SURVIVING SURPRISE: HOW FIRMS WERE AFFECTED BY – AND RESPONDED TO – UNEXPECTED, DISRUPTIVE, DISCONTINUOUS CHANGE IN THE MARKETING ENVIRONMENT

EXAMINING THE IMPACT OF SEPTEMBER 11, 2001
ON THE MOTOR CARRIER INDUSTRY

A Dissertation
Submitted to
the Temple University Graduate Board

---

in Partial Fulfillment
of the Requirements for the Degree
DOCTOR OF PHILOSOPHY

---

by
Craig A. Atwater
August, 2010

Examining Committee Members:

Richard Lancioni, Ph.D. (Chair), Marketing and Supply Chain Management
James Hunt, Ph.D., Marketing and Supply Chain Management
Ram Gopalan, Ph.D., Marketing and Supply Chain Management
Gerald Zeitz, Ph.D. (External Member), Human Resources Management

©
by
Craig A. Atwater
2010
All Rights Reserved

ABSTRACT

Changes to the marketing environment occur in numerous ways and with a wide range of characteristics. This research examines the effects of – and responses to – surprise, which is defined as disruptive, discontinuous events that result in unexpected changes to the environment. Some authors have suggested that organizations have tended to overestimate their ability both to predict and to control calamitous environmental events, resulting in relatively little attention being paid to environmental surprise in the marketing literature (Cunha et al, 2006). Indeed, much of the research in this domain has focused on improving organizations' ability to recognize – or even anticipate – such events, thus rendering them *not* surprises (Ansoff, 1975; Lampel & Shapira, 2001). But, as Cunha and associates respond, "… researchers *should* investigate how organizations might deal with unanticipated events," not just how to avoid them (2006, p.320, emphasis added). This research addresses a portion of the identified gap.

Just as there is a range of possible changes and change types, organizations' responses also vary. Depending on the nature of the environmental event(s), the appropriate form of strategic response can be quite different. Therefore, how organizations respond to environmental change is a critical element of their marketing strategies. Remaining properly aligned with their external surroundings has repeatedly been shown to produce significant benefits in terms of marketing performance and financial success (Venkatraman & Prescott, 1990). Barney and associates state that "... to the extent some firms in a rapidly changing environment are more nimble, more able to change quickly, and more alert to changes in their competitive environment, they

will be able to adapt to changing market conditions more rapidly than competitors, and thus gain competitive advantage" (2001, p.631).

Study 1

What happens when firms are confronted by a *strategic surprise* – defined as "sudden, urgent, unfamiliar change" (Ansoff 1975, p. 22) – such as the terrorist attacks that occurred on September 11, 2001? Numerous studies have examined how *strategic change,* in the aftermath of a significant environmental event, contributes to organizational survival and success. But, is strategic change the appropriate response to unexpected and disruptive environmental change? And is there a preferred trajectory for change, such that certain strategies are better suited than others to the post-surprise environment?

This exploratory research examines whether or not strategic change is an appropriate response to strategic surprise by considering the actions of motor carriers in the aftermath of 9/11. The data evidences significant disruption to the trucking industry following the event; for example, among the sample, mean operating ratios declined by more than 50%. But while nearly 40% of the carriers studied changed their strategies in the post-9/11 environment, this did not guarantee better performance. In fact, all carriers fared worse following the attacks, but those carriers that changed strategies actually performed significantly worse than those that persisted with their pre-9/11 strategies.

Study 2

In Study 2, a scoring model of strategic resilience is developed that enables motor carriers to assess their likelihood of withstanding disruptive environmental change. Supply chain resilience is an emergent research stream that considers the ability of a supply chain network to anticipate, prepare for, and adapt to significant environmental risks in the form of disruptions and unanticipated events (Ponomarov & Holcomb, 2009). This study examines the ability of motor carriers – a critical and essential component of most supply chains – to survive such events.

Using variables identified in Study 1, together with those from numerous previous studies in the prediction-model research domain, the second study considers which factors are significant and contribute the most utility to an overall resilience score. In addition, this study approaches the model-building process using a proven methodology (conjoint analysis) which previously has not been applied to this type of research, while examining an especially broad range of possible alternatives. The resultant model provides firms in the motor-carrier industry with a "resilience score" that suggests their likelihood of survival in the post-event marketing environment.

The resilience model enables motor carriers to self-assess their ability to withstand disruptive events in the marketing environment, including strategic surprises such as 9/11. Motor carriers with weaker scores (i.e., less than 600, on a scale from 300 to 900) are more likely to exit – though clearly are not guaranteed to do so. This model correctly identified nearly 70% of carriers that ultimately exited from the industry.

In addition, the model provided evidence of where motor carriers should focus their attention in a post-disruption marketing environment. Six factors emerged as most significant to carriers' resilience as evidenced by the model. These elements are recommended as the metrics to which carriers themselves – and dependent supply chain network members – pay most attention following an environmental disruption.

ACKNOWLEDGEMENTS

The completion of my dissertation and doctoral degree would not have been possible without the support and assistance of several people.

First, I would like to thank my dissertation committee chair, Dr. Richard Lancioni. Over the past few years, as I have worked my way through the Ph.D. program and dissertation process, he has provided research guidance together with friendly encouragement. Dr. Lancioni freely offered valuable and practical advice that will continue to guide me throughout my academic career, as both a researcher and an instructor. And so I gratefully acknowledge his many contributions to my success.

Second, I want to thank Dr. James Hunt, another committee member and career guide. Dr. Hunt has continuously offered insights and points of view regarding my research in terms of what should be considered in the early models, as well as how to interpret my results, and even where this research may take us in the future. He, too, has always provided friendly encouragement to help keep me focused and on course.

Third, I owe special thanks to Dr. Ram Gopalan, a committee member who was drafted into his role, but who provided me with extensive feedback throughout the research and dissertation development process. It was Ram who ensured that the quantitative and analytical components of my research were performed properly and with sufficient rigor to (hopefully) enable this work to be published in top-quality, peer-reviewed journals. Ram pushed me throughout this process, but with a level of support and friendship that always rewarded my efforts. For that, Ram has my lasting gratitude.

I also want to thank the external member of my committee, Dr. Gerald Zeitz, who took time away from his own research and teaching to provide feedback on this pair of studies. Dr. Zeitz not only assisted during the review and completion of my dissertation, he also provided a notable part of the foundation for these studies by teaching two key research seminars during my doctoral program.
I appreciate his contributions to both facets of my development as a researcher.

Aside from my colleagues, there are many others who have been supportive throughout my Ph.D. education and the dissertation process; it would require several additional pages to list all their names and contributions. I would like to thank my entire family for their continuous support through this lengthy – and occasionally frustrating – endeavor. Finally, *but most importantly*, I want to offer a special thank you to my best friend and wife, Dotti Atwater, who has always been a source of love, understanding, and encouragement. Without a doubt, I would never have been able to complete this journey without her being by my side all along the way.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Change happens; it is both inevitable and unrelenting.

That the marketing environment will not remain the same is certain, but how soon, how much, and how often environmental change will occur is generally not known.

Changes to the marketing environment occur in numerous ways and with a wide range of characteristics. A simple taxonomy of environmental changes could include the following four basic dimensions:

- Intensity – Changes range from mild or minimal, to severe or disruptive.
- Frequency – Changes range from common or frequent, to unique or discontinuous
- Expectation – Changes range from planned or anticipated, to sudden or unexpected
- Scope – Changes range from narrow or limited, to broad or extensive

This research examines the effects of – and responses to – one form of environmental change: Surprise. Surprise refers to disruptive, discontinuous events that result in unexpected changes to the marketing environment. Some authors have suggested that organizations have tended to overestimate both their level of control and their ability to predict calamitous environmental events, resulting in relatively little attention being paid to environmental surprise in the marketing literature (Cunha et al, 2006). To be sure, much of the research in this domain has focused on improving organizations' ability to recognize – or even anticipate – such events, thus rendering them *not* surprises (Ansoff, 1975; Lampel & Shapira, 2001). But, as Cunha and associates respond, "… researchers should investigate how organizations might *deal with* unanticipated events," not just how to avoid them (2006, p.320; emphasis mine). This research therefore addresses a portion of this identified gap.

Just as there is a range of possible changes and change types, so too do organizations' responses vary. Depending on the nature of the environmental event(s), the appropriate form of strategic response can be quite different. Small adjustments can keep an organization correctly aligned and on course following mild and recurring changes; overcorrecting or complete transformations are generally unnecessary and often not well tolerated. Conversely, in the wake of wrenching, discontinuous changes to the environment, entirely different approaches may be essential, as small, subtle corrections may not be sufficient to deal with the new "reality."

Therefore, how organizations respond to environmental change is a critical element of their marketing strategies. Remaining properly aligned with their external surroundings has repeatedly been shown to produce significant benefits in terms of marketing performance and financial success (Venkatraman & Prescott, 1990). Barney and associates state that "... to the extent some firms in a rapidly changing environment are more nimble, more able to change quickly, and more alert to changes in their competitive environment, they will be able to adapt to changing market conditions more rapidly than competitors, and thus gain competitive advantage" (2001, p.631).

This research considers these questions by performing two related studies in the U.S. motor carriers' domain. In Study 1, how firms responded to an unexpected, disruptive environmental change – also known as a “strategic surprise” – is examined in detail, as well as contrasted with another prior event that was not a surprise. The study examines not only whether organizations made strategic changes in the wake of a surprise, and if such changes were warranted (and hence improved performance), but also considers the trajectory of these changes (i.e., what type of strategy did these firms begin with, and where did they end up). In doing so, Study 1 also considers the underlying organizational characteristics that may – or may not – lead to such appropriate changes in marketing strategies.

In Study 2, a scoring model of strategic resilience is developed that enables motor carriers to assess their likelihood of withstanding environmental change. Supply chain resilience is an emergent research stream that considers the ability of a supply chain network to anticipate, prepare for, and adapt to significant environmental risks in the form of disruptions and unanticipated events (Ponomarov & Holcomb, 2009). Therefore, the second study examines the ability of motor carriers – a critical and essential element of many supply chains – to survive such events.

Using variables identified in Study 1, together with those from numerous previous studies in the prediction-model research domain, Study 2 considers which variables are most significant and contribute the most utility to an overall resilience score. In addition, this study approaches the model-building process using a unique methodology while examining an especially broad range of possible alternatives. The resultant model provides firms in the motor-carrier industry with a “resilience score” that indicates their likelihood of survival in the post-event marketing environment.

Environmental Change

Ever since marketing's general acceptance of the open-system model of the firm (see for example Reidenbach & Oliva, 1981), the external environment has been viewed as a key element in framing a company's strategy. A firm's environment includes everything outside the organization that affects its strategy and operational effectiveness.

Environments are not always stable, however, and environmental change and its resulting impact are critical elements of strategic change theory. As noted earlier, environmental change runs the gamut, from small, frequent, and somewhat consistent changes – often referred to as environmental turbulence or uncertainty – to large, singular, discontinuous events termed jolts, crises, or surprises.

Following Meyer et al (1990), the environmental-change domain is segmented according to first- versus second-order change. First order or continuous change occurs within a stable system that remains relatively unchanged (Meyer et al, 1990). An organization continually adjusts to these minor changes without undertaking any major or strategic change. In fact, as the authors note, maintaining a system's stability often requires frequent though minor changes (e.g., think of the relatively small steering adjustments needed to keep a car driving in a straight line).

Second-order or discontinuous change has significant impacts and may actually destabilize the entire system (Meyer et al, 1990). Examples of second-order change include socio-political upheavals in Europe in 1989 (Meyer et al, 1990); deregulation and policy changes among railroads, airlines, and motor carriers (Smith & Grimm, 1987; Corsi & Stowers, 1991; Audia et al, 2000); and "frame-braking" technological change, such as in the minicomputer industry (Tushman, et al, 1989). Second-order change is more radical and transforming, often changing the "basic structure, culture, defining values, and overall form" (Esterhuyse, 2003, p. 2).

Within the environmental change domain, first-order change has received considerably more empirical attention (Ginsberg et al, 1988). Second-order change, especially that affecting an entire industry, has been much less thoroughly explored.

Within discontinuous change, another dimension of environmental change has been relatively unstudied: Suddenness or rate of change. Most research examining second-order change has looked at events which, while discontinuous and disruptive, did not occur without warning. There may be a set date on which the change will occur (e.g., deregulation or significant policy changes), or there is general awareness that such change is taking place (e.g., social, technological, or economic change). In either instance, while it may be unclear prior to the actual change how organizations should respond and what the right strategy and direction may be, there is time to consider options. Unanticipated and unprecedented change, on the other hand, is the strategic equivalent of the "sucker punch;" it comes without warning and likely has firm-altering, if not industry-altering, consequences. Fortunately, these types of changes are relatively rare, but also less studied.

These dimensions are used to compile the typology in Figure 1 that classifies the types of discontinuous change and the events that are exemplars. The figure's top-left quadrant, firm-level anticipated change, includes a variety of infrequent events that have been widely studied., including market entry and exit, merger and acquisition, CEO turnover, and bankruptcy.

	Anticipated / Planned	Unexpected / Sudden
Firm-Level	Corporate Change CEO change Merger & Acquisition Structural reorganization Market entry & exit Bankruptcy	Corporate Crisis Three Mile Island (1979) (Bowman & Kunreuther, 1988) Union Carbide, Bhopal (1984) (Bowman & Kunreuther, 1988) Exxon Valdez (1989) (Lampel & Shapira, 2001)
Industry-Level	Industry Change Regulatory change Economic change Technological change	Strategic Surprise Pearl Harbor (1941) OPEC – U.S. oil crisis (1973) Sept. 11 terrorist attacks (2001)

Figure 1. Typology of Discontinuous Change.

The top-right corner focuses on firm-level events that happen suddenly and without warning. These include events such as the Union-Carbide Bhopal disaster, the Exxon Valdez oil spill, and Three Mile Island. In each case, the firm's ability (or lack thereof) to respond to these unexpected, disruptive changes not only became cautionary tales for other firms, the effects reverberated throughout the industry and resulted in policy and regulatory changes.

In the lower-left corner are the changes that have industry-wide impact, but offer either a planned date of implementation (e.g., deregulation) or the buildup to the change was more gradual. While the change itself is significant and disruptive, it did not happen overnight, so there was time for an organization to evaluate courses of action and develop a plan.

The figure's final quadrant – the lower right – concerns changes that affected entire industries or markets, and that happened suddenly, without warning. These types of events are broad in scope, unexpected, and without precedent (Ansoff, 1975). As suggested earlier, the U.S. economy has experienced relatively few of these events.

To date there have been some studies of the activities surrounding the corporate crises. These have largely focused on managing the event's communications and repercussions, and have not evaluated the more general aspects. The only study that considers something akin to surprise was the Meyer et al (1982, 2005) examination of California hospitals and their response to an unexpected doctors' strike resulting from a major change in policy. Yet even while referring to this environmental "jolt" as sudden and unprecedented, Meyer (1984) discusses how the hospitals in his study responded to forewarning.

Little is known about the industry-wide effects of sudden, discontinuous, unprecedented changes that happen with no warning. Indeed – and fortunately so – the number of such events remains quite small. The specific nature of what the political and social science literature refers to as "strategic surprise" – because there is no warning or anticipation of such events until they occur – is discussed in the next section.

Strategic Surprise

Nearly nine years ago, the terrorist attacks of September 11, 2001, had a devastating and permanent impact on the U.S., both politically and economically. In addition to the direct effects and the immediate changes this event forced in terms of building access and public transportation, 9/11 also altered, fundamentally, how Americans look at safety, security, and the possibility of future terrorist activity. Most notably, these attacks caught everyone by surprise – they were sudden, unexpected, and unprecedented.

The term "strategic surprise" has been used to describe military events "which caught the victims offguard and completely flatfooted" (Byman, 2005, p. 146). The Japanese attacks on Pearl Harbor (1941) and the Egyptian attack on Israel at the start of the Yom Kippur War (1973) have both been called strategic surprises. The general focus of research in understanding the impact of strategic surprise in the social sciences – and especially now in political science – has been on how government, the military, and even intelligence agencies were caught so totally unawares. (Note, however, that significant research streams – well beyond the scope of this research – suggest that 9/11, like Pearl Harbor and other strategic surprises, afforded numerous warnings and "weak signals" that were unheeded (see for example Wirtz, 2006; or Byman, 2005).

In the marketing-strategy domain, Ansoff (1975) defined strategic surprise more than 30 years ago when referring to events that occur when a firm confronts an unfamiliar, singular event that is potentially survival-threatening with respect to the organization. In the corporate environment, such surprises have included Three Mile Island in 1979; the Bhopal, India, disaster in 1984; and the Exxon Valdez oil spill in Alaska in 1989 (Bowman & Kunreuther, 1988; Lampel & Shapira, 2001). While these events had significant and dire consequences for the firms at their epicenters, and certainly altered how they were viewed by their publics and regulated by authorities, the effects were mostly limited to these firms and their immediate industries. These events have therefore been characterized as corporate crises (see Figure 1. Typology of Discontinuous Change, that precedes this section).

External surprises, on the other hand, result from forces outside the firm and its industry, and have more far-reaching impacts. For example, in 1973 the Oil Producing Export Countries (OPEC) not only affected the petroleum industry by significantly and unexpectedly doubling the cost and reducing the flow of crude oil, they disrupted the entire U.S. economy (Lampel & Shapira, 2001). Similarly, recent actual surprises – such as Hurricane Katrina (2005) – or even potential events – the threat of SARS or the Avian Flu – can be highly disruptive and even industry-altering. OPEC's sudden increase in the price of oil, to continue with this example, has been identified as the first volley in the competitive battle that led to the U.S. decline in the automobile industry (Lampel & Shapira, 2001). The fact that GM and others had never seriously considered such a scenario left them exposed and provided Asian manufacturers with their first real opportunity to change the overall market's dynamic.

