic" aspect of the model allows the SFA to appropriately handle measurement error problems and other stochastic influences that would otherwise appear as causes of inefficiency. Second, the SFA provides a means of accommodating unmeasured heterogeneity.[23] Third, the frontier model provides a means to employ information on measured heterogeneity. The most welcomed characteristic of the SFA is that a researcher can use standard statistical methods to test hypotheses on model specification and significance of the variables included in a model. However, as Coelli, Prasada, Rao, and Battese (1998) pointed out, the need of functional form and production technology specifications under some circumstances is a weakness of the SFA model. In addition, that no general criterion on the assumptions on the distribution of the error term limits the application of the SFA.

To date, researchers have not implemented frontier-based estimation approaches in the investigation of the impact of a product recall on a firm's stock price and market value. Furthermore, no research has used two types of stochastic frontier to verify the misevaluation problem for the stock price of a company, which would lead to biases in traditional event study.

[23] According to Greene (2006), heterogeneity in the frontier model is classified into measured heterogeneity and unmeasured heterogeneity. Measured heterogeneity is the difference between input variables, which we can measure and incorporate into the model structure. Unmeasured heterogeneity is the information we recognize but can not be expressed in the model.

2.3. Methodology

As described in the introduction, I compare results from the traditional event study method with three frontier based estimation techniques. First, I use the standard OLS method to analyze if the announcement of a product recall and a product withdrawal had significant effects on the market value of each company. Second, I used the data envelopment analysis method (DEA), the corrected ordinary least squares method (COLS), and stochastic frontier analysis (SFA) to measure the recall events' effects on stock returns. Last, I take both the upper and lower SFA into account to overcome the problem of overvaluation or undervaluation.[24] In this section, I describe these approaches in detail.

2.3.1. Event Study Method

The event study technique examines the existence of significant changes in a company's securities price (abnormal returns, which is defined as actual returns after the event minus forecasted returns that in the situation if the event never occurred) due to the announcement of a product recall event.[25] The methodology relies on the assumption that the stock market operates efficiently and any unanticipated event that has an impact on a firm's value will be immediately reflected in security prices. It assumes that the stock price of a firm provides an unbiased estimate of the firm's present value of expected future profits. According to Campbell, Lo, and MacKinlay

[24] Researchers can also apply lower frontier approaches for both DEA and COLS. However, both DEA and COLS methods suffer from outliers. In this study, I only employ the commonly used upper frontier DEA and COLS models.

[25] Return is defined as the percentage change in the value of the security, which is a company's stock price.

(1997), the event study design follows these procedures: event definition, predictive model selection, normal and abnormal returns measurement, procedure estimation, empirical results, and interpretation. That is, first, define the event which we are going to study, including the scope and length of the event window, the pre-event window and post-event window. Second, we need locate a predictive model to predict the stock return for the related company or companies. Third, based on the predictive returns and real returns of the stocks, calculate the abnormal returns. Last, test whether or not the abnormal returns are significant during different time periods and interpret the results.

One of the most commonly used normal return estimation models is the market model (Fama, 1976: chapter 3). Other models that can be used for the measurement of normal performance in an event study include the constant-mean-return model (CMRM), the capital asset pricing model (CAPM), and the arbitrage pricing theory model (APT).[26, 27] After studying the test power of these analytical models, Brown and Warner (1985, p.13) pointed out that the CMRM, the CAPM and the APT yielded similar test power for a well-specified test statistic. In this study, I use the market model as a base model to measure abnormal stock returns.

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[26] The Capital Asset Pricing Model (CAPM) is a common economic model. According to Sharpe (1964) and Lintner (1965), the model is based on an equilibrium theory where the expected return of a given asset is a linear function of its covariance with the return of the market portfolio. The CAPM is commonly used in event studies during the 1970s (Campbell, Lo and MacKinlay, 1997).

[27] According to Ross (1976), the Arbitrage Pricing Theory (APT) is an asset pricing theory. It claims that in the absence of asymptotic arbitrage, the expected return of a given asset is determined by its covariances with multiple factors (Campbell, Lo and MacKinlay, 1997).

In an event study, one must identify two distinct time periods: the pre-event period and the post-event period.[28] The pre-event period is defined as the period prior to the occurrence of an event. The post-event period is the period beginning immediately after the occurrence of an event. Assume that the joint distribution of all stock returns $(R_{1t}, R_{2t}, \cdots, R_{nt})$ in the market has a multivariate normal distribution. The stock return of company i at day t is defined as the ratio between capital gain plus dividend and the initial stock price:

$$R_{it} = \frac{d_{it} + (p_{it} - p_{i,t-1})}{p_{i,t-1}},$$

where d_{it} is the dividend per share of the common stock of company i during the end of day $t-1$ and the end of day t, p_{it} is the stock price at the end of day t and $p_{i,t-1}$ is the stock price at the end of day $t-1$. If there are no dividends, this is simply the percentage change in the stock price.[29] The abnormal return for company i on day t is

$$AR_{it} = R_{it} - E(R_{it}|I_t), \tag{1}$$

where $E(R_{it}|I_t)$ measures the forecasted return from the selected model, and I_t is the information available in the market until the end of day t. The abnormal return AR_{it} measures the impact of an event on company i' s return at day t. If the event has a negative (positive) impact on the value of the company, AR_{it} will be negative (positive). Otherwise, the abnormal return AR_{it} will be zero, where $t > 0$ if the event day is $t = 0$.

[28] In this study, the event day is defined as the exact day when the event happens.

[29] The dividend is defined as the amount of dollars each share receives (dividends per share). The stock price in this study is Adjusted Closing Price. It is defined as a stock's closing price on any given day of trading that has been amended to include any distributions and corporate actions occurred at any time prior to the next open day.

The market model approach assumes a linear relationship between the stock return and the market return. Assume the market return is denoted as R_{mt}. Usually, $\mathrm{R_{mt}}$ is a linear combination of the individual stock returns that may be weighted either equally or by their respective market shares in order to construct the market return. The market return could be a market index such as the Dow Jones Industrial Average (DJIA). But it might be also represented by average returns over a designated industry portfolio. Therefore, the expected return from a stock, conditional on the information available in the market until day t is

$$\mathrm{E}(R_{it}|I_t) = \mathrm{E}(R_{it}|R_{mt}) = \alpha_i + \beta_i R_{mt}.$$

And the market model can be written as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}, \quad \mathrm{E}(\epsilon_{it}) = 0 \text{ and } \mathrm{Var}(\epsilon_{it}) = \sigma^2_{\epsilon_{it}}. \tag{2}$$

Ordinary least squares (OLS) estimation of α_i and β_i are consistent and efficient for model (2), and I use $\hat{\alpha}_i$ and $\hat{\beta}_i$ to represent the OLS estimates of α_i and β_i.

The abnormal return, $AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt})$, measures the effect of an event on company i's returns at time t. For an event that affects returns for more than one day, the abnormal returns are summed to obtain the cumulative abnormal return

$$CAR_{iT} = \sum_{\mathrm{t}=1}^{\mathrm{T}} AR_{it},$$

where T is the length of time in which returns are affected, the post-event period or window. If the cumulative abnormal returns of a product recall are significantly different from zero, the event's impact on the stock market value is significant.

Typically, the event study approach can be used to analyze (1) an event that is common among different firms belonging to different markets, and/or (2) an event that is specific to a company or a group of companies within the same market.

2.3.2. Data Envelopment Analysis

DEA is a mathematical programming approach aimed at constructing a frontier based on actual data. It is one of the most popular non-parametric approaches to measure the distance of an observation to a frontier. The DEA does not assume a fixed functional form for a data generation mechanism. Instead, the method uses linear programming techniques to draw an "envelope" around data observations.[30] In the study of the relationship between the stock return and the return of the market portfolio, I use a vector, $x = (x_1, \cdots, x_N) \in R_+^N$, to denote the return of the market portfolio, R_{mt} , $t = 1, \cdots T$, the independent variables. I also use a vector, $y = (y_1, \cdots, y_M) \in R_+^M$, to denote the return of stock i, R_{it} , $t = 1, \cdots T$, the dependent variable.

I define the feasible variable combination set as

$F = \{(x, y)\colon x \text{ can produce or lead to } y\}$.

The feasible variable combination set can also be represented by the independent variables and the dependent variables. The feasible variable combination set can be represented by the dependent vector as

$P(x|V, S) = \{(x_1, \cdots, x_N)\colon$

[30] Assume that the technology satisfies variable returns to scale. In the construction of the DEA frontier, I only explored the upper frontier method in this study. Regarding the lower bound frontier DEA method, refer to Zhu (2003).

$$y_m^t \leq \sum_{t=1}^{T} z^t\, y_m^t\,,\;\; m = 1, \dots, M,$$

$$\sum_{t=1}^{T} z^t\, y_m^t \leq x_n^t\,,\;\; n = 1, \dots, N,$$

$$\sum_{t=1}^{T} z^t \;\geq 0\,, \qquad t = 1, \dots, T\;\},$$

where V stands for variable returns to scale, and S stands for strong disposability. In this study, because I only considered one market return and one stock returns, $N, M = 1$.

I list the properties of the dependent variable set (output set) as follows. (1) $0 \in P(x)$ is impossible to produce zero output by using a zero set of inputs. (2) Positive output levels require positive levels of inputs. (3) $P(x)$ is strongly disposable if y $\in P(x)$ and $y^* \leq y$ then $y^* \in P(x)$. (4) $P(x)$ satisfies strong disposability in inputs if y can be produced from x, and y can be produced from any $x^* \leq x$. (5) The set $P(x)$ is closed. (6) The set $P(x)$ is bounded. (7) The set $P(x)$ is convex.

In production theory in which there is a single dependent variable (output), the production function is often used to represent the feasible variable combination set F. This is defined by

$$F(x) = \max\{y: (x, y) \in F\}.$$

In order to use the DEA approach with financial data, I need to forecast the post-event period stock return based on the DEA frontier formed by the data during the pre-event window. An output distance function is the natural approach for frontier approach research.[31] The distance functions are very useful when describing the

[31] I use the distance function as a method to generate the DEA frontier. The output quantity is the exogenous dependent variable, and input quantities are independent endogenous variables. A distance

feasible variables combination set. More important, an output distance function can characterize the feasible variables combination set corresponding to the maximal proportional expansion of a dependent vector, depending on the existing market return level. Hence, I use a distance function for the DEA frontier and use it to forecast the stock return during the post-event period in this study.

According to Shephard (1970), the output distance function is defined by

$D_o(x, y) = inf\{\theta: (x, \frac{y}{\theta}) \in F\}$.

This function is homogeneous of degree 1. It is a complete characterization of the feasible variables combination set F provided dependent variables are weakly disposable.[32]

A few properties of the output distance function are described as follows. (1) It equals zero for all nonnegative values of x. (2) It will neither decrease in y nor increase in x. (3) It is linearly homogeneous in y. (4) It is quasi-convex in x and convex in y. (5) It is less than or equal to 1 in value if y is a part of the possibility set of x. (6) If y is on the frontier, the value of $D_o(x, y) = 1$. As in the case for the input-oriented efficiency metric, technology efficiency is normally measured as the inverse of $D_o(x, y)$. $(1/D_o(x, y)) - 1$ indicates the proportion by which outputs could be expanded with a change in inputs.[33]

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function may have either an input or an output orientation. An input orientation examines how much the input vector may be proportionally contracted if the output vector is held fixed. An output orientation examines how much the output vector may be proportionally expanded if the input vector is held fixed.

[32] Outputs are weakly disposable if $(x, y) \in F$ and $0 \leq \theta \leq 1$ implies $(x, \theta y) \in F$.

[33] A systematic introduction of the properties and characteristics of the distance function can be found in the study by Färe and Primont (1995).

2.3.3. Corrected Ordinary Least Squares

Another way to estimate a frontier is to use corrected ordinary least squares (COLS). COLS keeps the same estimated slope (gradient, β_i) as the OLS regression line. However, COLS changes the intercept (α_i) until no return bundle data is above (or low) the OLS regression line. Hence, the COLS is an extreme version of the regression technique.

The COLS approach is a two-stage procedure. At the first stage, the frontier is estimated by ordinary least squares (OLS) regression. At the second stage, the frontier is shifted upwards so that the resulting COLS frontier envelops all data. As discussed previously, the residuals in the OLS model are

$$\varepsilon_{it}(AR_{it}) = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}).$$

The OLS residuals take both positive and negative values, but the COLS residuals take only negative values in the production example. I denote the OLS residuals as ε_{it}^{OLS}, in a COLS model. Because these error terms are attributed to systematic shifting, the error estimates are adjusted as

$$\hat{\varepsilon}_{it}^{COLS} = \varepsilon_{it}^{OLS} - max_t \ \varepsilon_{it}^{OLS},$$

where $\widehat{\varepsilon}_{it}^{COLS} \in [0, -\infty)$, with $\hat{\varepsilon}_{it}^{COLS} = 0$ for the observation with the largest positive ε_{it}^{OLS}. This is accomplished by increasing the intercept terms, such that

$$\hat{\alpha}_i^{COLS} = \alpha_i^{COLS} + max_t \ \varepsilon_{it}^{OLS}.$$

The slope parameter $\widehat{\beta}_i$ is the same as that in OLS.

2.3.4. Stochastic Frontier Analysis

In the traditional market model in Section 2, a key assumption is that ϵ_{it} is normally distributed around zero. This assumption may be violated for companies that are over or under valued in the stock market. Both the DEA and COLS methods can partially solve this problem by shifting the estimation line up (or down). However, if the original direction is wrong or outliers exist, both methods will fail. An alternative approach is to consider constructing the market model based on the stochastic frontier approach.

The stochastic frontier method was proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). SFA attempts to estimate a frontier that accounts for the possibility of measurement error or chance. Usually the error term has two components: one accounts for random effects and another accounts for the distance to the frontier. The advantage of this approach is that it allows researchers to define the overvaluation as the positive distance to the lower frontier (the undervaluation as the negative distance to the upper frontier). This model can be expressed in the following forms:

Upper stochastic frontier method:

$$y_{it} = \alpha_i + x_{it}\beta_i + (\vartheta_{it} - \mu_{it}), \;\; t = 1, \dots, T. \tag{3}$$

Lower stochastic frontier method:

$$y_{ti} = \alpha_i + x_{it}\beta_i + (\vartheta_{it} + \mu_{it}), \;\; t = 1, \dots, T. \tag{4}$$

$\mathrm{E}(\vartheta_{it}) = 0$ and $\mathrm{Var}(\vartheta_{it}) = \sigma^2_{\vartheta_{it}}$, where ϑ_{it} is the stochastic component and distributed as normal, $N(0, \sigma^2_{\vartheta_{it}})$. The other stochastic component, μ_{it}, is a non-negative random variable, and is assumed to account for a systematic shift from the frontier. μ_{it} is assumed to be i.i.d. and a non-negative random variable.[34] In this study, I assume that μ_{it} has a positive half normal distribution. In other words, $\mu_{it} \in N^+(0, \sigma^2_{\mu_i})$, which was proposed by Aigner, Lovell and Schmidt (1977). However, μ_{it} can also be assumed to follow the exponential, gamma, or truncated normal distribution.[35]

The stochastic frontier model can be classified into two categories: the lower stochastic frontier analysis model (LSFA) and the upper stochastic frontier analysis model (USFA). The LSFA can be used to test for overvaluation. If the non-negative random variable μ_{it} is zero, it means that no overvaluation is present. If the variance of μ_{it} is significantly different from zero, then overvaluation exists. On the other hand, the USFA can be used to test for undervaluation. If the non-negative random variable μ_{it} is zero, there is no undervaluation. If the variance of μ_{it} is significantly different from zero, then there exists undervaluation.[36]

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[34] In probability theory and statistics, a sequence or other collection of random variables is independent and identically distributed (i.i.d.) if each random variable has the same probability distribution as the others and all are mutually independent.

[35] Papers by Kumbhakar and Lovell (2000) and Coelli et al. (2005) provide extensive discussion about the potential distributions of the inefficiency term.

[36] Stochastic frontiers may also be classified as production and cost frontiers based on the sign before μ_{it}.

2.4. Data and Empirical Results

In this study, I extract the daily stock adjusted return data for Johnson & Johnson, Bridgestone, and Toyota from Google financial.[37, 38] Specifically, in order to measure and estimate the relationship between market return and firm stock return, I use trade data one year before each product recall event (i.e., 252 trading days) in order to form the pre-event period. I select the Dow Jones Industrial Average Index (DOW)[39] to measure the New York Stock Exchange (NYSE) market average return for Johnson & Johnson and Toyota recalls. I use the NIKKEI 225 market index to measure the Tokyo Stock Exchange (TSE) market index for the Firestone tire recall.[40] The data summary for the three stock returns and two market index returns are shown in Table 2.1. The Table shows that the mean daily adjusted returns for Johnson & Johnson, Bridgestone, and Toyota are 0.17, -0.08, and 0.17 percent during the pre-event window; the market returns are 0.04, 0.07, and 0.03 percent.

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[37] Available at http://www.google.com/finance/historical.

[38] Johnson & Johnson is publicly listed on the New York Stock Exchange (NYSE) under JNJ. Its common stock is a component of the Dow Jones Industrial Average. Bridgestone is majorly listed on the Tokyo Stock Exchange (TSE) under company code NIKKEI: 5108. It is a component of the NIKKEI 225. Toyota is listed on the New York Stock Exchange under NYSE: TM. Toyota is also publicly traded on the Tokyo, Osaka, Nagoya, Fukuoka, and Sapporo exchanges under company code TYO: 7203. Toyota is listed on the London Stock Exchange under LSE: TYT as well. According to Ward's data (Ward, 2001 to 2010), North America is the largest sales market during at least the past 10 years.

[39] The Dow Jones Industrial Average (DJIA) is a stock market index. It is also called the Industrial Average, the Dow Jones, the Dow 30, or simply the Dow. The DJIA is an index created by Wall Street Journal editor and Dow Jones & Company co-founder Charles Dow. It is an index that shows how 30 large and publicly owned companies based in the United States have traded during a standard trading session in the stock market. The major difference between the DJIA and Standard & Poor's 500 (S&P 500) is that DJIA includes a price-weighted average of 30 stocks, whereas S&P 500 is a market value-weighted index of 500 stocks. However, according to Ilina and Daragan (2003), the high correlation (0.94) between DJIA and S&P 500 makes the choice of market index of not much concern.

[40] The NIKKEI 225 is a stock market index for the Tokyo Stock Exchange (TSE). It is more commonly called the NIKKEI, the NIKKEI index, or the NIKKEI Stock Average. The NIKKEI 225 is the most widely quoted average of Japanese equities, similar to the Dow Jones Industrial Average.

[Insert Table 2.1 here.]

In this study, I use traditional event study and different frontier estimation approaches to estimate the impact on the value of company of a negative event. The models include: the traditional model (OLS), the data envelopment analysis model (DEA), the corrected ordinary least squares model (COLS), and the upper/lower stochastic frontier analysis model (USFA/LSFA). At the first stage, I estimate the cumulative abnormal returns (CAR) by OLS, COLS, DEA, and SFA[41] in order to compare the different performance of these four models. At the second stage, in order to examine the overvaluation and undervaluation problem, I use both the upper stochastic frontier analysis model (USFA) and the lower stochastic frontier analysis model (LSFA) to estimate and compare the results with those from the OLS.

2.4.1. The Results from the CARs Analysis of Three Product Recalls

Similar to the research by Campbell, Lo, and MacKinlay (1997), in order to show the effects of the recalls, I estimate the intercepts and parameters of traditional market models (OLS) and displaye them in Table 2.2.[42] Using the OLS models, I calculate the forecasting values of the accumulative abnormal return over the post-event period. I summarize the OLS results from 41 trading days of data (20 days in

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[41] At this stage, the stochastic frontier analysis model (SFA) is actually an upper stochastic frontier analysis model (USFA). At the next stage, I will compare the performance study between lower stochastic frontier analysis model (LSFA) and upper stochastic frontier analysis model (USFA).

[42] In Table 2.2, the Analysis of Variance (ANOVA) shows that the F value is significant for Johnson & Johnson and Toyota models. The F value for the Bridgestone model is relatively low because the sum of squares of the difference (residual sum of squares) between the values of stock return predicted by the OLS market model and the actual values of stock returns is larger than the value between the stock return and the average stock market return (total sum of squares).

both pre-event and post-event windows, and one event day) for Johnson & Johnson (Table 2.3), Bridgestone (Table 2.4), and Toyota (Table 2.5). Overall, the $adjusted\ R^2$ from the OLS models for Johnson & Johnson and Toyota are 0.3965 and 0.4577, respectively, but the $adjusted\ R^2$ for the Bridgestone model is relatively low, 0.0054.

[Insert Table 2.2 here.]

[Insert Table 2.3 here.]

[Insert Table 2.4 here.]

[Insert Table 2.5 here.]

As shown in Tables 2.3, 2.4 and 2.5, the cumulative market abnormal return (CAR) until the last day of the pre-event window are 2.13%, 3.03%, and 4.69%, and all three CARs are positive and relatively small.

The t-value of the one-day CAR for Johnson & Johnson is -2.99.[43] Hence, the null hypothesis that the event has no impact is strongly rejected based on the results of first post-event day. The t-values for other post-event days are also significant at the 1 percent level. The other two companies—Bridgestone and Toyota—showed similar results (t-values are -2.96 and 1.52 on the first post-event day). The first day CARs in the post-event period are -7.17% and 2.64%, respectively.

However, the results show that, four days after the recall event, Johnson & Johnson, Bridgestone, and Toyota suffered a decline of 17.34%, 24.43%, and 7.69% of their CARs, respectively. The average abnormal returns during the first 10 days of

[43] The formulas for standard errors and t-values of the CAR are defined and calculated as in the footnote 11 of Mitchell (1989, p. 607).

post-event period are -16.58%, -28.73%, and -7.03%, respectively. Twenty days after the event (i.e., the middle run), the companies suffered 24.26%, 65.56%, and 17.52% of CAR losses. All of these values are more than two standard errors from zero. As expected, the results are consistent with the results from the research on the stock negative information announcement of earnings event study by Campbell, Lo and MacKinlay (1997).

Figure 2.1 shows the plots of CARs for the three events based on the traditional OLS approach. The CARs immediately dropped after the product recall announcements. The trend of plots for Johnson & Johnson and Toyota are similar, but the CAR levels are slightly different. The CAR for Bridgestone decreased to about -40% within 7-16 days and decreased further to -60% starting from the 19th day in the post-event period. The Bridgestone stock lost more than 65% within the first 30 days in the post-event window.

[Insert Figure 2.1 here.]

2.4.2. The Results from Comparison among Four Approaches

I use the frontier estimate techniques to evaluate the impact of the product recall events on the market value of three companies. The purpose is to compare the traditional OLS approach with alternative frontier approaches. I present the result on the event day and during the 30 post-event days from the four models (OLS, DEA, COLS and USFA) in the following tables.[44]

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[44] The frontier technique can be classified into upper frontier and lower frontier. In this section, I focus on the upper frontier technique. Because all the estimations are for an upper bound frontier, I chose to

Table 2.6 shows the results for Johnson & Johnson.[45] The results from the four approaches consistently show that Tylenol suffered a deep loss on CAR after the 1982 recall event. During the 30-day post-event window, the estimated CAR based on the OLS and the USFA model is 21.98% and 19.92%, respectively. The estimated CAR from the DEA and the COLS model is 153.63% and 167.15%, respectively. On average, CARs from the event day to the 30th post-event day are 19.83%, 94.76%, 83.30%, and 19.52% for the OLS, the COLS, the DEA, and the USFA models, respectively. I plotted the four estimations for Johnson & Johnson in Figure 2.2. The OLS and the USFA models have similar performance on the estimation of further return, but the COLS and the DEA models are far from the real return bundles. The post-event return bundles are evenly distributed on the return plane and have a bigger dispersion degree compared to the pre-event return bundles. Hence, both the COLS and the DEA models have larger values of CARs than either the OLS or the USFA model. A possible economics explanation is that companies experience substantial volatility on the returns during an event and a post-event window, and the volatility was enlarged by upper frontier model. The CAR evolutions for all four models are plotted in Figure 2.3 for Johnson & Johnson.

[Insert Table 2.6 here.]

[Insert Figure 2.2 here.]

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use USFA. In the next section, I will explore the difference between USFA and LSFA. However, the lower frontier for DEA and COLS will not be examined in this study.

[45] I use 30 trading days in the post-event period to measure the AR and CAR for these events in order to have a large enough range to compare the result with previous studies. For example, Mitchell (1989) used 20 trading days to design the post-event window for the Tylenol recall, and Govindaraj, Jaggi and Lin (2004) used 27 trading day post-event windows for the Firestone recall.

[Insert Figure 2.3 here.]

Table 2.7 shows the results for Bridgestone. Results from the four approaches show that Bridgestone also suffered a deep loss in CAR after the 2000 recall event. During the 30-day post-event window, the estimated CAR based on the OLS model and the USFA model is -57.65% and -58.14%, respectively. The estimated CAR by the DEA model and the COLS model is -484.01% and -296.50%, respectively. On average, CARs during the period from the day of the event to the 30th post-event day are -45%, -162.69%, -244.35% and -45.26% for the OLS model, the COLS model, the DEA model, and the USFA model, respectively. I plotted the four estimations in Figure 2.4. The OLS model and the USFA model have similar performance on the estimation of future returns, but the COLS model and the DEA model are far from the real return bundles. Similar to the case of Johnson & Johnson, the post-event return bundles are evenly distributed on the return plane and have a bigger dispersion degree compared to the old return bundles. As a result, both the COLS model and the DEA model have large CARs than the OLS model and the USFA model. The CAR evolutions for all four models are plotted in Figure 2.5 for Bridgestone. Another possible reason that the average CAR in the COLS model and the DEA model is large is that the relationship between market return and Bridgestone stock return is negative. This negative relationship indicates that the Bridgestone stocks are weaker than the market index. Hence, when the recall event happened, stock returns were weaker than previously anticipated.

[Insert Table 2.7 here.]

[Insert Figure 2.4 here.]

[Insert Figure 2.5 here.]

Table 2.8 shows the results for Toyota. The results from four models indicate that Toyota suffered a deep loss in CAR after the 2010 Toyota sticking accelerator pedal recall event. At the end of the 30-day post-event period, the OLS model indicates a total loss of 14.28%, the COLS model a loss of 156.80%, the DEA model a loss of 121.74%, and the USFA model a loss of 14.29%. The average loss is 11.57%, 89.14%, 68.72% and 11.58% for each model respectively. I plotted the four different estimations for Toyota in Figure 2.6. Both the OLS model and the USFA model have similar performance on the estimation of future returns, and both the COLS model and the DEA model provide appropriate interpretation. The results show that the four approaches explained the product return event shock in different ways. CARs varied among the four models. The four models' CAR evolution situation is plotted in Figure 2.7 for Toyota.

[Insert Table 2.8 here.]

[Insert Figure 2.6 here.]

[Insert Figure 2.7 here.]

In order to examine the relationship between the four approaches, I adopted the paired t-test to examine their performance compared to the real stock return. I treated the difference between the return of stock *i* and market as the base variable, $d_{it}^{Base} = R_{it} - R_{mt},\ t = 1, \cdots T$. I also denoted the differences between stock return and the estimated stock return (from the four models) as variables, $d_{it}^{M} = R_{it} -$

$R_{it}^{M}, t = 1, \cdots T,\ M = OLS, COLS, DEA\ or\ USFA$. The assumption for the paired t-test is that the mean difference between the two variables is normally distributed. The null hypothesis for the paired t-test is that the difference between these two variables is significantly different from zero. For each recall event, I first listed all disparity return data (d_{it}^{Base}, d_{it}^{OLS}, d_{it}^{COLS}, $d_{it}^{DEA}\ and\ d_{it}^{USFA}$). Then, I conducted the paired t-test for each pair, (d_{it}^{Base}, d_{it}^{OLS}), (d_{it}^{Base}, d_{it}^{COLS}), ($d_{it}^{Base}, d_{it}^{DEA}$), and ($d_{it}^{Base}, d_{it}^{USFA}$), and evaluated the relationship between the four models. The results are shown in Table 2.9.

[Insert Table 2.9 here.]

At the statistical significance level of 0.05, the results show that two of the three OLS models appear to be significant. This means that these two set of abnormal returns from the OLS models are significantly different from the market return data after the product recalls. The analysis shows that the results from the DEA model and the COLS model are generally different from those from the OLS model and the USFA model, and the results from the USFA model are closer to the OLS model on most metrics, an indicator that the stock market overvaluation for those companies.