In the context of politics, strategic surprises often result in substantial changes in attitudes and policies in order to reduce the likelihood of such events recurring in the future (Wirtz, 2002). But in the marketing strategy domain, strategic surprise can result in changes to regulatory policy and increased vigilance to reduce the possibility of – and vulnerability to – such situations should they occur again (Lampel & Shapira, 2001). As Winter (2004) notes, however, the major shortcoming of such focus may be that examining past surprises does not prepare firms – or industries, for that matter – to confront future events … because they are, *by definition*, unprecedented and unexpected. Furthermore, a strategic surprise can actually represent more than mere threat – it might, in some instances, actually pose a market opportunity (Winter, 2004). Thus, how firms diagnose and learn the potential positive and negative impacts of a strategic surprise is a key challenge.

CHAPTER 2

TO CHANGE OR NOT TO CHANGE: EXAMINING THE LIKELIHOOD, TRAJECTORY, AND SPEED OF STRATEGIC CHANGE IN RESPONSE TO STRATEGIC SURPRISE [1]

Strategic change in response to significant environmental change has repeatedly been shown to have a positive impact, both on the likelihood of firm survival and on subsequent firm performance. Numerous studies and at least three review articles have examined how strategic change contributes to long-term success, making this among the most researched questions in the marketing-strategy domain.

But when confronted by *strategic surprise* – defined as "… sudden, urgent, unfamiliar change …" (Ansoff, 1975, p. 22) – such as the terrorist attacks on September 11, 2001 – a significant question arises: Is strategic change the appropriate response? Second, what is the best trajectory for such change; that is, are some strategies better suited than others to a post-surprise environment? Further, given the unexpectedness and suddenness of such an event, is a *faste*r response necessary? Or, since a strategic surprise is by definition without precedent, and therefore firms have neither predetermined guidelines nor familiar patterns to follow, is a patient, reflective, wait-and-

----

1 Note: The phrase "*To be or not to be*" comes from Shakespeare's Hamlet, Prince of Denmark, Act III, scene I. The soliloquy begins as follows:

"To be or not to be, that is the question;
Whether 'tis nobler in the mind to suffer
The slings and arrows of outrageous fortune,
Or to take arms against a sea of troubles,
And by opposing, end them. …"

see reaction preferred? Finally, whether or not a strategic change occurs, how is success measured and assessed: What determines the proper fit?

Fortunately, strategic surprises remain exceedingly rare events; but each has had profound environmental effects and afforded virtually no advance warning or lead time for planning and preparation. Such unprecedented and impactful events as the attack on Pearl Harbor in 1941, OPEC's doubling of oil prices in 1973, and even Hurricane Katrina in 2005, disrupted economies and undoubtedly affected numerous industries and organizations. In the future, the possibility of equally unexpected, major events, such as a natural disaster (e.g., massive earthquake or meteorite impact), an epidemic (e.g., avian flu or anthrax outbreak), a severe economic jolt (e.g., the Middle East again doubles the price per barrel of oil shipped to the U.S.), or even another terrorist attack, could dramatically impact parts of the U.S. economy. Though such events, in themselves, are almost unthinkable – and their outcomes are virtually unpredictable – researchers should begin to ponder what strategy (or strategies) would best enable firms impacted by these abrupt and disruptive surprises to survive, and perhaps even flourish, under such circumstances.

Although there is notably little research regarding strategic surprise, the literature examining strategic change is fairly extensive; for the past 30 years it has been a major focus of study. In their review study of strategic change, Rajagopalan & Spreitzer (1996) identified two principal research streams: The first considers the ecological (or inertia) model and the second follows the adaptation (or strategic management) model. The ecological model suggests that choice of an industry is the most important decision a firm makes; resultant success or failure is more about what the organization *is* (its size and age, for example) than what it *does*. The adaptation model, on the other hand, suggests that strategic choice and strategic change are what matter most; the right decisions by managers can result in greater likelihood of firm survival and better firm performance. While both models have seen dozens of empirical studies (and the debate remains heated), this research follows the strategic adaptation stream.

Within the widely studied domain of strategic change, strategic surprise is a relatively new and unexplored concept. While Ansoff (1975) seems to have coined the term and provided its DNA, the marketing-strategy domain has produced little examination – and no known empirical research to date. Two recent articles in the political science literature use the term in referring to the events of September 11, and so this research will examine the implications of strategic surprise in the context of strategic change for the first time.

This study, therefore, focuses on closing two identified gaps in the marketing strategy and strategic change research streams. One, understanding how the suddenness and the lack of precedent of a strategic surprise affect organizations and strategic changes. And two, given this impact, examining what and how underlying factors impact this relationship, and developing a prescriptive model.

The industry under the microscope for this research is U.S. motor carriers (also know as "trucking"), chosen for several important reasons. First, the motor carrier industry has a history of extensive study in the context of pre- and post-deregulation, so there is broad empirical research and a tested basis for comparison. The intent was to be able to compare how motor carriers responded following a surprising change to their marketing environment with how they dealt with another disruptive event that was not a surprise.

Second, the trucking industry was significantly affected by the events of 9/11; following the attacks, new regulatory and safety guidelines were imposed by the Federal government, and there were additional insurance costs and inspection requirements – so a before-and-after examination appears to be meaningful. And third, the industry is highly competitive – some authors have even suggested “perfectly” so – such that there are numerous competing firms, with no one dominant provider.

In addition, motor carriers were chosen versus studying another industry that was also significantly affected by 9/11 – air carriers – for two critical reasons. First, although airlines suffered a pronounced and dramatic impact, exacerbated by a weak economy at the time of the attacks, the federal government helped reduce the financial impact on air carriers by contributing almost $5 billion, and so altered market conditions. And second, airlines are a more concentrated industry, with significant barriers to entry (such as enormous capital requirements), so larger sample size and more strategic diversity may be meaningful factors. Motor carriers by contrast are a broad, competitive, and diverse industry – an ideal testbed in which to study the effects of these factors.

The research questions that emerge from this domain – and that this study will attempt to address – therefore include the following:

RQ1: How likely are organizations to change strategies following a strategic surprise? Which factors predispose firms to making such strategic changes, and which do not? Do size, age, pre-surprise performance, and focus affect the likelihood and possible success of such changes?

RQ2: How do, and *how should*, organizations respond to strategic surprise? Is there a better trajectory for making a strategic change, and is, indeed, a change even warranted under these circumstances?

RQ3: Should firms react quickly, changing their strategies to more closely align with their new environment, or is a "wait-and-see" approach preferable? Which strategies are best under the circumstances?

RQ4: How does strategic surprise compare with other disruptive events that lead to strategic change (e.g., deregulation)?

Literature Review

The question of how organizations respond to environmental changes has emerged as perhaps the key topic in marketing-strategy literature. As firms carefully monitor their environments, how do they – and *how should* they – respond to significant changes?

The focus of this research is on examining what is most frequently referred to as strategic change (although the terms strategic adaptability, strategic flexibility, and strategic realignment have sometimes been used). An organization is said to follow a strategy – what Mintzberg defined as "a deliberate conscious set of guidelines that determines decisions into the future" (1978, p. 935) – in order to match or align what the organization does with the environment in which it operates (Boeker, 1991; Porter, 1980). A fundamental tenet of strategic management is that an organization's strategy should adapt to changes that occur in its environment; failure to do so would result in poorer alignment, and the organization's performance would be expected to suffer (Smith & Grimm, 1987). Strategic change occurs when an organization changes its strategy in order to regain its alignment with the external environment (Rajagopalan & Spreitzer, 1996). Better alignment is expected to result in improved performance.

Looking back at the past three decades in the literature, more than 30 empirical studies which have examined strategic change in various forms have been identified. Of the studies identified, almost 40 percent (13) examined the effects of deregulation on an industry (e.g., railroads and motor carriers), seven looked at substantial changes in the legal and regulatory environment (e.g., in health care and financial services), four considered major economic turmoil (e.g., in Spain and the U.S. computer industry), and the remaining nine were affected by unspecified, but significant, environmental turbulence. In each of these studies, significant environmental changes were variously referred to as disruptive or radical changes, jolts, or even crises; in all cases, the environmental event or disturbance was clearly considered "out of the ordinary." (See Appendix A for a summary examination of all 33 studies identified as part of this research domain.)

Despite the significant scope of these changes, and the fact that both the authors and the study participants viewed the events being studied as extremely disruptive, none of these events came as a sudden or complete surprise. In the case of deregulation, for example, years had passed while lawmakers debated the merits and verbiage of a new law, time was allotted for planning and implementation in the industry, and the rules were often phased in over a period of time. Substantial regulatory and policy changes are often similar in their impact, but may involve shorter timeframes (for example the change in Medicare Payment policy that radically affected hospitals in the 1980s). Even economic crises, while both sweeping and relatively unexpected, do not happen overnight or without dire predictions and warnings by analysts and pundits. In every instance, there was time for firms in the impacted industry to examine alternatives and execute a planned, if not totally desired, approach. That is, firms could choose whether to stay with the current strategy or to change to a different and (hopefully) better-aligned strategy. In either instance, there is substantial business risk involved.

Strategic surprise, however, provides no warning, and has no precedents with which to frame decisions or analyze choices. Strategic surprise is by definition, a sudden, urgent, unfamiliar environmental change (Ansoff, 1975). Firms have no choice regarding their exposure to a surprise – they must deal with the event's impact, regardless. Nor do organizations have time to plan and consider their alternatives prior to being in the midst of the turmoil. Because of these different and unique circumstances, most of the previous research regarding strategic change may not be applicable when the environmental event is a strategic surprise.

Based on a detailed examination of the extant literature, Figure 2 provides a general framework for the strategic change process. This overarching model comprises five elements as described below:

1. Organizational Strategy – What is the organization's current strategy? The model assumes that the organization is a current market participant, not a new entrant or recent startup.

2. Environmental Change – What are the characteristics of the environmental change/event? These can range from continuous, relatively mild disturbances to discontinuous, severe events.

3. Management Interpretation – How does management analyze and interpret the environmental change? Various characteristics of the management team can affect this, including training, experience, and orientation (e.g., marketing, entrepreneurial). (Note that while shown as part of a comprehensive framework, this element is outside the scope of the current research.)

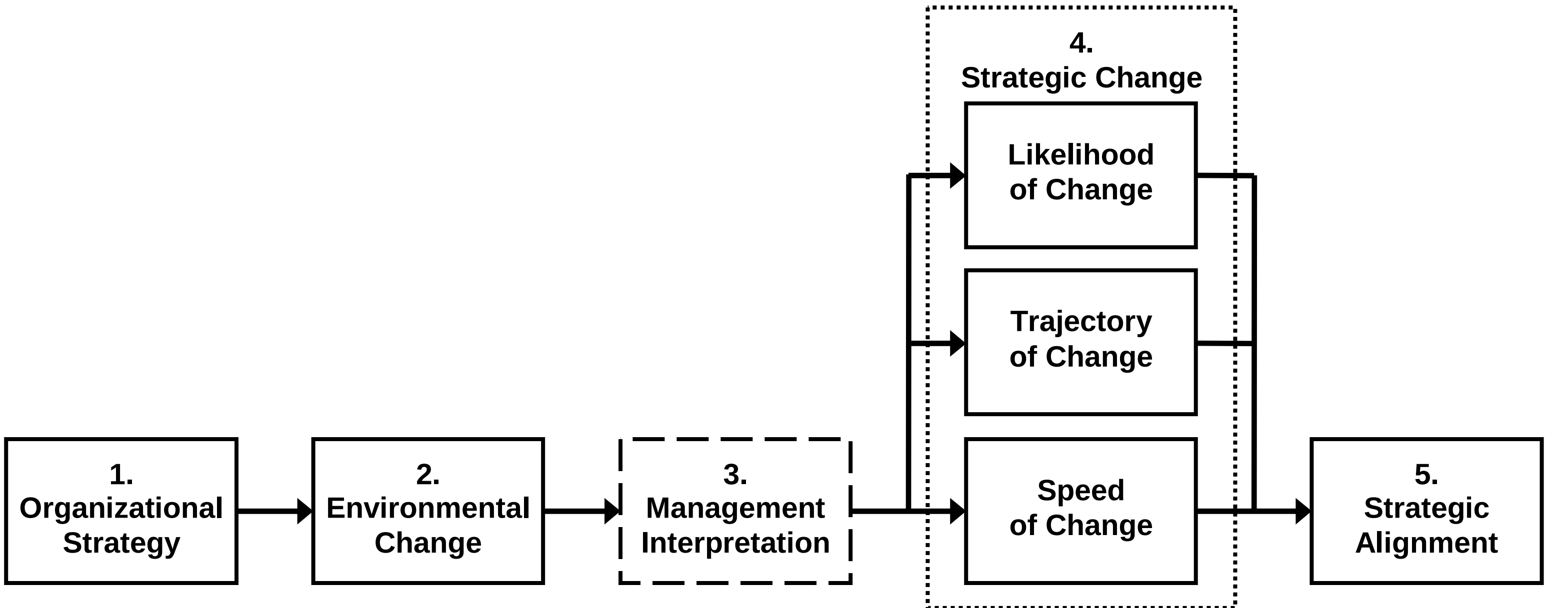


Figure 2. General Framework. Environmental Change, Strategic Change, and Strategic Alignment Process

4. Strategic Change – This component Includes three distinct parts:

    - Likelihood – How likely is the organization to change its strategy following an environmental change or event? Various organizational characteristics can affect the likelihood of change occurring.

    - Trajectory – What trajectory is the organization on, and which is better under the circumstances? Strategic change can move the organization in various directions and to several different forms, with some changes better than others.

    - Speed – How quickly will the organization change? Is immediate change warranted, or is a wait-and-see approach preferable?

5. Strategic Alignment – How well does the organization's strategy align with the altered environment following the change? Traditionally alignment is assessed in terms of performance outcomes, such as ROA, ROS, and industry-specific operating measures.

Strategy And Strategic Choice

Chandler's often-quoted definition states that strategy is "the determination of the basic long-term goals and objectives of an [organization], and the adoption of courses of action and allocation of resources necessary to carry out these goals" (1962, p. 13). His definition is lacking, however, with respect to the role of an organization's environment in shaping and limiting what firms can do. As Child (1997) later notes, the environment limits a firm's ability to act because it imposes certain conditions for the organizations to perform well. Thus, strategy and environment must be considered together; organizations both respond to, and are constrained by, the environments in which they operate. There is an ongoing balance between these two elements, such that changes in the environment can require – or at least, indicate – the need for responsive changes in organization.

There exist, however, two distinct schools regarding the nature of this strategy-environment interface: Organizational ecology and strategic choice. Organizational ecology provides a deterministic perspective (Carroll, 1984; Hannan & Freeman, 1977). It suggests that natural selection "allows only those firms with appropriate variance to [survive]" (Hrebinak & Joyce, 1985, p. 338). Actions and decisions by management have little impact, and so adaptation is merely reactive with minimal consideration for environmental signals.

Strategic choice, on the other hand, views adaptation as a process of managerial decision-making and design (Hrebinak & Joyce, 1985). Strategic choice is a process whereby organizations decide on courses of action based on their evaluations of their environments and the changes that take place within them. As Miles and Snow suggest, "The strategic choice approach argues that the effectiveness of organizational adaptation hinges on … perceptions of environmental conditions and the decisions [an organization] makes concerning how [to] cope with these conditions" (1978, p. 21). As the organization responds to changes in the environment, it embarks on new courses of action and reallocates resources in order to achieve its updated goals and objectives (Chandler, 1962).

Although debate over these two constructs continues – and there are strong arguments in both sides favor – this research is grounded in the latter approach. Strategic choice and with it, strategic change, are the bases for examining how organizations respond to strategic surprise.

Strategic Change

Extensive research has examined the antecedents, processes, and consequences of strategic change. This author's robust – though not exhaustive – examination has identified more than 30 empirical studies of strategic change that have appeared in major academic journals and been cited numerous times.

Strategic change refers to the proposition that an organizations may alter its existing strategy in response to a change that occurs within the organization or its environments. The notion of strategic change reflects the strategic choice/adaptation stream which, unlike the organizational ecology stream that suggests that an organization's capabilities are part of its DNA and that success (survival) or failure (bankruptcy) are the result of economic natural selection, that an organization can control its own destiny. The strategic change paradigm suggests that, in response to environmental change, an organization may need to change its strategy to reflect the new reality.

But change is not a given, nor does it guarantee better performance. Whether or not an organization chooses to change must be tempered by whether or not it *should* change – that is, change for change sake may not be preferable or even viable. There are many reasons that an organization should change its strategy, given a significant environmental jolt, but there are also circumstances where not changing may be more appropriate, such as when an organization is already following the preferred strategy for the environmental situation, or when a firm takes a wait-and-see approach until the dust has settled from the event, or even simply waiting for the environment to rebound and "return to normal." All four approaches are potentially valid and may prove successful over the long haul. A potentially lethal choice, however, is an unresponsive lack of action due to paralysis or inability to recognize environmental change.

Likelihood of Change

Likelihood of change is a measure of both the antecedents to change – such as organizational factors – and the organization's willingness and ability to change. As Kim and McIntosh suggest (1999), strategic change is expensive and a firm may choose not to undertake such change, fearing that it will incur costs that might outweigh the potential benefits.