2.4.3 The Impact of Overvaluation and Undervaluation on the Method Selection

From section 2.4.2, in most cases the frontier approaches generate bigger CAR estimates after an event, compared to the traditional OLS market model. It seems that the OLS model is the most appropriate among OLS and the upper frontier DEA, COLS and SFA models. However, the problem of overvaluation and undervaluation is common regarding a company's stock price, and the purpose of this study is to find an alternative model when markets are overvalued or undervalued. Hence, in this section, I take the misevaluation problem into account by using a frontier model.

The stochastic frontier analysis (SFA) includes the USFA model and the LSFA model. However, without knowing which frontier is better, I estimate the market model using both the USFA model and the LSFA model. Parameter estimates for the LSFA model, the USFA model, and traditional market models (OLS) are displayed in Table 2.10. I use the LSFA model to test for overvaluation and the USFA model to test for undervaluation. In Table 2.10, the variances for μ_{it} in all three USFAs are almost zero and all the non-zeroes are in the LSFA models. This shows that all three companies were not undervalued and all were overvalued during the pre-event period.

[Insert Table 2.10 here.]

The results from Table 2.10 also show that the USFA model estimates are very close to OLS parameters because all the μ_{it} in three USFA models are almost zero. This confirms the findings in section 2.4.2: CARs from the OLS model and the USFA models are very close.

Table 2.11 shows the results of the LSFA, USFA and OLS return estimates, abnormal returns (AR), and cumulative abnormal returns (CAR) for the Johnson & Johnson recall event. Figure 2.8 compares CARs for the three models for Johnson & Johnson.

[Insert Table 2.11 here.]

[Insert Figure 2.8 here.]

I also present the comparison of CARs for Bridgestone in Table 2.12 and Figure 2.10.

[Insert Table 2.12 here.]

[Insert Figure 2.9 here.]

I present the comparison of CARs for Toyota in Table 2.13 and Figure 2.10.

[Insert Table 2.13 here.]

[Insert Figure 2.10 here.]

In these three cases, the results support the concern of overvaluation. Estimates from all three USFA models are almost identical with all three OLS models, and the CAR curves from LSFA models are above those from the USFA. This suggests that undervaluation did not appear in the pre-event period for all three companies. Hence, the LSFA model is a potential approach to correct the overvaluation problem by decreasing the negative effect of their product recalls.[46] However, both Figure 2.8 and Figure 2.9 show an interesting result for the CAR curves from the LSFA model. These curves are not only higher than those from the USFA model and the OLS model, they also turn into positive territory after the 18th day for Johnson & Johnson and the 11th day for Bridgestone during the post-event period. I provide two explanations. First, the negative impact from a product recall

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[46] The lower frontier DEA and OCLS models are also possible candidates. However, since DEA and OCLS are both suffer the influence from outliers, the performances are not as good as LSFA. I do not list the results here.

for a company truly vanished. Second, the remedy for overvaluation may too strong, and needs to be more specific through the model setting.

2.4.4. The Influence on a Firm’s Market Value from Different Sources of Shocks

Generally speaking, shocks include both endogenous shocks and exogenous shocks. As shown in Appendix A, the 1982 Johnson & Johnson Tylenol poisoning event was not due to reasons from inside the company. Throughout the incident, Johnson & Johnson insisted that the Tylenol capsule bottles had been tampered outside the factory premises. Johnson & Johnson took multiple actions on public relationships that solidified confidence among customers. The public later believed that Johnson & Johnson was innocent.

The 2010 Toyota sticking accelerator pedal event was another example of the influence of exogenous shocks. However, the recall event was more complicated and lasted longer than the Tylenol recall case. Initially, the media and the public believed that mechanical or electrical design fault was responsible for the accidental deaths. Under the pressure from public and the National Highway Traffic Safety Administration (NHTSA), Toyota recalled eight Toyota models and over four million vehicles worldwide. However, after eight months of investigation by the NHTSA, Toyota announced on August 10, 2010 that no evidence of electrical problems was found with Toyota automobiles. Both Toyota and Johnson & Johnson suffered exogenous shocks and both events resulted in reduced market values, even though both companies adopted efficient marketing and public relationship activities that reduced much negative influence.

Regarding the 2000 Firestone tires recall event, the real reason that the Firestone recall was not revealed to the public for a long time is that both Ford and Bridgestone/Firestone blamed each other for the failure. This led to severing of the relations between the two companies. In November, 2000, the NHTSA implemented the TREAD Act that raised the bar for tire safety, and the TREAD Act directly cited the safety issue of Firestone tires.[47] Researchers such as Gibson (2000), Noggle and Palmer (2005) argued that if Firestone tires had been of higher quality, Ford SUVs would not have caused significant problems. The 2000 Firestone tire recall event was hence caused by production or engineering errors rather than exogenous shocks.

Due to its close relationship with the magnitude of an enterprise's market value, studying recall characteristics helps explain the degree of abnormal returns. To recover the different effect on a company's value between different sources of shocks, researchers can observe the CAR in the short and middle run. In Figure 2.1, all three CARs dropped after the recall events, and Bridgestone suffered a bigger loss than Johnson & Johnson and Toyota. In the short run, the impact of a product recall on the stock market is not substantially different between endogenous shocks and exogenous shocks. For example, the CARs during the first four post-event days were -16.65%, -15.56%, and -10.80% for Johnson & Johnson, Bridgestone and Toyota, respectively. When the public and the media were exposed to more and more accurate and detailed

[47] According to NHTSA (2002), the Transportation Recall Enhancement, Accountability and Documentation (TREAD) Act was enacted on November 1, 2000. It is a direct consequence of hearings after the Committee on Energy and Commerce on the safety of Firestone tires and related matters. The TREAD Act contains provisions requiring vehicle and equipment manufacturers to report periodically to NHTSA on a wide variety of information that could indicate the existence of a potential safety defect. The Act also requires manufacturers to advise NHTSA of foreign safety recalls and other safety campaigns.

information and shock sources, the impact difference appeared. The average CARs during the first 10 days in post-event period was -27.68%. CARs were -24.37%, -42.84%, and -15.82% for Johnson & Johnson, Bridgestone and Toyota, respectively. After the 20th post-event trading day, the average CARs was -35.78%; and CARs were -24.26%, -65.56% and -17.52% for Johnson & Johnson, Bridgestone, and Toyota, respectively.

However, the estimation results from the LSFA and USFA models show that all three companies were overvalued in the pre-event period. The LSFA models seem more appropriate than the USFA model regarding measuring the impact on a company's value, because the markets exist over valuation before all three recalls. Combing the results from these Tables and Figures, I found results from the USFA model are not consistent over three recalls.

2.5. Conclusions

In order to analyze a disastrous product recall's effect on a company's stock market performance, the traditional approach is to estimate a market model using OLS and calculate the effect of an event on the company's cumulative abnormal return. However, as Lunney (2008) pointed out, the traditional event study approach suffers from many weaknesses, such as overreaction to bad news in the market and reliance on the efficient market hypothesis. If irrational investors always overvalue or undervalue a particular company's stocks, stock prices do not reflect a firm's true value. In an event study, researchers need to carefully select an event, the length of the pre-event period and post-event period, and a model to describe the relationship between market return and stock return. Among them, the most important work in practice is to find a suitable model to predict the stock return when markets are not rational. Researchers should explore methodologies that may be more powerful than a traditional OLS approach.

2.5.1. The Results from the Traditional OLS Approach and Frontier Estimation Techniques

In this paper, I first utilized the traditional event study method to study three representative disastrous product recall events: 1982 Tylenol poisonings, 2000 Firestone tire recall, and 2010 Toyota sticking accelerator pedal recall. I evaluated the magnitude of reaction to the product recalls on the stock market in the short and middle run. Second, I explored alternative methodologies to conduct a comparative qualitative analysis of the product recall events without address the over and under valuation problem. These methodologies include the commonly used upper frontier data envelopment analysis (DEA), upper frontier corrected ordinary least squares (COLS) methodology, and upper stochastic frontier analysis (USFA).[48] I found that the event study method (OLS) exhibits similar performance as that from the USFA approach, but results from the DEA model and the COLS model are very different from those from the OLS model and the USFA model. If a stock's return is negatively related to market returns, results from the COLS and DEA analysis are hard to explain. In addition, the COLS and DEA methods are sensitive to the influence of outliers, which resulted in greater variability.

[48] To make the results comparable and simplify the analysis, I use only one type of frontier model (upper frontier) for DEA, COLS and SFA in this section.

Regarding the misevaluation problem, the traditional event study model may not be appropriate. It ignores the possibility of overvaluation or undervaluation. Furthermore, the results from one-sided frontier models may also be misleading if we do not select a suitable evaluation frontier model. The selection of upper or lower frontier model (USFA or LSFA) needs to reflect the common view that traders overvalue or undervalue a company's stock price. A carefully chosen frontier estimation approach is the key in an event study.

Results from the event study indicate that initial losses in the market value for the three companies were large. As further information about the actual situation of crisis and cost became available, the companies recovered their losses in the stock market to different levels. However, the pace of the recovery varies among the companies. According to the traditional market model analysis, both Johnson & Johnson and Toyota showed a gradual loss on the CARs in the middle run.

2.5.2. Contributions of this Study

This study has several important contributions. First, in contrast to most other event studies that used a large sample but did not conduct relatively deep analysis on a particular event, this paper addresses the problem of overvaluation or undervaluation of stock prices by using upper and lower stochastic frontier methods. Second, by comparing the OLS model, the DEA model, the COLS model, and the USFA model in the estimation of a product recall's impact, I conducted a more complete investigation of each event. I explored not only traditional methods but also other frontier-based methodologies. This helps select an appropriate approach to study recall events in the future. Lastly, a discussion of market reaction to harmful product recalls under endogenous and exogenous causes provides a better understanding of the mechanism of stock price variability.

2.5.3. Recommendations for Future Research

In this paper, I explored several frontier estimation techniques, including the DEA method, the COLS method and the upper/lower SFA method. Furthermore, the analysis of the difference between the USFA model and the LSFA model can partially overcome the misevaluation problem on the stock price.

Over the past decades, the event study method has been widely employed in the field of product recalls. However, the evaluation of the long-run impact of a disastrous product recall is a difficult task because sometimes the results are controversial. For example, Knight and Pretty (1998) found that Johnson & Johnson suffered a long-time downside trend of loss and did not recover even one year after the recall. But other researchers concluded that Johnson & Johnson fully recovered and won a better market share (Moore 1982). Researchers such as Klein and Leffler (1981), Jarrell and Peltzman (1985), and Mitchell (1989) suggested using the brand name theory to evaluate long-time loss. [49] Hence, in the future, researchers need to find a suitable and powerful event-based method or other approaches to assess effects in the long run.

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[49] Brand name theory was initially proposed by Klein and Leffler (1981). They developed a model to describe the presence of firm-specific sunk capital investments.

Regarding the application of the SFA model, I adopted the most popular Normal-Half Normal frontier estimation model in this study. In the future, researchers should try other distribution specifications available for comparative analysis.

2.5.4. Summation

To sum up, I lay out four arguments. (1) The market value and stock return of Johnson & Johnson, Bridgestone, and Toyota are significantly influenced by the product recall events in the short run. (2) The traditional market model and upper stochastic frontier approaches produce similar results for the three recall events, an indication of robustness of the event study method when markets are rational. (3) The traditional event study approach may not be appropriate when markets are not fully rational. A carefully selected stochastic frontier model can effectively offset the influence from pre-event misevaluation (e.g., traders overvalue or undervalue the price of stocks). (4) Endogenous events are significantly different from exogenous events in terms of their impact on a firm's economic value when we are using the traditional event study method. However, the differences are not always significant when we use the stochastic frontier method.

References

Agrawal, J. and Kamakura, W. A., (1995), "The Economic Worth of Celebrity Endorsers: an Event Study Analysis," *Journal of Marketing*, 59, 56-62.

Aigner, D. J., Lovell, C. A. K. and Schmidt, P., (1977), "Formulation and Estimation of Stochastic Frontier Production Functions," *Journal of Econometrics*, 6, 21-37.

Ball, R. and Brown, P., (1967), "Some Preliminary Findings on the Association Between the Earnings of a Firm, its Industry and the Economy, Empirical Research in Accounting: Selected Studies," *Journal of Accounting Research*, 5, 55-77.

Barberis, N., Shleifer, A. and Vishny, R., (1998), "A Model of Investor Sentiment," *Journal of Financial Economics*, 49, 307-343.

Barber, B. M., Odean, T. and Zhu, N., (2009), "Systematic Noise," *Journal of Financial Markes*, 12, 547–569.

Bauer, P., (1990), "A Survey of Recent Econometric Developments in Frontier Estimation," *Journal of Econometrics*, 46, 21-39.

Brown, S. and Warner, J., (1980), "Measuring Security Price Performance," *Journal of Financial Economics*, 8, 205-285.

Brown, S. and Warner, J., (1985), "Using Daily Stock Returns: The Case of Event Studies," *Journal of Financial Economics*, 4, 3-32.

Campbell, J., Lo A. W., and MacKinlay, C. A., (1997), *The Econometrics of Financial Markets*, Princeton University Press: Princeton, NJ.

Chen, Y., Ganesan, S and Liu, Y., (2009), “Does a Firm’s Product-recall Strategy Affect its Financial Value? An Examination of Strategic Alternatives During Product-harm Crises,” *Journal of Marketing*, 73, 214–226.

Isidore, C., (2010), “Toyota Recall Costs: $2 billion,” http://money.cnn.com/2010/02/04/news/companies/toyota_earnings.cnnw/?postversion=20100204108, accessed September 8, 2011.

Charnes, A., Cooper, W. W. and Rhodes, E., (1978), “Measuring the Efficiency of Decision Making Units,” *European Journal of Operations Research*, 2, 429-444.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J. and Battese, G. E. (2005), *An Introduction to Efficiency and Productivity Analysis*, 2nd Edition, Springer: New York.

Coelli, T. J., Rao, D. S. P. and Battese, G., (1998), *An Introduction to Efficiency and Productivity Analysis*, Kluwer Academic Publishers: Boston.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A., (1997), “A Theory of Overconfidence, Self-attribution, and Security Market Under- and Over-reactions,” Unpublished working paper, University of Michigan.

Davidson, W. N. and Worrell, D. L., (1992), “Research Notes and Communications: The Effect of Product Recall Announcements on Shareholder Wealth. Strategic,” *Management Journal*, 3, 467-473.

Debreu, G., (1951), “The Coefficient of Resource Utilization,” *Econometrica*, 19, 3, 273-92.

Dolley, J. C., (1933), “Characteristics and Procedure of Common Stock Split-Ups,” *Harvard Business Review,* 11, 316-326.

Dowdell, T., Govindaraj, S. and Jain, P., (1992), “The Tylenol Incident, Ensuing Regulation and Stock Prices,” *Journal of Financial and Quantitative Analysis,* June, 283-300.

Fama, E. F., Fisher, L., Jensen, M., and Roll, R., (1969), “The Adjustment of Stock Prices to New Information,” *International Economic Review,* 1, 10.

Fama, E. F., (1970), “Efficient Capital Markets: A Review of Theory and Empirical Work,” *Journal of Finance,* 25, 383-417.

Fama, E. F., (1976), *Foundations of Finance: Portfolio Decisions and Security Prices*, Basic Books: New York.

Fama, E. F., (1998), “Market Efficiency, Long-term Returns, and Behavioral Finance,” *Journal of Financial Economics,* 49, 283-306.

Farrell, M. J., (1957), “The Measurement of Productive Efficiency,” *Journal of the Royal Statistical Society,* 120, 3, 253-81.

Färe, R., Grosskopf, S. and Lovell, C. A. K., (1994), *Production Frontier,* Cambridge University Press: Cambridge.

Färe, R. and Primont, D., (1995), *Multi-output and Duality: Theory and Application,* Kluwer-Nijhoff Publishing: Boston.

Førsund, F., Lovell, C. A. K. and Schmidt, P., (1980), “A Survey of Frontier Production Functions and of Their Relationship to Efficiency Measurement,” *Journal of Econometrics*, 13, 5-25.

Geyskens, I., Gielens, K. and Dekimpe, M. G., (2002), “The Market Valuation of Internet Channel Additions,” *Journal of Marketing*, 66, 102-119.

Gibson, D. C., (2000), “Firstone’s Failed Recalls, 1978 and 2000: A Public Relations Explanation,” *Public Relations Quarterly*, January 1.

Govindaraj, S., Jaggi, B. and Lin, B., (2004), “Market Overreaction to Product Recall Revisited – The Case of Firestone Tires and the Ford Explorer,” *Review of Quantitative Finance and Accounting*, 23, 31-54.

Greene, W., (1993), “The Econometric Approach to Efficiency Analysis,” in H. Fried, K. Lovell, and S. Schmidt, eds., *The Measurement of Productive Efficiency*, Oxford University Press: Oxford.

Greene, W., (2006), “The Econometric Approach to Efficiency Analysis,” to appear as Chapter 2 in *The Measurement of Productivity Efficiency*, Oxford University Press: Oxford.

Hilliard, J. E. and Savickas, R., (2003), “On the Statistical Significance of Event Effects on Unsystematic Volatility,” *Journal of Financial Research*, 25, 447-462.

Hoffer, G. E., Pruitt, S. W. and Reilly, R. J., (1988), “The Impact of Product Recalls on the Wealth of Sellers: A Reexamination,” *Journal of Political Economy,* 96, 3, 663-700.

Horsky. D. and Swyngedouw, P., (1987), “Does It Pay to Change Your Company's Name? A Stock Market Perspective,” *Science*, 6, 320-335.

Ilina, E. and Daragan, V., (2003), "Correlation of the Stock Indices," http://www.basicsoftrading.com/journal/2-investment-strategies/2-002/index.shtml, accessed September 8, 2011.

Jarrell, G. and Peltzman, P., (1985), "The Impact of Product Recalls on the Wealth of Sellers," *Journal of Political Economy*, 93, 3, 512-536.

Klein, B., and Leffler, K. B., (1981), "The Role of Market Forces in Assuring Contractual Performance," *Journal of Political Economy,* 21, 615-41.

Khansa, L. and Liginlal, D., (2011), "Predicting Stock Market Returns from Malicious Attacks: A Comparative Analysis of Vector Autoregression and Time-delayed Neural Networks," *Decision Support Systems*, Article in Press.

Knight, R. F. and Pretty, D. J., (1998), "Corporate Catastrophes, Stock Returns and Trading Volumes," *Corp. Rep. Rev.*, 2, 4, 363-37.

Koopmans, T., (1951), *Activity Analysis of Production and Allocation*, John Wiley and Sons: New York.

Kothari, S. and Warner, J., (2004), "Econometrics of Event Studies", University of Rochester working paper.

Kumbhakar, S. C. and Lovell, C. A. K., (2000), *Stochastic Frontier analysis*. Cambridge University Press: Cambridge.

Lane, V. and Jacobson, R., (1995), "Stock Market Reactions to Brand Extension Announcements: The effects of Brand Attitude and Familiarity," *Journal of Marketing*, 59, 63-77.

Lintner, J., (1965), “The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets,” *Review of Economics and Statistics,* 47, 13-37.

Lunney, G. S., (2008), “On the Continuing Misuse of Event Studies: the Example of Bessen and MEurer,” *Journal of Intellectual Property Law*, Fall.

MacKinlay, C., (1997), “Event Studies in Economics and Finance,” *Journal of Economic Literature,* 35, 13-39.

Maddala, M. S., (1992), *Introduction to Econometrics*, 2nd ed. Macmillan: New York.

McWilliams, A. and Siegel, D., (1997), “Event Studies in Management Research: Theoretical and Empirical Issues,” *Academy of Management Journal,* 40, 626–57.

Meeusen, W., and van den Broeck, J., (1977), “Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error,” *International Economic Review*, 18, 435-444.

Mitchell, M. L. and Netter, J. M., (1994), “The Role of Financial Economics in Securities Fraud Cases: Applications at the Securities and Exchange Commission,” *Business Lawyer,* 49, 545-59.

Mitchell, M., (1989), “The Impact of External Parties on Brand-Name Capital: The 1982 Tylenol Poisonings and Subsequent Cases,” *Economic Inquiry,* October, 601-617.

Moore, T., (1982), “The Fight to Save Tylenol,” Fortune, November 29, 1982, 44 & plus.

Mullan, J. Gibson, (2004), “Reporting Safety Problems: U.S. Perspective,” http://www.icphso.org/oldfiles/international/2004Euro/2004/London1.pdf, accessed September 8, 2011.

NHTSA, (2002), February 28, 2002, http://www.nhtsa.gov/nhtsa/announce/testimony/tread.html, accessed September 8, 2011.

Noggle, T. and Palmer, G., (2005), “Radials, Rollovers and Responsibility: An Examination of the Ford-Firestone Case,” *Journal of Business Ethics*, 56, 2, 185-204.

Pearsall, N. A., (2002), “Use of Event Studies to Estimate Brand Value: A Comparison of Methodologies,” Unpublished working paper, Virginia Polytechnic Institute and State University.

Ross, S. A., (1976), “The Arbitrage Theory of Capital Asset Pricing,” *Journal of Economic Theory*, 13, 341-360.

Sharpe, W. F., (1964), “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk,” *Journal of Finance*, 19, 425-442.

Shephard, R. W., (1970), *Theory of Cost and Production Functions*, Princeton University Press: Princeton.

Simar, L., (1992), “Estimating Efficiencies From Frontier Models with Panel Data: A Comparison of Parametric, Nonparametric, and Semiparametric Methods with Bootstrapping,” *Journal of Productivity Analysis*, 3, 167-203.

Thomsen, M. R. and McKenzie, A. M, (2001), “Market Incentives for Safe Foods: An Examination of Shareholder Losses from Meat and Poultry Recalls,” *American Journal of Agricultural Economics,* 83, 3, 526-38.

Winsten, C., (1957), “Discussion on Mr. Farrell's Paper,” *Journal of the Royal Statistical Society,* Series A, General, 120, 282-284.

Ward's Communications, (2001 - 2010, various years), *Ward's Motor Vehicle Facts and Figures,* Southfield: Detroit, MI.

Zhu, J., (2003), “Imprecise Data Envelopment Analysis (IDEA): A Review and Improvement with an Application,” *European Journal of Operational Research*, 144, 3, 513-529.

Appendix

Appendix A: Background of the 1982 Tylenol Poisonings

On October 1, 1982, The Wall Street Journal and the New York Times reported deaths of five Chicago suburban dwellers from consumption of cyanide-laced extra strength Tylenol capsules. The makers of Tylenol, Johnson & Johnson, which controlled 37 percent of its market with revenue of about $1.2 million, immediately recalled two shipment lots and also recalled all extra strength Tylenol capsules from the Chicago area. Later, on October 5, 1982, the company recalled Tylenol capsules nationwide; an estimated 31 million bottles were in circulation, with a retail value of over US$100 million. The company also advertised in the national media for individuals not to consume any products that contained acetaminophen. When it was determined that only capsules were tampered with, they offered to exchange all Tylenol capsules already purchased by the public with solid tablets. Throughout the incident, the company maintained that the bottles had been tampered with outside the factory premises. The Food and Drug Administration (FDA) initiated investigations and imposed new stringent packaging regulations for pharmaceutical products soon after the Tylenol poisonings. The case remains unsolved and no suspects have been charged. A $100,000 reward, offered by Johnson & Johnson, for the capture and conviction of the "Tylenol Killer", has never been claimed. The media gave Johnson & Johnson much positive coverage for its handling of the crisis; for example, an article in The Washington Post said, "Johnson & Johnson has effectively demonstrated how a major business ought to handle a disaster." The article further stated that "this is no Three Mile Island accident in which the company's response did more damage than the original incident," and applauded the company for being honest with the public.[50]

Appendix B: Background of the 2000 Firestone Tires Recall

On August 7, 2000, Bridgestone Corporation of Japan made a sudden announcement recalling 6.5 million of a class of Firestone Radial ATX, ATXII and Wilderness AT brands tires. It was reported that these tires exhibited tendencies to come apart at high speed causing the vehicle to roll over. Particularly noteworthy was the fact that although many vehicles used Firestone tires, it was only the popular Ford Explorer SUV that consistently displayed tendencies to roll over, which pointed toward design flaws in the Ford Explorer. Either exacerbating or exceeding the design limitations of the Firestone tires caused the vehicle to rollover. Thus, the Ford Motor Company could not avoid sharing some of the blame and responsibility for the accidents. A federal investigation found at least 88 deaths and more than 300 accidents involving Bridgestone/Firestone tires that had shredded on the highway. The majority of the accidents held the same situation of the driver maintaining a speed of 65 miles per hour, the tires shredded and the rubber peeled away from the rim. Most of the tire failures involved Ford Explorer sport utility vehicles. The date of the recall was also the day the first lawsuits were filed. It became quite clear by August 23, 2000, that the government was taking an active interest in the case. By

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[50] Jerry Knight, " The Bad News on Tylenol," *Washington Post*, Oct. 11, 1982 at http://www.washingtonpost.com/wp-dyn/content/article/1982/10/11/AROLD1982001395.html, accessed September 8, 2011.

September 13, 2000, a new law called the Transportation Recall Enhancement, Accountability, and Documentation (TREAD) Act was introduced and its passage was virtually certain. The Act increased the standards of transportation safety, steeply increased the monetary penalties, and imposed criminal charges for violations.

Appendix C: Background of the 2010 Toyota Sticking Accelerator Pedals

The first recall was in November 2009 due to gas pedals catching on floor mats resulting in uncontrolled acceleration causing accidents. The second recall, begin on January 21, 2010, was begun after some crashes were shown not to have been caused by floor mat incursion. The defect was identified as a possible mechanical sticking of the accelerator pedal causing unintended acceleration, referred to as Sticking Accelerator Pedal by Toyota. In some cases the “gas pedal mechanism” gets problematic because it becomes harder, does not push, or returns slowly. That means the car will keep on accelerating even when the driver has moved his foot off the pedal. The problem occurs in humid environments or due to the moisture in the mornings. As of January 28, 2010, Toyota had announced recalls of approximately 5.2 million vehicles for the pedal entrapment/floor mat problem, and an additional 2.3 million vehicles for the accelerator pedal problem. Approximately 1.7 million vehicles were subject to both. Certain related Lexus and Pontiac models were also affected. The next day, Toyota widened the recall to include 1.8 million vehicles in Europe and 75,000 in China. By then, the worldwide total number of cars recalled by Toyota stood at 9 million. The issue has led to Congressional hearings, damaged the reputation of a company once known for its bulletproof reliability, and left millions of

Toyota owners with questions about their own safety. On August 10, 2011, NHTSA’s preliminarily report showed no evidence of electrical problems with Toyota. Driver error or pedal misapplication was found responsible for most of the incidents. The report ended stating, “Our conclusion is Toyota's problems were mechanical, not electrical.” This included sticking accelerator pedals, and pedals caught under floor mats.