Ginsberg (1988) notes there are numerous factors that influence, as well as constrain, strategic change. Firms that experience external forces – such as significant shifts in the environment – are more likely to change strategies than those firms that do not encounter differences; in other words, strategic change is not a random event – it occurs because of changes in the environment in which the firm operates. There are other factors, however, that can positively or negatively influence the potential for such change, such as firm size, firm age, and past performance (Ginsberg, 1988; Rajagopalan & Spreitzer, 1997).

This research examines four organizational factors that are believed to impact its likelihood to undertake a strategic change following a strategic surprise: Age, size, past performance, and strategic focus.

Age

As organizations age they tend to become more bureaucratic and develop greater inertia. As a result, older firms are more likely to be rigid and steadfast, and therefore less likely to change their strategies.

Hannan and Freeman state that "levels of reliability and accountability of organizational action should increase with age" (1984, p. 157). This increase over time results in the so-called "liability of newness" – that is, a younger firm is more vulnerable and less likely to survive, whereas an older organization's mortality rate declines exponentially as its age increases. But with this ability to survive comes more rigidity and inertia, and employees' stake in maintaining the organization "as is" and unchanged also tends to increase with its age (Hannan & Freeman, 1984).

Empirical results regarding age's effects on the likelihood of strategic change, however, have been somewhat mixed. Kelly and Amburgey (1991) and Amburgey et al (1993) found that older firms in the airline and newspaper industries (respectively) were less likely that younger firms in the same industries to change strategies following a significant environmental change. Similarly Feitler et al (1997) determined that age had a significant impact on strategic change: Older firms were much less like to change strategies than their younger counterparts. As the authors opine, older organizations have adopted a successful, balanced strategy, and maintained that strategy over time (Feitler et al, 1997). Older firms have weathered previous environmental changes; they have developed sustainability and an ability to learn and adapt to various environments and challenges (Feitler et al, 1997).

Conversely, Boeker (1989) found that older firms in the semiconductor industry were *more likely* to change than younger ones, and the magnitude of these changes was greater. The author suggests that older firms have experienced more environmental variation – but that this may be less meaningful when a significant environmental change occurs. In addition, the industry itself may be a factor as mature firms in a turbulent industry – like semiconductors – may have a competitive advantage if they are more willing and able to change.

A contingent outcome was proposed by Zajac and Kraatz (1993), who found support for age as a factor, depending on the type of change the colleges in their sample undertook. Both the sign of the effect and the significance varied as different forms of strategic change were attempted. More recently, Vicente-Lorente and Zúniga-Vicente (2006) found no significant support for age as a factor in the likelihood of strategic change among Spanish banks.

While previous strong support appears to be called into question by more recent studies, the type of environmental change may be a significant – and uncontrolled for – factor. Both Feitler (1997) and Amburgey (1991; 1993) and their associates examined before-and-after effects from discontinuous, disruptive environmental changes, though not strategic surprises; other studies reflected less substantial environmental changes. Therefore, it is hypothesized that:

H_1: Following a strategic surprise that disrupts the marketing environment, younger organizations are *more likely* to make a strategic change than older ones.

Size

Organizations' size may also impact their ability to change, acting in ways that are similar to how age affects the likelihood of strategic change. Larger firms are more complex structurally and tend to be more established in terms of their personnel roles. With greater complexity comes the increased possibility that information about the environment, moving through internal systems, may be misdirected, altered, or even blocked by managers who are protecting the status quo (Galbraith, 1977). Existing policies become formalized and entrenched, and forces for change may be stifled or ignored. Conversely, smaller organizations tend to be more flexible and responsive to their environments and changes. These firms have less formal structures and less inertia than their bigger counterparts, and are therefore much more able – and likely – to respond to environmental change (Hannan & Freeman, 1984).

As fundamental and intuitive as this concept appears, empirical research has not provided clearcut evidence. Kelly and Amburgey (1991), looking at U.S. air carriers, found only weak support for their prediction that the likelihood of strategic change decreased as firm size increased. Grimm et al (1993) determined that small motor carriers were significantly more likely to change strategies than larger carriers in a post-deregulation environment; yet Feitler et al (1997), looking at the very same domain, found no support for their similar hypothesis.

Haveman identified "an inverted U-shaped relationship between size and [strategic] change" (1993, p. 20). Very small organizations lacked the "slack resources" needed and the ability to change and/or enter new markets, whereas larger firms had these resources and abilities. At the same time, however, very large firms were much more bureaucratic and prone to inertia (Haveman, 1993). Thus, mid-size organizations were most likely to change strategies.

More recently, D'Aunno et al (2000) found no support for increasing relative size of rural hospitals having an impact on strategic change over time. Similarly, Vicente-Lorente and Zúniga-Vicente (2007) found mixed effects of Spanish bank size on strategic change, with a significant negative relationship: The larger the bank, the more likely it was to change strategy before an environmental change, but no significant relationship existed after such an event. The authors note that these results appeared time- and/or context-dependent, so that the type of event and its timing (sudden versus gradual) might be impactful.

Once again previous support seems to be called into question by more recent studies. Here, too, the type of environmental change may be both significant and uncontrolled for in the research. Therefore, it is hypothesized that:

H_2: Following a strategic surprise that disrupts the marketing environment, smaller organizations are *more likely* to make a strategic change than larger ones.

Past performance

Past performance is a key indicator of organizations' success that management uses to determine how they are doing and whether changes are necessary. Poor performance is likely to motivate managers to make strategic changes in order to improve the situation, whereas good performance is more likely to encourage mangers to stand pat and maintain their current strategies (Feitler et al, 1997).

Child, in explaining the importance of past performance, suggests that “performance levels achieved by an organization constitute an input of information to its managers which is likely to stimulate them to make adjustments in policies or modes of operation” (1974, p. 176). Such adjustments can be either an attempt to correct previous poor performance, or an effort to maintain good performance outcomes.

Graham and Richards (1979) found that strategic change was more likely following a company’s poor performance. Likewise, Feitler et al (1997) determined that motor carriers’ operating ratios (a key measure of business performance) and return on assets (ROA) were very significant and influenced changes in the expected direction, evidencing that poorer performance – on either factor – increased the likelihood of strategic change. But Grimm et al (1993), while examining the same motor carrier domain as Feitler, found no effects of past performance toward increasing the likelihood of strategic change, and Boeker (1988) identified only limited support for his hypothesis that poorer past performance led to an greater likelihood of strategic change.

In a more recent study of both air and motor carriers, Audia et al (2000) found that better past performance, prior to a radical change, actually led to greater strategic persistence – i.e., *less* likelihood of change – and this in turn resulted in poorer performance after a change was made. And Parnell, while finding that “poor performing businesses … were more likely than high performers to change strategies,” noted that these changes did not result in better performance during the next two subsequent years (1998, p. 19). In fact those firms that did not change actually outperformed those that did in the short run.

Ginsberg (1988), in a review of strategic change literature, suggested that the impact of poor performance on change varied based on the research domain and circumstances: For example, one study found strategic change was likely only when the poor performance was very severe (Schendel & Patton, 1976), while another found an inverted U-shape: Very high and very low performers were far less likely to change strategies than those in the middle. Still other researchers in this review found that poor performance *alone* did not motivate change; but, when poor performance was accompanied by a significant external change (such as deregulation), strategic change occurred (Oster, 1982; Graham & Richards, 1979).

Thus, once again the results of prior research are equivocal, and it is therefore hypothesized that:

H_3: Following a strategic surprise that disrupts the marketing environment, poorer performing organizations are *more likely* to make a strategic change than better performing organizations.

Focus

Some strategies depend on significant commitments to – and investments in – specific assets. Haveman (1992) found that, in general, as the costs to change strategies increased, the less likely firms were to make such changes, while Grimm et al (1993) saw that in the motor-carrier domain, specifically, the less a firm's strategy depended on commitments to fixed assets, the more likely it was to change its strategy following deregulation. Nickerson and Silverman proposed that "in the face of a changing environment, a firm with significant investments in durable specialized assets … is likely to [change] more slowly and less completely … than a firm without such investments" (2003, p. 436). The authors found that motor carriers "that focus more heavily on LTL carriage undertake less changes than those that focus more on [truckload] carriage" (Nickerson & Silverman, 2003, p. 449).

In the motor carrier industry, less-than-truckload (LTL) carriers make substantial investments in specialized assets, such as facilities and equipment, as well as in hiring and training personnel. Thus, the more a motor carrier is focused on its LTL business, the more it has invested in this business and the less likely the firm is to change this basic strategy.

Thus, the results of this prior research are somewhat less equivocal; nevertheless, it is hypothesized that:

H_4: Following a strategic surprise that disrupts the marketing environment, less strategically focused organizations are *more likely* to make a strategic change than less focused organizations.

Trajectory of Change

The early literature regarding strategic change suggested that the appropriate response to an environmental change – particularly a disruptive event such as deregulation – was a change in strategy. But as noted in the preceding section discussing likelihood of change, research results have been mixed.

Strategic changes, when they do occur, may not yield meaningful benefits to firms in terms of improved performance. An expanding body of research has examined the form of the organizations' strategies (e.g., which "generic strategy" was selected). This research stream has suggested that some strategies are better suited to certain environments than others – thus, changing strategies that entails leaving forms that are actually better suited to the new environment would be inappropriate. Therefore, the trajectory of change – the starting point as well as the direction of change – is a second critical consideration in understanding strategic change.

Zajac and Shortell (1989) noted a significant difference in the strategies pursued by the hospitals in their sample before and after change in the Medicare payment environment transpired. Simply changing strategies did not assure a performance advantage versus those hospitals that remained unchanged. Further, "prior strategy [was] a major discriminator between the group of organizations that changed and the group that did not" (Zajac & Shortell, 1989, p. 427).

Likewise, Ginn (1990), Corsi et al (1991), and Haveman (1992) all saw significant differences in performance following environmental changes depending on the trajectories chosen by the organizations in their studies. In addition, Corsi et al (1991) and Haveman (1992) specifically noted that direct, short-run financial performance benefits accrued to organizations that chose to move in the right strategic directions.

Further, Smith and Grimm (1987) found support for their hypothesis that some types of change would be more beneficial than other types, following the environmental change caused by deregulation. The authors stated that railroads in their study that moved to more focused, yet flexible strategies had greater success than those that changed to unfocused or less-flexible forms (Smith & Grimm, 1987).

Looking further at motor carriers in a similarly deregulated environment, Kim and McIntosh (1999) determined that different strategic change trajectories resulted in very different outcomes. Motor carriers with focused strategies that remained focused after deregulation performed the best – as predicted – while focused carriers that moved to unfocused strategies performed the worst; unfocused strategies that changed or did not remained in the middle of the pack (Kim & McIntosh, 1999). Taking this a step further, Forte et al (2000) found confirmatory results among hospitals, stating that strategic change alone was not a sufficient predictor of improved results. In their study, organizations with a desirable form prior to the environmental change were not better off if they changed, while those hospitals that moved from less well-aligned strategies to better aligned forms did have positive performance improvements (Forte et al, 2000).

Although none of the environmental changes investigated were as sudden or as disruptive as strategic surprise, the research seems fairly consistent in pointing to the benefits of strategic change that follows an appropriate trajectory. Based on these outcomes, it is hypothesized that trajectory has a typology as depicted in Figure 3.

It is therefore hypothesized that:

H_{5A}: Following a strategic surprise, organizations that had appropriate strategies prior to the event, and do not change their strategies, will experience better performance than those that do change.

ACTION	**Change Required**	***NO* Change Required**
***NO* Strategic Change**	Type 1 Error	Best Strategic Performance
Strategic Change	Better Strategic Performance	Type 2 Error

Figure 3. Typology of Strategic Trajectory.

H_{5B}: Following a strategic surprise, organizations that *did not* have appropriate strategies prior to the event, but change their strategies to better-aligned forms, will perform better than those that remain unchanged.

H_{5C}: Following a strategic surprise, organizations that had appropriate strategies prior to the event, but change their strategies to less-aligned forms, will experience poorer performance than those that do not change.

H_{5D}: Following a strategic surprise, organizations that *did not* have appropriate strategies prior to the event, and do not change to better-aligned forms, will perform poorer than all other groups.

Speed of Change

While strategic change clearly matters, the speed with which the change occurs may also be important (Meyer, 2001; Eisenhardt, 1990). Speed has emerged as a key factor in studying business performance, and Meyer (2001) argued, for example that accelerated operations – including shorter times in product development and faster manufacturing – have resulted in improved performance across the board. Meyer also suggested, however, that the focus should now turn to strategy and that “the companies that can make decisions fast, change direction nimbly, and figure out when to enter and exit markets will enjoy an edge” (Meyer, 2001, p. 24).

So far, little empirical research has emerged regarding speed and strategic change. As Kim & McIntosh point out “…conventional wisdom prescribes that firms facing significant environmental change may improve their chances of survival and subsequent high performance by quickly changing their strategy…” (1996, p.35). Several researchers have suggested that the ability to quickly respond to changes puts these firms in advantageous competitive positions, but the results remain somewhat mixed.

Bourgeois & Eisenhardt (1988) found that in “high-velocity environments” with high uncertainty and rapid, discontinuous change, firms that made faster decisions tended to achieve higher levels of performance than their slower counterparts; and Eisenhardt, in a follow-up and more extensive study, found further support for this result (1989). While confirming their predecessors’ results, Judge & Miller (1991) suggested that higher performance *only* occurred in high-velocity environments like the minicomputer domains that Eisenhardt examined. More recently, Baum & Wally (2003), looking at a much broader sample of companies, found that faster decision-making predicted subsequent firm growth and profits. But Forbes (2005), uncovered a strong relationship between decision speed and firm closure, such that making quick decisions increased the likelihood of closing sooner.

In the only study to date that specifically looks at the speed of strategic change, Kim & McIntosh found that, in a new and highly uncertain environment – namely (and coincidentally) motor carriers after deregulation – "…faster change may not necessarily improve either the firm's performance or its chances of survival" (1996, p.40).

The mixed results of the limited research suggest that the speed of strategic change requires further exploration; hence it is hypothesized that:

H $_6$: Following a strategic surprise that disrupts their environment, firms that make strategic changes more quickly will outperform those that "wait and see."

Strategic Alignment

Simply stated, the concept of strategic alignment (also referred to as fit) suggests that the better an organization's strategy aligns with its external environment, the better its performance – in terms of business or market measures – is likely to be (Corsi et al, 1991; Venkatram & Prescott, 1990; Porter, 1985). As Miles and Snow succinctly state:

> Successful organizations achieve strategic fit with their market environment and support their strategies with appropriately designed structures and management processes. Less successful organizations typically exhibit poor fit externally and/or internally. (1984, p. 10)

Hence, following an environmental change, an organization must do whatever is needed in order to align – or realign – its strategy with the new environmental reality. Moreover, when this environmental change is sudden and discontinuous, such as in the case of strategic surprise, whether the organization responds and changes its strategy – or does not – takes on critical importance.

Numerous authors have examined the strategic alignment construct in a range of industries and under varying circumstances. Smith and Grimm (1987) found that railroads which changed strategies following a significant environmental change – the deregulation of rail carriers – outperformed those that did not change. Similarly, Feitler et al (1998) uncovered additional strong evidence in support of this theory among motor carriers in the post-deregulation environment. In fact, the authors' model showed that the more motor carriers changed strategies, the more their performance (as measured by operating ratio) improved (Feitler et al, 1998).

However, other researchers have seen opposite results. Corsi et al (1991), looking at the same motor-carrier research domain as Feitler, determined that firms that changed strategies performed significantly worse following the change. The authors justified the disconnect between their results and Smith and Grimm's findings in the railroad industry by noting that the final environments differed following deregulation: While railroads' deregulated domain resulted in better performance and higher profits throughout the industry, the change in the motor-carrier industry had the opposite effect – more competition and a significant decrease in performance (Corsi et al, 1991). While not specifically identified in either study, the likelihood that high barriers to entry among railroads, due to the large investments and specialized assets required, may have limited the number of new entrants. In the motor carrier industry, such barriers are less significant, and so many new entrants appeared in the market.

Likewise, Zajac and Shortell (1989), in their analysis of hospitals following industry-wide changes in the Medicare payment system, found that organizations were likely to change strategies following such an environment jolt. But while performance differences between strategies were identified, no support was determined for the proposition that hospitals that changed strategies improved their performance versus those that did not (Zajac & Shortell, 1989).

Later research by Zajac and Kraatz (1993) and Zajac et al (2000) found further support for the hypotheses that firms – in the higher-education and savings-and-loan industries, respectively – did improve firm performance by changing strategies in response to environmental shifts. But in both of these cases, the domains examined did not experience specific or sudden changes – such as deregulation or the Medicare jolt. Rather, colleges and S&Ls witnessed ongoing, though substantial, changes or shifts in the external environment and adjusted their strategies to better align resources with the (perceived) new reality.

More recently, Forte et al (2000) has advanced a contingent perspective. These authors found that when looking at the same post-Medicare payment domain that Zajac and Shortell had examined, hospitals did respond to this discontinuous environmental change by altering strategies. But, these authors saw that success, measured in terms of better performance, depended on the circumstances of the change, including the prior strategy and the proper choice of a new strategy that aligned properly with the new environment. Similarly, Lukas et al (2001) determined that even in China's transitional economy, strategic change had a performance impact, but only under certain environmental circumstances. Thus, the direction of strategic fit research suggests that strategic change without context and justification is not desirable, and may actually harm firms' performance; strategic change must reflect the new environmental reality and improve alignment to better their performance.

Finally, there is a new and emergent stream that proposes that the nature of the environmental change – permanent versus transient, and sudden versus gradual – can also affect both the appropriateness of strategic change and the performance outcomes that result from it (Lengnick-Hall & Beck, 2005). These authors propose that an organization's "resilience capacity" may enable it to effectively respond to surprise without a strategic change to maintain its close strategic fit (Lengnick-Hall & Beck, 2005); however, they offer limited empirical support.

Given the equivocal nature of the strategic alignment findings, combined with the uncertain picture resulting from strategic surprise, it is proposed that both of the following apply:

H $_7$: Organizations that respond to sudden and disruptive changes in the external marketing environment (i.e., strategic surprises) by changing their strategies, will have better strategic alignment and therefore *will outperform* their counterparts that do not change strategies.

Conceptual Framework

The fundamental model of adaptive strategic change suggests that firms reorient in response to environmental conditions and change. Many authors indicate two distinct sets of influences affect the likelihood of strategic change (see for example Ottesen & Grønhaug, 2004; Mavondo, 1999): (1) external factors, including both the macro- (including economic, cultural, technological, political, and natural) and micro-environment (including customers, competitors, suppliers, intermediaries, and publics); and (2) internal or organizational factors, such as a firm's age, size, prior performance, strategic focus, and current strategy. In addition, there are 10 strategic factors which shape the organization's current strategy; these are explained further in a later section.

Research Domain

Motor Carriers

Now more than a century old, the motor carrier industry (also known as trucking) plays a vital role in the U.S. economy. In 2003, for example, trucking represented approximately 87 percent of all domestic freight revenues (some $610 billion), versus some five percent for railroads, the next largest method (Donath et al, 2005). In total, more than nine billion tons of goods are moved annually, and the industry employs more than 10 million people (Donath et al, 2005; Corsi & Infanger, 2004).

The U.S. Department of Transportation (hereinafter DOT) and the Federal Motor Carrier Safety Administration (FMCSA) – a unit of the DOT – divide the trucking industry into

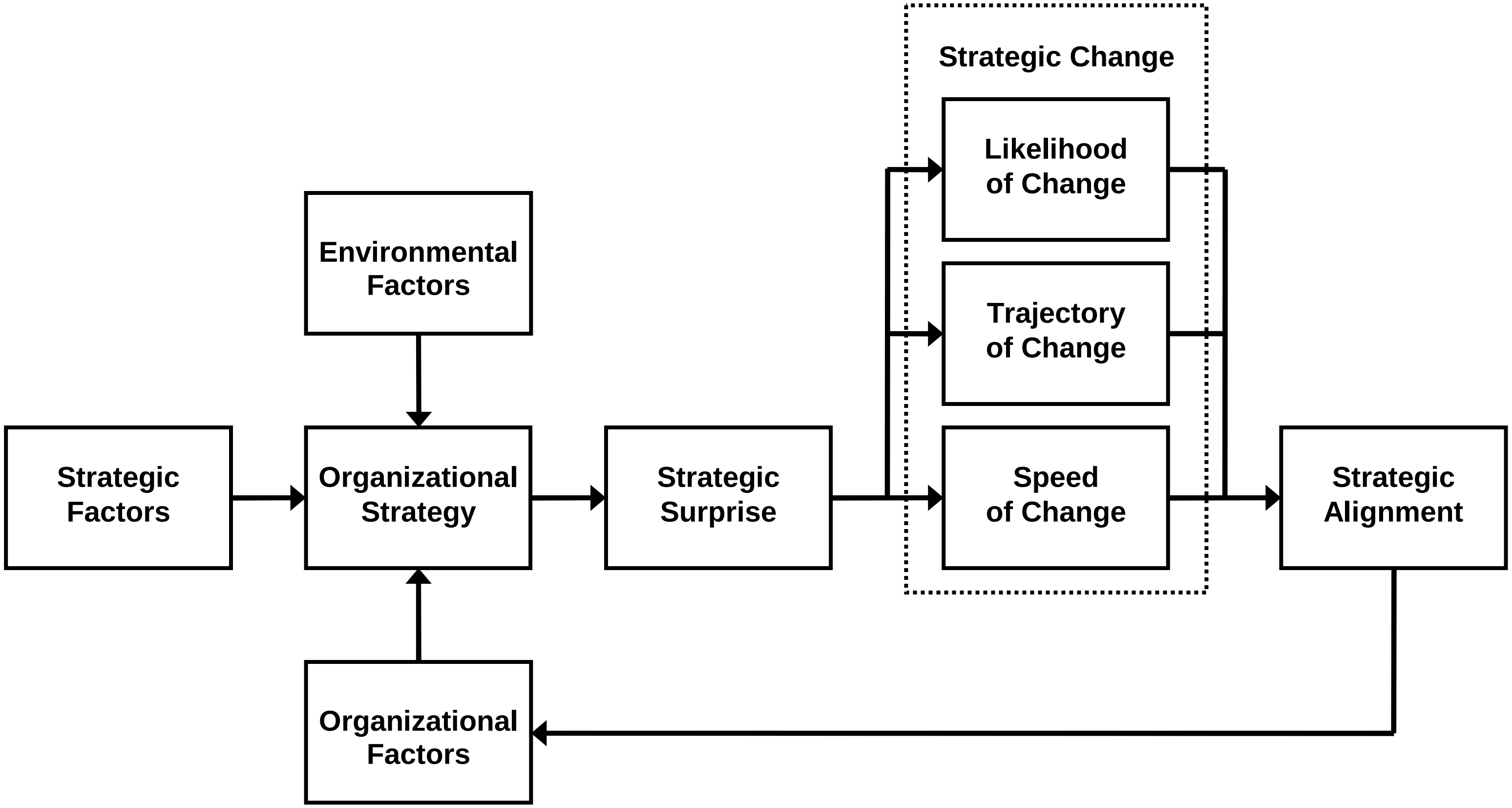


Figure 4. Conceptual Model. Strategic Surprise and Strategic Change

three major sectors: private carriers, for-hire truckload, and for-hire less-than-truckload carriers. Private carriers handle freight for specific firms and supply chains (e.g., Wal-Mart) and do not engage in for-hire operations. In 2002, private carriers represented roughly 47 percent of trucking revenues or ~$277 billion (Corsi & Infanger, 2004). Note that private carriers, strictly speaking, do not receive payment for their services; the cost is covered through accounting transfers. For-hire truckload (TL) firms represented another 43 percent of the total ($274 billion in 2002), while less-than-truckload (LTL) carriers handled about 8.6 percent or $58.4 billion (Corsi & Infanger, 2004).

DOT further categorizes motor carriers based on their annual revenues: Class I carriers generated more than $10 million in annual revenues, Class II carriers produced between $3 and $10 million, and Class III carriers received revenues of less than $3 million. According to the Annual Reports that Class I and II carriers file with FMCSA, in 2003 (the latest year for which data is currently available) there were a total of 2,137 motor carriers in these two groups. Of this, 196 (9.2 percent) classified themselves as LTL carriers, and 1,142 (53.4 percent) were classified as truckload (TL) carriers; the other 799 firms carried containers, parcels (UPS and FedEx) or did not provide any classification (based on author's calculations using 2003 annual reports data from Bureau of Transportation Statistics (BTS)).

The truckload segment typically focuses on "…dedicated movement of single loads between facilities or load centers…" (Donath et al, 2005: 5). As such, this portion of the industry includes many smaller firms with relatively low costs of entry, since all that is required to enter the business is drivers and tractors. By contrast, the LTL sector

"…typically provides business-to-business services with multiple pick-up and delivery locations…" (Donath et al, 2005: 7). LTL firms have fairly significant barriers to entry in terms of fixed assets and necessary costs, such as facilities, equipment, and staff. Another key distinction between these two segments is that LTL firms handle shipments of up to 10,000 lbs, whereas TL firms haul an entire trailer which is more than 10,000 lbs (Silverman et al, 1997).

Still another way of looking at the industry is based on what the trucks/trailers carry. Motor carriers self-categorize themselves based on their "…single, predominant type of operation as measured by revenue" (FMCSA). Based on this classification, of the Class I and II carriers reporting in 2003, there were 1,408 carriers of general freight (miscellaneous commodities generally not requiring special handling or equipment), 645 carriers of specialty freight (freight requiring special handling and/or equipment), and 84 carriers of household goods (such as office equipment, exhibit equipment, house furniture, and appliances) (definitions, FMCSA; numbers of carriers, author's calculations from annual reports data).

Deregulation and Change

Threatened by "…the dramatic increase in entry during the 1920s, [incumbent firms] lobbied intensively for [and won] regulatory constraints on price and entry" (Silverman et al, 1997: 33). The U.S. for-hire motor carrier industry, along with railroads, had been regulated by the Interstate Commerce Commission (ICC), which severely restricted expansion by current carriers as well as entry by new firms (Silverman et al, 1997; Corsi et al, 1992).

In 1980, however, the Motor Carrier Act (MCA) was enacted and put an end to the ICC's stiff controls. This reform led to a dramatic increase in entry by new firms, and "severe downward pressure on price" (Silverman et al, 1997: 33). For example, "[w]hile there were 18,045 for-hire interstate regulated firms in 1980, this number increased to 54,629 in 1993 – a tripling of firms in a 13-year period" (Feitler et al, 1997: 159). However, with this growth came severe turbulence and competition; more than 4,000 motor carriers failed between 1980 and 1984 (Feitler et al, 1997). The LTL segment, in particular, was considered hard hit; this group of carriers, that had benefited most from strict regulation and tight controls, lost a significant number of firms (Corsi et al, 1992). In 1976, 614 LTL firms had generated $11 billion in revenue, whereas by 1989 the LTL segment had shrunk to 237 firms, but produced $17 billion (Feitler et al, 1997). In 2002, this segment included only 155 firms, but by then generated almost $20 billion in revenue (Corsi & Infanger, 2004).

Motor Carriers and 9/11

Prior to September 11, 2001, trucks were not considered "a typical target – or conduit – for terrorism" (Donath et al, 2005: 5). In the U.S. there had only been a couple cases of large trucks used as weapons; "… [even] the Oklahoma City bombing fails to meet many post-9/11 terrorism standards since it utilized a smaller, straight truck…" (Donath et al, 2005, p. 5).

Nevertheless, "…the trucking industry possesses some important attributes associated with terrorism" and has come under increasing scrutiny by politicians, law enforcement, and national security (including the Department of Homeland Security) (Donath et al, 2005, p. 5). As a result, motor carriers experienced a significant upsurge in costs (e.g., insurance and other security measures), additional regulatory requirements (e.g., additional inspections, HAZMAT restrictions, and driver training), and longer lead times and shipping delays, particularly for border crossings. On top of an already weak and slowing economy, 9/11 had a significant disruptive business and financial effects.

According to the Truck Transportation Yearbook 2002 (published by DRI•WEFA, an industry analyst), immediately following 9/11 motor carriers were "… plagued with extensive border delays, rising security and insurance costs, and weaker demand." Plus, U.S. motor carriers faced increased competition from Mexican truckers as a result of NAFTA and recently approved new rules which took effect early in 2001. As a result, some 2,374 motor carriers failed in 2002 and another 1,800+ failed in 2003 (Corsi & Infanger, 2004). In fact, by another estimate, almost 11,000 firms exited the industry in the post-9/11 years (Lancioni et al, 2005).

Summary of Research Hypotheses

Likelihood of Strategic Change

H_1: Following a strategic surprise that disrupts the marketing environment, younger organizations are *more likely* to make a strategic change than older ones.

H_2: Following a strategic surprise that disrupts the marketing environment, smaller organizations are *more likely* to make a strategic change than larger ones.

H_3: Following a strategic surprise that disrupts the marketing environment, poorer performing organizations are *more likely* to make a strategic change than better performing organizations.

H_4: Following a strategic surprise that disrupts the marketing environment, less strategically focused organizations are *more likely* to make a strategic change than less focused organizations.

Trajectory of Strategic Change

H_{5A}: Following a strategic surprise, organizations that had appropriate strategies prior to the event, and do not change their strategies, will experience better performance than those that do change.

H_{5B}: Following a strategic surprise, organizations that *did not* have appropriate strategies prior to the event, but change their strategies to better-aligned forms, will perform better than those that remain unchanged.

H_{5C}: Following a strategic surprise, organizations that had appropriate strategies prior to the event, but change their strategies to less-aligned forms, will experience poorer performance than those that do not change.

H_{5D}: Following a strategic surprise, organizations that *did not* have appropriate strategies prior to the event, and do not change to better-aligned forms, will perform poorer than all other groups.

Speed of Strategic Change

H_6: Following a strategic surprise that disrupts the marketing environment, firms that make strategic changes more quickly will outperform those that "wait and see."

Alignment of Strategic Change

H $_7$: Organizations that respond to sudden and disruptive changes in the external marketing environment (i.e., strategic surprise) by changing their strategy, will have better strategic alignment and therefore *will outperform* their counterparts that do not change.

Research Approach And Methods

Data Sources

As noted by Zúñiga-Vicente & Vicente-Lorente (2006), Cool & Schendel, (1987), and others, the specification of strategy variables depends on the industry in question – its particular structure and economics. Therefore, data obtained for use in this research are drawn from sources specific to the motor carrier industry.

Annual Data

As discussed earlier, a number of studies have used the motor carrier industry as their research domain. Of 10 empirical studies of motor carriers identified in the list in Appendix A, for example, all focused on deregulation (MCA 1980) as the key environmental change variable and used FMCSA annual data as the primary source, though some added data from other sources.

Currently available data provides a detailed, five-year window of analysis; for strategic research involving sudden events and changes this has been considered sufficient. Lant et al, for example, noted that they chose a relatively short time period for their study of strategic change because “theorists argue that the organizational dimensions composing [strategic changes] change simultaneously; thus, [they] occur in relatively short periods of time” (1992, p. 594).

FMCSA Form M annual-report data for Class I and II motor carriers for the five years of 1999 through 2003 was obtained; in total, there are 12,069 records in this data set. These annual reports capture descriptive data (e.g., motor carrier number, location, and freight category); balance sheet data (e.g., assets & liabilities; numbers of trucks);

operational data (e.g., numbers of drivers and other employees); and more detailed income statement data (e.g., revenue by segment; expense items by category). While providing detailed financial data, it should be noted that Form M records are unaudited and there are often missing items; these potential problems were addressed by a comprehensive data cleaning process.

After calculating LTL Focus (LTL revenue divided by total revenue), firms with zero values for all reported years were excluded; this resulted in 1,726 records representing 345 motor carriers. Within this LTL-only data set, records were sorted by MC number, and firms that did not have at least three (of five possible) years of reported results were automatically excluded. In addition, carriers with two or more contiguous years of missing data were deleted (e.g., a motor carrier cannot be missing both 2000 and 2001 data). Carriers with blank records in the middle of the five-year span (i.e., *not* 1999 or 2003), were assumed to belong in the set, but unreported or missing. Missing values were calculated as the mean of the year before and year after values (where available).

Missing values for essential data items in the LTL data set were handled as follows:

- When a critical value was missing, but could be calculated from data provided (e.g., a total that was left blank, but the underlying components were provided), this step was manually performed to determine the value.

- When a value was missing, but previous and following records included the value, the missing value was calculated as the arithmetic mean of the two provided values, *unless* “0” was a reasonable possible value (e.g., LTL miles could be 0, even if the value had been a non-0 value in previous and subsequent years). In this latter case, an appropriate value could not be calculated.

- When a value was missing, and could not be calculated using either of the above methods, a value of "n/a" was inserted.

This cleaning process resulted in a complete data set of 270 LTL motor carriers with five years of useable figures.

Methodology

The goal of Study 1 was to investigate the relationship between strategic surprise and strategic change in the context of the motor carrier industry. Given the high degree of uncertainty resulting from both the lack of precedent in studying a strategic surprise as an environmental event, and the variability noted in reporting the results of research examining strategic change, Study 1 was largely exploratory in nature.

Numerous research studies have used cluster analysis to study the strategic change domain, comparing before-and-after clusters of strategic groups to determine whether a change took place (e.g., Forte et al, 2000; Corsi et al, 1991; Smith & Grimm, 1987). Two basic forms of analysis were performed in Study 1: Cluster analysis and analysis of variance (ANOVA). Cluster analysis has frequently been used to compare before-and-after effects resulting from environmental and strategic changes. ANOVA and certain other analytical techniques have been used to determine the characteristics of the differences before and after the strategic surprise occurred.

Cluster Analysis

Based on the literature review and various empirical studies of the motor carrier industry, 10 strategic factors were calculated for inclusion in the cluster analysis. These included:

Strategic Factors

1.	Service	Total employee wages and benefits paid per reported mile
2.	Efficiency	Miles per revenue unit (i.e., truck)
3.	Cost	Cost per reported mile
4.	Price	Revenue per reported mile
5.	LTL focus	LTL revenue as a percentage of total revenue
6.	LTL miles	Average length in miles of LTL shipments
7.	LTL tons	Average tonnage of LTL shipments
8.	Risk	Financial leverage or risk (i.e., total debt versus total equity)
9.	Op Ratio	Operating ratio (operating expense / operating revenue)
10.	Size	Total motor carrier revenue

The LTL data set was divided into pre- and post-9/11 data: 1999 and 2000 comprised the pre-9/11 subset; 2002 and 2003 comprised the post-9/11 subset. Strategic variables for each of the two years in each subset were averaged; if a value was missing, the one value was deemed the mean. For each set, normalized variables were calculated for the 10 strategic variables; when a normalized variable was missing, the variable was coded as “n/a.” The 10 strategic factors were sorted into quintiles based on where the normalized variable fell: Highest or best 20 percent values were coded as quintile one (1); lowest or worst 20 percent were coded as quintile five (5). The “n/a” variables were coded as threes (3s) *after* appropriate quintiles were determined for non-“n/a” data;

therefore, quintile values reflect the non-missing data, and there is an overweighting of quintile three (3) values.