Figure 2.1

Cumulative Market Model Abnormal Returns for Three Product Recall Events

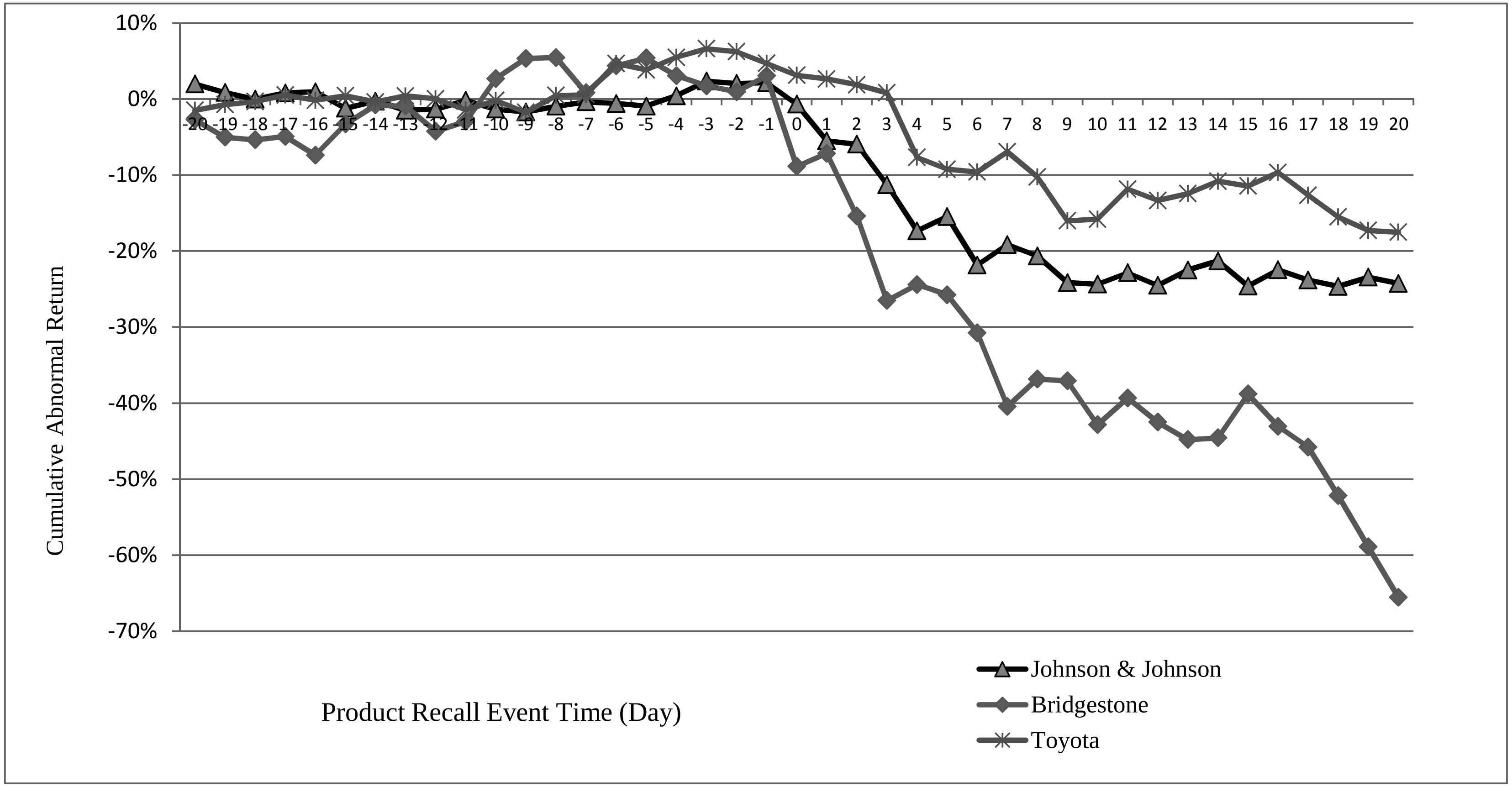

Figure 2.2

Four Approaches Comparison: Johnson & Johnson Stock Return vs. Market Index Return

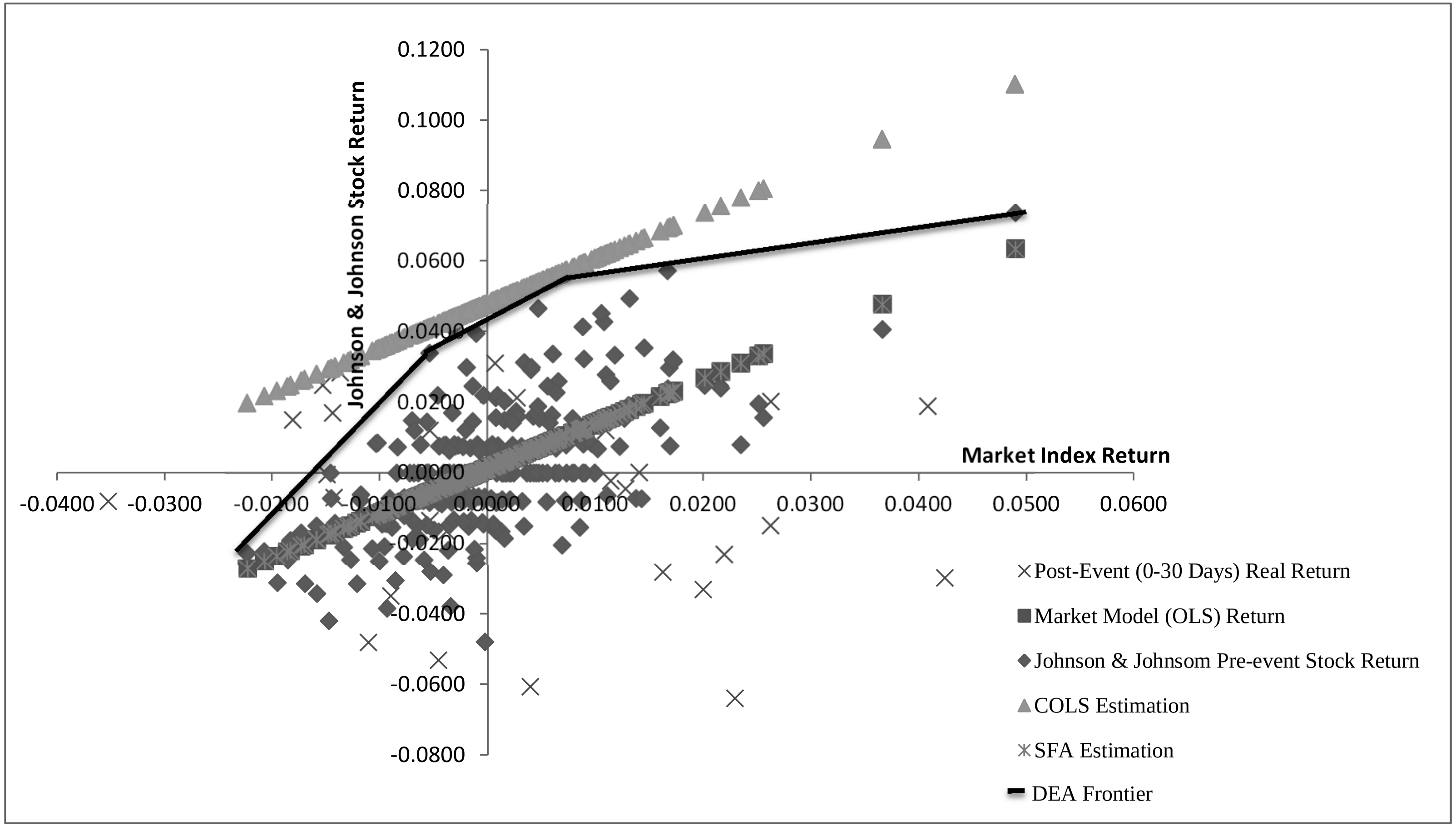

Figure 2.3
Johnson & Johnson Stock CARs from Four Models in the Post-event Period