SPSS K-means cluster analysis algorithm was used to perform the cluster analysis. As noted by previous researchers, the K-means algorithm does not provide data regarding how many clusters to select; five and six clusters have been used in previous studies, and this was chosen as the starting point for this analysis (see Corsi et al, 1991). All 10 strategic variables were very highly significant in the cluster analysis for five or six clusters as shown in Tables 2.1 and 2.2.

Cluster membership was compared by motor carrier between the pre- and post-9/11 sets. Motor carriers that changed cluster membership between the two periods were deemed to have experienced a strategic “Change;” those that remained the same were coded “No Change.” The resultant data set was parsed into two subsets: No Change and Change. T-tests were performed on the following combinations of variables: (1) Pre-9/11: No Change versus Change; (2) Post-9/11: No Change versus Change; (3) No Change: Pre- versus Post-9/11; and (4) Change: Pre- versus Post-9/11.

The pre- and post-9/11 data sets were also parsed according to demographic factors to determine whether there was a higher likelihood of strategic change by demographic characteristic. Four demographic variables were considered: Size, age, prior performance (i.e., operating ratio prior to the event), and LTL focus. For size, because total revenues are very skewed, the median was used: above the median was coded as large; below the median was coded as small. For age, no data is provided regarding the year of DOT certification; however, MC-numbers are issued sequentially, so the smaller the number, the older the firm. The data set was divided at the median, with the top half coded as older and the bottom half as younger. For past performance (based on operating ratio) and LTL focus, motor carriers above the mean were coded as higher; below the mean were coded as lower.

Table 2.1. Cluster Analysis ANOVA

VARIABLE	--- CLUSTER --- Mean Square	df	--- ERROR --- Mean Square	df	F	Signif
SERVICE	155.21	5	0.48	534	321.48	0.00
EFFICIENCY	111.01	5	0.86	534	129.21	0.00
COST PER MILE	154.65	5	0.49	534	316.87	0.00
PRICE PER MILE	107.67	5	0.93	534	116.04	0.00
LTL FOCUS	78.99	5	1.19	534	66.63	0.00
LTL TONS	40.80	5	1.12	534	36.32	0.00
LTL MILES	51.91	5	1.04	534	50.00	0.00
RISK	96.83	5	1.10	534	87.96	0.00
OPERATING RATIO	45.40	5	1.60	534	28.42	0.00
SIZE	78.24	5	1.29	534	60.66	0.00

Table 2.2. Final Cluster Centers

VARIABLE	CLUSTER 1	2	3	4	5	6
SERVICE	3	3	4	1	2	5
EFFICIENCY	3	3	2	4	4	2
COST PER MILE	3	3	4	1	2	5
PRICE PER MILE	3	3	4	2	2	4
LTL FOCUS	3	2	4	3	2	4
LTL TONS	3	4	2	3	4	2
LTL MILES	3	3	2	4	4	2
RISK	2	4	2	3	3	4
OPERATING RATIO	3	4	3	4	2	3
SIZE	2	4	3	4	2	3

Quintiles: 1 = Top 20%, 5 = Bottom 20%

Results

Clusters and Generic Strategies

The six-cluster solution appeared to be the best fit for pre- and post-9/11 motor-carrier data, and was similar to the results determined by earlier authors in this domain. By comparing the cluster centers (see Table 2.1) to Porter's generic strategy typology, the following relationships emerge:

- <u>Cluster 4</u> has the highest quintile for service level provided and cost per mile, and a tie for highest price per mile; this represents the differentiation/quality strategy where high levels of service are provided and premium prices are charged.

- <u>Cluster 5</u> is similar, but with the second highest service level and cost per mile, and a tie for price per mile; like cluster 4, this represents a version of the quality/differentiation strategy. A key differentiating factor between these two, similar clusters appears to be organization size: whereas cluster 4 comprises relatively small carriers, cluster 5 is larger firms.

- <u>Clusters 3 and 6</u> likewise represented two versions of Porter's low-cost provider strategy. Cluster 6 had the lowest service level, followed by cluster 3, and the two clusters tied for the greatest efficiency; both offered the lowest prices and keep costs low as well. The key differentiator between these two strategies appeared to be financial risk: whereas cluster 3 firms invested somewhat heavily to attain the low-cost strategy, cluster 6 members have incurred much less debt.

- <u>Clusters 1 and 2</u> represented Porter's "stuck in the middle" or lack of strategy, without any dominant strategic factors: they are neither highest or lowest in any category, though they do tie for lowest on three factors. The key distinguishing factor between these two clusters appeared to again be size – cluster 1 firms were significantly larger than cluster 2's carriers.

Thus, three of Porter's four strategic forms were represented, each with a pair of clusters evidencing a variation on the basic theme. The one Porter strategy not represented was focus; however, since all of these firms were specifically culled from the motor carrier industry data based on their LTL focus, it is perhaps not surprising that this factor did not vary much between clusters and did not result in a separately identified strategy.

General Findings: The Impact of 9/11

Among LTL carriers in the research data set, the impact of 9/11 was dramatic. Operating ratio is considered the key measure of performance in the trucking industry, representing the ratio of total expenses to total revenues; in other words, operating ratio is the inverse of gross operating margin. As operating ratio increases, expenses consume a larger portion of revenues; when an operating ratio is greater than 1.00, for example, it means operating expenses exceed revenues. Climbing operating ratios are a negative indicator, either because expenses are increasing, or revenues are declining, or both.

Prior to 9/11, operating ratios among motor carriers in this data set averaged .964 (or a gross operating margin of 3.6%). Following the strategic surprise of 9/11, average operating ratios increased to .982, reducing operating margins by 1.9% – meaning that overall performance dropped by more than half. The reasons behind this slide are fairly obvious: although operating revenues actually increased by 10% after 9/11, expenses surged by almost 12%, due to increased insurance expense, greater driver recruitment and training costs, and substantial delays in moving loads. As a resulting, the average carrier's pre-tax income dropped by some $1.2 million, or nearly 25%. Further details of this change are provided in Table 2.3.

Of the 270 motor carriers included in this data set, 106 were identified as members of a different cluster following the strategic surprise. As noted previously, this was considered a strategic change, suggesting that almost 40% of the LTL motor carriers altered their strategies following the 9/11 event.

As noted earlier, the overall data set shows a very significant change in several key business measures pre- and post-9/11, including operating ratio and operating income. The mean operating ratio increased (i.e., became worse) by almost two percentage points between these two periods; given that the mean operating ratio prior to the 9/11 event was more than 96 percent, an increase of almost two percent means a substantial drop of more than half in gross operating margin. Looked in another way, the LTL segment had a gross operating margin of less than four percent prior to 9/11, and this was reduced by more than half after 9/11.

Dividing the data set into two groups – motor carriers that did not change strategies (i.e., No Change) and those that did change (i.e., Change) – some specific patterns emerged. Motor carriers that changed strategies had significant increases in operating ratio, averaging .023, representing a substantial *decline* in their financial performance. Those that did not change, on the other hand, had an average increase of .015, about 30% less (or better) results (see TABLE 1.2 for details). Moreover, the No-Change segment had better financial performance in the first place – a possible marker for why the Change segment did so – and so widened this gap to more than 2%. In other words, firms that

Table 2.3. Total Data Set (N = 270)

	PRE-9/11	POST-9/11	DIFF	% DIFF
Operating Ratio	.964	.982	+0.018 ***	+1.9%
Operating Income ($000)	4,724.4	3,701.6	-1,022.8 ***	-21.7%
Operating Revenue ($000)	79,947.8	87,908.2	+7,960.4 ***	+10.0%
Operating Expense ($000)	75,223.4	84,206.6	+8,983.2 ***	+11.9%

*** Significant at .01 level (two-tailed)

previously had better operating ratios – and did not change their strategies – were less impacted by the event, resulting in an even greater performance advantage.
(See Table 2.4.)

Operating income, however, was a much different matter. While both groups experienced declines in income, motor carriers that did not change were significantly more affected. The No-Change segment experienced a very significant and steep decline in operating income of more than 26%, whereas the Change segment also had a drop, but it was not statistically significant.

Among carriers that changed strategies, operating revenue and expense increased at nearly twice the rate of the No-Change segment. The Change group experienced an 18.2% increase in revenue following the surprise, while No-Change had only an 8.9% increase. Similarly, expenses for the Change group increased 19.7%, compared to a

Table 2.4. Overall Data Set

	SEGMENT	N	PRE-9/11	POST-9/11	DIFF	% DIFF
OPERATING RATIO	All	270	.964	.982	+0.018 ***	+1.9%
	No Change	164	.959	.974	+0.015 ***	+1.6%
	Change	106	.972	.995	+0.023 **	+2.3%
OPERATING INCOME ($000)	All	270	4,998.3	3,755.8	-1,242.4 ***	-24.9%
	No Change	164	7,344.6	5,409.1	-1,935.5 ***	-26.4%
	Change	106	1,368.1	1,198.1	-170.5	-12.4%
OPERATING REVENUE ($000)	All	270	79,947.8	87,908.2	+7,960.4 ***	+10.0%
	No Change	164	116,612.7	126,990.7	+10,378.0 ***	+8.9%
	Change	106	1,368.1	1,198.1	-170.5	-12.4%
OPERATING EXPENSE ($000)	All	270	75,223.4	84,206.6	+8,983.2 ***	+11.9%
	No Change	164	109,664.9	121,661.7	+11,996.8 ***	+10.9%
	Change	106	21,936.5	26,257.2	+4,320.7 **	+19.7%
LTL OPERATING REVENUE ($000)	All	270	69,322.7	76,245.2	+6,922.5 ***	+10.0%
	No Change	164	99,811.9	108,761.2	+8,949.3 ***	+9.0%
	Change	106	18,835.2	22,401.5	+3,566,3 **	+19.7%

*** Significant at .01 level (two-tailed)

** Significant at .05 level (two-tailed)

* Significant at .10 level (two-tailed)

<u>*NOT*</u> significant

substantially less 10.9% for No-Change carriers. It should be noted, however, that the No-Change carriers were substantially larger than those carriers that Changed – on the average, five times larger in terms of operating income. In fact, operating income, operating revenue, and operating expense of the Change segment were all about 80% less than those of the No Change carriers.

Since operating ratios were much worse among motor carriers that changed strategies after 9/11, but average operating incomes were unchanged compared to the 26% drop in the No-Change group, support for H_1 is not consistent. Combined with the previously noted differences in the characteristics of these two segments, it is believed that other factors have significant effects on the appropriateness of a strategic change following a surprise.

Likelihood of Change

The overall data set shows a very significant change in several key business measures pre- and post-9/11, including operating ratio and operating income. The mean operating ratio increased (i.e., became worse) by almost two percentage points between these two periods; given that the mean operating ratio prior to the 9/11 event was more than 96 percent, an increase of almost two percent means a substantial drop of more than half in gross operating margin.

In three of the four circumstances shown in Table 2.5, while there is evidence of differences in the likelihood of strategic change between the two groups parsed into separate categories, the value of χ^2 indicates that these differences were not statistically significant. Thus, except when age is the demographic factor under consideration, the

Table 2.5. Likelihood of Strategic Change

AGE (N = 270)	Older 0.341 (N = 135)	Younger 0.444 (N = 135)	Difference .104 * χ^2 = 0.081
SIZE (N = 270)	Larger 0.378 (N = 135)	Smaller 0.407 (N = 135)	Difference .030 χ^2 = 0.618
PRIOR PERFORMANCE (N = 270)	Stronger 0.356 (N = 118)	Weaker 0.421 (N = 152)	Difference .065 χ^2 = 0.277
LTL FOCUS (N = 253)	Greater 0.356 (N = 132)	Lesser 0.413 (N = 121)	Difference .057 χ^2 = 0.350

[1] Cases with missing variable(s) excluded

* Significant at .10 level (two-tailed)

NOT significant

null hypothesis cannot be rejected. Younger motor carriers are much more likely to change their strategies after a strategic surprise than are older carriers; however smaller motor carriers are no more likely than larger carriers, less LTL-focused are no more likely than more LTL-focused, and stronger performing carriers are no more likely than weaker performing ones to change strategies following a strategic surprise (such as 9/11).

Thus, the research findings provide support for H_1, but do not support H_2 through H_4.

Trajectory of Change

The six clusters resulting from the cluster analysis are statistically different based on the ANOVA results. (See Table 2.6 for a detailed comparison.)

Clusters 3 and 6 represent versions of Porter's low-cost strategy, with variation between the two based on the level of LTL focus: cluster 3 has lower and cluster 6 has higher LTL focus. These two clusters are significantly more resilient to strategic surprise than the alternatives. Following 9/11, neither strategy experienced a statistically significant increase in either operating ratio or decrease in operating income (though cluster 3 dropped by 36.5% and cluster 6 fell 26.4%).

Clusters 4 and 5 represent Porter's quality/differentiation strategy, with the variance in these cases related to firm size: Cluster 4 has smaller motor carriers, while cluster 5 comprises larger carriers. Both clusters' operating ratios increased markedly following the strategic surprise – cluster 4 jumped 3.9% and cluster 5 climbed 3.1% - which was substantially greater than the 1.8% increase experienced by the LTL sector as a whole. Similarly, operating income among the smaller quality-focused carries dropped by nearly 200%, while larger quality carriers experienced a 21% decline, though the latter was not statistically significant. This suggests that the quality/differentiation strategy is particularly vulnerable to strategic surprise, especially among smaller motor carriers.

Clusters 1 and 2 represent the unfocused, "stuck-in-the-middle" strategy, with variance between the two clusters again based on firm size. Like the quality/differentiation strategy, size appears to provide some additional resistance to the effects of strategic surprise. Operating ratios in both clusters increased following 9/11, but only among smaller carriers was the increase significant (+4.2%). Similarly, while operating income

Table 2.6. Strategic Change by Cluster

		Measure	Pre-9/11	Post-9/11	Difference
1	**Stuck in the Middle**	N =	57	49	-8
		Operating Ratio	.965	.975	+0.010 (+1.1%)
		Operating Income	3,355,184	1,528,919	-1,826,246 (-54.4%)
2	**Stuck in the Middle**	N =	34	30	-4
		Operating Ratio	.996	1.038	+0.042 * (+4.2%)
		Operating Income	(19,600)	(405,944)	-386,345 * (-1971.2%)
3	**Cost Leadership** (Lower LTL Focus)	N =	47	50	+3
		Operating Ratio	.971	.976	+0.005 (+0.5%)
		Operating Income	1,451,697	921,207	-530,490 (-36.5%)
4	**Differentiation / Quality** (Smaller)	N =	42	43	+1
		Operating Ratio	.978	1.016	+0.038 *** (+3.9%)
		Operating Income	106,176	(95,120)	-201,296 ** (-189.6%)
5	**Differentiation / Quality** (Larger)	N =	49	52	+3
		Operating Ratio	.923	.951	+0.029 *** (+3.1%)
		Operating Income	21,376,760	16,871,534	-4,505,226 (-21.1%)
6	**Cost Leadership** (Higher LTL Focus)	N =	41	46	+5
		Operating Ratio	.963	.964	+0.001 (+0.1%)
		Operating Income	946,666	696,971	-249,695 (-26.4%)
	ANOVA (Single factor)	Operating Ratio	**F:** 7.9815 ***	**F:** 10.2205 ***	
		Operating Income	**F:** 9.6026 ***	**F:** 10.6533 ***	

*** Significant at .01 level (two-tailed)

** Significant at .05 level (two-tailed)

* Significant at .10 level (two-tailed)

Shaded cells are NOT significant

declined substantially in both clusters, larger carriers were not statistically worse off,

surprise. Operating ratios in both clusters increased following 9/11, but only among smaller carriers was the increase significant (+4.2%). Similarly, while operating income declined substantially in both clusters, larger carriers were not statistically worse off, while smaller carriers plummeted almost 2000%.

Strategic Groups

Due to the documented similarities among each of these three pairs, they are combined into what are hereinafter referred to as strategic groups: group C is the overall Cost-leadership strategy, combining clusters 3 and 6; group D is the Differentiation/quality strategy made up of clusters 4 and 5; and group S is the Stuck-in-the-middle strategy morass of clusters 1 and 2.

When viewed in this fashion, a somewhat clearer pattern emerges. Group C members, on average, had the lowest operating ratios pre-9/11 and did not experience significantly poorer performance post-9/11 in terms of either operating ratio or operating income. The low-cost strategy was virtually unaffected and thus appears more resilient to strategic surprise.

Conversely, group D firms were the most seriously impacted by 9/11's effects, with operating ratios jumping a highly significant 3.4% on average, representing a performance drop of almost 60%. This group's drop in operating income, though averaging more than 20%, was not statistically significant.

Last, group S carriers saw a significant degradation of their operating ratios. Though already the poorest performing strategy before 9/11, operating ratios increased still further by an average of 2.1%, indicating their performance was substantially worse. But while operating income fell a whopping 62.1%, it was not statistically significant.

Trajectory

Comparing pre-and post-9/11 strategies, there are nine possible group trajectories. Not surprisingly, in each instance, staying with the existing strategy from before the event was the most likely scenario. For example, the cost-leadership strategy (group C) had 88 followers prior to 9/11 – 72 stayed with this strategy (82%), while 16 went elsewhere (mostly to group S), and 24 other firms joined this group, for a net increase of eight motor carriers. (See Table 2.7.)

Looking at all nine trajectories, it appeared that certain trajectories were more beneficial than others. Interestingly, the benefits of the low-cost strategy apparently accrued to all firms that stayed with – or moved to – this strategy; regardless of their starting point, carriers that ended up as low-cost providers were virtually unaffected by 9/11. Those companies that chose the quality/differentiation strategy were very negatively affected by following this strategy. Group S firms were less noticeably impacted. It even appears that firms that used the low-cost strategy before 9/11 were untouched even if they made a strategic change after the surprise.

Change Versus No Change

Following the strategic surprise of 9/11, the motor carrier industry – or at least the firms in this sample – experienced a dramatic business impact. As noted previously, operating ratios increased by almost 2%, cutting gross margin in half and resulting in a significant decline in operating income of about 25%. But within this sample, results varied in accordance with actions taken: carriers that did not change strategies were able to maintain better operating ratios – nearly 50% better than their peers that changed strategies. But operating income dropped across the board, and there was virtually no difference between the two groups in their percents of decline. Meanwhile, operating revenue, operating expense, and LTL revenue among carriers that changed grew at nearly twice the rate of carriers that remained unchanged.

Findings by Segment

Although there is a substantial body of research suggesting that strategic in the wake of environmental disruption leads to better strategic alignment (or fit), and hence rewards those firms with better performance, the strategic change paradigm has tended to be somewhat binary – the change is applied across the board, for all firms in the industry subject to these environmental forces. But as firms vary in their circumstances, management teams, and resources, so might their benefits differ following strategic surprise; in other words, is change the right response under all situations, or might some firms benefit more, while others benefit less, or even not at all (see, for example, Feitler, et al, 1998).

Two patterns emerged during the initial exploratory research, that bear further examination. First, parsing the data set along the strategic change dimension – that is, No Change versus Change – evidenced significant differences between the two segments. Motor carriers in the no-change group (n = 164) are, on average, much larger, older, more profitable (i.e., lower operating ratios), and have larger LTL market shares; conversely, change group members are smaller, younger, and less profitable. Some of these differences are quite dramatic, as the fact that no-change carriers are five

Table 2.7. Strategic Trajectory by Group – Sources & Changes in Operating Ratio

		POST-9/11			
		COST LEADERSHIP	DIFFERENTIATION / QUALITY	STUCK IN THE MIDDLE	TOTAL
	COST LEADERSHIP (C)	72 +0.007	1 -0.000	15 +0.002	88
PRE-9/11	DIFFERENTIATION / QUALITY (D)	6 +0.003	71 +0.029 ***	14 +0.066	91
	STUCK IN THE MIDDLE (S)	18 +0.004	23 +0.020 ***	50 +0.017 *	91
	TOTAL (CHANGE)	96 (+8)	95 (+4)	79 (-12)	270

Table 2.8. Strategic Trajectory by Group – Changes in Operating Ratio by Trajectory

TRAJECTORY #	TRAJECTORY	N	CHANGE IN OPERATING RATIO
1	C → C	72	0.007
2	D → C	6	0.003
3	S → C	23	0.004
4	C → D	1	n/a
5	D → D	71	0.029 ***
6	S → D	23	0.020 *
7	C → S	15	0.002
8	D → S	14	0.066
9	S → S	50	0.017 *
	TOTAL:	**270**	**0.018**

*** Significant at .01 level (two-tailed)
** Significant at .05 level (two-tailed)
* Significant at .10 level (two-tailed)
NOT significant

times the size of their change counterparts. (See Table 2.9 for further details). Second, not all motor carriers benefited equally from the no-change versus change dichotomy. Certain corporate factors appear to influence the effect of strategic change on alignment, and so certain characteristics may moderate this relationship. Examining how the four control variables – size, age, past performance, and LTL focus – influenced the outcomes provided interesting results as shown in the following sections.

Size X Change

Larger motor carriers that did not change strategies performed significantly worse after 9/11 (by 2.0%); while the change group saw its performance decline even more (2.2%), this change was not statistically significant. However, the performance of the no-change segment was significantly better performing than the change one, both before and after the strategic surprise. (See Table 2.10.)

Smaller carriers were almost unaffected by no change versus change segmentation. Both groups performed significantly worse following 9/11, with the change segment declining at twice the rate of the no-change segment. Neither group evidenced significant differences between the segments pre- or post-9/11.

Size was not a consistent factor with respect to performance. Larger motor carriers that changed strategies were less affected by strategic surprise, but were still very poor performers; smaller carriers performed worse after 9/11 regardless, though the Change group seemed more negatively affected by the surprise.

Age X Change

Among older motor carriers, both the no-change and change segments showed very

Table 2.9. No Change Versus Change by Size Segment

	SEGMENT	N	PRE-9/11	POST-9/11	DIFF	% DIFF
OPERATING RATIO	All	270	.964	.982	+0.018 ***	+1.9%
	No Change	164	.959	.974	+0.015 ***	+1.6%
	Change	106	.972	.995	+0.023 **	+2.3%
OPERATING INCOME ($000)	All	270	4,998	3,756	-1,242 ***	-24.9%
	No Change	164	7,345	5,409	-1,936 ***	-26.4%
	Change	106	1,368	1,198	-171	-12.4%
OPERATING REVENUE ($000)	All	270	79,948	87,908	+7,960 ***	+10.0%
	No Change	164	116,613	126,991	+10,378 ***	+8.9%
	Change	106	23,221	27,441	+4,220 **	+18.2%
OPERATING EXPENSE ($000)	All	270	75,223	84,207	+8,983 ***	+11.9%
	No Change	164	109,665	121,662	+11,997 ***	+10.9%
	Change	106	21,937	26,257	+4,321 **	+19.7%

*** Significant at .01 level (two-tailed)

** Significant at .05 level (two-tailed)

* Significant at .10 level (two-tailed)

NOT significant

Table 2.10. No Change Versus Change by Size Segment

	SEGMENT	N	PRE-9/11	POST-9/11	DIFF	% DIFF
OPERATING RATIO SIZE = LARGER	All	135	.955	.982	+0.018 ***	+1.9%
	No Change	84	.946	.965	+0.019 ***	+2.0%
	Change	51	.969	.990	+0.021	+2.2%
OPERATING RATIO SIZE = SMALLER	All	135	.973	.990	+0.017 **	+1.6%
	No Change	80	.972	.984	+0.012 **	+1.2%
	Change	55	.975	.999	+0.024 **	+2.4%
OPERATING INCOME SIZE = LARGER ($000)	All	135	9,303.9	7,318.3	-1,985.6 **	-21.3%
	No Change	84	14,169.5	10,436.6	-3,733.9 ***	-26.4%
	Change	51	2,675.1	2,443.4	-231.8	-8.7%
OPERATING INCOME SIZE = SMALLER ($000)	All	135	144.9	84.8	-60.1 **	-41.5%
	No Change	80	178.5	131.3	-47.2	-26.5%
	Change	55	156.2	43.4	-112.8 *	-72.2%

*** Significant at .01 level (two-tailed)

** Significant at .05 level (two-tailed)

* Significant at .10 level (two-tailed)

NOT significant

significant increases in operating ratios following a strategic surprise. Prior to 9/11, the two groups were not significantly different; however, following 9/11, the change group members were significantly worse performing. Indeed, while no-change members' average operating ratio increased by 1.7%, the change groups' operating ratio increased by 4.3% – nearly 2.5 times as much. (See Table 2.11.)

Younger motor carriers evidenced a very different and almost opposite pattern. The no-change portion of the younger demographic group had its operating ratio increase by 1.5% after the surprise. The change segment, on the other hand, showed no significant increase in operating ratio. While the no-change group had performed significantly better than its counterpart prior to 9/11, following 9/11 there was no significant difference.

Overall, age was not a consistent factor with respect to performance. With regard to operating ratios, older motor carriers did better following a strategic surprise, by not changing their strategies, but younger carriers did better by making strategic changes.

Past Performance X Change

Stronger performing motor carriers, pre-9/11, performed much poorer following the surprise, regardless of whether they changed or did not change strategies, except that the change group's operating ratio was 75% worse than that of the no-change group. While these two groups' performance was not significantly different pre-9/11, following 9/11 the gap was the widest of any two segments in this analysis. (See Table 2.12)

Weaker performers, statistically speaking, were unscathed. Both the no-change and the change groups performed no differently following the strategic surprise than they did

Table 2.11. No Change Versus Change by Age Segment

	SEGMENT	N	PRE-9/11	POST-9/11	DIFF	% DIFF
OPERATING RATIO	All	135	.963	.988	+0.025 ***	+2.6%
AGE = OLDER	No Change	84	.961	.977	+0.017 ***	+1.7%
	Change	51	.967	1.008	+0.042 ***	+4.3%
OPERATING RATIO	All	135	.965	.976	+0.011	+1.2%
AGE = YOUNGER	No Change	75	.956	.970	+0.014 ***	+1.5%
	Change	60	.976	.984	+0.008	+0.8%
OPERATING INCOME	All	135	6,642.5	5,339.3	-1,303.2 **	-19.6%
AGE = OLDER	No Change	89	9,504.3	7,004.5	-2,499.7 **	-26.3%
($000)	Change	46	2,588.0	2,160.4	-427.5	-16.5%
OPERATING INCOME	All	135	2,806.3	2,063.9	-742.4 **	-26.5%
AGE = YOUNGER	No Change	75	4,781.8	3,515.8	-1,266.0 ***	-26.5%
($000)	Change	60	432.9	460.3	+27.4	+6.3%

*** Significant at .01 level (two-tailed)

** Significant at .05 level (two-tailed)

* Significant at .10 level (two-tailed)

NOT significant

Table 2.12: No Change Versus Change by Past Performance Segment

	SEGMENT	N	PRE-9/11	POST-9/11	DIFF	% DIFF
OPERATING RATIO	All	118	.919	.961	+0.042 ***	+4.6%
PERF = STRONGER	No Change	76	.914	.947	+0.033 ***	+3.6%
	Change	42	.927	.986	+0.059 ***	+6.3%
OPERATING RATIO	All	152	.999	.999	+0.000	+0.0%
PERF = WEAKER	No Change	88	.997	.998	+0.000	+0.0%
	Change	64	1.002	1.000	-0.001	-0.1%
OPERATING INCOME	All	118	9,308.0	7,386.4	-1,921.6 ***	-20.6%
PERF = STRONGER	No Change	76	13,602.8	10,148.9	-3,453.9 ***	-25.4%
($000)	Change	42	3,284.5	2,823.3	-461.2	-14.0%
OPERATING INCOME	All	135	1,166.1	841.0	-325.1	-27.9%
PERF = WEAKER	No Change	75	1,939.8	1,315.6	-624.2	-32.2%
($000)	Change	60	110.5	131.6	+21.1	+19.0%

*** Significant at .01 level (two-tailed)
** Significant at .05 level (two-tailed)
* Significant at .10 level (two-tailed)
NOT significant

before the event, and the two groups remained in virtual lock step throughout. It should be noted that weaker performers had the worst operating ratio performance of any demographic segment, and so, in some respects, could not perform much worse, regardless of the circumstances.

Past performance – and not change versus no change – was the key determinant of post-surprise performance. Stronger performers, pre-9/11, performed much worse post-9/11, regardless of strategic change or no change; whereas weak performers pre-9/11 were essentially unchanged, again regardless of strategic change or not. In particular, stronger performers that changed strategies were dramatically poorer post-9/11, performing more than 3½ times worse than the overall data set average.

Focus X Change

More LTL-focused carriers performed significantly worse following 9/11, regardless of whether or not they changed strategies. The change group's post-9/11 performance became much worse than the no-change group, though this difference was not statistically significant. (See Table 2.13.)

The less-focused segment evidenced far less decline after the surprise. Carriers in this demographic that changed strategies had no decline in their performance, while those that did not change performed somewhat worse. Once again, in this case, the no-change group performed significantly better than its counterpart pre-9/11, but caught up after the event such that the performance difference between the two groups was not meaningful. More-focused carriers that changed their strategies performed far worse after 9/11 than those that did not change, though both segments experienced substantial

Table 2.13: No Change Versus Change by LTL-Focus Segment

	SEGMENT	N	PRE-9/11	POST-9/11	DIFF	% DIFF
OPERATING RATIO	All	132 [1]	.962	.987	+0.025 ***	+2.6%
LTL FOCUS = MORE	No Change	85	.963	.980	+0.016 ***	+1.7%
	Change	47	.960	1.001	+0.041 **	+4.2%
OPERATING RATIO	All	121 [1]	.967	.975	+0.008	+0.9%
LTL FOCUS = LESS	No Change	71	.958	.970	+0.011 *	+1.2%
	Change	50	.979	.982	+0.003	+0.3%
OPERATING INCOME	All	132 [1]	8,252.1	6,652.9	-1,599.2 **	-19.4%
LTL FOCUS = MORE	No Change	85	12,147.9	9,137.5	-3,010.4 **	-24.8%
($000)	Change	47	2,575.1	2,275.8	-299.2	-11.6%
OPERATING INCOME	All	121 [1]	1,350.1	878.6	-471.5 **	-34.9%
LTL FOCUS = LESS	No Change	71	2,095.5	1,252.1	-843.4 **	-40.3%
($000)	Change	50	482.0	434.5	-47.6	-9.9%

*** Significant at .01 level (two-tailed)

** Significant at .05 level (two-tailed)

* Significant at .10 level (two-tailed)

NOT significant

drops in operating ratios. Less-focused carriers that changed strategies saw no significant declines, while those that failed to change performed worse.

Conclusions

Of eight demographically determined, pre-to-post-9/11 scenarios based on operating ratios, in four cases the No-Change segment outperformed the Change segment; in two instances, the Change segment surpassed the No-Change segment; and twice there was no significant difference between the two groups. In no significant instances did Change outperform No Change for a specific demographic characteristic. It should also be noted that in every instance, the No-Change segments of each demographic group performed significantly ***worse*** after 9/11. The Change segments, on the other hand, did not perform significantly worse following the strategic surprise in four (50%) of the cases.

In general, the findings support the contingent perspective. Two characteristics – age and focus – seemed to suggest that how a firm is classified (high versus low) does NOT matter in terms of post-9/11 performance, but whether the firm changes strategy does affect the outcome. Conversely, two other characteristics – size and past performance – suggested that classification (at the top versus at the bottom) mattered more than whether or not a change in strategy is implemented. (See Table 2.14 for a summary).

Even more interestingly, the impact seemed not to follow what conventional wisdom would pre-suppose. That is, larger carriers, that would be expected to be better able to withstand a surprise than smaller ones, were more affected than their counterparts by the surprise, and stronger-performing carriers, that similarly would be expected to have used their resources to mitigate the effects of surprise, were devastated by 9/11, while weaker-performing firms were almost unchanged (though extremely weak).

Thus, no clear and consistent pattern emerged; strategic change improved performance in some instances, but was detrimental in others. And while operating ratios and operating incomes generally tracked with one another, there were instances where they did not. So not only was the situation a key factor, so was the metric that was used to determine whether there was success or not.

Table 2.14. Summary of Segments Performing Better Post-9/11

CORPORATE FACTOR	SEGMENT	OPERATING RATIO	OPERATING INCOME
SIZE	Larger	No Change	Change
	Smaller	No Change	No Change
AGE	Older	No Change	Change
	Younger	Change	Change
PREVIOUS PERFORMANCE	Stronger	No Change	No Change
	Weaker	Neither	Neither
LTL FOCUS	More	No Change	Change
	Less	Change	Change

Table 2.15. Study 1 – Research Hypotheses' Results

	STATEMENT OF HYPOTHESIS	SUPPORT?
H_1	Following a strategic surprise that suddenly and severely disrupts their external environment, organizations that respond by changing strategies, will have *poorer strategic alignment* and *will underperform* their counterparts that *do not change*.	Supported
H_2	Following a strategic surprise that disrupts their environment, younger motor carriers are more likely to make a strategic change than older ones.	Supported
H_3	Following a strategic surprise that disrupts their environment, smaller motor carriers are *more likely* to make a strategic change than larger ones.	Not Supported
H_4	Following a strategic surprise that disrupts their environment, weaker performing motor carriers are *more likely* to make a strategic change than stronger performing ones.	Not Supported
H_5	Following a strategic surprise that disrupts their environment, less LTL-focused motor carriers are *more likely* to make a strategic change than more LTL-focused ones.	Not Supported
H_6	Following a strategic surprise that disrupts their environment, firms that make strategic changes more quickly will outperform those that "wait and see."	Untested
H_7	Following a strategic surprise, motor carriers *with appropriate* strategies prior to the event that …	
	(1) *do not change* strategies, will experience better performance than those that *do change*;	Not Supported
	(2) *do not change* strategies, will experience better performance than *ALL* other groups.	Supported

CHAPTER 3

RESILENCE SCORING MODEL: PREDICTING MOTOR CARRIERS' ABILITY TO WITHSTAND ENVIRONMENTAL SURPRISE

Significantly increased attention to supply chain management (SCM) over the past 30 years has resulted in leaner and more profitable supply chains (Craighead et al, 2007; Natarajarathinam et al, 2009). But such trends as fewer suppliers, shorter lead times, and smaller inventories, coupled with greater globalization and outsourcing, have also substantially "increased the risks in the supply chain, making them more vulnerable to crisis" (Natarajarathinam et al, 2009, p. 536).