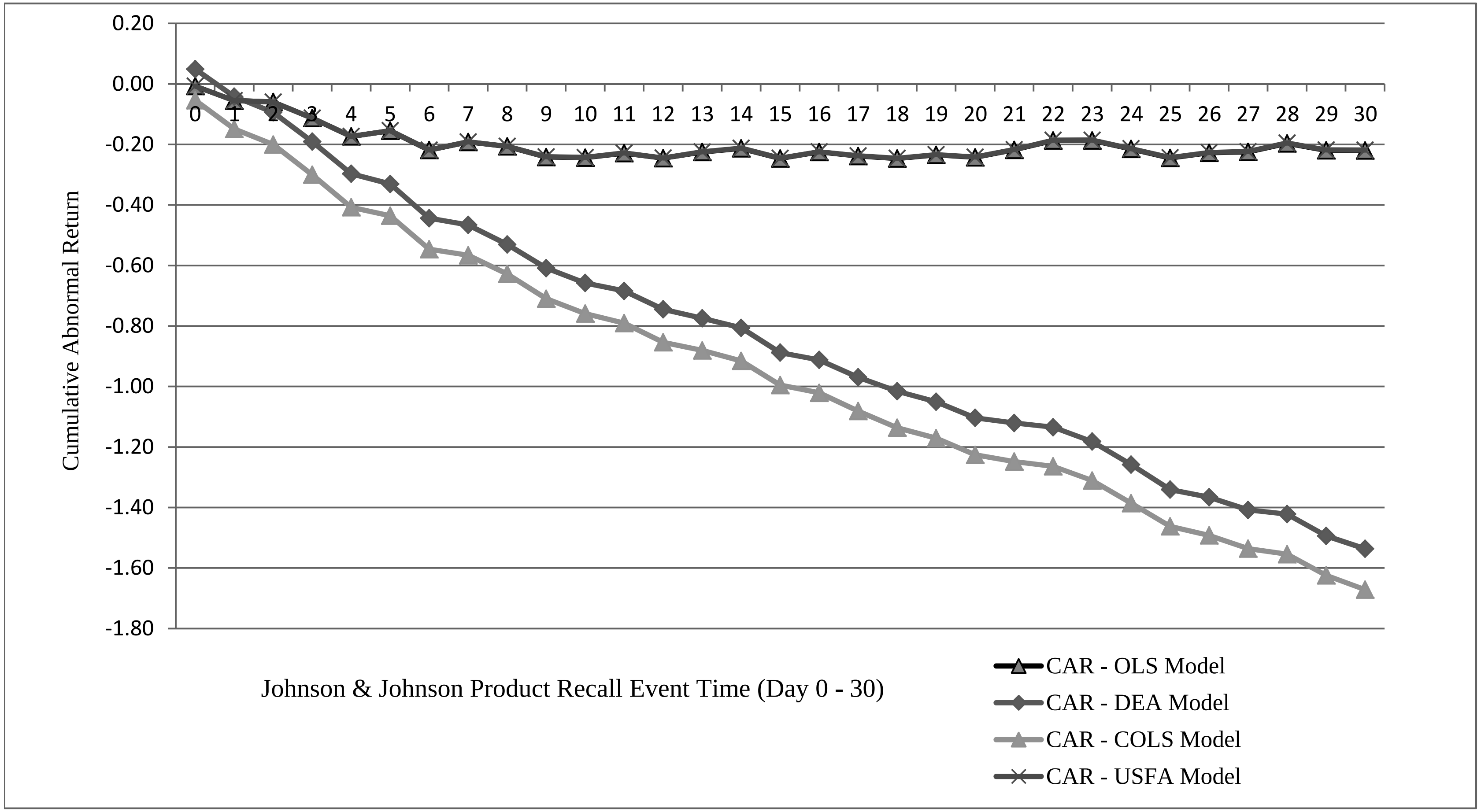

Figure 2.4

Four Approaches Comparison: Bridgestone Stock Return vs. Market Index Return

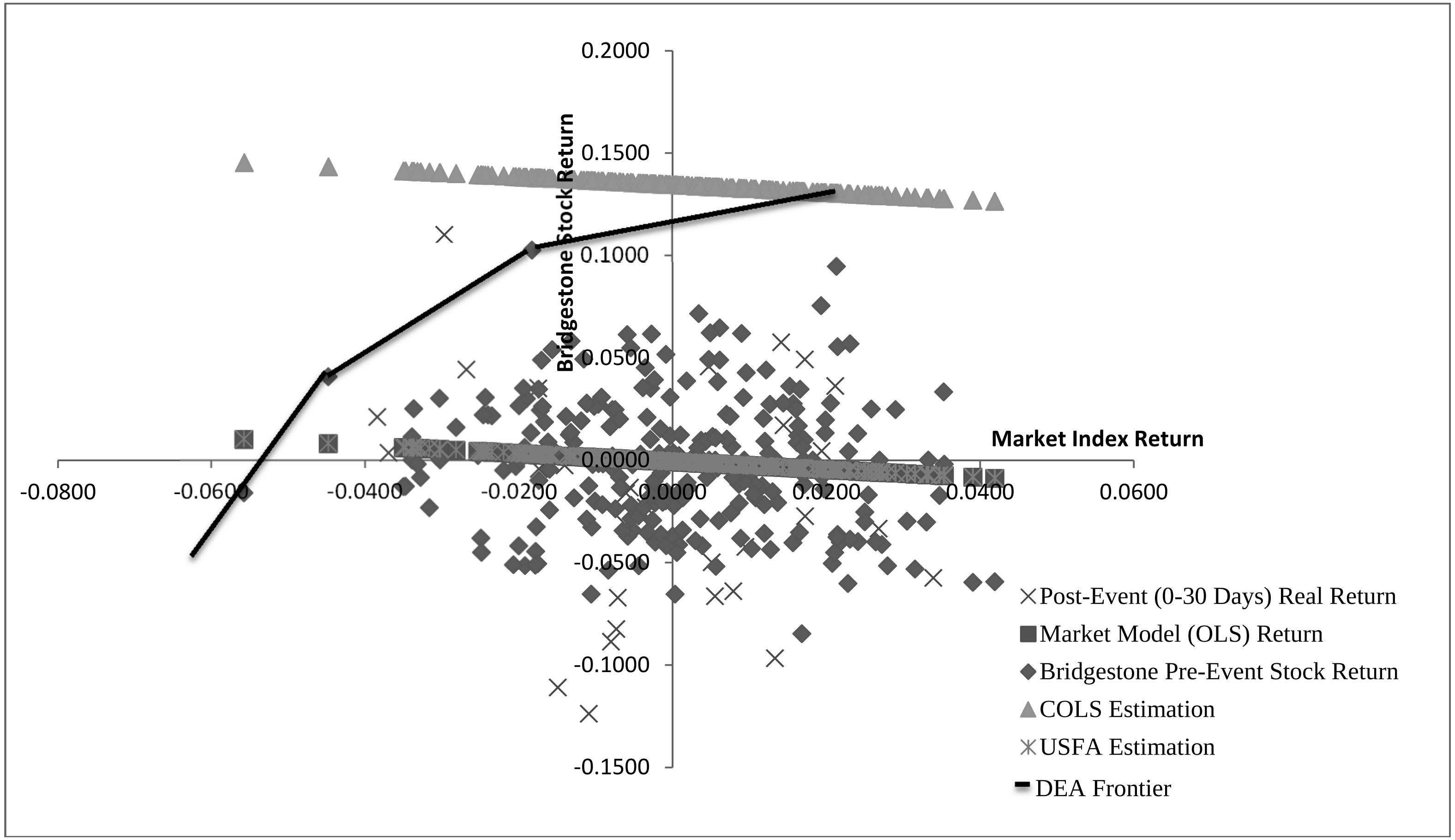

Figure 2.5
Bridgestone Stock CARs from Four Models in the Post-event Period

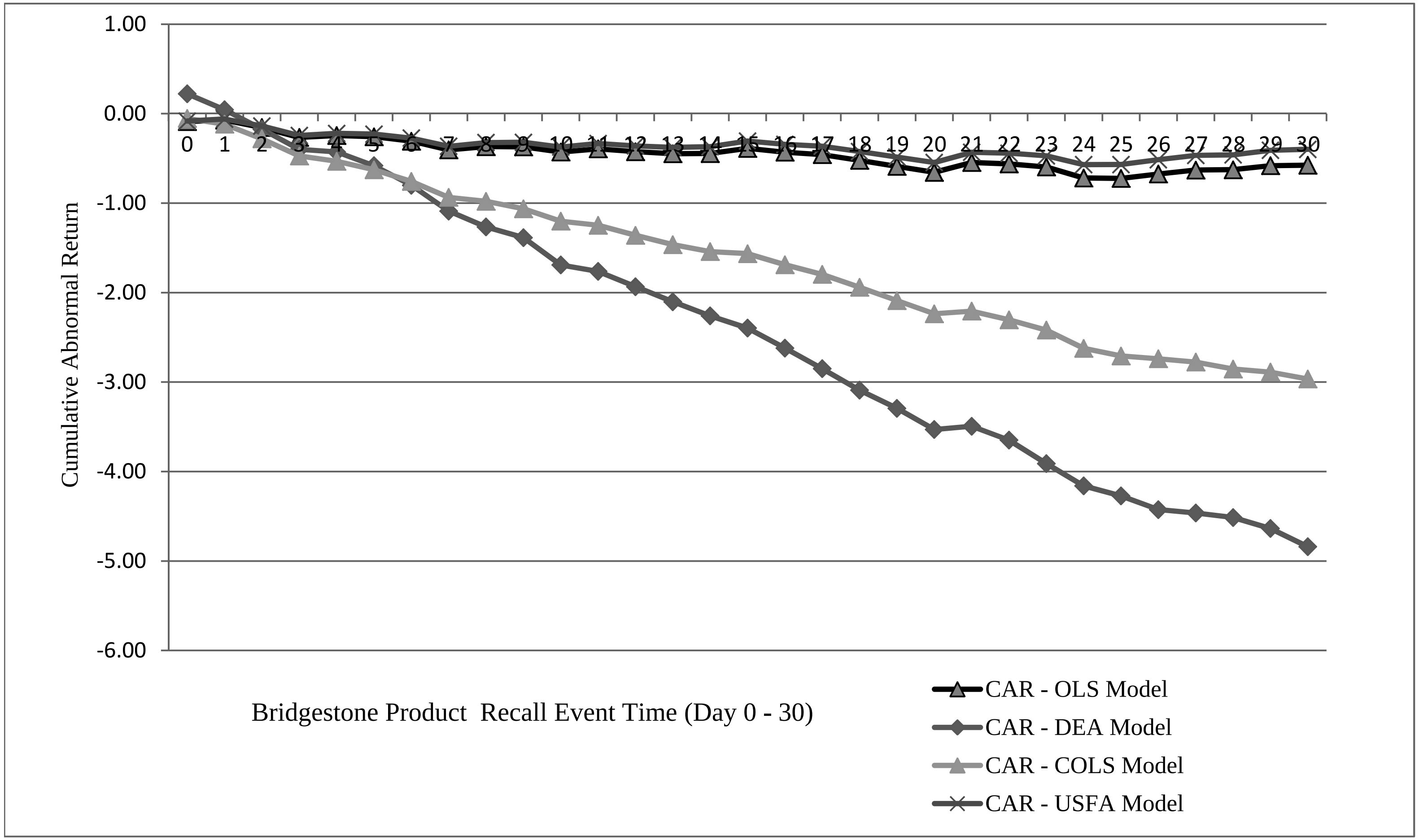

Figure 2.6

Four Approaches Comparison: Toyota Stock Return vs. Market Index Return

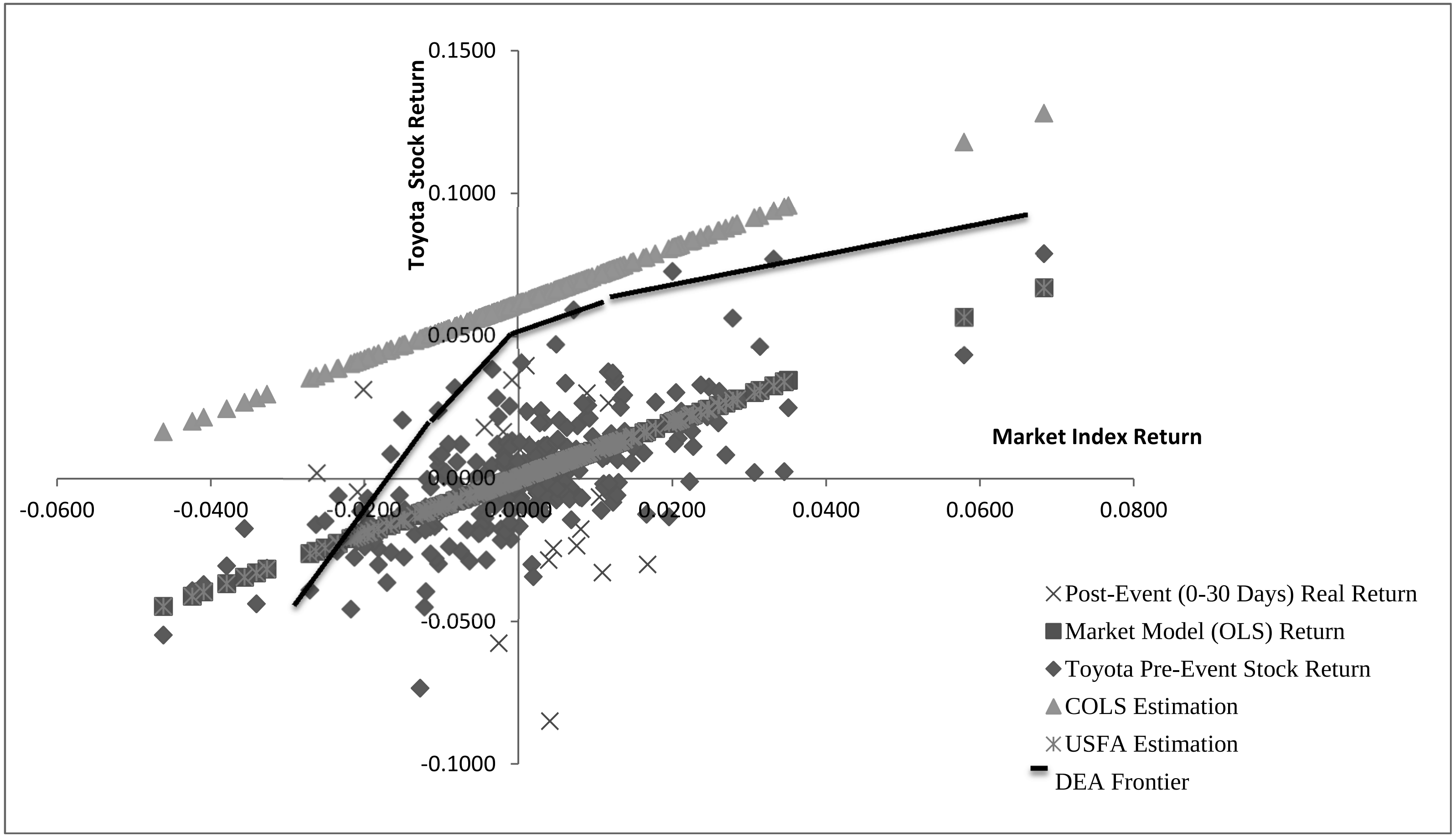

Figure 2.7
Toyota Stock CARs from Four Models in the Post-event Period

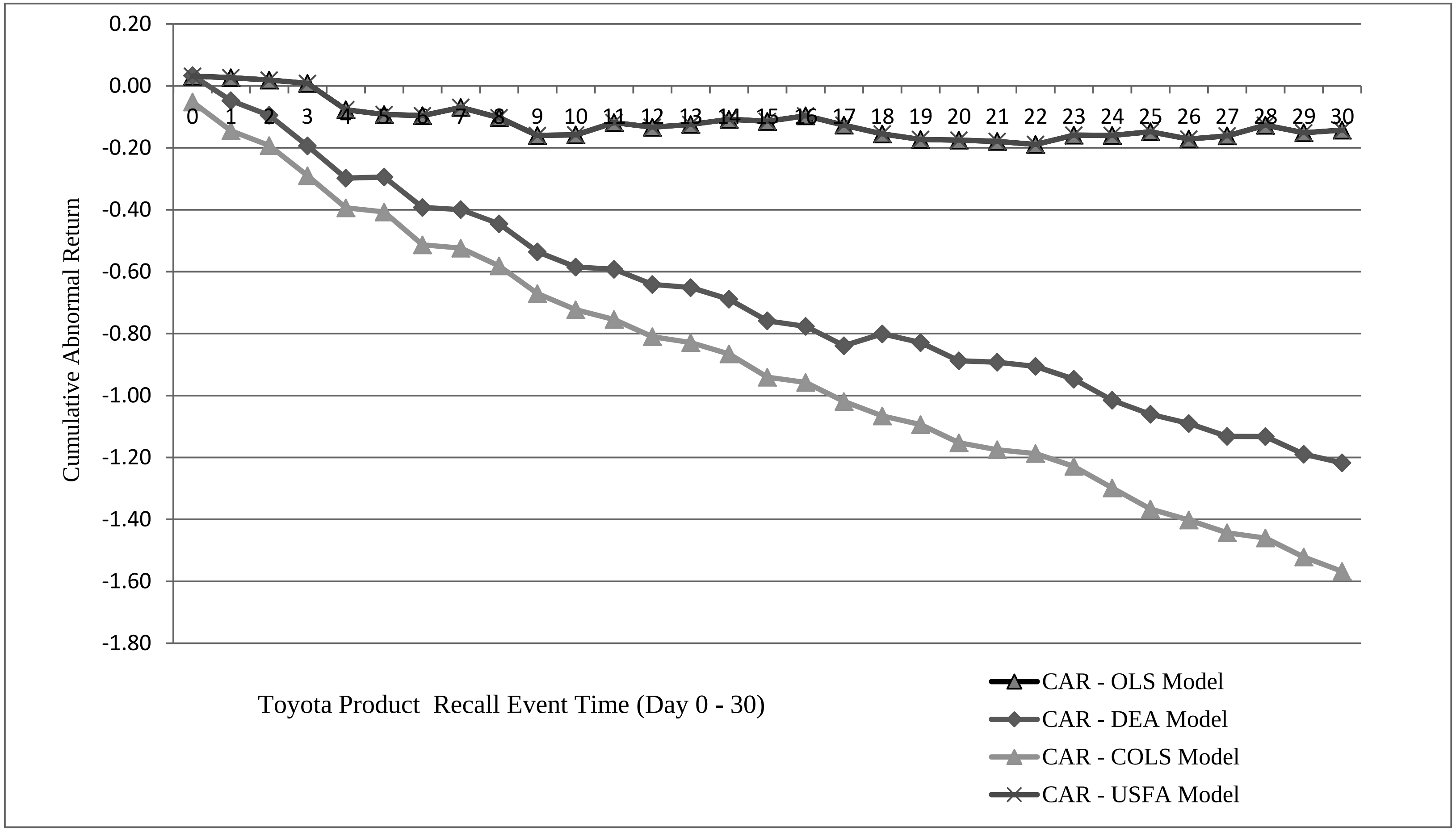

Figure 2.8

The Cumulative Abnormal Returns (LSFA, USFA and OLS) for Johnson & Johnson

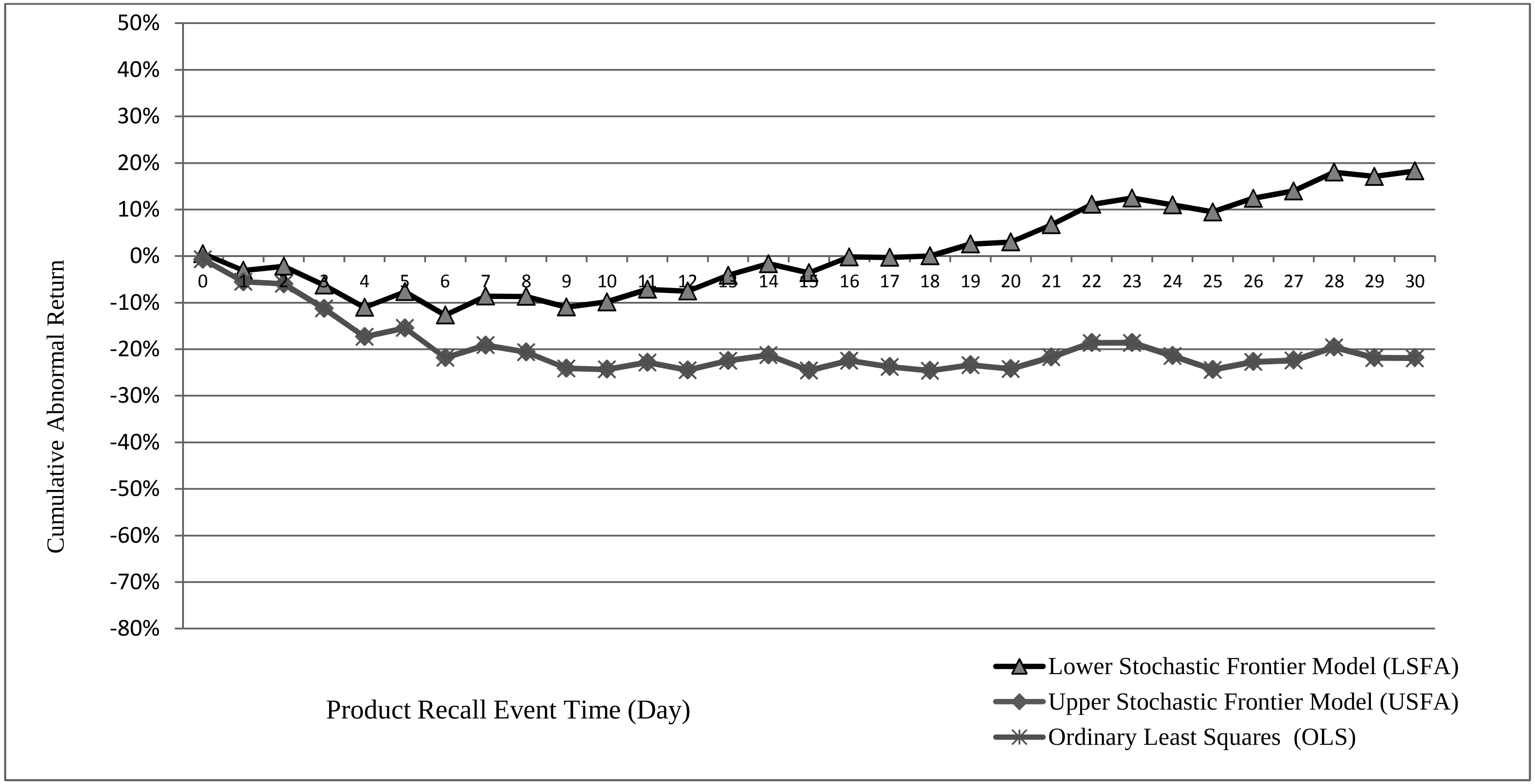

Figure 2.9

The Cumulative Abnormal Returns (LSFA, USFA and OLS) for Bridgestone

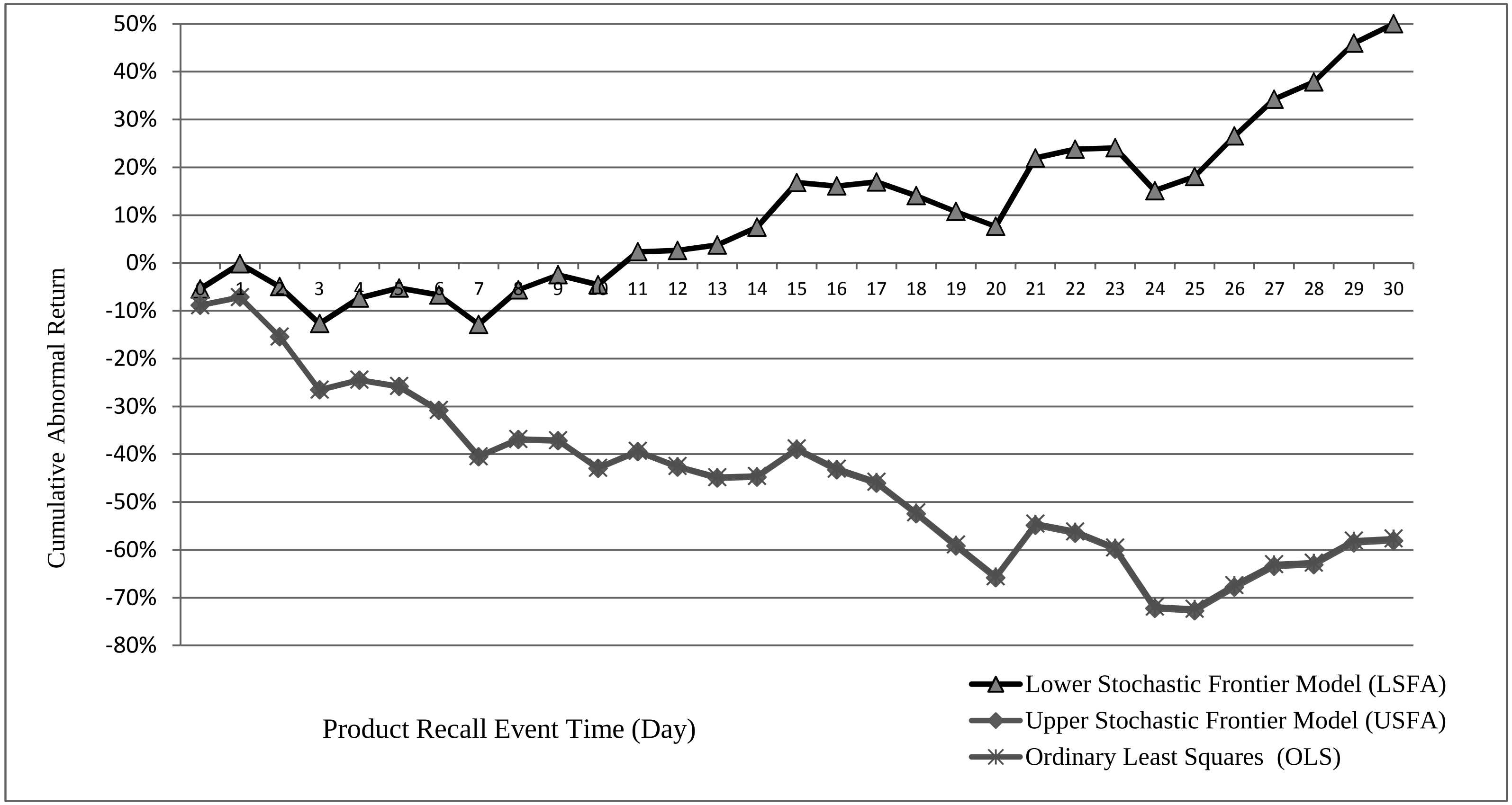

Figure 2.10

The Cumulative Abnormal Returns (LSFA, USFA and OLS) for Toyota

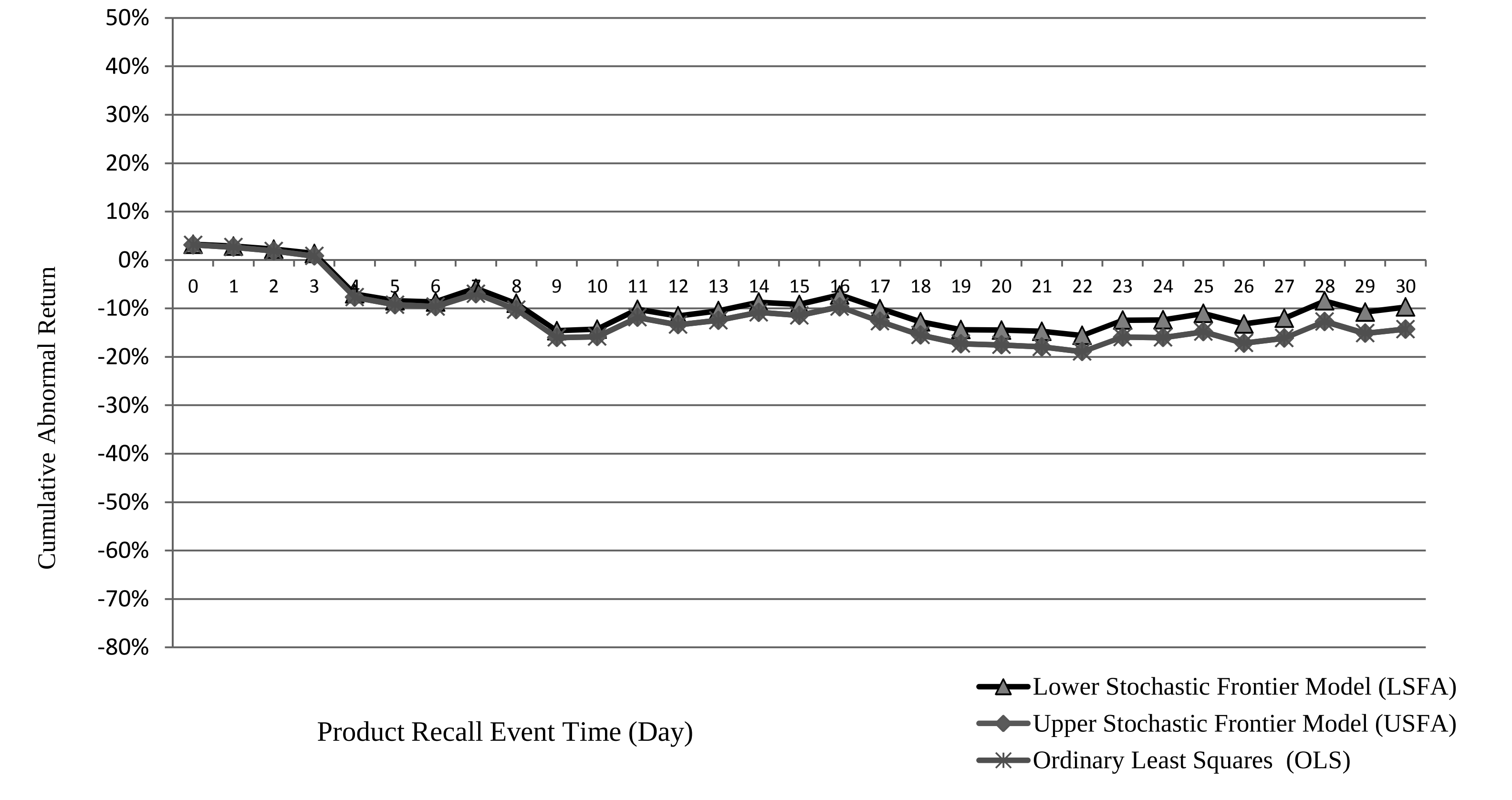

Table 2.1

Descriptive Statistics of Data

Variable	Event Date	Pre-Event (estimation) Window		Pre-Event (estimation) Window Data			
		Starting Date	Ending Date	Mean	Std Dev	Maximum	Minimum
Johnson & Johnson Stock Price	1982/10/1	1981/9/29	1982/9/28	1.3453	0.1234	1.6800	1.1300
Johnson & Johnson Returns		1981/9/29	1982/9/28	0.0017	0.0186	0.0735	-0.0480
Dow Jones Index		1981/9/29	1982/9/28	845.49	33.95	934.79	776.92
Dow Jones Index Returns		1981/9/29	1982/9/28	0.0004	0.0092	0.0490	-0.0223
Bridgestone Stock Price	2000/8/7	1999/7/28	2000/8/4	2609.17	357.07	3550.00	2030.00
Bridgestone Returns		1999/7/28	2000/8/4	-0.0008	0.0336	0.1626	-0.0848
Nikkei 225 Index		1999/7/28	2000/8/4	10278.20	999.94	11979.85	8303.39
Nikkei 225 Index Returns		1999/7/28	2000/8/4	0.0007	0.0167	0.0419	-0.0557
Toyota Stock Price	2010/1/21	2009/1/20	2010/1/20	77.0525	7.6321	91.7800	57.6800
Toyota Returns		2009/1/20	2010/1/20	0.0017	0.0186	0.0735	-0.0480
Dow Jones Index		2009/1/20	2010/1/20	8980.36	1073.93	10725.43	6547.05
Dow Jones Index ReturnsJohnson & Johnsor		2009/1/20	2010/1/20	0.0003	0.0097	0.0476	-0.0232

Table 2.2

Summary of Three Market Models

Regression Statistics

	Johnson & Johnson	Bridgestone	Toyota
Multiple R	0.631660	0.096530	0.678143
R Square	0.398995	0.009318	0.459878
Adjusted R Square	0.396591	0.005355	0.457726
Standard Error	0.014458	0.033504	0.015515
Observations	252	252	252

ANOVA (Johnson & Johnson)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.034696	0.034696	165.970	1.81667E-29
Residual	250	0.052262	0.000209		
Total	251	0.086958			

ANOVA (Bridgestone)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.002639	0.002639	2.357	0.126432189
Residual	250	0.280626	0.001123		
Total	251	0.283266			

ANOVA (Toyota)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.051441	0.051441	213.710	1.97722E-35
Residual	250	0.060417	0.000241		
Total	251	0.111858			

Market Model

Johnson & Johnson

		SE	*t Stat*	*P-value*
Intercept	0.001215	0.000912	1.332746	0.183829
Market Return	1.269725	0.098559	12.882925	1.82E-29

Bridgestone

		SE	*t Stat*	*P-value*
Intercept	-0.000782	0.002113	-0.370115	0.711610
Market Return	-0.193613	0.126261	-1.533439	0.126432

Toyota

		SE	*t Stat*	*P-value*
Intercept	0.000211	0.000979	0.215678	0.829414
Market Return	0.975017	0.066696	14.618826	0.000000

Table 2.3

Summary of Traditional Market Model for Johnson & Johnson

# of Days Before/After Event Day	Adjusted Stock Return	Market Model (OLS) Return	Abnormal Return	Cumulative Abnormal Return	t-value
-20	0.0323	0.0126	0.0197	0.0197	
-19	-0.0188	-0.0076	-0.0111	0.0085	
-18	0.0127	0.0216	-0.0088	-0.0003	
-17	0.0314	0.0232	0.0083	0.0079	
-16	-0.0122	-0.0137	0.0015	0.0094	
-15	-0.0185	0.0033	-0.0218	-0.0123	
-14	0.0063	-0.0032	0.0095	-0.0028	
-13	-0.0188	-0.0067	-0.0120	-0.0148	
-12	0.0191	0.0178	0.0013	-0.0136	
-11	0.0187	0.0072	0.0116	-0.0020	
-10	0.0000	0.0115	-0.0115	-0.0135	
-9	-0.0061	-0.0024	-0.0037	-0.0172	
-8	-0.0062	-0.0136	0.0075	-0.0097	
-7	0.0062	0.0003	0.0059	-0.0038	
-6	0.0247	0.0268	-0.0021	-0.0060	
-5	-0.0120	-0.0085	-0.0035	-0.0095	
-4	0.0122	-0.0013	0.0135	0.0040	
-3	0.0120	-0.0074	0.0194	0.0234	
-2	0.0000	0.0031	-0.0031	0.0203	
-1	0.0000	-0.0009	0.0009	0.0213	
0	-0.0238	-0.0168	-0.0070	-0.0070	
1	-0.0610	-0.0128	-0.0482	-0.0551	-2.9931 *
2	0.0130	0.0175	-0.0045	-0.0596	-2.4123 *
3	-0.0577	-0.0046	-0.0531	-0.1128	-4.0294 *
4	-0.0544	0.0062	-0.0607	-0.1734	-5.4114 *
5	0.0719	0.0531	0.0188	-0.1546	-3.5624 *
6	-0.0336	0.0304	-0.0640	-0.2186	-4.6583 *
7	0.0556	0.0287	0.0269	-0.1917	-3.4108 *
8	0.0197	0.0346	-0.0149	-0.2065	-3.3306 *
9	-0.0452	-0.0102	-0.0350	-0.2415	-4.1013 *
10	0.0135	0.0158	-0.0022	-0.2437	-4.2785 *
11	-0.0067	-0.0217	0.0150	-0.2287	-4.1262 *
12	-0.0201	-0.0036	-0.0165	-0.2453	-4.3356 *
13	0.0548	0.0346	0.0202	-0.2251	-3.4951 *
14	0.0065	-0.0055	0.0120	-0.2130	-3.3311 *
15	-0.0065	0.0267	-0.0331	-0.2462	-3.6201 *
16	0.0260	0.0047	0.0212	-0.2249	-3.1515 *
17	-0.0190	-0.0055	-0.0134	-0.2384	-3.3911 *
18	-0.0516	-0.0435	-0.0081	-0.2465	-3.5024 *
19	0.0272	0.0152	0.0120	-0.2344	-2.9915 *
20	-0.0066	0.0016	-0.0082	-0.2426	-3.1716 *
Average CAR(1-3 Days)				-0.0759	-3.1449
Average CAR(1-10 Days)				-0.1658	-3.8188
Average CAR(11-20 Days)				-0.2345	-3.5116

*Represents statistical significance at 1% level, two tailed test.
**Represents statistical significance at 5% level, two tailed test.
***Represents statistical significance at 10% level, two tailed test.

Table 2.4

Summary of Traditional Market Model for Bridgestone

# of Days Before/After Event Day	Adjusted Stock Return	Market Model (OLS) Return	Abnormal Return	Cumulative Abnormal Return	t-value
-20	-0.0287	-0.0015	-0.0272	-0.0272	
-19	-0.0232	0.0000	-0.0232	-0.0504	
-18	-0.0022	0.0012	-0.0034	-0.0538	
-17	0.0000	-0.0043	0.0043	-0.0495	
-16	-0.0238	0.0007	-0.0245	-0.0739	
-15	0.0333	-0.0076	0.0409	-0.0330	
-14	0.0300	0.0051	0.0250	-0.0081	
-13	-0.0042	-0.0026	-0.0016	-0.0097	
-12	-0.0377	-0.0049	-0.0327	-0.0424	
-11	0.0109	-0.0019	0.0127	-0.0297	
-10	0.0581	0.0018	0.0563	0.0266	
-9	0.0305	0.0039	0.0266	0.0532	
-8	0.0020	0.0007	0.0012	0.0544	
-7	-0.0531	-0.0069	-0.0463	0.0081	
-6	0.0353	0.0000	0.0354	0.0435	
-5	0.0100	-0.0002	0.0103	0.0538	
-4	-0.0298	-0.0067	-0.0231	0.0306	
-3	-0.0164	-0.0028	-0.0136	0.0171	
-2	-0.0021	0.0056	-0.0077	0.0093	
-1	0.0209	-0.0001	0.0210	0.0303	
0	-0.0879	0.0008	-0.0887	-0.0887	
1	0.0135	-0.0036	0.0170	-0.0717	-2.9601 *
2	-0.0819	0.0006	-0.0825	-0.1542	-3.3744 *
3	-0.1089	0.0021	-0.1110	-0.2652	-3.6920 *
4	0.0276	0.0067	0.0209	-0.2443	-3.5608 *
5	-0.0132	0.0003	-0.0135	-0.2577	-3.6061 *
6	-0.0517	-0.0018	-0.0500	-0.3077	-3.8485 *
7	-0.1001	-0.0034	-0.0968	-0.4045	-4.0796 *
8	0.0313	-0.0049	0.0361	-0.3683	-3.8617 *
9	-0.0006	0.0019	-0.0025	-0.3709	-3.9637 *
10	-0.0649	-0.0073	-0.0575	-0.4284	-4.3044 *
11	0.0376	0.0026	0.0350	-0.3934	-4.0578 *
12	-0.0313	0.0004	-0.0316	-0.4251	-4.1623 *
13	-0.0232	-0.0001	-0.0231	-0.4482	-4.9190 *
14	0.0013	-0.0011	0.0025	-0.4457	-4.8565 *
15	0.0541	-0.0035	0.0576	-0.3881	-3.9695 *
16	-0.0451	-0.0026	-0.0424	-0.4306	-4.8377 *
17	-0.0315	-0.0041	-0.0273	-0.4579	-5.0412 *
18	-0.0663	-0.0023	-0.0640	-0.5219	-5.0583 *
19	-0.0667	0.0006	-0.0673	-0.5892	-5.6000 *
20	-0.0683	-0.0018	-0.0665	-0.6556	-6.5722 *
Average CAR(1-3 Days)				-0.1637	-3.3422
Average CAR(1-10 Days)				-0.2873	-3.7251
Average CAR(11-20 Days)				-0.4756	-4.9075

*Represents statistical significance at 1% level, two tailed test.
**Represents statistical significance at 5% level, two tailed test.
***Represents statistical significance at 10% level, two tailed test.

Table 2.5

Summary of Traditional Market Model for Toyota

# of Days Before/After Event Day	Adjusted Stock Return	Market Model (OLS) Return	Abnormal Return	Cumulative Abnormal Return	t-value
-20	-0.0068	0.0083	-0.0150	-0.0150	
-19	0.0127	0.0050	0.0078	-0.0072	
-18	0.0041	0.0004	0.0037	-0.0035	
-17	0.0139	0.0052	0.0086	0.0051	
-16	-0.0042	0.0027	-0.0070	-0.0018	
-15	0.0060	0.0001	0.0060	0.0042	
-14	-0.0076	0.0005	-0.0081	-0.0040	
-13	-0.0030	-0.0109	0.0080	0.0040	
-12	0.0109	0.0148	-0.0039	0.0001	
-11	-0.0154	-0.0009	-0.0145	-0.0144	
-10	0.0128	0.0004	0.0124	-0.0020	
-9	-0.0124	0.0033	-0.0156	-0.0176	
-8	0.0235	0.0013	0.0223	0.0046	
-7	0.0051	0.0044	0.0007	0.0054	
-6	0.0383	-0.0031	0.0414	0.0468	
-5	-0.0035	0.0051	-0.0086	0.0382	
-4	0.0195	0.0029	0.0166	0.0548	
-3	0.0023	-0.0090	0.0113	0.0661	
-2	0.0070	0.0109	-0.0038	0.0622	
-1	-0.0263	-0.0109	-0.0154	0.0469	
0	0.0117	-0.0194	0.0311	0.0311	
1	-0.0249	-0.0201	-0.0047	0.0264	1.5203 *
2	-0.0052	0.0025	-0.0077	0.0187	0.5219 **
3	-0.0106	0.0000	-0.0106	0.0081	0.2725
4	-0.0808	0.0042	-0.0850	-0.0769	-1.9198 *
5	-0.0263	-0.0108	-0.0155	-0.0924	-2.1620 *
6	-0.0086	-0.0049	-0.0037	-0.0961	-2.2510 *
7	0.0382	0.0117	0.0265	-0.0696	-1.8831 *
8	-0.0220	0.0109	-0.0329	-0.1025	-2.3624 *
9	-0.0600	-0.0023	-0.0577	-0.1602	-3.7416 *
10	-0.0233	-0.0253	0.0020	-0.1582	-3.2285 *
11	0.0408	0.0012	0.0396	-0.1186	-2.9223 *
12	-0.0249	-0.0099	-0.0150	-0.1335	-3.1350 *
13	0.0240	0.0150	0.0090	-0.1245	-3.0067 *
14	0.0146	-0.0018	0.0164	-0.1082	-2.6829 *
15	0.0041	0.0105	-0.0064	-0.1145	-2.8330 *
16	0.0138	-0.0041	0.0179	-0.0966	-2.2978 *
17	-0.0135	0.0166	-0.0301	-0.1267	-3.0456 *
18	-0.0245	0.0040	-0.0285	-0.1552	-3.1998 *
19	-0.0096	0.0081	-0.0177	-0.1729	-3.9848 *
20	-0.0012	0.0011	-0.0023	-0.1752	-4.8941 *
Average CAR(1-3 Days)				0.0177	0.7715
Average CAR(1-10 Days)				-0.0703	-1.5234
Average CAR(11-20 Days)				-0.1326	-3.2002

*Represents statistical significance at 1% level, two tailed test.
**Represents statistical significance at 5% level, two tailed test.
***Represents statistical significance at 10% level, two tailed test.

Table 2.6

Summary of OLS, COLS, DEA and USFA Estimates for Johnson & Johnson Stock Returns

Day	Johnson & Johnson Return	OLS (Market Model) Return	CAR-OLS	COLS Return	CAR-COLS	DEA Return	CAR-DEA	USFA Return	CAR-USFA
0	-0.0238	-0.0168	-0.0070	0.0300	-0.0538	-0.1538	0.0491	-0.0191	-0.0202
1	-0.0610	-0.0128	-0.0551	0.0340	-0.1488	-0.2488	-0.0418	-0.0154	-0.0657
2	0.0130	0.0175	-0.0596	0.0643	-0.2001	-0.3001	-0.0936	0.0158	-0.0686
3	-0.0577	-0.0046	-0.1128	0.0423	-0.3001	-0.4001	-0.1907	-0.0074	-0.1189
4	-0.0544	0.0062	-0.1734	0.0531	-0.4076	-0.5076	-0.2969	0.0037	-0.1770
5	0.0719	0.0531	-0.1546	0.0999	-0.4356	-0.5356	-0.3307	0.0582	-0.1632
6	-0.0336	0.0304	-0.2186	0.0772	-0.5464	-0.6464	-0.4438	0.0306	-0.2274
7	0.0556	0.0287	-0.1917	0.0755	-0.5663	-0.6663	-0.4659	0.0285	-0.2003
8	0.0197	0.0346	-0.2065	0.0814	-0.6280	-0.7280	-0.5305	0.0355	-0.2161
9	-0.0452	-0.0102	-0.2415	0.0366	-0.7098	-0.8098	-0.6086	-0.0129	-0.2484
10	0.0135	0.0158	-0.2437	0.0626	-0.7588	-0.8588	-0.6579	0.0139	-0.2488
11	-0.0067	-0.0217	-0.2287	0.0251	-0.7906	-0.8906	-0.6842	-0.0235	-0.2320
12	-0.0201	-0.0036	-0.2453	0.0432	-0.8540	-0.9540	-0.7449	-0.0064	-0.2457
13	0.0548	0.0346	-0.2251	0.0814	-0.8807	-0.9807	-0.7745	0.0355	-0.2264
14	0.0065	-0.0055	-0.2130	0.0413	-0.9155	-1.0155	-0.8063	-0.0084	-0.2116
15	-0.0065	0.0267	-0.2462	0.0735	-0.9954	-1.0954	-0.8880	0.0262	-0.2442
16	0.0260	0.0047	-0.2249	0.0516	-1.0210	-1.1210	-0.9122	0.0021	-0.2203
17	-0.0190	-0.0055	-0.2384	0.0413	-1.0813	-1.1813	-0.9694	-0.0084	-0.2310
18	-0.0516	-0.0435	-0.2465	0.0033	-1.1362	-1.2362	-1.0157	-0.0406	-0.2420
19	0.0272	0.0152	-0.2344	0.0620	-1.1710	-1.2710	-1.0505	0.0133	-0.2280
20	-0.0066	0.0016	-0.2426	0.0484	-1.2260	-1.3260	-1.1036	-0.0012	-0.2335
21	0.0067	-0.0182	-0.2178	0.0287	-1.2480	-1.3480	-1.1206	-0.0203	-0.2065
22	0.0331	0.0022	-0.1868	0.0490	-1.2639	-1.3639	-1.1346	-0.0006	-0.1727
23	0.0192	0.0191	-0.1867	0.0659	-1.3106	-1.4106	-1.1820	0.0177	-0.1712
24	-0.0063	0.0219	-0.2149	0.0687	-1.3856	-1.4856	-1.2580	0.0208	-0.1982
25	0.0253	0.0551	-0.2447	0.1020	-1.4623	-1.5623	-1.3408	0.0608	-0.2337
26	0.0000	-0.0170	-0.2277	0.0298	-1.4921	-1.5921	-1.3659	-0.0193	-0.2144
27	0.0062	0.0031	-0.2247	0.0499	-1.5359	-1.6359	-1.4080	0.0004	-0.2086
28	0.0123	-0.0161	-0.1963	0.0307	-1.5543	-1.6543	-1.4218	-0.0184	-0.1779
29	0.0061	0.0291	-0.2194	0.0760	-1.6242	-1.7242	-1.4938	0.0291	-0.2010
30	-0.0181	-0.0176	-0.2198	0.0292	-1.6715	-1.7715	-1.5363	-0.0198	-0.1992
Mean	-0.0004	0.0067	-0.1983	0.0535	-0.9476	-1.0476	-0.8330	0.0055	-0.1952

Table 2.7

Summary of OLS, COLS, DEA and USFA Estimates for Bridgestone Stock Returns

Day	Bridgestone Stock Return	OLS (Market Model) Return	CAR-OLS	COLS Return	CAR-COLS	DEA Return	CAR-DEA	USFA Return	CAR-USFA
0	-0.0879	0.0008	-0.0887	0.1360	-0.0538	-0.1538	0.2220	0.0009	-0.0889
1	0.0135	-0.0036	-0.0717	0.1317	-0.1176	-0.2176	0.0444	-0.0034	-0.0720
2	-0.0819	0.0006	-0.1542	0.1359	-0.2809	-0.3809	-0.1733	0.0008	-0.1547
3	-0.1089	0.0021	-0.2652	0.1374	-0.4727	-0.5727	-0.3986	0.0023	-0.2659
4	0.0276	0.0067	-0.2443	0.1419	-0.5325	-0.6325	-0.4277	0.0069	-0.2452
5	-0.0132	0.0003	-0.2577	0.1356	-0.6268	-0.7268	-0.5812	0.0005	-0.2588
6	-0.0517	-0.0018	-0.3077	0.1335	-0.7575	-0.8575	-0.8003	-0.0016	-0.3089
7	-0.1001	-0.0034	-0.4045	0.1319	-0.9350	-1.0350	-1.0887	-0.0032	-0.4058
8	0.0313	-0.0049	-0.3683	0.1304	-0.9797	-1.0797	-1.2658	-0.0048	-0.3698
9	-0.0006	0.0019	-0.3709	0.1372	-1.0630	-1.1630	-1.3851	0.0021	-0.3725
10	-0.0649	-0.0073	-0.4284	0.1279	-1.2013	-1.3013	-1.6908	-0.0073	-0.4301
11	0.0376	0.0026	-0.3934	0.1379	-1.2471	-1.3471	-1.7630	0.0028	-0.3953
12	-0.0313	0.0004	-0.4251	0.1357	-1.3595	-1.4595	-1.9333	0.0006	-0.4271
13	-0.0232	-0.0001	-0.4482	0.1352	-1.4635	-1.5635	-2.1020	0.0001	-0.4504
14	0.0013	-0.0011	-0.4457	0.1341	-1.5418	-1.6418	-2.2599	-0.0010	-0.4481
15	0.0541	-0.0035	-0.3881	0.1317	-1.5649	-1.6649	-2.3962	-0.0034	-0.3906
16	-0.0451	-0.0026	-0.4306	0.1326	-1.6882	-1.7882	-2.6199	-0.0025	-0.4332
17	-0.0315	-0.0041	-0.4579	0.1311	-1.7963	-1.8963	-2.8496	-0.0040	-0.4607
18	-0.0663	-0.0023	-0.5219	0.1329	-1.9411	-2.0411	-3.0904	-0.0022	-0.5248
19	-0.0667	0.0006	-0.5892	0.1359	-2.0891	-2.1891	-3.2934	0.0008	-0.5923
20	-0.0683	-0.0018	-0.6556	0.1334	-2.2364	-2.3364	-3.5302	-0.0017	-0.6589
21	0.1150	0.0050	-0.5456	0.1402	-2.2071	-2.3071	-3.4941	0.0052	-0.5491
22	-0.0157	0.0004	-0.5617	0.1356	-2.3040	-2.4040	-3.6488	0.0006	-0.5653
23	-0.0395	-0.0060	-0.5952	0.1293	-2.4183	-2.5183	-3.9110	-0.0059	-0.5989
24	-0.1225	0.0013	-0.7191	0.1366	-2.6229	-2.7229	-4.1602	0.0015	-0.7230
25	-0.0018	0.0026	-0.7235	0.1378	-2.7081	-2.8081	-4.2722	0.0028	-0.7276
26	0.0451	-0.0041	-0.6742	0.1311	-2.7397	-2.8397	-4.4254	-0.0040	-0.6785
27	0.0484	0.0044	-0.6303	0.1397	-2.7765	-2.8765	-4.4632	0.0046	-0.6347
28	0.0099	0.0064	-0.6268	0.1416	-2.8538	-2.9538	-4.5138	0.0066	-0.6314
29	0.0440	-0.0017	-0.5810	0.1336	-2.8888	-2.9888	-4.6363	-0.0015	-0.5859
30	0.0000	-0.0045	-0.5765	0.1307	-2.9650	-3.0650	-4.8401	-0.0044	-0.5814
Mean	-0.0191	-0.0005	-0.4500	0.1347	-1.6269	-1.7269	-2.4435	-0.0004	-0.4526