Among the most actively studied current topics in the SCM domain is examination of supply chain risk and its various forms and components (Rao & Goldsby, 2009). An emergent term, supply chain risk management, refers to the identification and management of potential disruptions to the increasingly global supply chain (Manju & Mentzer, 2008). Supply chain risk can result from a wide range of sources of disruption, and produces myriad outcomes. In their review of current research, Rao and Goldsby (2009) identify three major risk factors – environmental risk, industry risk, and organization risk – which form the basis for the authors' proposed typology.

In addition to the research attention that has been paid to defining and explaining supply chain risk, the very real presence of disruptive environmental events that have severely – and negatively – impacted various supply chains, such as the terrorist attacks on the World Trade Center in 2001, the Indian Ocean tsunami in 2004, and Hurricane Katrina on the U.S. Gulf Coast in 2005, has led to publication of a significant number of studies in this research stream. A recent review of supply chain disruption literature, for example, identified 118 articles on the subject found in peer-reviewed business journals, of which 64 (54%) had been published in just the past four years, from 2005 to 2008 (Natarajarathinam et al, 2009). Among the identified articles, 74 dealt with external (to the organization) events, of which 48 discussed events that were regional or national in scope.

Supply Chain Resilience

It is therefore not surprising that an even more recent research stream has emerged, focusing on what has become known as "supply chain resilience." Although resilience has been an accepted term in the management and HRM literature for some time, as Ponomarov and Holcomb note, it remains an evolving concept that has been used in conjunction with a diverse range of important issues. The authors offer their own definition of supply chain resilience which will be applied in this study. They say supply chain resilience is:

> The ***adaptive capability*** of the supply chain to prepare for ***unexpected events***, respond to ***disruptions***, and recover from them by maintaining ***continuity of operations*** at the desired level of connectedness and control over structure and function. (Ponomarov & Holcomb, 2009, p. 131, emphasis added)

Petit et al (2009) further expand this concept by incorporating a framework for supply chain resilience with seven vulnerability factors and 14 capability factors. But as both sets of authors acknowledge, their work is largely theoretical; very little empirical research has been performed to validate the construct, or to begin to develop meaningful metrics.

Motor Carrier Resilience

This study examines one potential aspect of the emerging supply chain resilience construct – motor carriers' ability to withstand disruptive changes in their external environment – a concept which will be referred to herein as motor carrier resilience. In measuring the ability to adapt to change, a scoring model is developed in order to predict motor carriers' likelihood to exit the industry (or fail), versus not exit – in other words, to be *resilient*. As such, the model examines a diverse set of financial and operational variables which may either contribute to – or detract from – motor carriers' performance and ultimately, their strategic resilience.

The motor carrier resilience model is therefore a diagnostic tool which will enable industry members to examine their strengths and/or weaknesses in a disrupted marketing environment. The scoring model will also allow other supply chain members to score and assess critical providers, in order to develop appropriate contingency plans in the event of unexpected exits. While weak scores do not pre-ordain failure, they can provide early warning signals for both the carriers themselves and the firms that depend upon them.

In addition, this study utilizes – for what is believed to be the first time in this field – a frequently-used marketing-research methodology, that has rarely been used elsewhere. Conjoint analysis, which has a lengthy research stream, is applied to the development of the motor-carrier-resilience model.

Conjoint analysis belongs to a class of multivariate research techniques that "decompose" participants' choices (the dependent variable) in order to estimate the underlying attribute relationships, enabling researchers to study trade-offs (Green &

Srinivasan, 1990). It has been the subject of hundreds of articles which sought to better understand the functioning and constraints of this successful methodology, as well as being used in thousands of different research applications. Over just one recent 12-month period, for example, more than 150 articles were published that used the term "conjoint analysis" either in their titles or as one of the key terms provided by the authors (from Business Source Premier, 2010). As it continues to evolve and offer new techniques, conjoint analysis is among the most discussed and applied research methods in marketing (Green et al, 2001).

Not only does use of this research method, as described in this study, appear to be unique in and of itself, but this application leads to further insights and additional research questions regarding the underlying assumptions and analysis.

Literature Review

Despite the popularity of prediction models and so-called scorecards (or now "dashboards") in the extant literature, there has been virtually no application of these tools to the supply-chain management domain in general, and the motor-carrier industry in particular. In the currently distressed and frequently volatile U.S. economy, a method that enables firm management – as well as other supply-chain members – to examine the performance stability of firms (or the lack thereof, and thus, the potential for failing to deliver or even bankruptcy) would seem to have significant value.

Numerous studies have been conducted in order to develop metrics or models which can help firms assess their performance status. Most research focuses on default or bankruptcy predictions, although a numeric value is developed which resembles the well-known consumer credit score. This score is then used to measure how close to – or distant from – the dire prediction of failure this firm is. Most models are focused on providing information for lending organizations or providers, rather than offering insights for the firm itself. In other words, the models tend to look at the likelihood of failure from the standpoint of the inability to repay loans or potentially default on financial obligations, rather than examining what actions the firm can take to avert such a calamity.

Prediction Models

Often cited as the earliest work in the failure-prediction domain, Beaver (1966) initially examined the usefulness of 30 distinct financial ratios in six accounting-oriented categories (ranging from cashflow to turnover). The result of his univariate analysis was a likelihood-of-failure ratio based on standard accounting data.

Altman, however, is the name that has become almost synonymous with this research domain. Beginning with his 1967 doctoral dissertation, Altman's research both extended and broadened the emergent stream, eventually creating scoring methods and models (such as his "Z-scores") which continue to be referred to and used. These relatively simple models provided the DNA for an extensive family of literature which continues to be actively studied.

Two recent and comprehensive review articles (Aziz & Dar, 2006; Balcaen & Ooghe, 2006) provided much of the requisite background for this study, examining quantitative methods and identifying potential gaps in this lengthy stream (though interestingly, ignoring Beaver's seminal work). Aziz and Dar (2006) documented 89 separate prediction models resulting from 45 articles, beginning with the work of Altman (who is probably the most prolific author in this field). Among the analytical results these authors compiled was that 64% of the studies used statistical models, 25% used expert systems, while 11% were simply theoretical (and therefore, non-quantitative). Of the statistical tools applied, multiple discriminant analysis (MDA) was the most commonly used method (30% of the models), followed by logistical regression – or logit – analysis (21%), and more recently, neural networks (9%); 12 other lesser used techniques were each employed by fewer than 6% of the studies (Aziz & Dar, 2006). Conjoint analysis has never been used in this type of modeling application.

In terms of results, Aziz and Dar also documented more than 81% of the statistical models with Type-I errors (i.e., the inability to properly classify failures as such) ranging from three to 19%, and type-II errors (incorrectly classifying non-failures, *as* failures) from zero to 22% (2006). Combining all of the studies they examined, the authors' weighted grand mean suggested prediction accuracy among these models of almost 85% (Aziz & Dar, 2006).

Balcaen and Ooghe (2006) examined failure-prediction models in terms of the potential problems posed by the statistical methods that were utilized. While similarly noting the popularity of MDA, the authors identified numerous potential statistical problems that could occur when this method is applied to these prediction models. In particular, they noted that technically it is inappropriate to use MDA in this fashion as it is a classification tool rather than a method for prediction; a firm is "… classified as failing because it most resembles a group of firms failing in the next year …" which is then treated as a prediction of such (Balcaen & Ooghe, 2006, p. 67). Furthermore, the authors concluded that, despite its popularity as a method, MDA-based prediction models often ignored (or at very least failed to consider) the impact of critical assumptions that underlie the technique and might therefore produce unsuitable and non-generalizable results (Balcaen & Ooghe, 2006; Joy & Tollefson, 1975).

Logistical regression analysis is a similarly popular – but also potentially flawed – methodology for developing business-failure prediction models. Logistic regression is generally considered less demanding than MDA in terms of its application because "… no assumptions are made regarding prior probabilities of failure or the distributions of [the models'] independent variables …" (Balcaen & Ooghe, 2006, p.69). But, logistic regression models are very sensitive to multicollinearity, and can be significantly affected by outliers and missing values (Balcaen & Ooghe, 2006). Since failure prediction models are generally based upon financial data and ratios – which almost by definition are highly correlated – multicollinearity is a significant problem with such applications.

In addition to these methodological issues, Balcaen and Ooghe (2006) also pointed out several other potential modeling flaws. First, they noted that, regardless of the methodology applied, the definition of “failure” is often arbitrary and subjective, and may not in fact be dichotomous, leading to significant issues when applying any models (but especially when logit is the method used, as it assumes a clearly dichotomous dependent variable). For example, is failure the same as bankruptcy, or financial distress, or loan default, or some other criterion? Filing for bankruptcy, it has been noted, may be a strategic decision or result from external events rather than from financial causes (Balcaen & Ooghe, 2006; Hill et al, 1996). In addition, Zmijewski (1984) had earlier suggested that because data for these distressed firms was often unavailable, researchers tended to select companies whose data was accessible, which led to sample-selection biases and other “built-in” sources of error.

Further, data instability and other forms of sampling selectivity have been identified as generally problematic when developing these models. In order for a classification methodology to be used in a predictive context, the relationship between variables must be assumed to be stable over time. However, there is ample evidence that financial data is often unstable due to changes in the market, environment, or corporate strategy (Charitou et al, 2004). In fact, such data instability may be particularly significant among failing – or about to fail – firms (Dambolena & Khoury, 1980).

Sample selectivity is especially problematic when using matched pairs of failing and non-failing firms, which has frequently been the case with prediction models, as it allows researchers to control for some variables that are believed to be significant (Balcaen & Ooghe, 2006). Such selective sampling may result in biased and, therefore, overstated, non-generalizable results due to its over-sampling of failed firms in the dataset (Platt & Platt, 2002; Zmijewsji, 1984). Moreover, if the matching criteria are in any way linked to failure probability –such as when size or age are the bases for the matching of these firms – this may result in a selection bias and limit the prediction power of the model (Taffler, 1982).

Thus, this research recognizes (based on these reviews) that many previous studies have used similar approaches, but may have been methodologically flawed in several respects. Instead, this study explores the application of a proven and very flexible method, which has not been used in this domain: Conjoint analysis.

Motor Carriers

In addition to the modeling and methodological concerns raised in this section, it is also noted that only rarely has the motor carrier industry been placed under this microscope. In fact, in a recent review article regarding all forms of empirical, management research in the supply-chain management (SCM) domain, only two articles were cited that looked at the transportation sector at all (Cheng & Grimm, 2006). Yet, as Platt and Platt note (1994), financial measures and determinants of failure may well be industry dependent – and therefore they suggest single-industry studies in order to deal with these issues. So while extensive single-industry studies have been conducted in the financial services and retail sectors, only one has examined the motor carrier industry and that study focused primarily on financial structure, rather than strategy (Zingales, 1998). Thus, an apparent gap in the research literature that this study will address is the lack of a motor carrier industry-specific prediction model.

Resilience Models

As noted earlier, supply chain resilience is an emergent stream of literature, building on the fast-growing field of supply chain risk by adding the relatively new concept of strategic resilience. To date there has been almost no empirical work in field; this study is believed to be among the very first quantitative studies to emerge from this domain.

The resilience scoring model that this research develops will enable motor carriers and other supply chain member firms to more accurately analyze the strengths and weaknesses of motor carriers and predict the likelihood of their exit from the industry. The resilience score is an adaptation of the familiar consumer-credit scoring model, with 900 being the highest (i.e., most positive) score, and 300 being the lowest (i.e., least positive) score. Thus, 600 was considered the midpoint or theoretically, the median score. Motor carriers' with scores above the model's midpoint value are expected to be more resilient and, therefore, better able to withstand disruptive environmental change in the subsequent year, whereas those with scores below the midpoint are less likely to withstand such change.

H $_{8}$ – Motor carriers with higher resilience scores (i.e., above the midpoint) are ***less likely to exit*** the industry in the following year; conversely, motor carriers with lower resilience scores (i.e., below the midpoint) ***are more likely to exit*** the industry in the following year.

Similarly, the resilience model is also expected to do a better job of identifying more- and less-resilient motor carriers *two years* into the future. Motor carriers' with scores above the model's midpoint value are expected to be more resilient and therefore are better able to withstand environmental change two years subsequent to having a higher score, whereas those with scores below the midpoint are less likely to withstand such change two years forward.

H $_{9}$ – Motor carriers with higher resilience scores (i.e., above the midpoint) are ***less likely to exit*** the industry in the second year following a high score; conversely, motor carriers with lower resilience scores (i.e., below the midpoint) ***are more likely to exit*** the industry in the second year following a low score.

Regardless of which timeframe is considered – looking forward either one or two years hence – the resilience model developed in this study is expected to provide better quality prediction results than previously developed models. The reasoning behind this better performance is, first, the use of a newer methodology, based on conjoint analysis, is anticipated to provide superior results. Second, by identifying and utilizing metrics that are specific to the motor carrier industry, it is believed that the model's results will exceed those achieved with non-specific data. Therefore:

H $_{10}$ – The motor carriers' resilience scoring model accuracy will outperform the grand mean accuracy of previous, generic prediction models (i.e., better than 85% accuracy).

Conjoint Analysis

Conjoint analysis is the most-used marketing research method for examining consumers' tradeoffs or choices among multi-attribute products or services (Green et al, 2001). Since its introduction in the mid-1970s, conjoint analysis (or CA) has been used in hundreds of published academic studies and doubtless thousands of commercial applications. “Marketing’s widespread utilization of conjoint analysis … led to its adoption in many other areas [besides New Product Development (NPD), for which it was initially developed], such as segmentation, industrial marketing, pricing, and advertising” (Hair et al, 2006, p. 459).

Conjoint analysis belongs to a class of multivariate techniques that “decompose” choice responses (the dependent variables) in order to estimate the dependence relationships, enabling researchers to study the underlying decision-making processes (Green & Srinivasan, 1990). Given an evaluation, the dependent variable is decomposed by relating the independent variables to the dependent one. With compositional research methods (such as MDA or logistical regression), on the other hand, researchers collect *both* independent and dependent variables from respondents and then use these data to estimate or “compose” a predictive model (Lohrke, Holloway & Wooley, 2010).

The conjoint model comprises two requisite elements. First, independent variables, usually referred to as attributes (or factors), must be categorical with a minimum of two levels each. The number of factors and levels can be varied, and significant streams of research have considered whether these choices might meaningfully impact the resulting preferences. For example, there is evidence that the more levels an attribute offers, the more important the factor is considered by evaluators (see for example Wittink et al, 1989).

The complete range of potential attributes and levels are combined in order to create a comprehensive set of unique choice alternatives, or *profiles*; a so-called full-profile model has one set of all possible combinations. But, as the number of factors and levels increases, the number of profiles to be evaluated grows exponentially (Timmermans &

Molin, 2009). Another substantial literature focuses on how this process can be performed efficiently when the number of profiles to be considered – often numbering well into the hundreds – is clearly beyond the ability of evaluators to meaningfully compare.

The second critical element of CA is the dependent variable. This is stated as a preference or score, and is viewed as a tradeoff based on the various alternatives the respondent has been offered. Preferences can be established in at least two specific ways, and these approaches have been examined for significant differences in results. (While such differences *have* been found in the research, such discussion is considered beyond the scope of this study. See for example Jaeger et al, 2001) The two most frequently used methods are ranking, in which the respondent orders the profiles from highest (most preferred) to lowest (least preferred), and scoring (or rating) each profile, most often on a scale from 1 (lowest) to 100 (highest). Each respondent typically evaluates the complete set of profiles – although, as noted earlier, various alternatives have been developed in order to reduce the respondent's decision-making burden.

Conjoint analysis partitions respondents' choices into underlying preference structures and decision rules by collecting data as respondents make their decisions; researchers therefore assess respondents' actual preference choices, rather than their recalled theories of action, which is frequently what is captured when surveying respondents about past decisions (Argyris & Schon, 1974). In doing so, conjoint avoids validity threats such as post-hoc revisionism based on social desirability, faulty memory, or inability to articulate complex decision processes (Lohrke, Holloway & Wooley, 2010). Moreover, conjoint analysis, unlike all other multivariate methods, can be performed at the individual level, comparing just a few – or even just one – evaluator's preferences across a range of potential profiles (Hair et al, 2006).

As previously noted, with a ‘‘compositional’’ research approach researchers obtain both independent and dependent variables from respondents and then use these data to estimate or ‘‘compose’’ the predictive model. But with CA, researchers identify the various attributes to be considered (e.g., expected product reliability, color, and packaging), specify levels or categories for each attribute (e.g., high/medium/low, red/blue/green, or A/B/C), and then present respondents with profiles based on combining the selected attributes at different levels. Because the levels are known, researchers need only collect respondents' ratings to use as the dependent variable and CA estimates or ‘‘decomposes' the importance that respondents assigned to each attribute (Hair et al, 2006). In short, whereas with compositional methods, independent variable levels are identified by the respondents, in conjoint analysis they are set by the researcher. The advantage of conjoint is that researchers can uncover how important different attributes are to respondents by forcing them to make tradeoffs, using pre-set attributes, in a realistic manner (Lohrke, Holloway & Wooley, 2010).

Conjoint analysis produces utility scores for each attribute and level, based on the decomposition of respondents' rankings across all possible combinations of attributes and levels. For example, the total utility of a product with medium (product reliability), green (color), and type A (packaging) would be the sum of the partial utility scores or "part worths" for each attribute and level specified in the model.

Total Utility = Product Reliability (Medium) Utility

+ Color (Green) Utility

+ Packaging (Type A) Utility

In addition to its broad application to a wide variety of study types, conjoint analysis has also seen the development of numerous alternative techniques and approaches. Though there have been extensive refinements in its application, the fundamental model has not changed: Conjoint analysis depends on choices or ranking behaviors where distinct alternatives are compared and a decision is made to prefer one combination of tactics (i.e., a profile) over another (Hair et al, 2006).