Table 2.8
Summary of OLS, COLS, DEA and USFA Estimates for Toyota Stock Returns

Day	Toyota Stock Return	OLS (Market Model) Return	CAR-OLS	COLS Return	CAR-COLS	DEA Return	CAR-DEA	USFA Return	CAR-USFA
0	-0.0238	-0.0194	0.0311	0.0282	-0.0520	-0.1520	0.0334	-0.0194	0.0311
1	-0.0610	-0.0201	0.0264	0.0321	-0.1451	-0.2451	-0.0478	-0.0201	0.0264
2	0.0130	0.0025	0.0187	0.0606	-0.1927	-0.2927	-0.0950	0.0025	0.0187
3	-0.0577	0.0000	0.0081	0.0398	-0.2902	-0.3902	-0.1938	0.0000	0.0081
4	-0.0544	0.0042	-0.0769	0.0493	-0.3939	-0.4939	-0.2981	0.0042	-0.0769
5	0.0719	-0.0108	-0.0924	0.0853	-0.4073	-0.5073	-0.2944	-0.0108	-0.0924
6	-0.0336	-0.0049	-0.0961	0.0725	-0.5133	-0.6133	-0.3924	-0.0049	-0.0961
7	0.0556	0.0117	-0.0696	0.0663	-0.5241	-0.6241	-0.3996	0.0117	-0.0696
8	0.0197	0.0109	-0.1025	0.0770	-0.5814	-0.6814	-0.4456	0.0109	-0.1025
9	-0.0452	-0.0023	-0.1602	0.0442	-0.6707	-0.7707	-0.5359	-0.0023	-0.1602
10	0.0135	-0.0253	-0.1582	0.0656	-0.7228	-0.8228	-0.5849	-0.0253	-0.1582
11	-0.0067	0.0012	-0.1186	0.0250	-0.7545	-0.8545	-0.5923	0.0012	-0.1186
12	-0.0201	-0.0099	-0.1335	0.0352	-0.8098	-0.9098	-0.6412	-0.0099	-0.1336
13	0.0548	0.0150	-0.1245	0.0740	-0.8290	-0.9290	-0.6513	0.0150	-0.1245
14	0.0065	-0.0018	-0.1082	0.0431	-0.8657	-0.9657	-0.6889	-0.0018	-0.1082
15	-0.0065	0.0105	-0.1145	0.0687	-0.9408	-1.0408	-0.7587	0.0105	-0.1146
16	0.0260	-0.0041	-0.0966	0.0430	-0.9578	-1.0578	-0.7768	-0.0041	-0.0966
17	-0.0190	0.0166	-0.1267	0.0424	-1.0193	-1.1193	-0.8392	0.0166	-0.1267
18	-0.0516	0.0040	-0.1552	-0.0050	-1.0659	-1.1659	-0.8009	0.0041	-0.1553
19	0.0272	0.0081	-0.1729	0.0554	-1.0941	-1.1941	-0.8290	0.0081	-0.1730
20	-0.0066	0.0011	-0.1752	0.0520	-1.1527	-1.2527	-0.8880	0.0011	-0.1753
21	0.0067	-0.0016	-0.1794	0.0288	-1.1749	-1.2749	-0.8926	-0.0016	-0.1794
22	0.0331	-0.0093	-0.1891	0.0457	-1.1875	-1.2875	-0.9060	-0.0093	-0.1891
23	0.0192	0.0089	-0.1591	0.0608	-1.2291	-1.3291	-0.9473	0.0089	-0.1591
24	-0.0063	-0.0048	-0.1601	0.0631	-1.2984	-1.3984	-1.0153	-0.0048	-0.1602
25	0.0253	0.0006	-0.1481	0.0933	-1.3664	-1.4664	-1.0605	0.0006	-0.1482
26	0.0000	0.0076	-0.1717	0.0356	-1.4020	-1.5020	-1.0902	0.0076	-0.1717
27	0.0062	0.0004	-0.1615	0.0472	-1.4431	-1.5431	-1.1320	0.0004	-0.1615
28	0.0123	-0.0007	-0.1270	0.0294	-1.4602	-1.5602	-1.1326	-0.0007	-0.1270
29	0.0061	0.0047	-0.1514	0.0674	-1.5216	-1.6216	-1.1895	0.0047	-0.1514
30	-0.0181	0.0116	-0.1428	0.0283	-1.5680	-1.6680	-1.2174	0.0116	-0.1429
Mean	-0.0004	0.0002	-0.1157	0.0501	-0.8914	-0.9914	-0.6872	0.0002	-0.1158

Table 2.9

Summary of the Paired t-test for the Results from OLS, COLS, DEA and USFA Estimates

	Johnson & Johnson					Bridgestone					Toyota				
Event Day	Stock Return - Market Return	AR - OLS	AR - COLS	AR - DEA	AR - USFA	Stock Return - Market Return	AR - OLS	AR - COLS	AR - DEA	AR - USFA	Stock Return - Market Return	AR - OLS	AR - COLS	AR - DEA	AR - USFA
0	-0.0096	-0.0070	-0.0538	-0.0491	-0.0070	-0.0799	-0.0887	-0.2240	-0.2220	-0.0889	0.0319	0.0311	-0.0520	-0.0334	0.0311
1	-0.0499	-0.0482	-0.0950	-0.0909	-0.0481	-0.0010	0.0170	-0.1182	-0.1776	0.0169	-0.0040	-0.0047	-0.0931	-0.0812	-0.0047
2	0.0002	-0.0045	-0.0513	-0.0518	-0.0044	-0.0745	-0.0825	-0.2178	-0.2177	-0.0827	-0.0076	-0.0077	-0.0476	-0.0472	-0.0077
3	-0.0531	-0.0531	-0.1000	-0.0971	-0.0531	-0.0940	-0.1110	-0.2463	-0.2253	-0.1112	-0.0104	-0.0106	-0.0975	-0.0988	-0.0106
4	-0.0584	-0.0607	-0.1075	-0.1062	-0.0606	0.0660	0.0209	-0.1143	-0.0291	0.0207	-0.0849	-0.0850	-0.1038	-0.1043	-0.0850
5	0.0311	0.0188	-0.0280	-0.0338	0.0190	-0.0076	-0.0135	-0.1487	-0.1535	-0.0136	-0.0150	-0.0155	-0.0133	0.0037	-0.0155
6	-0.0565	-0.0640	-0.1108	-0.1132	-0.0639	-0.0568	-0.0500	-0.1852	-0.2191	-0.0501	-0.0034	-0.0037	-0.1061	-0.0981	-0.0037
7	0.0339	0.0269	-0.0199	-0.0220	0.0270	-0.1134	-0.0968	-0.2320	-0.2884	-0.0969	0.0264	0.0265	-0.0107	-0.0071	0.0265
8	-0.0065	-0.0149	-0.0617	-0.0647	-0.0148	0.0101	0.0361	-0.0991	-0.1771	0.0360	-0.0329	-0.0329	-0.0573	-0.0461	-0.0329
9	-0.0362	-0.0350	-0.0818	-0.0781	-0.0349	0.0135	-0.0025	-0.1378	-0.1193	-0.0027	-0.0574	-0.0577	-0.0894	-0.0903	-0.0577
10	0.0021	-0.0022	-0.0491	-0.0493	-0.0022	-0.0988	-0.0575	-0.1928	-0.3057	-0.0576	0.0029	0.0020	-0.0520	-0.0490	0.0020
11	0.0114	0.0150	-0.0318	-0.0264	0.0150	0.0551	0.0350	-0.1002	-0.0723	0.0348	0.0398	0.0396	-0.0317	-0.0075	0.0396
12	-0.0164	-0.0165	-0.0634	-0.0606	-0.0165	-0.0251	-0.0316	-0.1669	-0.1703	-0.0318	-0.0145	-0.0150	-0.0554	-0.0488	-0.0150
13	0.0285	0.0202	-0.0266	-0.0296	0.0203	-0.0197	-0.0231	-0.1584	-0.1687	-0.0233	0.0089	0.0090	-0.0192	-0.0101	0.0090
14	0.0118	0.0120	-0.0348	-0.0318	0.0121	-0.0005	0.0025	-0.1328	-0.1579	0.0023	0.0166	0.0164	-0.0366	-0.0376	0.0164
15	-0.0265	-0.0331	-0.0799	-0.0818	-0.0330	0.0400	0.0576	-0.0776	-0.1363	0.0575	-0.0064	-0.0064	-0.0751	-0.0699	-0.0064
16	0.0232	0.0212	-0.0256	-0.0241	0.0213	-0.0545	-0.0424	-0.1777	-0.2237	-0.0426	0.0183	0.0179	-0.0170	-0.0180	0.0179
17	-0.0137	-0.0134	-0.0603	-0.0573	-0.0134	-0.0487	-0.0273	-0.1626	-0.2298	-0.0275	-0.0303	-0.0301	-0.0614	-0.0625	-0.0301
18	-0.0164	-0.0081	-0.0549	-0.0462	-0.0082	-0.0742	-0.0640	-0.1993	-0.2408	-0.0641	-0.0284	-0.0285	-0.0466	0.0384	-0.0285
19	0.0162	0.0120	-0.0348	-0.0349	0.0121	-0.0595	-0.0673	-0.2025	-0.2030	-0.0674	-0.0177	-0.0177	-0.0281	-0.0282	-0.0177
20	-0.0069	-0.0082	-0.0550	-0.0530	-0.0082	-0.0738	-0.0665	-0.2017	-0.2368	-0.0666	-0.0021	-0.0023	-0.0586	-0.0589	-0.0023
Mean	-0.0091	-0.0116	-0.0584	-0.0572	-0.0115	-0.0332	-0.0312	-0.1665	-0.1893	-0.0314	-0.0081	-0.0083	-0.0549	-0.0455	-0.0083
Varian	0.0008	0.0008	0.0008	0.0007	0.0008	0.0026	0.0022	0.0022	0.0041	0.0022	0.0008	0.0008	0.0009	0.0013	0.0008
t Stat		0.03402	8.1E-22	4.7E-17	0.03554		0.6386	1.2E-18	8.5E-18	0.66535		0.0018	2.8E-07	0.00012	0.00167
P(T<=t) two-tail		0.9784	1.0000	1.0000	0.9774		0.6382	1.0000	1.0000	0.6262		0.9989	1.0000	0.9999	0.9989
Significant (5%)		*	*	*	*			*	*			*	*	*	*

Table 2.10

Summary of the Results from Lower Stochastic Frontier Model (LSFA), Upper Stochastic Frontier Model (USFA), and OLS Model

Firm	Model	α_i	β_i	σ_{ϑ_i}	σ_{μ_i}	N	$adj.R^2$	F
Johnson & Johnson	LSFA	-0.011569* (202508)	1.223296* (0.096545)	1.057044* (0.120474)	1.607135* (0.244253)	252		
	USFA	0.001181 (23.431810)	1.267176* (0.097972)	1.438423* (0.063958)	0.000171 (29.634994)	252		
	OLS	0.0012148* (0.000912)	1.269725* (0.098559)			252	0.396591	165.97
Bridgestone(Firestone)	LSFA	-0.035576* (0.405229)	-0.251548** (0.113965)	1.987480* (0.286587)	4.410047* (0.484004)	252		
	USFA	-0.000626 (36.851915)	-0.195807 (0.125819)	3.339051* (0.148453)	0.000390 (46.186275)	252		
	OLS	-0.000782 (0.002113)	-0.193613 (0.126261)			252	0.005355	2.3514
Toyota	LSFA	-0.001260* (0.221276)	0.960284* (0.065183)	1.190317* (0.123565)	1.617853* (0.266881)	252		
	USFA	0.00021252 (26.567380)	0.975017* (0.066432)	1.545324* (0.068712)	0.000174 (33.297049)	252		
	OLS	0.000211 (0.009789)	0.97502* (0.06670)			252	0.457713	181.25

Numbers in parantheses are standard errors.
*Represents statistical significance at 1% level, two tailed test.
**Represents statistical significance at 5% level, two tailed test.
***Represents statistical significance at 10% level, two tailed test.

Table 2.11

Estimation of Returns, Abnormal Returns (AR) and Cumulative Abnormal Returns (CAR) by three Models for Johnson & Johnson

Event	Lower Stochastic Frontier Model (LSFA)			Upper Stochastic Frontier Model (USFA)			Ordinary Least Squares (OLS)		
Day	LSFA Return	LSFA AR	LSFA CAR	USFA Return	USFA AR	USFA CAR	OLS Return	OLS AR	OLS CAR
0	-0.0289	0.0051	0.0051	-0.0168	-0.0070	-0.0070	-0.0168	-0.0070	-0.0070
1	-0.0251	-0.0359	-0.0307	-0.0128	-0.0481	-0.0551	-0.0128	-0.0482	-0.0551
2	0.0041	0.0089	-0.0219	0.0174	-0.0044	-0.0596	0.0175	-0.0045	-0.0596
3	-0.0171	-0.0406	-0.0624	-0.0046	-0.0531	-0.1127	-0.0046	-0.0531	-0.1128
4	-0.0067	-0.0477	-0.1101	0.0062	-0.0606	-0.1733	0.0062	-0.0607	-0.1734
5	0.0384	0.0335	-0.0766	0.0530	0.0190	-0.1543	0.0531	0.0188	-0.1546
6	0.0166	-0.0501	-0.1267	0.0303	-0.0639	-0.2182	0.0304	-0.0640	-0.2186
7	0.0149	0.0407	-0.0860	0.0286	0.0270	-0.1912	0.0287	0.0269	-0.1917
8	0.0206	-0.0008	-0.0869	0.0345	-0.0148	-0.2060	0.0346	-0.0149	-0.2065
9	-0.0226	-0.0226	-0.1095	-0.0102	-0.0349	-0.2409	-0.0102	-0.0350	-0.2415
10	0.0024	0.0111	-0.0984	0.0157	-0.0022	-0.2431	0.0158	-0.0022	-0.2437
11	-0.0336	0.0270	-0.0714	-0.0217	0.0150	-0.2281	-0.0217	0.0150	-0.2287
12	-0.0162	-0.0039	-0.0754	-0.0036	-0.0165	-0.2446	-0.0036	-0.0165	-0.2453
13	0.0206	0.0342	-0.0412	0.0345	0.0203	-0.2243	0.0346	0.0202	-0.2251
14	-0.0181	0.0246	-0.0166	-0.0056	0.0121	-0.2123	-0.0055	0.0120	-0.2130
15	0.0130	-0.0194	-0.0360	0.0266	-0.0330	-0.2453	0.0267	-0.0331	-0.2462
16	-0.0082	0.0342	-0.0019	0.0047	0.0213	-0.2240	0.0047	0.0212	-0.2249
17	-0.0181	-0.0009	-0.0028	-0.0056	-0.0134	-0.2374	-0.0055	-0.0134	-0.2384
18	-0.0547	0.0030	0.0003	-0.0435	-0.0082	-0.2456	-0.0435	-0.0081	-0.2465
19	0.0019	0.0253	0.0256	0.0151	0.0121	-0.2335	0.0152	0.0120	-0.2344
20	-0.0112	0.0046	0.0302	0.0015	-0.0082	-0.2417	0.0016	-0.0082	-0.2426
21	-0.0302	0.0369	0.0671	-0.0182	0.0248	-0.2168	-0.0182	0.0248	-0.2178
22	-0.0107	0.0438	0.1109	0.0021	0.0310	-0.1858	0.0022	0.0310	-0.1868
23	0.0057	0.0136	0.1245	0.0190	0.0002	-0.1856	0.0191	0.0001	-0.1867
24	0.0084	-0.0146	0.1098	0.0218	-0.0281	-0.2137	0.0219	-0.0282	-0.2149
25	0.0404	-0.0151	0.0947	0.0550	-0.0297	-0.2434	0.0551	-0.0298	-0.2447
26	-0.0291	0.0291	0.1238	-0.0170	0.0170	-0.2265	-0.0170	0.0170	-0.2277
27	-0.0098	0.0159	0.1398	0.0031	0.0031	-0.2233	0.0031	0.0031	-0.2247
28	-0.0282	0.0405	0.1803	-0.0161	0.0284	-0.1950	-0.0161	0.0284	-0.1963
29	0.0153	-0.0093	0.1710	0.0290	-0.0230	-0.2180	0.0291	-0.0231	-0.2194
30	-0.0297	0.0116	0.1827	-0.0176	-0.0005	-0.2184	-0.0176	-0.0004	-0.2198
Mean	-0.0061	0.0014	-0.0473	0.0068	-0.0115	-0.1904	0.0069	-0.0116	-0.1909

Table 2.12

Estimation of Returns, Abnormal Returns (AR) and Cumulative Abnormal Returns (CAR) by three Models for Bridgestone

Event	Lower Stochastic Frontier Model (LSFA)			Upper Stochastic Frontier Model			Ordinary Least Squares (OLS)		
Day	LSFA Return	LSFA AR	LSFA CAR	USFA Return	USFA AR	USFA CAR	OLS Return	OLS AR	OLS CAR
0	-0.0336	-0.0544	-0.0544	0.0009	-0.0889	-0.0889	0.0008	-0.0887	-0.0887
1	-0.0392	0.0527	-0.0017	-0.0034	0.0169	-0.0720	-0.0036	0.0170	-0.0717
2	-0.0337	-0.0481	-0.0499	0.0008	-0.0827	-0.1547	0.0006	-0.0825	-0.1542
3	-0.0318	-0.0771	-0.1270	0.0023	-0.1112	-0.2659	0.0021	-0.1110	-0.2652
4	-0.0259	0.0535	-0.0735	0.0069	0.0207	-0.2452	0.0067	0.0209	-0.2443
5	-0.0342	0.0210	-0.0524	0.0005	-0.0136	-0.2588	0.0003	-0.0135	-0.2577
6	-0.0369	-0.0149	-0.0673	-0.0016	-0.0501	-0.3089	-0.0018	-0.0500	-0.3077
7	-0.0389	-0.0612	-0.1285	-0.0032	-0.0969	-0.4058	-0.0034	-0.0968	-0.4045
8	-0.0409	0.0721	-0.0564	-0.0048	0.0360	-0.3698	-0.0049	0.0361	-0.3683
9	-0.0320	0.0314	-0.0249	0.0021	-0.0027	-0.3725	0.0019	-0.0025	-0.3709
10	-0.0441	-0.0208	-0.0457	-0.0073	-0.0576	-0.4301	-0.0073	-0.0575	-0.4284
11	-0.0312	0.0688	0.0231	0.0028	0.0348	-0.3953	0.0026	0.0350	-0.3934
12	-0.0340	0.0028	0.0259	0.0006	-0.0318	-0.4271	0.0004	-0.0316	-0.4251
13	-0.0347	0.0115	0.0373	0.0001	-0.0233	-0.4504	-0.0001	-0.0231	-0.4482
14	-0.0360	0.0374	0.0747	-0.0010	0.0023	-0.4481	-0.0011	0.0025	-0.4457
15	-0.0391	0.0932	0.1679	-0.0034	0.0575	-0.3906	-0.0035	0.0576	-0.3881
16	-0.0380	-0.0071	0.1608	-0.0025	-0.0426	-0.4332	-0.0026	-0.0424	-0.4306
17	-0.0399	0.0085	0.1693	-0.0040	-0.0275	-0.4607	-0.0041	-0.0273	-0.4579
18	-0.0376	-0.0288	0.1405	-0.0022	-0.0641	-0.5248	-0.0023	-0.0640	-0.5219
19	-0.0338	-0.0329	0.1076	0.0008	-0.0674	-0.5923	0.0006	-0.0673	-0.5892
20	-0.0370	-0.0314	0.0763	-0.0017	-0.0666	-0.6589	-0.0018	-0.0665	-0.6556
21	-0.0281	0.1431	0.2194	0.0052	0.1098	-0.5491	0.0050	0.1100	-0.5456
22	-0.0340	0.0184	0.2377	0.0006	-0.0163	-0.5653	0.0004	-0.0161	-0.5617
23	-0.0423	0.0028	0.2405	-0.0059	-0.0336	-0.5989	-0.0060	-0.0335	-0.5952
24	-0.0328	-0.0897	0.1508	0.0015	-0.1240	-0.7230	0.0013	-0.1239	-0.7191
25	-0.0312	0.0294	0.1802	0.0028	-0.0046	-0.7276	0.0026	-0.0044	-0.7235
26	-0.0399	0.0850	0.2653	-0.0040	0.0491	-0.6785	-0.0041	0.0492	-0.6742
27	-0.0288	0.0772	0.3424	0.0046	0.0437	-0.6347	0.0044	0.0439	-0.6303
28	-0.0263	0.0362	0.3786	0.0066	0.0033	-0.6314	0.0064	0.0035	-0.6268
29	-0.0368	0.0808	0.4594	-0.0015	0.0456	-0.5859	-0.0017	0.0457	-0.5810
30	-0.0405	0.0405	0.4999	-0.0044	0.0044	-0.5814	-0.0045	0.0045	-0.5765
Mean	-0.0358	0.0036	0.0144	-0.0008	-0.0314	-0.3692	-0.0010	-0.0312	-0.3675

Table 2.13

Estimation of Returns, Abnormal Returns (AR) and Cumulative Abnormal Returns (CAR) by three Models for Toyota

Event	Lower Stochastic Frontier Model (LSFA)			Upper Stochastic Frontier Model (USFA)			Ordinary Least Squares (OLS)		
Day	LSFA Return	LSFA AR	LSFA CAR	USFA Return	USFA AR	USFA CAR	OLS Return	OLS AR	OLS CAR
0	-0.0206	0.0323	0.0323	-0.0194	0.0311	0.0311	-0.0194	0.0311	0.0311
1	-0.0213	-0.0036	0.0287	-0.0201	-0.0047	0.0264	-0.0201	-0.0047	0.0264
2	0.0010	-0.0062	0.0225	0.0025	-0.0077	0.0187	0.0025	-0.0077	0.0187
3	-0.0015	-0.0091	0.0134	0.0000	-0.0106	0.0081	0.0000	-0.0106	0.0081
4	0.0027	-0.0835	-0.0700	0.0042	-0.0850	-0.0769	0.0042	-0.0850	-0.0769
5	-0.0121	-0.0142	-0.0842	-0.0108	-0.0155	-0.0924	-0.0108	-0.0155	-0.0924
6	-0.0063	-0.0023	-0.0866	-0.0049	-0.0037	-0.0961	-0.0049	-0.0037	-0.0961
7	0.0100	0.0282	-0.0584	0.0117	0.0265	-0.0696	0.0117	0.0265	-0.0696
8	0.0092	-0.0313	-0.0896	0.0109	-0.0329	-0.1025	0.0109	-0.0329	-0.1025
9	-0.0037	-0.0563	-0.1459	-0.0023	-0.0577	-0.1602	-0.0023	-0.0577	-0.1602
10	-0.0264	0.0031	-0.1428	-0.0253	0.0020	-0.1582	-0.0253	0.0020	-0.1582
11	-0.0003	0.0411	-0.1017	0.0012	0.0396	-0.1186	0.0012	0.0396	-0.1186
12	-0.0112	-0.0137	-0.1154	-0.0099	-0.0150	-0.1336	-0.0099	-0.0150	-0.1335
13	0.0133	0.0107	-0.1047	0.0150	0.0090	-0.1245	0.0150	0.0090	-0.1245
14	-0.0032	0.0178	-0.0869	-0.0018	0.0164	-0.1082	-0.0018	0.0164	-0.1082
15	0.0089	-0.0048	-0.0916	0.0105	-0.0064	-0.1146	0.0105	-0.0064	-0.1145
16	-0.0055	0.0193	-0.0723	-0.0041	0.0179	-0.0966	-0.0041	0.0179	-0.0966
17	0.0149	-0.0284	-0.1007	0.0166	-0.0301	-0.1267	0.0166	-0.0301	-0.1267
18	0.0025	-0.0270	-0.1277	0.0041	-0.0285	-0.1553	0.0040	-0.0285	-0.1552
19	0.0065	-0.0161	-0.1438	0.0081	-0.0177	-0.1730	0.0081	-0.0177	-0.1729
20	-0.0004	-0.0008	-0.1446	0.0011	-0.0023	-0.1753	0.0011	-0.0023	-0.1752
21	-0.0030	-0.0027	-0.1473	-0.0016	-0.0042	-0.1794	-0.0016	-0.0042	-0.1794
22	-0.0106	-0.0083	-0.1557	-0.0093	-0.0097	-0.1891	-0.0093	-0.0097	-0.1891
23	0.0073	0.0315	-0.1241	0.0089	0.0299	-0.1591	0.0089	0.0299	-0.1591
24	-0.0062	0.0004	-0.1237	-0.0048	-0.0010	-0.1602	-0.0048	-0.0010	-0.1601
25	-0.0009	0.0135	-0.1103	0.0006	0.0120	-0.1482	0.0006	0.0120	-0.1481
26	0.0060	-0.0219	-0.1322	0.0076	-0.0235	-0.1717	0.0076	-0.0235	-0.1717
27	-0.0011	0.0116	-0.1206	0.0004	0.0102	-0.1615	0.0004	0.0102	-0.1615
28	-0.0021	0.0360	-0.0846	-0.0007	0.0345	-0.1270	-0.0007	0.0345	-0.1270
29	0.0031	-0.0229	-0.1075	0.0047	-0.0244	-0.1514	0.0047	-0.0244	-0.1514
30	0.0100	0.0102	-0.0973	0.0116	0.0085	-0.1429	0.0116	0.0085	-0.1428
Mean	-0.0021	-0.0069	-0.0795	-0.0006	-0.0083	-0.0951	-0.0006	-0.0083	-0.0951

Chapter 3

Mergers, Efficiency, and Productivity in the US Railroad Industry: An Attribute-Incorporated Data Envelopment Analysis Approach

3.1. Introduction

In the last 30 years since passage of the Staggers Act of 1980,[1] the U.S. railroad industry has experienced a tremendous increase in productivity and decreases in rates and costs.[2] A significant feature during the partial deregulation period is the consolidation of firms, where the number of Class I railroad firms in the U.S. dropped from 40 to 7 primarily through a series of mergers.[3] On the one hand, mergers can lead to the realization of scale economies, and cost saving due to improvements in productivity. Given the size of firms and mergers, these allow for improvements in industry's performance through cost savings. On the other hand, mergers can also result in gains to the market power of the surviving firm, which leads to rising prices and a loss of social warfare (Williamson, 1968).[4] In this study, we focus on the

[1] In 1980, the railroad industry was partially deregulated by the Staggers Act, which removed most price controls and gave railroad firms the power to merge with one another and increase profitability.
[2] In the post Staggers Act period, railroad productivity, measured by total factor productivity, increased by 163 percent from 1980 to 2007 (American Association of Railroads (AAR), 2008). The Rail Rate Index falls from 1985 to 2000, flattens out until 2004, and, since 2005, rates have begun to go up (Surface Transportation Board (STB), 2009).
[3] Railroad firms in the U.S. are separated into three categories based on their annual revenues: Class I for freight railroads with annual operating revenues above $346.8 million (in 2006 dollars), Class II for freight railroads with revenues between $27.8 million and $346.7 million (in 2006 dollars), and Class III for all other freight railroads. These classifications are set by STB. Studies differ in the number of Class I railroads in 1980. This information is consistent with Wilson (1997), Bitzan and Wilson (2007), and AAR (1980, 2010).
[4] For discussions of the relationship between deregulation and rates, efficiency, and innovation, see Berndt et al. (1993), Wilson (1994), Wilson (1997), Gallamore (1999), Ellig (2002), Bitzan and Wilson (2007), Waters (2007). For discussions of the relationship between deregulation and productivity growth, see Bitzan and Keeler (2003) and Winston (2005). See Smith (1983) and Wilner (1997) for the summary of railroad mergers and policy.

measurement and level of firm level efficiencies, how efficiency and productivity have been affected by merger activity, and how the sources of efficiency gains. Unlike the bulk of the related literature,[5] our study uses Data Envelopment Analysis (DEA). While there are a few studies of rail efficiency and productivity that use DEA, we differ from these in that we introduce, to this literature, an attribute-incorporated Malmquist productivity index that allows the frontier to vary across firms and through time in terms of measurable attributes, e.g., average length of haul, miles of road, etc.

In the past decades, the cost function approach has been widely used in railroad research to examine efficiency, productivity and the effects of mergers. Before the 1980s, a wide range of studies, including Borts (1952), Friedlaender (1971), Keeler (1974), Harris (1977), used the classic cost and production method.[6] Later, Brown, Caves, and Christensen (1979), Caves, Christensen, and Swanson (1980, 1981), and Friedlaender and Spady (1981) started to estimate railroad costs using translog cost functions.[7] More recently, a number of the papers, including Berndt et al. (1993), Friedlaender et al. (1993), Wilson (1997), Ivaldi and McCollough (2001), Ivaldi and McCullough (2005), Bitzan and Keeler (2003, 2007), Bitzan and Wilson (2007), explored the effects of partial deregulation on costs,

[5] See, for example, Berndt et al. (1993), Wilner (1997), Wilson (1997), Ivali and McCollough (2001), Gallamore (1999), Bitzan and Keeler (2003), Bitzan and Wilson (2007), Lim and Lovell (2008, 2009).
[6] For example, Friedlaender (1971) estimated short- and long-run cost functions for railroads, Keeler (1974) used a Cobb-Douglas production function to model railroads.
[7] Translog cost function was first used by Christensen, Jorgenson, and Lau (1973). A translog cost function can be used to estimate the properties of a technology without the functional form placing a priori restrictions on the technology. For example, Caves, Christensen, and Swanson (1980; 1981) used a translog production structure to estimate the productivity growth in railroad industry, and found that the productivity growth was more different from the previous studies that used index procedures.

productivity, and mergers.[8] At the same time, other research on railroads also made use of index number theory (Lim and Lovell (2008, 2009) to measure the change of efficiency and productivity.[9] In these latter studies, DEA measures were developed given the technology is the same for all firms. In this study, we use a ratio-based index number approach and attribute-incorporated Malmquist productivity index (AMPI) model introduced by Färe et al. (1995) and assess the historical trends of efficiency and productivity, examine the effects of merger activity on efficiency, and identify the major factors associated with productivity growth in the U.S. railroad industry during the period 1983 to 2008.[10, 11]

The DEA approach, which popularized by Charnes et al. (1978), have been conducted in various fields' production analysis during the past several decades. The DEA approach does not assume specific parametric functional (or cost) forms for the production frontiers and it does not use distributional assumptions on the noise and inefficiency components. More importantly, DEA analysis can easily accommodate multiple inputs and multiple outputs simultaneously, which makes it a suitable evaluation tool in many service oriental industries, such as transportation. According to the index number theory literature, measures are usually classified into indicators

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[8] For example, Bitzan and Wilson (2007) estimated a translog cost function of firm by a three-stage-least squares approach with miles of road (MOR) and revenue ton mails (RTM) treated as endogenous, and then use the results to estimate the cost effects of mergers. They focused on the efficiency gains of fourteen mergers that took place between 1983 and 2003, and found that consolidation in industry level accounts for about an 11.4 percent reduction in costs.

[9] See Kumbhakar (1988), Chapin and Schmidt (1998), Coelli and Perelman (2000), Atkinson et al. (2003), Lan and Lin (2005), and Lim and Lovell (2008, 2009).

[10] A ratio-based index number is a percentage ratio of prices, quantities or values comparing two time periods or two points in time. The time period that serves as a basis for the comparison is called the base period and the period that is compared to the base period is called the given or current period.

(the form of differences) and indexes (the form of ratios) (Diewert, 1998). Accordingly, the DEA applications on efficiency measurement have two approaches: the indicator (decomposition) model and index (decomposition) model.[12,13] In two recent studies, Lim and Lovell (2008, 2009) modeled changes in costs and profits to identify how productivity change contribute to changes in costs and profits over time and across railroads. In their analyses, changes in costs or profits are decomposed into changes in prices, inputs and outputs, using the indicator decomposition model.[14] However, as noted by Cross and Färe (2008), lacking "an axiomatic framework for the difference-based indicator", the indicator decomposition approach does not fully explore the sources of productivity changes. In Lim and Lovell (2008, 2009) measured are developed given the technology is the same for all US Class I firms studied. In our approach, there are important differences captured in observables e.g., average length of haul, miles of road, etc. To capture these effects, we adopt the index approach (AMPI approach). This allows the technologies to be indexed and measured. Furthermore, we use a non-price and ratio-based index number theory to

[12] The indicator (decomposition) model associates with the difference-based index number, which is the difference of prices, quantities or values comparing two time periods or two points in time.

[13] On the definition of efficiency, McCullough (2007) made a comprehensive study about railroad efficiency measure. He pointed out that there were two economic aspects of efficiency: productive efficiency (PE) and allocative efficiency (AE). PE occurs when an economy cannot produce more of one good or service without producing less of another, and AE occurs when the economy cannot raise one consumer's satisfaction without lowering another's. PE generally occurs when firms produce at minimum average total cost. AE occurs when price signals to consumers are based on marginal costs. In Ellig (2002), PE refers dynamic efficiency, and author describes that dynamic efficiency occurs when firms find ways to lower their costs (shift the production function), improve quality (shift the demand curve), or services (create a new demand curve). Although different studies have slightly different definitions of efficiency, in this paper, we use the distance function based efficiency definition, and pay attention on the technical and AE components.

[14] This model was built on difference-based Bennet input price and quantity indicators. See Bennet (1920) for the definition of Bennet input price and quantity indicators.

directly examine the merger effects on efficiency and productivity. We also use the AMPI model to explore the contributions of efficiency change in the productivity evolution in U.S. railroad industry during 1983 to 2008. To our knowledge, no other study used both the ratio-based distance function efficiency approach and AMPI model to conduct the research concerning the relationships between mergers, efficiency, and productivity in the U.S. railroad industry.

The AMPI version of DEA allows us to specify the level of productivity and evaluate the sources and changes of productivity by decomposing the AMPI into the technical, efficient and attribute components. This is particularly important in railroads industry, because operating conditions are significantly different across railroads. In the application, we develop full specific efficiency measures over time, estimate the effects of mergers on efficiency and productivity performance as well as the real sources of the productivity growth. We found that (1) the technology efficiency performance of the 7 survivor firms each grows gradually through time; (2) the mergers overall do not lead to a significant TE and SE gains, but three of survivor firms experience a significant technology efficiency increases after merger; (3) the mergers happened in the 1980s have a higher impact on efficiency change than those in the 1990s; and (4) the productivity gains were mostly contributed by the network and operation attributes change and technology improvement during this period. Overall the mergers have no real impact on the efficiency gains or losses in the long run.

This paper is organized as follows. In Section 3.2 and Section 3.3, we describe the methodological approaches and data. In Section 3.4, we present the empirical models and display the results along efficiency performance; merger effect and productivity change three lines. Finally, Section 3.5 presents the conclusions. A detailed description of AMPI is in an Appendix.

3.2. Conceptual Framework

In this section, we first describe the tools used to measure efficiency degree and the productivity change, which are the input distance function and the Malmquist productivity index (MPI). We then introduce the linear programming DEA method to compute the distance function (and also TE and SE) and MPI. The final part of this section introduces our main analysis framework - the AMPI method.

3.2.1. General Setting and the Distance Function

Economic efficiency has technical and allocative components. The technical component refers to the ability to avoid waste, either by producing as much output as technology and input usage allow or by using as little input as required by technology and output production. Thus, the analysis of TE can have an output augmenting orientation or an input conserving orientation. The AE component refers to the ability to combine inputs and/or outputs in optimal proportions. Optimal proportions satisfy the first-order conditions for the optimization problem assigned to the Decision Making Unit.

Debreu (1951) and Farrell (1957) introduce a measure of TE. With an input conserving orientation their measure is defined as (one minus) the maximum equiproportionate reduction in all inputs that is feasible with given technology and outputs. With an output augmenting orientation their measure is defined as the maximum radial expansion in all outputs that is feasible with given technology and inputs. To define the Debreu-Farrell input-oriented measure of TE, the distance function needs to be introduced.

In general, we setup the production technology on the input and output subspace. Assume that a vector of inputs $x = (x_1, \cdots, x_N) \in R_+^N$ produces a vector of output $y = (y_1, \cdots, y_M) \in R_+^M$, production technology can be represented by the production set $\mathrm{T} = \{(x, y): x \text{ can product } y\}$. Technology can also be represented by input sets $\mathrm{L}(y) = \{x : (x, y) \in \mathrm{T}\}$ and output sets $\mathrm{P}(x) = \{y : (x, y) \in \mathrm{T}\}$. Shephard (1953) introduces the input distance function to provide a functional representation of production technology, and Shephard's (1970) output distance function provides another functional representation of production technology.[15] The input distance function is

$$\mathrm{D_i(y, x) = max\{\lambda: (x/\lambda) \in \ L(y)\}}.$$

For $\in L(y)$, $D_i(y, x) \geq 1$, and for $x \in I(y)$, where $I(y) = \{x : x \in L(y), \lambda x \notin L(y) \text{ if } \lambda < 1\}$ is the input isoquants, $D_i(y, x) = 1$.[16]

Figure 3.1 shows that the value of the distance function for point A is equal to the ratio OA/OB. Given standard assumptions on T, the input distance function $D_i(y, x)$ is nonincreasing in y and is nondecreasing in x, homogeneous of degree +1,

[15] We illustrate the theoretical framework and result using the input-oriented distance function. But, the derivation and results are similar in output-oriented situation.

[16] For a system introduction of distance function and its properties, please refer to standard textbook, for instance, Färe and Primont (1995).

and convex in x. From now, using the formal interpretation as the value of the function, the Debreu-Farrell input-oriented measure of TE is $\mathrm{TE}_i(y,x) = \min\{\lambda: \lambda x \in L(y)\}$, and it follows that $\mathrm{TE_i}(y,x) = 1/D_i(y,x)$.

[Insert Figure 3.1 here.]

The distance function (or the Debreu-Farrell measure TE), which has often served as a theoretical device for efficiency measurement, has been widely computed using the linear programming method. Furthermore, to explore the SE aspect, we establish the technology frontier model under assumptions of constant returns to scale (CRS) and variable returns to scale (VRS). The calculation of SE can be expressed as $\frac{\mathrm{TE_i(y,x|C)}}{\mathrm{TE_i(y,x|V)}}$ using the CRS and VRS efficiency scores.[17] SE can be used to determine whether a given producer is operating at decreasing, increasing or constant return to scale (see, for instance, Färe et al., 1985). If $\frac{\mathrm{TE_i(y,x|C)}}{\mathrm{TE_i(y,x|V)}} = 1$, the producer is operating under CRS and is scale efficient; if $\frac{\mathrm{TE_i(y,x|C)}}{\mathrm{TE_i(y,x|V)}} < 1$, the producer is operating under VRS and is scale inefficient; if $\frac{\mathrm{TE_i(y,x|C)}}{\mathrm{TE_i(y,x|V)}} > 1$, the producer is operating under increasing returns to scale.

3.2.2. Malmquist Productivity Index

In 1982, Caves et al. (1982) introduce the MPI, which measures productivity

[17] The optimal scale size is a constant mix of inputs and outputs. In a single input single output context, optimal scale size is offered by the unit (s) offering maximum output to input ratio (i.e., maximum average product). The distance of the scale size of an input output bundle from optimal bundle is reflected in its SE. This measure is defined in either an input or an output orientation as the ratio between technical (i.e., CRS) efficiency and pure technical (i.e., VRS) efficiency. Another way to see SE is as a measure of the distance between the CRS and VRS boundaries at the scale size of the bundle. The larger the divergence between VRS and CRS efficiency ratings, the lower the value of SE and the more adverse the impact of scale size on productivity.

as the ratio of input/output distance functions. Färe et al. (1994a) suggest using MPI and its decompositions to measure the productivity changes between two periods of activities. Using the period t benchmark technology, the period t+1 input-oriented MPI is defined as

$$M_i^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \frac{D_i^{t+1}(y^{t+1},x^{t+1})}{D_i^{t+1}(y^t,x^t)} = \frac{TE_i^{t+1}(y^t,x^t)}{TE_i^{t+1}(y^{t+1},x^{t+1})}. \qquad (1)$$

Färe et al. (1994b) specify that the MPI can be decomposed into two components: efficiency change (catch-up effect, or technical efficiency change) and technology frontier shift (technological change).

$$M_i^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t|C,S)$$
$$= EFFCH(y^{t+1}, x^{t+1}, y^t, x^t|C,S) \cdot TECH(y^{t+1}, x^{t+1}, y^t, x^t|C,S) \qquad (2)$$

Efficiency change:

$$EFFCH(y^{t+1}, x^{t+1}, y^t, x^t|C,S) = \frac{TE_i^t(y^t, x^t|C,S)}{TE_i^{t+1}(y^{t+1}, x^{t+1}|C,S)}$$

$$= \frac{TE_i^t(y^t,x^t|V,W)}{TE_i^{t+1}(y^{t+1},x^{t+1}|V,W)} \cdot \frac{SE_i^t(y^t,x^t)}{SE_i^{t+1}(y^{t+1},x^{t+1})} \cdot \frac{CO_i^t(y^t,x^t)}{CO_i^{t+1}(y^{t+1},x^{t+1})}, \qquad (3)$$

where the first term $\frac{TE_i^t(y^t,x^t|V,W)}{TE_i^{t+1}(y^{t+1},x^{t+1}|V,W)}$ measures change in purely technical efficiency; the second term $\frac{SE_i^t(y^t,x^t)}{SE_i^{t+1}(y^{t+1},x^{t+1})}$ measures change in scale efficiency; the third term $\frac{CO_i^t(y^t,x^t)}{CO_i^{t+1}(y^{t+1},x^{t+1})}$ measures change in congestion.[18]

Technology frontier change:

$$TECH(y^{t+1}, x^{t+1}, y^t, x^t|C,S) = \sqrt{\frac{TE_i^{t+1}(y^{t+1},x^{t+1}|C,S)}{TE_i^t(y^{t+1},x^{t+1}|C,S)} \cdot \frac{TE_i^{t+1}(y^t,x^t|C,S)}{TE_i^t(y^t,x^t|C,S)}} \qquad (4)$$

[18] The decomposition operations are based on Färe et al. (1994a).

The capitol letters C, V, W and S in the above expressions stand for the technology assumptions of CRS, VRS, weak disposability of input and strong disposability of input respectively.[19]

3.2.3. Data Envelopment Analysis

DEA is a mathematical programming approach which constructs the frontier and measures the efficiency relative to the constructed frontiers. It does envelop a data set, but it makes no accommodation for noise. Moreover, subject to certain assumptions about the structure of production technology, it envelops the data as tightly as possible. DEA was proposed by Charnes et al. (1978), which generalized the single input/output efficiency measures into the multiple cases by constructing a relative efficiency score as the ratio of single virtual output to single virtual input.

In this study, the distance function is mainly employed as a computational tool, so here we give the $\mathrm{TE_i}(\mathrm{y},\mathrm{x})$ or $\mathrm{D_i}(\mathrm{y},\mathrm{x})$ version of DEA method.

First the technology can be described by input requirement set as:

$$L^t(y^t|C,S) = \{(x_1^t, \cdots, x_N^t):$$

$$y_{k,m}^t \leq \sum_{k=1}^{K} z_k^t y_{k,m}^t \quad m = 1, \cdots, M$$

$$\sum_{k=1}^{K} z_k^t x_{k,n}^t \leq x_{k,n}^t \quad n = 1, \cdots, N$$

$$z_k^t \geq 0 \qquad k = 1, \cdots K \}.$$

Then the Debreu-Farrell input measure of TE model is:

$$\mathrm{TE}_i^t(y_k^t, x_k^t|C,S) = \min_z \lambda$$

[19] The definitions of CRS, VRS, weak disposability and strong disposability can refer to any standard productivity textbook, for instance, Färe et al. (1985).

$$\text{s.t.} \quad y_{k,m}^{t} \leq \sum_{k=1}^{K} z_k^t y_{k,m}^{t} \quad m = 1, \cdots, M$$

$$\sum_{k=1}^{K} z_k^t x_{k,n}^{t} \leq \lambda x_{k,n}^{t} \qquad n = 1, \cdots, N$$

$$z_k^t \geq 0 \qquad k = 1, \cdots K \}. \tag{5}$$

3.2.4. Attributes-Incorporated Malmquist Productivity Index

As pointed out by Ray (1995), any change in the quality of output(s) without any change in the input-output quantities implies a corresponding change in productivity. Therefore, productivity indices unadjusted for attributes changes are misleading. To solve this problem, Färe et al. (1995) extends the productivity index in Färe et al. (1992) to incorporate attributes into the technology in a productivity analysis of Swedish pharmacies. In the application, the attributes are used together with ratios of distance functions to measure the service quality of each pharmacy. In our study, some major network and operation attributes are treated as the quality output variables as in Färe et al. (1995), which makes it possible to include those attributes into our conventional analysis of railroad productivity changes. The AMPI is an extension of MPI, and also can be measured by distance function and DEA. In our AMPI model, three network and operation attributes are incorporated into the technology to study the relationship between productivity growth and these major attributes.

The main decomposition result of AMPI (in simplest form) can be expressed as:

$$\text{AMPI} = \text{ACH} \cdot \text{EFFCH} \cdot \text{TECH}$$

where the first term of left hand of formula ACH measures attribute change, the second part EFFCH measures efficiency change and the last part TECH indicates technical change. It means that the productivity progress can be seen as the result of joint action of adjusting attributes degree, changing technical efficiency, and shifting of the technology frontier. For more details, see Appendix 3.B.

3.3. Data Collection and Procedures

The data used in this study come primarily from Class I railroad annual reports to the Interstate Commerce Commission and its successor, the STB. The panel data set is firm specific, consist of all class I railroad firms annual observations from 1983 to 2008.

On the selection of input and output variables, we follow most recently studies, for instance, Wilson (1997), Bitzan (1999), Bitzan and Keeler (2003, 2007), Bitzan and Welson (2007). Revenue ton mails (RTM) is used as a measure of output.[20] Labor (LABOR), fuel (FUEL), equipment (WE), materials and supplies (WM), and investment in miles of road (INVR), are chosen as inputs.

RTM, the movement of a ton of freight over one mile for revenue, is the preferred measure for the output, which is actually demanded by shippers, and used by most railroad authorities. LABOR is measured by the average number of total employees; FUEL is measured by the total gallons of diesel oil consumed; WE is the

[20] Revenue tonmiles are the tonmiles that produce revenues. It is a commonly used measure of output. In some studies, these are indexed in a hedonic framework with a set of observables, while in other studies, the technology is indexed by a set of observables. These include: percentage of bulk traffic, unit train traffic, average length of haul, and a variety of others. We follow this latter approach in our analysis.

total locomotives and freight cars in services; MW is measured by expenditures on input.

To properly reflect operating and network characteristics in the railroad industry, most recent cost analysis models consider the attribute variables, namely, miles of road (MOR), unit train percentage (UTP),[21] average length of haul (ALH), etc. These variables capture differences in firm operating and network characteristics. MOR, is a common variable in specifications and represents the size of the network. Unit trains are considered the least costly of the different types of activities used to produce ton-miles; UTP is an idea indicator of low short-run cost and profitability of network.[22] As regards ALH, the average number of miles a ton of freight travels, given all else constant, ALH increases, total costs are expected to decline. Hence, in this study, the above three network and operating attribute variables – UTP, MOR, and ALH – are included. We expect that mergers can have a sizable impact on these variables, and meanwhile, these impacts may explain partial efficiency and productivity evolutions of railroad firms.

In 1983, there were 28 R-1 firms. During 1983-2000, over that time period six

[21] Railroads produce freight ton-miles through three distinct production activities: way, through, and unit train operations. Way train services are essentially a gathering and distributing activity wherein small shipments are initially gathered and consolidated over low-density lines and (after the line haul) eventually distributed, again over low-density lines. Operations occur over short distances, small shipment sizes, and slow speeds. These are generally considered the high cost mode of operations. Through train services are provided between major terminal with longer hauls, larger shipment sizes, and faster speeds than way train services. Unit train services are large shipments over long distances, occurring at fast speeds, and, typically are "dedicated" in the sense that these services generally occur between a single origin and destination.

[22] Railroads produce output with "unit" train traffic wherein the railroad travels point to point with large volumes of traffic or they produce through a set of "way and through" train movements, where local shipments (way) are consolidated into trainloads and shipped between major points (Through) and then switched to complete the movement. The latter is commonly thought to be more expensive than the former.

firms were declassified as Class 1 firms, but continue to operate. The remaining firms have largely been consolidated into seven firms which we lable as BN, CN, CSX, KCS, NS, SOO and UP [23] firms in the post-merger period (2001-2008). In total, there are 319 firm year observations in the data to form the technology frontier, and use 182 firm year observations to compute the MPI and AMPI.

Because the time series data for survivor firms are preferable to detect the impact of mergers on efficiency and productivity, in data processing, we use the "mother firm" approach (MFA) to represent the data of railroads over time.[24] MFA approach can be described as following: we use the final merged firms name over all the period, in the pre-merger year, data were calculated by summing up those two or more "mother firms" that merged to form the corresponding firms operating in the post-merger period. Therefore, factors used to measure efficiency and productivity were assumed to be additive.

3.4. Empirical Models and Results

The primary interest of this study is to evaluate the effects of industry and firm-level consolidation activities and the different sources of efficiency and productivity changes. There are two primary ways to deal with unbalanced panel data within the context of DEA. One is to treat the panel as a single cross-section (each firm year being considered as an independent observation) and pool the observations. This way, a single frontier is computed, and the relative efficiency of each firm in

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[23] The abbreviations of railroad firms are provided in Appendix 3 along with a disposition of firm names and consolidation over time. This is based on Bitzan and Wilson (2007). .

[24] This approach was used in Odeck (2008) to study the mergers impact on efficiency and productivity of public transport services.

each period is calculated by reference to this single frontier (see, for instance, Chapin and Schmidt (1998) and Atkinson et al. (2003)). Another possibility is to compute a frontier for each period and compare the efficiency of each firm relative to the frontier in each period (see, for instance, Kumbhakar (1988) and Odeck (2008)). We employ both approaches in our study, in order to emphasize that the different research routes give consistent results. The single technology output-oriented model is chosen because it is an efficient way to evaluate the efficiency change mode for the whole industry and the effect of firm-level mergers; the dynamic (time series) technology model is chosen because it helps us understanding the different causes which lead the productivity changes. More important, the MPI, and hence AMPI is built on and analyzed by the dynamic CRS model (Färe et al., 1994).

3.4.1. Efficiency Performance

Using the inputs and outputs data of all Class I railroad firms in U.S. from 1983 to 2008, the technology efficiencies and scale efficiency were calculated by solving the accordingly linear programming problems in section 3.2.3 under the single technology setting. The summary of value of TEs and SEs of survivor firms is displayed in Table 3.1. The TE and SE scores show that each firm's annual technology and scale efficiency performance position in the whole period, and we use them to analyze the efficiency effect of all the mergers happened during 1983 and 2008.

[Insert Table 3.1 here.]

We also visualize the evolutions of the TE and SE in Figure 3.2 and Figure

3.3.

[Insert Figure 3.2 here.]

[Insert Figure 3.3 here.]

In Figure 3.2, the TE scores for the 7 survivor firms have been plotted over time. Since our survivor firms' data have included all the information of their predecessors,[25] the change of efficiency score reflects the evolution of railroad industry TE performance. There is an obvious increasing trend on the average values of the TE (output distance function) for all the survivor firms during the period 1983-2003, the average values of the TE grow from 0.587 to 0.869, the geometric average growth rate is 1.1579 percent. The ranking among survivor firms is relatively stable, BN, SOO and UP hold the top 3 places for almost all the years, the average efficiency scores are 0.851, 0.752 and 0.737. On the other hand, NS, CSX and CN are the firms with lowest average efficiency score. Although the average efficiency scores of CN are low, CN shows a strong increasing trend during this period, it reached the efficient level in 2008. NS always has a relatively low efficiency performance, especially after 2000.

In Figure 3.3, we present the evolution of the SE for the 7 survivor firms during the period 1983-2008. There is an obvious characteristic - all the firms' scores are almost stagnant all over time. The average value of SE is 0.929 in 1983 and 0.917 in 2008, the geometric average growth rate is -0.0005 percent. The SE ranking among

[25] But the information provided in Table 1 is still not absolutely complete; there are six firms (include BLE, BM, DH, DMIR, FEC, and PLE) lost class I status during 1983-1989. Those firms are out of our research scope.

survivor firms is also relatively stable, BN and UP hold the top 2 places almost for the whole period, the average efficiency scores are 0.997 and 0.966. Since SE describes the divergence of the decision making units from the most productive scale size, the small change of SE reflects that the railroads maintained a relatively stable size through time (after using the MFA procedure).

3.4.2. The Mergers Effect on the Efficiency Performance

Merger Effect Model (Single Technology Model): The single technology frontier output-oriented model is chosen to capture the mergers effect on the efficiency performance evolution of the industry and specific firms. In this model, we use only one output technology setting to calculate the efficiency scores for each firm during 1983-2008 period.

To test the effects of mergers on industry, we regress the TE and SE on a constant, a time trend, and a dummy variable indicating whether the firm has experienced a merger. Many of the unobserved and observed variables are highly correlated with time, the time trend allows for the possibility that efficiency has increased during the period for reasons other than mergers. On the selecting a nonlinear time trend specification, there are three considerations. First, from the real TE data trend in Table 3.1 and Figure 3.2, we observe many firms experience a distinct efficiency gain after merger and slowdown after several years (i.e., SOO merges MILW in 1985, UP merges SSW in 1990, and CSX merges CR in 1999). Second, the average TE score also shows a waning rising trend during periods 1990-1995 and 2000-2008, which are the periods after each merger waves (1980s and

1990s). Finally, as discussed by Winston (1998) and used in Wilson and Wilson (2001), the effect of mergers on efficiency may smooth in over time. Following Wilson and Wilson (2001), Chapin and Schmidt (1998), we use a nonlinear specification including interaction terms. The time trend is given by:

$$\text{trend} = \beta_{2,m} * \text{time} + \beta_{3,m} * (\text{time}/(\text{time}+1)) * \text{merger}_m.$$

In figure 3.4, we give two examples of the nonlinear time trends for firm CSX and SOO.

[Insert Figure 3.4 here.]

And the regressions take the form:

$$y_m = \beta_{0,m} + \beta_{1,m} * \text{time} + \beta_{2,m} * (\text{time}/(\text{time}+1)) * \text{merger}_m + \varepsilon_m ,$$

where the suffix m stands for the a specific merger which have happen during 1983-2008. y_m stands for the TE and SE., merger_m is the dummy variable and time variable takes integer 1 in the year merger happened, and 2, 3,… and -1, -2,… to indicate the years after merger and before merger.

One of the primary purposes of this study is to investigate the efficiency impact of mergers from 1983-2008. In examining mergers, we use a total 16 years data for each merger, 6 years data before merger and 10 years after merger. If the interval of two mergers less than 10 years, we repeatedly use those overlapping time data. Using pooling section data technique, we first get the regression results on all the mergers of railroads happened between 1983 and 2008. The regression results are presented in Table 3.3, which utilizes the nonlinear time trend we described above.

[Insert Table 3.3 here.]

We found that the industry level mergers do not have a significant effect on the efficiency performance, neither for the TE scores, nor the SE. However, the nonlinear time trend for the TE is significant, the estimate value is 0.01937, it means an average 2 percent increase each year. The SEs do not has any significant time trend; this result is consistent with our observation from Table 3.1. The most likely reason that the SEs maintain relatively stable levels is we have applied the MFA procedure on the data of survivor firms, which keeps the size of firm stable even if the firm experiences mergers.

Next, consider the different impacts between two merger groups. We divide the whole sample into two subsamples, one is the 1980s subsample, which includes 7 merger activities happened in 1980s, and the other is 1990s subsample, which also includes 7 merger activities happened in 1990s. When we use TE as regressand, as we expect, the estimation of time trend for both subsample are positive and significant, the estimated parameter for the 1980s is 0.01767, and 0.0157 for 1990s, which shows that efficiency time trend effect for the 1980s is slight stronger than those in the 1990s. However, the effects of merger are not significant for both subsamples. When we use SE as regressand, almost all the regressions results are not significant. In general, we get the results that the mergers do not affect the average efficiency performance for the industry during this period, and the efficiency time trend for 1980s mergers are relatively high that those for 1990s.

Of special interest was to examine the effect of each merger on individual firm. We select 6 main mergers for 6 survivor firms based on the total quality of

RTMs of firms involved in consolidation.[26] On these regressions, we use the total 26 years data for each firm. No matter which year the merger occurred, we use a nonlinear time trend to catch the impact of merger. The regression results are presented in Table 3.4.

[Insert Table 3.4 here.]

In this Table, each merger was regressed by both Efficiency Score (TE under CRS) and SE. First, the TE regression results data shows that these models overall have a high level of fitness, the smallest R square value is 0.6926. The intersection terms and time trend terms are both significant and positive, but estimations of the effect of merger term are not unified, half of the 6 firms have significant and positive impact on efficiency change, including BN, CSX, and SOO. When we use SE as regressand, half of the time trend terms and almost all the nonlinear time trend are not significant. As a comparison, the results for firm KCS have significant result for both regressands and all the terms, which shows that the efficiency performance gains effects may be not a result of merger.

3.4.3. The Decomposition of Productivity

Productivity Decomposition Model (Dynamic Technology Model): in this empirical model, we take the network and operation attributes into account. Three network and operation attributes (UTP, MOR, and ALH), which capture various dimensions of network characteristics, are treated as attributes outputs in the DEA models.

[26] There is no consolidation activity happened on KCS during 1983-2008, but the firm KCS is still include in Table 4 for comparison.

To detect the impact of mergers on efficiency and productivity, we use MFA processing. The summing up of units in the pre-merger period is a necessary condition for making comparisons between the two periods, and it also an efficient way to apply our AMPI analysis model. Moreover, using the MFA processing, our unbalanced panel data becomes a balanced panel data set, which is a basic data requirement of employ MPI and AMPI performance evaluation models.

Under the above setting, first the effect of network and operation attributes will be estimated by a comparison of the single output DEA model and an attribute-incorporated multi-output DEA model. Furthermore, by computing each firm's AMPI from 1983 to 2008, and decomposing AMPI into attribute change, efficiency change (catch-up effect, or technical efficiency change) and technical change (technology frontier shift) components, the mergers effect on efficiency and productivity will be conveniently evaluated. The AMPI indices and its decompositions were calculated using the method showed in section 3.3.4 and Appendix B for those 7 survivor firms, using a balanced panel data from 1983 to 2008 and MFA data procedure. The values of the AMPI and its decompositions are displayed in Table 3.2, these results are used to analyze the productivity change over time and the real sources of productivity improvement.

[Insert Table 3.2 here.]

As in the results from the from the Merger Effect Model, we still do not find any efficiency effects of merger activity. More precisely, the effects of mergers are idiosyncratic. Although three firms' mergers have positive and significant effects on the TE scores, the overall merger data does not lend any support to the notion that mergers have improved efficiency. According to AAR (2008), overall the productivity of the U.S. railroads Class I have improved for 163 percent from 1980 to 2007, or an average 3.1 percent increase rate annually. Using our Productivity Decomposition Model (AMPI model), as displayed in Table 3.2, we observe that the average (geometric mean) railroad industry growth rate is 3.6 percent, the network attribute change rate is 1.4 percent, the technology growth rate is 2.1 percent, but the TE change rate is almost stagnant with only a 0.1 percent annual growth. However, we need pay attention to that the AMPI are not the real Productivity index, it is a Malmquist productivity index incorporating with several network and operation attributes.

Because the adjusting network and operation attributes come at a cost, railroads may not have sufficient incentives to improve their network attribute under regulatory scheme. Some firms (like firm BN and SOO) have the highest attributes growth rate during 1982-2008, yet NS has the lowest attributes growth rate. In fact, since most attributes are also measures of operating and management level of firms, these network and operation attributes change are also impacted by the change of technology efficiency performance.

From Table 3.2, the AMPI on average has positive growth except for five year periods (1984-1986, 1995-1997, and 1999-2000). Not only the AMPI, but also two of its components (ACH and TECH) grow modestly. From the volatility perspective, the ACH is the smallest, which shows that the network attributes growth for the whole industry gradually. The average growth rate of TECH is 2.1, which is another explanation of the time trend effect on the efficiency scores in Merger Effect Model.

In this paper, we focused on the sources of productivity change in the industry. Our findings point to three results. First, the largest source of productivity improvement is changes in the technology frontier. It is the largest source of productivity gains in the industry, accounting for about two-thirds of the AMPI growth rate. Second, there have been significant changes in network and/or operational characteristics over time, and with these changes, there have been substantial changes in efficiency. Third, the effects of mergers, long held to have substantial effects on efficiency, are not found to have significant effects (in magnitude or statistically) on productivity.

3.5. Summary and Conclusions

To analyze the efficiency impact of consolidation activity in an industry, attention must be paid to the correlative industry characteristics, a pure input-output production system is just a simplify model of industry reality. The incorporation the network and operation attributes into production system or productivity index analysis provides an operational and managerial perspective of railroad industrial activity.

This study offers an analysis of railroad economic performance using the U.S. railroad industry and firm level annual data. In this paper, we use a nonparametric approach (DEA) to specify and estimate the technical inefficiency for the U.S. railroad industry. The approach allows mergers to impact efficiency. We found that the efficiency performance changes are not the result of mergers. This conclusion is similar to the result of Bitzan and Wilson (2007), which found that the efficiency gains of fourteen mergers in the railroad industry accounts for about an 11.4 percent reduction in industry cost, and Berndt et al. (1993), which found that mergers explain only 10 percent of cost changes under partial deregulation. The major explanations of the slight differences between our results and those from the Bitzan and Wilson (2007) and Berndt et al. (1993) are the different assumptions of the production technology and different measurement method of efficiency.

There are several contributions from this paper. First, our study adopts both fixed technology frontier and dynamic technology frontiers, which makes it easy to compute and analyze the efficiency impacts and productivity change sources. Second, by adoption the mother firm approach data process, we are able to generate an integrated panel data set. This allows for a dynamic technology mode that is used to track the efficiency changes over time. Third, the distance function and Malmquist index method does not need the prices of the inputs and outputs, which avoids the impact of big fluctuations on some factors' price during study period. Finally, comparing to frequently used cost analysis approach, we introduce the AMPI into railroad efficiency change and productivity growth analysis in terms of important network and operation attributes.

We found that the TE performances of the railroad and survivor firms grow through the period 1983-2008, and the mergers do not have significant effect on the TE and SE gains. We also find that the productivity improvement was mostly contributed by the major network and operation attributes and technology improvement. Our findings indicate that railroad efficiency improvement is highly dependent upon the improvement of industry technology level, the adjusting of network and operation attributes is also a big push force on the productivity improvement, and mergers are nature consequences of business activities, the leakage between efficiency and merger are weak, the more possible reasons for the efficiency improvement maybe origin from the deregulation of the Staggers Act of 1980.

References

Association of American Railroads, (1980), *Railroad Facts* (formerly titled *Yearbook of Railroad Facts*). Washington, DC.

Association of American Railroads, (2008), "Freight Railroads: A Historical Perspective," http://www.aar.org/IndustryInformation/~/media/AAR/BackgroundPapers, accessed September 8, 2011.

Association of American Railroads, (2010), "Class I railroad statistics," http://www.aar.org/pubcommon/documents/abouttheindustry/statistics.pdf, accessed September 8, 2011.

Atkinson, S. E., Färe, R. and Primont, D., (2003), "Stochastic Estimation of Firm Inefficiency Using Distance Functions," *Southern Economic Journal*, 69, 596-611.

Bennet, T. L., (1920), "The Theory of Measurement of Changes in Cost of Living," *Journal of the Royal Statistical Society,* 83, 455-462.

Berndt, E., Friedlaender, A., Wang Chiang, J. and Vellturo, C., (1993), "Cost Effects of Mergers and Deregulation in the U.S. Rail Industry," *The Journal of Productivity Analysis*, 4, 127-144.

Bitzan, J. D., (1999), "The Structure of Railroad Costs and the Benefits," *Research in Transportation* Economics, 5, 1-52.

Bitzan, J. D. and Keeler, T. E., (2003), "Productivity Growth and Some of Its Determinants in the Deregulated U. S. Railroad Industry," *Southern Economic Journal,* 70, 2, 232-253.

Bitzan, J. D. and Keeler, T. E., (2007), "Economies of Density and Regulatory Change in the U.S. Railroad Freight Industry," *Journal of Law and Economics,* 50, 1, 157-179.

Bitzan, J. D. and Wilson, W. W., (2007), "Industry Costs and Consolidation: Efficiency Gains and Mergers in the U.S. Railroad Industry," *Review of Industrial Organization,* 30, 81-105.

Borts, G. H., (1952), "Production Relations in the Railway Industry," *Econometrica,* 20, 1, 71-79.

Brown, R. S., Caves, D. W. and Christensen, L. R., (1979), “Modelling the Structure of Cost and Production for Multiproduct Firms,” *Southern Economic Journal,* 46, 1, 256-273.

Caves, D. W., Christensen, L. R. and Diewert, W. E., (1982), “The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity,” *Econometrica*, 50, 6, 1393-1414.

Caves, D. W., Christensen, L. R. and Swanson, J. A., (1980), “Productivity in U.S. Railroads, 1951-74,” *Bell Journal of Economics,* 11, 1, 166-81.

Caves, D. W., Christensen, L. R. and Swanson, J. A., (1981), “Productivity Growth, Scale Economies, and Capacity Utilization in U.S Railroads, 1955-74,” *American Economic Review,* 71, 5, 994-1002.

Chapin, A. and Schmidt, S., (1998), “Do Mergers Improve Efficiency? Evidence from Deregulated Rail Freight,” *Journal of Transport Economics and Policy,* 33, 2, 147-62.

Charnes, A., Cooper, W. W. and Rhodes, E., (1978), “Measuring the Efficiency of Decision Making Units,” *European Journal of Operations Research*, 2, 429-444.

Christensen, L. R., Jorgenson, D. W. and Lau, L. J., (1973), “Transcendental Logarithmic Production Frontiers,” *The Review of Economics and Statistics,* 55, 1, 28-45.

Coelli, T. and Perelman, S., (2000), “Technical Efficiency of European Railways: a Distance Function Approach,” *Applied Economics,* 32, 67-76.

Cross, R. M. and Färe, R., (2008), “Value Data and the Bennet Price and Quantity Indicators,” *Economics Letters*, 102, 1, 19-21.

Debreu, G., (1951), “The Coefficient of Resource Utilization,” *Econometrica*, 19, 3, 273-92.

Diewert, W. E., (1998), “Index Number Theory Using Differences Rather than Ratios,” Department of Economics, UBC, Discussion paper No. 98-10.

Ellig, J., (2002), “Railroad Deregulation and Consumer Welfare,” *Journal of Regulatory Economics*, 21, 2, 143-67.

Farrell, M. J., (1957), “The Measurement of Productive Efficiency,” *Journal of the Royal Statistical Society,* 120, 3, 253-81.

Färe, R., Grosskopf, S., Lindgren, B. and Roos, P., (1992), "Productivity Changes in Swedish Pharmacies 1980-1989: a Nonparametric Malmquist Approach," *Journal of Production Annual*, 85-101.

Färe, R., Grosskopf, S. and Lovell C.A.K., (1985), *The Measurement of Efficiency of Production*, Kluwer-Nijhoff Publishing: Boston.

Färe, R., Grosskopf, S. and Lovell, C.A.K., (1994a), *Production Frontiers*, Cambridge University Press: Cambridge.

Färe, R., Grosskopf, S., Norris, M. and Zhang, Z., (1994b), "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries," *American Economic Review*, 84, 1, 66-83.

Färe, R., Grosskopf, S. and Roos, P., (1995), "Productivity and Quality Changes in Swedish Pharmacies," *International Journal of Production Economics*, 39, 137-144.

Färe, R. and Primont, D., (1995), *Multi-Output and Duality: Theory and Application*, Kluwer-Nijhoff Publishing: Boston.

Friedlaender, A. F., (1971), "The Social Costs of Regulating the Railroads," *American Economic Review*, 61, 2, 226-34.

Friedlaender, A. F., Berndt, E. R., Chiang, J. S. W., Showalter, M. and Vellturo, C. A., (1993), "Rail Costs and Capital Adjustments in a Quasi-Regulated Environment," *Journal of Transport Economics and Policy*, 27, 2, 131-152.

Friedlaender, A. F. and Spady, R. H., (1981), "Freight Transport Regulation," The MIT Press: Cambridge.

Gallamore, R. E., (1999), "Regulation and Innovation: Lessons from the American Railroad Industry," In Essays in *transportation economics and policy: A handbook in honor of John R. Meyer*, edited by Gomez-Ibanez, J., Tye, W. B. & Winston, C., Brookings Institution Press: Washington, DC, 493-530.

Harris, R. G., (1977), "Economies of Traffic Density in the Rail Freight Industry," *Bell Journal of Economics*, 8, 2, 556-564.

Ivaldi, M. and McCllough, G. J., (2001), "Density and Integration Effects on Class I U.S. Freight Railroads," *Journal of Regulatory Economics*, 19, 200, 161-182.

Ivaldi, M. and McCllough, G. J., (2005), "Welfare Tradeoffs in U.S. Rail Mergers," CEPR Discussion Paper No. 5000.

Keeler, T. E., (1974), “Railroad Costs, Returns to Scale, and Excess Capacity,” *Review of Economics and Statistics,* 56, 2, 201-208.

Kumbhakar, S., (1988), “On Estimation of Technical and Allocative Inefficiency Using Stochastic Frontiers Functions: the Case of US Class I Railroads,” *International Economic Review,* 3, 727-33.

Lan, L. W. and Lin, E. T. J., (2005), “Measuring Railway Performance with Adjustment of Environmental Effects, Data Noise and Slacks,” *Transportmetrica, 1*, 161-189.

Lim, S. H. and Lovell, C. A. K., (2008), “Short-Run Total Cost Change and Productivity of US Class I Railroads,” *Journal of Transport Economics and Policy*, 42, 155-188.

Lim, S. H. and Lovell, C. A. K., (2009), “Profit and Productivity of U.S. Class I Railroads,” *Managerial and Decision Economics*, 30, 423-442.

McCullough, G. J., (2007), *U.S. Railroad Efficiency: A Brief Economic Overview, in Research to Enhance Rail Network Performance*, Publisher: Transportation Research Board.

Odeck, J., (2008), “The Effect of Mergers on Efficiency and Productivity of Public Transport Services,” *Transportation Research Part A: Policy and Practice,* 42, 4, 696-708.

Ray, S. C., (1995), “Productivity and Quality Changes in Swedish Pharmacies: a Comment,” *International Journal of Production Economics,* 39, 145-146.

Shephard, R. W., (1953), *Cost and Production Functions*, Princeton University Press: Princeton.

Shephard, R. W., (1970), *Theory of cost and production functions*, Princeton University Press: Princeton.

Smith, D., (1983), “The Evolution of Rail Merger Policy,” Proceedings of the Transportation Research Forum, 24, 558-565.

Surface Transportation Board, (2009), “Study of Railroad Rates: 1985-2007,” http://www.stb.dot.gov/econdata.nsf/142bd9233122e76285256605006100e0/e2dde951ff7a815a8525753e004e1236?OpenDocument, accessed September 8, 2011.

Waters, W. G., (2007), "Evolution of Railroad Economics," in Dennis, S. M. & Talley, W. K., eds., *Railroad Economics (Amsterdam, Elsevier Science), Research in Transportation Economics*, 20,11-67.

Williamson, O. E., (1968), "Economies as an Antitrust Defense: The Welfare Tradeoffs," *The American Economic Review*, 58, 1, 18-36.

Wilner, F. N., (1997), *Railroad Mergers: History Analysis Insight.* Simmons-Boardman Books, Inc: Omaha.

Wilson, W. W., (1994), "Market-Specific Effects of Rail Deregulation," *Journal of Industrial Economics*, 42, 1, 1-22.

Wilson, W. W., (1997), "Cost Savings and Productivity Gains in the Railroad Industry," *Journal of Regulatory Economics*, 11, 21–40.

Wilson, Wesley W. and Wilson, William W., (2001), "Deregulation, Rate Incentives, and Efficiency in the Railroad Market," in B. Starr McMullen (ed.), *Research in Transportation Economics*, 6, 1-24.

Winston, C., (1998), "U.S. Industry Adjustment to Economic Deregulation," *The Journal of Economic Perspectives*, 12, 3, 89-110.

Winston, C., (2005), "The Success of the Staggers Rail Act of 1980," Brookings Institute, http://www.brookings.edu/~/media/Files/rc/papers/2005/10_railact_winston/10_railact_winston.pdf, accessed September 8, 2011.

Appendix

Appendix 3.A

Railroad Firms and Acronym

Firm Name	Abbreviation	Note
Atchison, Topeka & Santa Fe	ATSF	Merged with BN in 1996
Bessemer and Lake Eric	BLE	Lost Class I Status in 1985
Boston and Maine	BM	Lost Class I Status in 1989
Burlington Northern	BN	
Baltimore & Ohio Railroad	BO	Merged with CO and SCL to form CSX
Canadian National Railway	CN	
Chicago & Northwestern	CNW	Merged with UP in 1995
Chesapeake & Ohio Railway	CO	Merged with BO and SCL to form CSX
Consolidated Rail Corporation	CR	Merged with CSX in 2000
CSX Transportation	CSX	
Delaware and Hudson	DH	Lost Class I Status in 1988
Duluth, Missabe, and Ironton	DMIR	Lost Class I Status in 1985
Denver & Rio Grande Western	DRGW	Merged with SP in 1994
Detroit, Toledo & Ironton	DTI	Merged with GTW in 1984
Florida East Coast	FEC	Lost Class I Status in 1992
Grand Trunk Western Railroad	GTW	Merged with DIT in 1984
Kansas City Southern	KCS	
Milwaukee Road	MILW	Merged with SOO in 1985
Modesto & Empire Traction	MET	Merged with UP in 1988
Missouri Pacific	MP	Merged with UP in 1986
Norfolk Southern	NS	
Pittsburgh, Lake Eric	PLE	Lost Class I Status in 1985
Seaboard Coast Line	SCL	Merged with BO and CO to form CSX
Soo Line	SOO	
Southern Railway	SOU	Merged with NW to form NS
St. Louis Southwestern Railway	SSW	Merged with UP in 1990
Union Pacific	UP	
Western Pacific	WP	Merged with UP in 1986

Source: Htttp://www.trainweb.org/rosters/marks.html

Appendix 3.B

Attributes-Incorporated Malmquist Productivity Index

We denote inputs by $\mathrm{x^t} = (\mathrm{x_1^t}, \cdots, \mathrm{x_N^t}) \in \mathrm{R_+^N}$, outputs by $\mathrm{y^t} = (\mathrm{y_1^t}, \cdots, \mathrm{y_M^t}) \in \mathrm{R_+^M}$ and attributes by $\mathrm{a^t} = (\mathrm{a_1^t}, \cdots, \mathrm{a_J^t}) \in \mathrm{R_+^J}$, then production technology at time t can be represented by the production set $\mathrm{T^t} = \{(\mathrm{x^t}, \mathrm{y^t}, \mathrm{a^t})\colon \mathrm{x^t} \text{ can product } \mathrm{y^t} \text{ with } \mathrm{a^t}\}$. The input distance function is $\mathrm{TE_i^t}(\mathrm{y^t}, \mathrm{a^t}, \mathrm{x^t}) = \inf\{\lambda\colon (\mathrm{x^t}/\lambda, \mathrm{y^t}, \mathrm{a^t}) \in \mathrm{T^t}\}$.

The attribute change index between time t and t+1 is defined as:

$$\mathrm{ACH_i^{t,t+1}}(\mathrm{y^{t+1}}, \mathrm{a^{t+1}}, \mathrm{x^{t+1}}, \mathrm{y^t}, \mathrm{a^t}, \mathrm{x^t}) = \sqrt{\frac{\mathrm{TE_i^t}(\mathrm{y^t},\mathrm{a^t},\mathrm{x^t})}{\mathrm{TE_i^t}(\mathrm{y^t},\mathrm{a^{t+1}},\mathrm{x^t})} \cdot \frac{\mathrm{TE_i^{t+1}}(\mathrm{y^{t+1}},\mathrm{a^t},\mathrm{x^{t+1}})}{\mathrm{TE_i^{t+1}}(\mathrm{y^{t+1}},\mathrm{a^{t+1}},\mathrm{x^{t+1}})}}.$$

AMPI between period t and t+1 can be expressed as:

$$\mathrm{MA_i^{t,t+1}}(\mathrm{y^{t+1}}, \mathrm{a^{t+1}}, \mathrm{x^{t+1}}, \mathrm{y^t}, \mathrm{a^t}, \mathrm{x^t}) = \sqrt{\frac{\mathrm{TE_i^t}(\mathrm{y^t},\mathrm{a^t},\mathrm{x^t})}{\mathrm{TE_i^t}(\mathrm{y^{t+1}},\mathrm{a^{t+1}},\mathrm{x^{t+1}})} \cdot \frac{\mathrm{TE_i^{t+1}}(\mathrm{y^t},\mathrm{a^t},\mathrm{x^t})}{\mathrm{TE_i^{t+1}}(\mathrm{y^{t+1}},\mathrm{a^{t+1}},\mathrm{x^{t+1}})}}.$$

As in section 3.2.2, this expression can be decomposed into technology change and efficiency change components:

$$MA_i^{t,t+1}(y^{t+1}, a^{t+1}, x^{t+1}, y^t, a^t, x^t)$$

$$= \frac{TE_i^t(y^t, a^t, x^t)}{TE_i^{t+1}(y^{t+1}, a^{t+1}, x^{t+1})} \cdot \sqrt{\frac{TE_i^{t+1}(y^{t+1}, a^{t+1}, x^{t+1})}{TE_i^t(y^{t+1}, a^{t+1}, x^{t+1})} \cdot \frac{TE_i^{t+1}(y^t, a^t, x^t)}{TE_i^t(y^t, a^t, x^t)}}$$

The AMPI can also be decomposed as:

$$MA_i^{t,t+1}(y^{t+1}, a^{t+1}, x^{t+1}, y^t, a^t, x^t)$$

$$= ACH_i^{t,t+1}(y^{t+1}, a^{t+1}, x^{t+1}, y^t, a^t, x^t) \cdot \sqrt{\frac{TE_i^t(y^t,a^{t+1},x^t)}{TE_i^t(y^{t+1},a^{t+1},x^{t+1})} \cdot \frac{TE_i^{t+1}(y^t,a^t,x^t)}{TE_i^{t+1}(y^{t+1},a^t,x^{t+1})}} \qquad (6)$$

If we impose a separability assumption on the distance functions, that is, $\mathrm{TE_i^t}(\mathrm{y^t}, \mathrm{a^{t+1}}, \mathrm{x^t}) = \mathrm{R^t}(\mathrm{a^{t+1}}) \cdot \overline{\mathrm{TE_i^t}}(\mathrm{y^t}, \mathrm{x^t})$ and similarly for the other time distance functions, where $R^t(a^{t+1})$ is the separability variable. In this case, expression (6) can also be expressed as

$$MA_i^{t,t+1}(y^{t+1},a^{t+1},x^{t+1},y^t,a^t,x^t)$$

$$= ACH_i^{t,t+1}(y^{t+1},a^{t+1},x^{t+1},y^t,a^t,x^t) \cdot \sqrt{\frac{\overline{TE_i^t}(y^t,x^t)}{\overline{TE_i^{t+1}}(y^{t+1},x^{t+1})} \cdot \frac{\overline{TE_i^{t+1}}(y^t,x^t)}{\overline{TE_i^{t+1}}(y^{t+1},x^{t+1})}} \qquad (7)$$

The second part in the right hand of above expression is exactly the same with Malmquist productivity index. Hence, we have

$$MA_i^{t,t+1}(y^{t+1},a^{t+1},x^{t+1},y^t,a^t,x^t) = ACH_i^{t,t+1} \cdot EFFCH^{t,t+1} \cdot TECH^{t,t+1}$$
(8)

The first part of right hand side of (8) measures attribute change, the second part shows the efficiency change and the last part indicates the technical change. A note on the computation of $R^t(a^{t+1})$, $\overline{TE_i^t}(y^t,x^t)$ and other similar expressions in (7) is that we need to solve the following problem for each observation k',

$$\overline{TE_i^t}\left(y_{k'}^t, x_{k'}^t | C,S\right) = \min_z \lambda$$

$$\text{s.t.} \quad y_{k',m}^t \le \sum_{k=1}^K z_k^t y_{k,m}^t \quad m = 1,\cdots,M$$

$$\sum_{k=1}^K z_k^t x_{k,n}^t \le \lambda x_{k',n}^t \qquad n = 1,\cdots,N$$

$$z_k^t \ge 0 \qquad k = 1,\cdots K \}.$$

Figure 3.1
The Input Distance Function

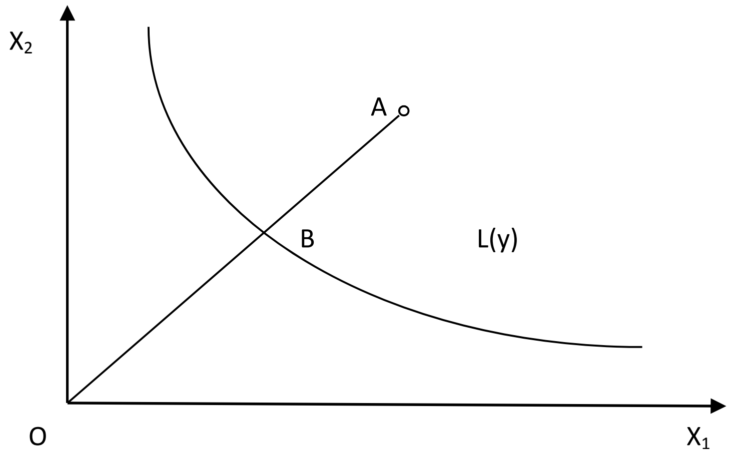


Figure 3.2
Efficiency Scores (TE) Evolution for Survival Firms

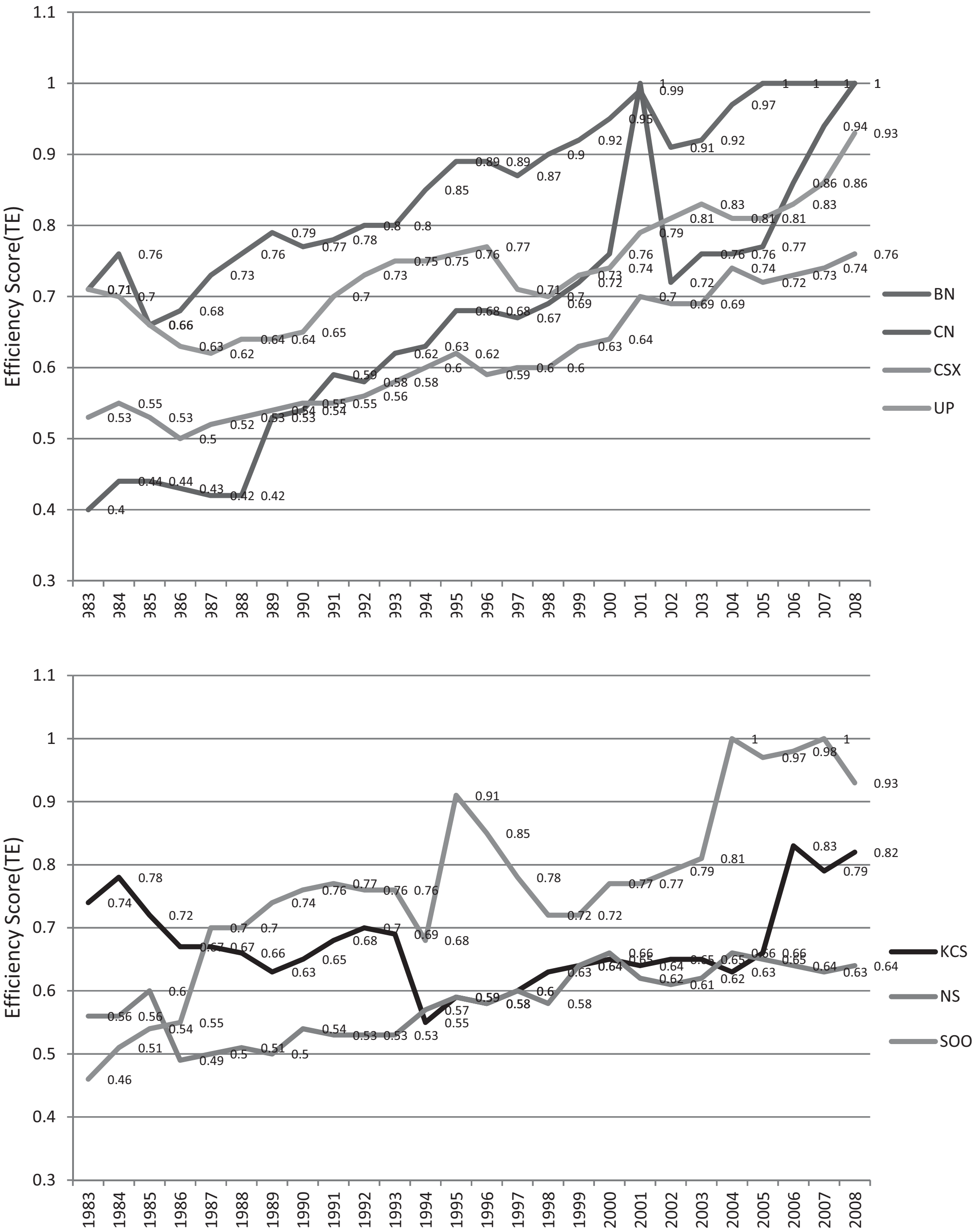


Figure 3.3
Scale Efficiency Evolution for Survival Firms

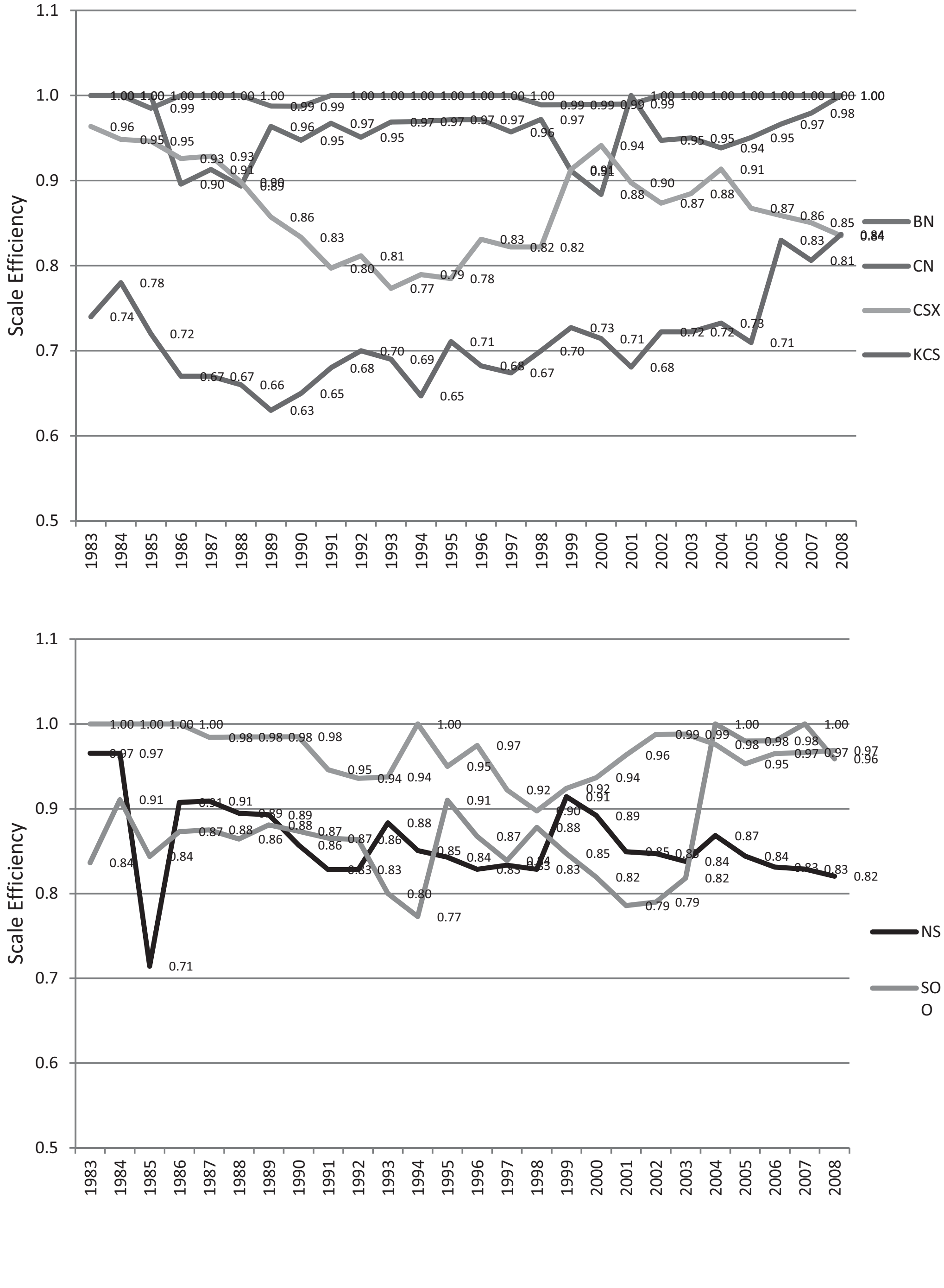
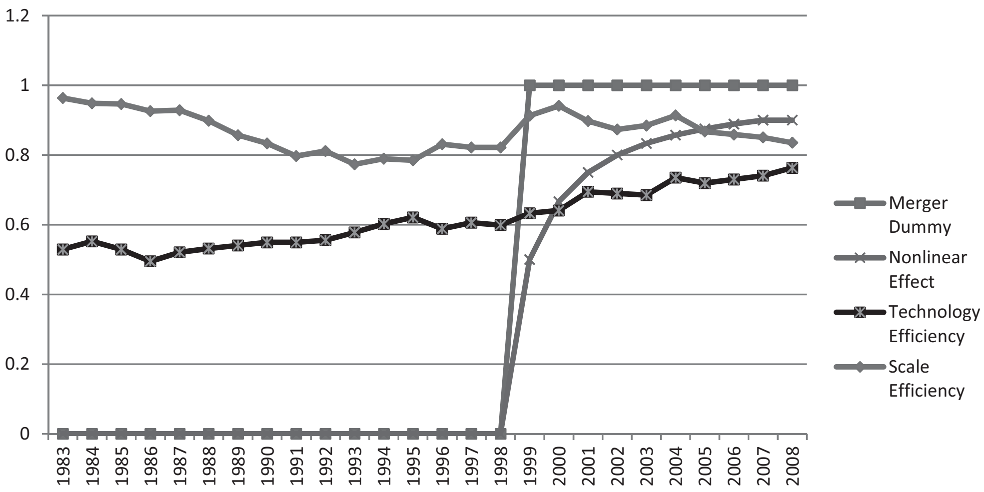
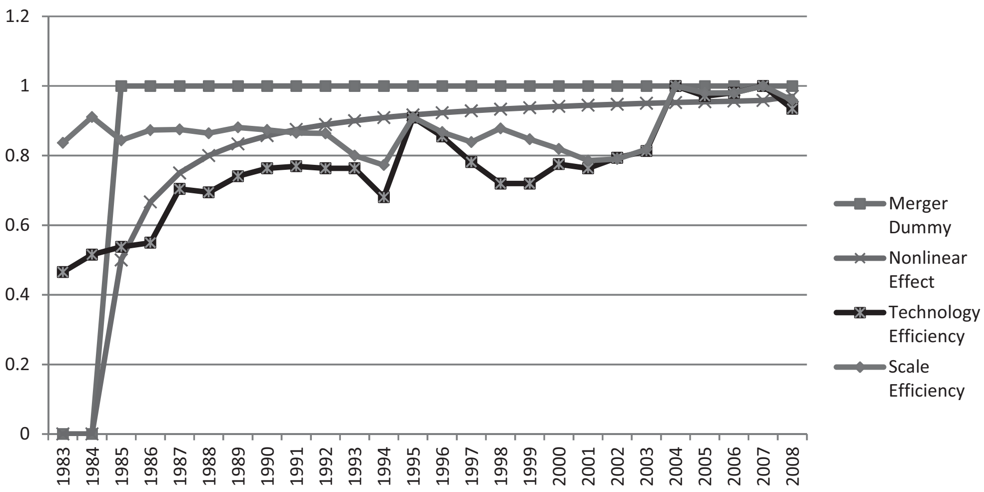


Figure 3.4
Two Nonlinear Time Trend Examples



Example 1: CSX



Example 2: SOO

Table 3.1
Summary of Efficiency Scores

Year	Efficiency Score (CRS)								Scale Efficiency							
	BN	CN	CSX	NS	SOO	UP	KCS	Mean	BN	CN	CSX	NS	SOO	UP	KCS	Mean
1983	0.710	0.400	0.530	0.560	0.460	0.710	0.740	0.587	1.000	1.000	0.964	0.966	0.836	1.000	0.740	0.929
1984	0.760	0.440	0.550	0.560	0.510	0.700	0.780	0.614	1.000	1.000	0.948	0.966	0.911	1.000	0.780	0.944
1985	0.660	0.440	0.530	0.600	0.540	0.660	0.720	0.593	0.985	1.000	0.946	0.714	0.844	1.000	0.720	0.887
1986	0.680	0.430	0.500	0.490	0.550	0.630	0.670	0.564	1.000	0.896	0.926	0.907	0.873	1.000	0.670	0.896
1987	0.730	0.420	0.520	0.500	0.700	0.620	0.670	0.594	1.000	0.913	0.929	0.909	0.875	0.984	0.670	0.897
1988	0.760	0.420	0.530	0.510	0.700	0.640	0.660	0.603	1.000	0.894	0.898	0.895	0.864	0.985	0.660	0.885
1989	0.790	0.530	0.540	0.500	0.740	0.640	0.630	0.624	0.988	0.964	0.857	0.893	0.881	0.985	0.630	0.885
1990	0.770	0.540	0.550	0.540	0.760	0.650	0.650	0.637	0.987	0.947	0.833	0.857	0.874	0.985	0.650	0.876
1991	0.780	0.590	0.550	0.530	0.770	0.700	0.680	0.657	1.000	0.967	0.797	0.828	0.865	0.946	0.680	0.869
1992	0.800	0.580	0.560	0.530	0.760	0.730	0.700	0.666	1.000	0.951	0.812	0.828	0.864	0.936	0.700	0.870
1993	0.800	0.620	0.580	0.530	0.760	0.750	0.690	0.676	1.000	0.969	0.773	0.883	0.800	0.938	0.690	0.865
1994	0.850	0.630	0.600	0.570	0.680	0.750	0.550	0.661	1.000	0.969	0.789	0.851	0.773	1.000	0.647	0.861
1995	0.890	0.680	0.620	0.590	0.910	0.760	0.590	0.720	1.000	0.971	0.785	0.843	0.910	0.950	0.711	0.881
1996	0.890	0.680	0.590	0.580	0.850	0.770	0.580	0.706	1.000	0.971	0.831	0.829	0.867	0.975	0.682	0.879
1997	0.870	0.670	0.600	0.600	0.780	0.710	0.600	0.690	1.000	0.957	0.822	0.833	0.839	0.922	0.674	0.864
1998	0.900	0.690	0.600	0.580	0.720	0.700	0.630	0.689	0.989	0.972	0.822	0.829	0.878	0.897	0.700	0.870
1999	0.920	0.720	0.630	0.640	0.720	0.730	0.640	0.714	0.989	0.911	0.913	0.914	0.847	0.924	0.727	0.889
2000	0.950	0.760	0.640	0.660	0.770	0.740	0.650	0.739	0.990	0.884	0.941	0.892	0.819	0.937	0.714	0.882
2001	0.990	1.000	0.700	0.620	0.770	0.790	0.640	0.787	0.990	1.000	0.897	0.849	0.786	0.963	0.681	0.881
2002	0.910	0.720	0.690	0.610	0.790	0.810	0.650	0.740	1.000	0.947	0.873	0.847	0.790	0.988	0.722	0.881
2003	0.920	0.760	0.690	0.620	0.810	0.830	0.650	0.754	1.000	0.950	0.885	0.838	0.818	0.988	0.722	0.886
2004	0.970	0.760	0.740	0.660	1.000	0.810	0.630	0.796	1.000	0.938	0.914	0.868	1.000	0.976	0.733	0.918
2005	1.000	0.770	0.720	0.650	0.970	0.810	0.660	0.797	1.000	0.951	0.867	0.844	0.980	0.953	0.710	0.901
2006	1.000	0.860	0.730	0.640	0.980	0.830	0.830	0.839	1.000	0.966	0.859	0.831	0.980	0.965	0.830	0.919
2007	1.000	0.940	0.740	0.630	1.000	0.860	0.790	0.851	1.000	0.979	0.851	0.829	1.000	0.966	0.806	0.919
2008	1.000	1.000	0.760	0.640	0.930	0.930	0.820	0.869	1.000	1.000	0.835	0.821	0.959	0.969	0.837	0.917
Geometric Mean	0.851	0.633	0.610	0.580	0.752	0.737	0.670	0.694	0.997	0.956	0.866	0.859	0.872	0.966	0.709	0.890

Table 3.2
Attribute-incorporated Malmquist Productivity Index and Decomposition

Year	BN				CN				CSX				KCS			
	AMPI	ACH	EFFCH	TECH	AMPI	ACH	EFFCH	TECH	AMPI	ACH	EFFCH	TECH	AMPI	ACH	EFFCH	TECH
1983-1984	1.11	0.99	1.00	1.12	1.14	1.01	1.03	1.10	1.12	1.04	1.04	1.04	1.09	1.07	0.98	1.04
1984-1985	0.99	1.02	1.00	0.97	1.22	0.99	1.22	1.01	0.96	1.01	0.90	1.06	1.05	1.09	0.95	1.01
1985-1986	1.07	1.05	1.00	1.02	0.98	0.99	1.06	0.93	0.93	0.94	1.13	0.88	1.01	1.06	0.99	0.96
1986-1987	1.14	1.02	1.00	1.12	0.88	0.89	0.85	1.16	1.13	0.99	0.98	1.16	1.00	1.00	0.86	1.16
1987-1988	1.06	1.01	1.00	1.05	1.21	1.13	1.01	1.06	1.02	0.98	0.98	1.06	1.01	1.06	0.90	1.06
1988-1989	1.01	1.01	1.00	1.00	0.97	0.99	0.98	1.00	1.06	1.03	1.03	1.00	1.01	1.03	0.98	1.00
1989-1990	1.01	1.03	1.00	0.98	1.11	1.05	1.08	0.98	1.03	1.03	1.03	0.97	1.06	1.03	1.05	0.98
1990-1991	1.01	1.04	1.00	0.97	1.02	0.90	1.16	0.98	0.91	0.97	0.98	0.96	1.03	1.00	1.05	0.98
1991-1992	1.09	1.07	1.00	1.02	1.01	1.03	0.94	1.04	1.04	1.05	0.93	1.07	1.00	1.00	0.96	1.04
1992-1993	1.09	1.07	1.00	1.02	1.08	0.99	1.07	1.02	0.98	1.00	0.90	1.09	0.95	0.95	0.98	1.02
1993-1994	1.08	1.02	1.00	1.06	0.98	0.98	0.95	1.05	0.98	0.95	0.97	1.06	0.94	0.94	0.95	1.05
1994-1995	1.14	1.06	1.00	1.08	1.09	0.98	1.03	1.08	1.04	1.01	1.03	1.00	1.01	0.99	0.94	1.08
1995-1996	1.00	1.01	1.00	0.99	0.96	1.04	0.93	0.99	1.02	1.05	0.92	1.06	1.05	1.05	0.99	1.01
1996-1997	1.10	1.12	1.00	0.98	1.02	1.02	1.02	0.98	1.05	1.00	1.19	0.88	1.20	1.15	1.08	0.97
1997-1998	1.19	1.11	1.00	1.07	0.97	0.93	1.00	1.04	0.95	0.95	0.93	1.08	1.08	0.94	1.10	1.04
1998-1999	1.04	1.00	1.00	1.04	1.06	0.96	1.06	1.04	0.96	1.01	0.92	1.03	0.74	0.78	0.90	1.05
1999-2000	1.02	1.02	1.00	1.00	1.05	0.99	1.08	0.98	1.06	1.05	1.03	0.98	0.86	0.89	0.95	1.02
2000-2001	1.00	1.01	1.00	0.99	1.05	1.07	0.97	1.01	1.10	1.05	1.04	1.01	0.85	0.93	0.94	0.97
2001-2002	0.99	1.02	1.00	0.97	0.81	1.05	0.78	0.99	0.99	1.00	0.98	1.01	0.97	1.00	1.00	0.97
2002-2003	1.03	1.01	1.00	1.02	0.91	1.00	0.89	1.02	0.97	0.95	1.00	1.02	1.01	1.00	0.99	1.02
2003-2004	1.02	1.01	0.99	1.02	0.92	1.00	0.93	0.99	1.24	1.04	1.00	1.19	0.98	1.02	0.94	1.02
2004-2005	1.09	1.03	1.00	1.06	1.04	1.04	1.02	0.98	0.93	1.05	0.95	0.93	1.00	1.00	0.99	1.01
2005-2006	1.11	1.03	1.00	1.08	1.16	1.10	1.01	1.04	0.93	1.00	1.01	0.92	1.10	1.05	1.08	0.97
2006-2007	1.03	1.04	1.00	0.99	1.15	1.06	1.06	1.02	1.10	1.02	1.05	1.03	1.14	1.15	0.95	1.04
2007-2008	1.09	1.07	1.00	1.02	1.03	0.97	1.08	0.98	1.03	0.99	1.00	1.04	1.13	1.10	0.98	1.05
Geometric Mean	1.059	1.034	1.000	1.025	1.027	1.005	1.004	1.018	1.019	1.006	0.995	1.019	1.005	1.008	0.978	1.020

Table 3.2
Attribute-incorporated Malmquist Productivity Index and Decomposition (continued)

Year	NS				SOO				UP				Industry Average			
	AMPI	ACH	EFFCH	TECH	AMPI	ACH	EFFCH	TECH	AMPI	ACH	EFFCH	TECH	AMPI	ACH	EFFCH	TECH
1983-1984	1.07	1.00	1.02	1.05	1.09	1.02	0.96	1.11	1.18	1.10	1.01	1.06	1.128	1.035	1.014	1.075
1984-1985	0.93	1.02	0.84	1.09	1.04	1.08	0.97	0.99	0.86	0.78	1.00	1.10	0.956	0.949	0.963	1.046
1985-1986	0.95	0.96	1.11	0.89	1.03	0.99	1.02	1.02	0.79	1.01	0.87	0.90	0.939	1.000	1.005	0.934
1986-1987	1.02	1.01	0.87	1.16	1.28	1.03	1.15	1.08	1.15	1.01	0.98	1.16	1.120	1.006	0.970	1.146
1987-1988	0.99	0.94	0.99	1.06	0.99	1.01	0.95	1.03	1.04	1.03	0.95	1.06	1.036	1.004	0.977	1.056
1988-1989	0.98	0.96	1.02	1.00	0.96	0.94	1.03	0.99	1.07	1.04	1.03	1.00	1.033	1.015	1.018	1.000
1989-1990	1.14	1.02	1.15	0.97	1.30	1.21	1.10	0.98	1.10	1.07	1.06	0.97	1.069	1.045	1.050	0.974
1990-1991	0.95	1.02	0.97	0.96	0.98	0.99	1.01	0.98	1.14	1.07	1.11	0.96	1.024	1.029	1.032	0.964
1991-1992	1.03	1.02	0.94	1.07	1.05	1.02	0.99	1.04	1.17	1.09	1.01	1.06	1.095	1.063	0.980	1.050
1992-1993	0.99	0.97	0.93	1.10	0.95	0.94	0.99	1.02	1.16	1.06	1.00	1.09	1.075	1.035	0.974	1.067
1993-1994	1.02	0.93	1.03	1.06	1.01	1.08	0.89	1.05	1.07	1.01	1.00	1.06	1.045	0.991	0.995	1.059
1994-1995	1.04	1.02	1.03	0.99	1.29	1.06	1.13	1.08	1.07	1.06	1.00	1.01	1.088	1.044	1.011	1.031
1995-1996	1.12	1.10	0.96	1.06	1.04	1.04	0.99	1.01	0.93	0.88	1.00	1.06	0.998	0.983	0.980	1.035
1996-1997	0.99	0.97	1.16	0.88	1.01	0.99	1.05	0.97	0.86	0.98	1.00	0.88	0.995	1.030	1.055	0.917
1997-1998	0.94	0.97	0.90	1.08	1.00	1.07	0.90	1.04	1.07	1.09	0.91	1.08	1.071	1.052	0.948	1.074
1998-1999	0.85	0.92	0.90	1.03	1.19	1.10	1.03	1.05	1.16	1.06	1.06	1.03	1.038	1.008	0.995	1.034
1999-2000	1.01	0.99	1.04	0.98	1.11	1.06	1.03	1.02	0.89	0.88	1.03	0.98	0.981	0.972	1.021	0.988
2000-2001	1.12	1.02	1.11	0.99	1.26	1.21	1.07	0.97	0.98	0.98	0.99	1.01	1.026	1.011	1.016	1.000
2001-2002	0.91	0.93	1.01	0.97	0.99	0.99	1.03	0.97	1.11	1.09	1.01	1.01	1.016	1.031	0.995	0.990
2002-2003	0.99	1.02	0.95	1.02	0.96	1.03	0.91	1.02	1.02	1.00	1.00	1.02	1.007	0.999	0.989	1.020
2003-2004	0.94	0.94	0.93	1.08	1.12	1.01	1.03	1.08	1.07	1.00	1.11	0.96	1.058	1.003	1.022	1.033
2004-2005	1.06	0.97	1.03	1.06	0.94	0.94	0.99	1.01	0.97	0.91	1.01	1.06	1.022	0.986	1.000	1.037
2005-2006	0.88	0.99	0.90	0.99	1.06	0.99	1.05	1.02	1.04	1.06	1.00	0.98	1.036	1.033	0.992	1.011
2006-2007	1.03	1.01	0.96	1.06	0.93	0.99	0.90	1.04	1.03	1.03	0.99	1.01	1.044	1.032	0.999	1.012
2007-2008	1.02	1.00	1.16	0.88	1.06	0.98	1.03	1.05	0.93	0.91	1.01	1.01	1.024	0.997	1.023	1.004
Geometric Mean	0.996	0.987	0.993	1.017	1.060	1.029	1.006	1.024	1.028	1.005	1.004	1.019	1.036	1.014	1.001	1.021

Table 3.3
Efficiency Effect of All Mergers Results

Estimation Period: 1983-2008

		Intercept		Linear Time Trend		Non-linear Time Trend		R square
All Mergers	Efficiency Score (CRS)	0.69784	***	0.01937	***	-0.09787		0.1338
		(0.02611)		(0.00550)		(0.06059)		
	Scale efficiency	0.93356	***	0.0004275		-0.02425		0.0123
		(0.01370)		(0.00288)		(0.03170)		
Mergers in the1980s	Efficiency Score (CRS)	0.60479	***	0.01767	**	-0.09817		0.1076
		(0.03274)		(0.00768)		(0.07400)		
	Scale efficiency	0.94682	***	-0.00934	**	-0.022		0.2787
		(0.01962)		(0.00460)		(0.04434)		
Mergers in the1990s	Efficiency Score (CRS)	0.72999	***	0.0157	***	-0.02488		0.2791
		(0.02680)		(0.00547)		(0.06388)		
	Scale efficiency	0.92176	***	0.00153		0.00453	*	0.0173
		(0.01721)		(0.00351)		(0.04103)		

Note: The standard errors are in parentheses

*,**, and *** indicate statistical significance at the 90, 95, 99 percent levels, respectively.

Table 3.4
Survival Firms Efficiency Effect of Mergers

Firm	Merger Year	Regressand	Intercept		Linear Time Trend		Non-linear Time Trend		R square
BN	1996	Efficiency Score (CRS)	0.85685	***	0.01258	***	0.01725		0.9243
			(0.01629)		(0.00194)		(0.03446)		
		Scale efficiency	1.00089	***	0.0005647		-0.00914		0.1103
			(0.00281)		(0.00033447)		(0.00594)		
CN	1999	Efficiency Score (CRS)	0.7354	***	0.02199	***	-0.00864		0.8771
			(0.03317)		(0.00340)		(0.06441)		
		Scale efficiency	0.99701	***	0.00010479		-0.00103		0.0073
			(0.00128)		(0.00015132)		(0.00532)		
CSX	1999	Efficiency Score (CRS)	0.61417	***	0.00657	***	0.07772	***	0.9528
			(0.00941)		(0.00096458)		(0.01831)		
		Scale efficiency	0.7571	***	-0.01211	***	0.22343	***	0.7001
			(0.01649)		(0.00169)		(0.03206)		
NS	1999	Efficiency Score (CRS)	0.57466	***	0.00294	*	0.05855	*	0.6926
			(0.01590)		(0.00163)		(0.03092)		
		Scale efficiency	0.81815	***	-0.00567	**	0.07233		0.2075
			(0.02423)		(0.00248)		(0.04710)		
SOO	1985	Efficiency Score (CRS)	0.49358	***	0.01184	***	0.18237	**	0.7787
			(0.04954)		(0.00264)		(0.07703)		
		Scale efficiency	0.8939	***	0.00546	**	-0.09438		0.2134
			(0.04156)		(0.00221)		(0.06462)		
UP	1997	Efficiency Score (CRS)	0.77175	***	0.01084	***	-0.03895		0.7628
			(0.02111)		(0.00240)		(0.04317)		
		Scale efficiency	0.9603	***	-0.00185		0.00927		0.1425
			(0.01454)		(0.00165)		(0.02972)		
KCS		Efficiency Score (CRS)	0.60485	***	0.00398	*	0.34728	***	0.2687
			(0.03203)		(0.00196)		(0.12194)		
		Scale efficiency	0.61394	***	0.00622	***	0.3139	***	0.6256
			(0.01722)		(0.00105)		(0.06555)		

Note: The standard errors are in parentheses.
*, **, and *** indicate statistical significance at the 90, 95, 99 percent levels, respectively.

Chapter 4

General Conclusion

This dissertation investigates the effect of endogenous and exogenous events on firm behavior and performance. These are fundamental questions in economics. The contribution of this study is threefold. First, it provides estimates of the impact of mergers on railroad efficiency, which has important antitrust implications. Second, it provides new estimates of the effect of negative events on the market value of Johnson & Johnson, Bridgestone, and Toyota, which is important to our understanding of how markets punish corporate errors. Third, it develops better ways of estimating these effects.

Chapter 2 uses the event study approach to determine how product recalls due to exogenous and endogenous shocks affect the value of the firm. Three recalls from Johnson & Johnson, Bridgestone, and Toyota have been studied in this chapter. Johnson & Johnson recalled Tylenol capsules in 1982 after the unexpected exogenous shock. Seven people died by taking cyanide-laced Extra-Strength Tylenol capsules. Bridgestone recalled 6.5 million Firestone tires in 2000 after an accumulative endogenous shock. More than a hundred people died in accidents involving defective tires. Toyota voluntary recalled approximately 2.3 million vehicles on eight specific Toyota models in 2010 to correct the exogenous shock, sticking accelerator pedals. The traditional event study method assumes that markets are efficient, a questionable assumption in the short run. Thus, the current stock value of a firm may not reflect its true market value. To address this potential problem, frontier based methods are used, including data envelopment analysis, corrected ordinary least squares, and stochastic frontier regression analysis. Stochastic frontier methods are shown to be more appropriate when market behavior is not fully rational. The evidence shows that endogenous events due to firm errors are more detrimental to firm value than are exogenous negative events that are beyond the control of the firm. That is, the market is more forgiving of negative shocks that the company cannot control.

Chapter 3 studies the effects of merger activity on the efficiency and productivity growth of U.S. Class I railroads from 1983 to 2008. This is accomplished by using an attribute-incorporated Malmquist productivity index that is derived using data envelopment analysis. The results show that firm productivity has grown during the sample period and that changes in technology account for approximately two-thirds of the productivity growth. Mergers did not significantly contribute to technological change or improve scale efficiency. The results are similar to previous studies that have used parametric regression models. The slight differences between previous results and the results here are most likely due to the different assumptions of the production technology and different methods of measuring efficiency.

The application of these techniques to product recalls and railroad merger models demonstrates how they can provide superior estimates over traditional estimation techniques. It is hoped that these applications will motivate the use of these techniques in other settings.