Despite its widespread usage and diverse set of approaches, however, conjoint analysis has not been used when the resultant outcome is *not* a respondent's choice or a tradeoff – that is, where the dependent variable is an objective measure such as a performance metric and not a subjective pick. There were no identified studies where the rating or evaluation of profiles was not based on human behavior; that is, where the task of choosing among a set of identified alternatives was not performed by an evaluator (either as an individual or within a group).

Therefore, the goal of this study's exploration of conjoint analysis as an alternative methodology for predictive model development is to determine whether this approach has value and can produce results which are comparable to (or perhaps exceed) those resulting from other research methodologies.

Research Approach And Methods

Apart from the basic tenet of this study, that conjoint analysis was used in an unprecedented way, the methodology described in this section is believed to be distinctive along several other dimensions.

First, a broad and purposefully diverse array of 46 independent variables was assembled in order to assess the impact of various measures upon the ultimate model's development. While logistical regression analysis was used, its role was only as a method for culling this herd of attributes down to a significant and more meaningful set … from the initial 46 independent variables to a more useful set of 16. Second, rather than only examining the failure (or exit) of motor carriers as the basis for disruption, three other events were studied and incorporated within the models. Third, after running conjoint analysis and reviewing its results, a further reduction in the number of independent variables was performed based on their importance ratings in the models. Six variables appeared more frequently at a high level of importance in the conjoint output than the remaining 10, and so were used as basis for a subsequent running of conjoint analysis using the so-called parsimonious (or PARS) attribute set. And fourth, because both full and parsimonious attribute sets, multiple attribute levels, and three separate forms of dependent variables were tried, 72 different models were implemented in SPSS conjoint analysis. The results of these models were analyzed and compared, providing a unique perspective on which model could reasonably be considered "best."

Process Model

A 10-step process for creating and testing the various models was developed. (See Figure 5 below). Each step in the process model is explained in the section that follows.

1. Initial Model

Based on previous research – including various prediction models, as well as studies focusing on the motor-carrier industry – 46 ratios and independent variables were identified as being potentially significant to the development of this model. This robust set of variables includes financial ratios, operational measures, change variables, and control (demographic) data. (See Table 3.1 for a complete list of the independent variables used in the model.)

Financial ratios were identified from the ratio-analysis and bankruptcy prediction literature, including many of the ratios that Altman identified as significant in his identification of the z-score model, as well as several that were found to be important in the few transportation industry studies found. The 21 ratios in this category focus primarily on four components: Assets (total and property only), debt, total expenses, and total revenue.

Operational metrics have been mentioned extensively in the motor carrier literature as the bases for comparing performance. These 12 data include measures of size, efficiency, and focus that help differentiate motor carriers and their strategies.

Change variables were calculated in order to compare year-over-year changes in the motor carriers themselves and with respect to their external environment. Four, key operational metrics were compared from one year to the next to determine overall expansion or contraction; two financial ratios that focused on assets and were believed to be especially sensitive to change were included; and two ratios that compare the rate of change in the motor carriers to benchmarks of the industry were also calculated.

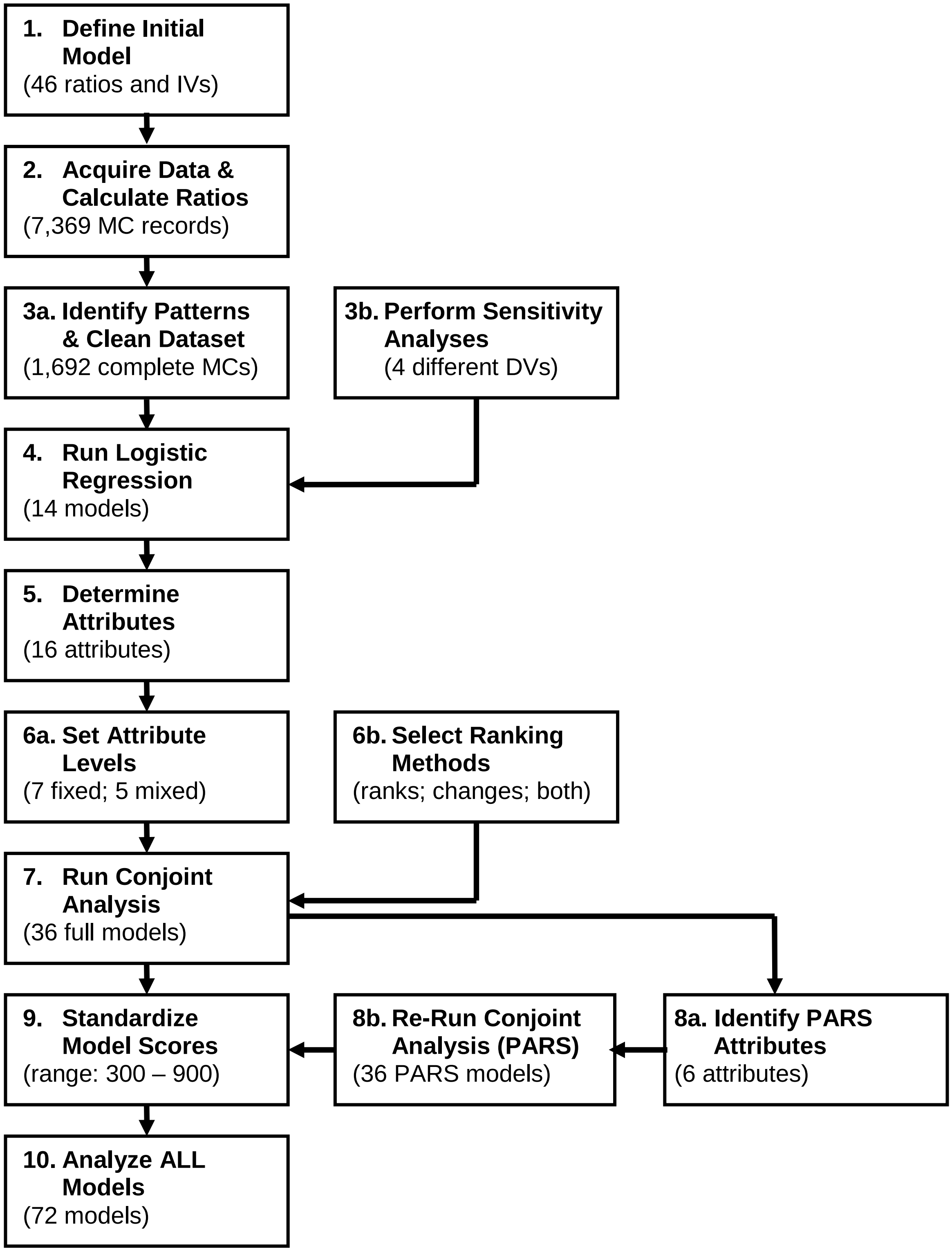


Figure 5. Resilience Scoring Model. Model Development Process Diagram

Table 3.1. Motor Carrier Resilience Model Variables – Descriptive Statistics

VAR	NAME	MEAN	MAX	MIN	STD DEV
1 Financial Ratios					
x01	Working Capital / Total Assets	0.09	14.25	-184.73	2.69
x02	Retained Earnings /Total Assets	0.23	23.11	-184.74	2.83
x03	EBIT / Total Assets	0.05	16.33	-23.54	0.56
x04	Sales / Total Assets	4.13	819.98	-38.79	11.65
x05	Market Value of Equity / Book Value of Debt	6.73	7174.91	-690.81	140.94
x06	Operating Ratio	0.9954	54.49	0.11	0.74
x07	Return on Sales	0.01	0.89	-53.49	0.74
x08	Total Debt/ Total Assets	0.70	185.73	-13.39	2.73
x09	Net Current Assets / Total Assets	0.52	4.45	-1.65	0.27
x10	Net Current Assets / Total Operating Revenue	0.18	45.60	-349.00	4.23
x11	Total Op Revenue / Total Operating Property	109.15	72692.13	-126.13	1254.84
x12	Total Maintenance / Total Operating Property	3.72	2129.60	-12.77	39.22
x13	Total Fuel / Total Operating Property	5.33	5869.95	-0.17	81.34
x14	Total Wages / Total Operating Property	19.19	10399.45	-16.74	207.03
x16	Cash Flow / Fixed Expenses	40.4	28576.44	-9028.03	482.27
x20	Leverage (Total Debt / Total Equity)	19.95	145835.57	-13265.76	1715.33
x30	Wages et al / Total Operating Expenses	0.35	1.00	-0.01	0.16
x31	Debt-to-capital	0.70	185.73	-13.39	2.73
x32	Net Debt-to-capital	0.61	185.73	-13.39	2.75
x33	Interest / Total Op Expenses	0.01	1.38	-0.18	0.03
x34	A/R / Total Op Revenue	0.14	113.29	-0.30	1.43

Table 3.1. (continued)

VAR	NAME	MEAN	MAX	MIN	STD DEV
2 Operational Metrics					
x15	LTL Focus	0.07	2.90	0.00	0.23
x17	AGR	0.04	8.13	-1.00	0.23
x19	lnSize (Natural Log Revenue)	16.38	23.49	5.01	1.18
x21	Market Share	0.0003	0.09	0.00	0.003
x24	Service (Wages / Total Miles)	3.99	9273.34	-0.02	109.68
x25	Efficiency (Total Miles / Units)	51328	17625600	0.00	245676.23
x26	Cost Per Mile (Total Op Expenses / Total Miles)	9.7428	17182.98	0.09	211.36
x27	Price Per Mile (Total Op Revenue / Total Miles)	9.8861	17030.85	0.10	211.00
x28	Insurance (per Mile)	0.34	615.48	-0.05	7.58
x29	Fuel / Total Operating Expenses	0.10	0.73	0.00	0.07
x41	Operating Income (000)	2473	1249516	-123803	28492
x45	Operating Revenue (000)	55836	15950097	150	447276
3 Change Variables					
x40	Change in Operating Revenue *vs*. Change in TSI	-0.0054	0.66	-5.53	0.13
x22	Change in Operating Ratio	0.0134	33.05	-1.00	0.45
x23	Change in Operating Revenue	0.04	8.13	-1.00	0.23
x39	Change in Operating Revenue *vs*. Change in ISM	0.0031	1.06	-2.73	0.10
x42	Change in Operating Income (000)	-69295	204263	-285999	8323
x43	Change in Total Debt	0.2338	1496.18	-552.01	18.82
x44	Change in Total Debt to Total Assets	0.4092	2076.19	-154.13	27.81
x46	Change in Operating Revenue	0.0379	8.13	-1.00	0.23

Table 3.1. (continued)

VAR	NAME	MEAN	MAX	MIN	STD DEV
4 Control Variables					
x18	Age	2270.36	3769.00	22.00	957.54
x35	Carrier Type	n/a	7	1	n/a
x36	FMCSA Region	n/a	4	1	n/a
x37	MCs in FMCSA Region by Year	410.85	612	211	129.73
x38	MCs of Type by Year	574.16	930	8	286.23

<u>Control variables</u> include five basic identifiers such as relative age and FMCSA region. Also part of this category are two measures of density: Motor carriers in the region and motor carriers of a given type.

2. *Data and Ratios*

Raw data were acquired from several sources, the primary one being the Federal Motor Carrier Safety Administration (FMCSA) – a unit of the U.S. Department of Transportation (hereinafter DOT). FMCSA data includes five years (1999 – 2003) of self-reported, detailed financial and operational data for Class I and Class II motor carriers.

DOT divides the trucking industry into three major sectors: Private carriers, for-hire truckload (TL) carriers , and for-hire less-than-truckload (LTL) carriers. Private carriers handle freight for specific firms and supply chains (e.g., Walmart) and do not engage in for-hire operations; these motor carriers were excluded from this analysis.

DOT further categorizes for-hire motor carriers based on their annual revenues: Class I carriers generated more than $10 million in annual revenues; Class II carriers produced between $3 and $10 million; while Class III carriers produced revenues of less than $3 million. According to the 2003 Annual Reports that Class I and II carriers filed with FMCSA (the latest year for which data is currently available), there was a total of 2,137 motor carriers in these two groups. Of this, 196 (9.2 percent) classified themselves as LTL carriers, and 1,142 (53.4 percent) were classified TL carriers; the other 799 firms carried containers, parcels (UPS and

FedEx) or did not provide any classification (based on author's calculations using 2003 annual reports' data from Bureau of Transportation Statistics).

Until 2003, Class I motor carriers were required to report to DOT both quarterly (on an estimated basis) and annually; Class II motor carriers only reported annually; and Class III motor carriers did not have to report at all. Despite this reporting requirement, not all Class I and II motor carriers had complete, 5-year sets of data for a variety of reasons discussed further in section 3, below. The acquired dataset included 3,769 unique motor carriers (as determined by their U.S. DOT numbers), with reporting firms having from one- to five-years' worth of data. (The total number of motor carriers' records obtained was 12,069.)

Each of the 46 independent variables was calculated from the acquired dataset, except for four (4) variables which required external data to be determined (two density measures and two change measures, based on change in operating revenues versus two external indices). All variables were standardized based on the five-year model timeframe, and z-scores that exceeded ±4 standard deviations in either direction from the mean (i.e., outliers) were replaced with an "n/a" designation.

3a. Patterns and Clean Dataset

The dataset was "expanded" such that each unique motor carrier had a full set of five-year records, though only those years with reported data were populated. This resulted in various "patterns" of data records, ranging from five complete to just one year of data, with zero to four years of empty records.

Gaps in data records can occur for several possible reasons: (1) Failing to report (since the data is self-reported, this happens surprisingly frequently for a mandated filing); (2) Changes in classification, such as falling below the $3 million annual revenue requirement minimum for Class II carriers, and therefore not being required to report for a given year; and (3) Exiting the industry altogether, either due to bankruptcy – which could be considered an extreme form of reason (2) – or acquisition. Of the full dataset, there were:

- 1,128 – complete, 5-year record sets
- 654 – 4-year record sets (i.e., one "missing" year)
- 589 – 3-year record sets
- 648 – 2-year record sets
- 750 – 1-year record sets

As this research is based on longitudinal analysis, certain motor-carrier data-set patterns were deemed unusable. The following prerequisites were imposed in order for a motor carrier's reported data to be included in the subsequent analysis data-set:

- Motor carriers must have reported data in 1999; firms which entered the industry after 1999 were not considered in the model
- Motor carrier had to have a minimum of two reported years (i.e., 1999, plus one more)

In the only known previous study to apply a prediction model to motor carriers, Zingales (1998) defined industry "exit" as occurring when a motor carrier disappeared from the American Trucking Associations' (ATA) dataset. Although carriers can cease reporting to the U.S. DOT (whose data are cleaned and subsequently published by the ATA) for several reasons, as noted earlier, remaining in the dataset year over year was considered a surrogate for survival as a separate organization (Zingales, 1998). Therefore, in determining which members of the dataset had exited over the course of the five years examined here, the following additional rules were applied:

- To be considered an "exit" a motor carrier had to have two or more contiguous years of *non-reported* data – and not subsequently appear in any later year

- To be considered a "non-exit," a motor carrier must have had two or more years of reported data, including 1999 and 2003, and have no more than one missing year

Hence, certain data patterns were deemed acceptable and included in the subsequent analysis. The first four listed below are considered non-exit patterns; the remaining three are exit patterns:

<u>Non-Exit Patterns</u> (Data for each of the identified years; blank years are "missing")

1. 1999 / 2000 / 2001 / 2002 / 2003 (n = 1,128)

2. 1999 / ____ / 2001 / 2002 / 2003 (n = 44)

3. 1999 / 2000 / ____ / 2002 / 2003 (n = 55)

4. 1999 / 2000 / 2001 / ____ / 2003 (n = 33)

Exit Patterns

5. 1999 / 2000 / 2001 / ____ / ____ (Exited in 2002) (n = 189)

6. 1999 / ____ / 2001 / ____ / ____ (Exited in 2002) (n = 16)

7. 1999 / 2000 / ____ / ____ / ____ (Exited in 2001) (n = 227)

The resulting data set has a total of 1,692 motor carriers retained for further analysis based on their having meaningful data and reporting patterns. Motor carriers with a missing, non-exit year (patterns 2, 3, 4, and 6) were identified and the missing year of data was inserted as the mean of the two, immediately adjacent years (the one before, and the one after). When a field within a reported year was empty, one of the following methods was used to fill this void:

- If the missing field could be determined from the existing data (such as the sum of two other fields), the appropriate value was calculated and inserted.
- If the missing field could not be determined as above, the mean of the two adjacent years' data (before and after) was calculated and inserted.
- If the missing field was descriptive (such as a classification code), no value was inserted and an "n/a" was used to denote this.

Therefore, the final dataset comprised 1,260 motor carriers that displayed a non-exit pattern (74.5%), and 432 (24.5%) that were considered to be exits – 227 exiting in 2001, and 205 exiting in 2002 – for a total of 1,692 motor carriers.

3b. Sensitivity Analyses

Nearly all prediction models have used failure or bankruptcy as dichotomous outcomes in their analyses (despite the fact that the definition of these events is open to interpretation; see for example Cybinski, 2001). As a scoring model, it was appropriately noted that there are other forms of disruptive events which – while not necessarily resulting in failure – *do* very negatively impact these firms. Besides exits, three other events were identified as representing highly disruptive outcomes: (1) Substantial decreases in operating revenue; (2) Substantial increases in operating ratio (due either to increases in expenses, decreases in revenues, or both), and (3) substantial decreases in operating income.

Unlike exits, however, these three outcomes are not, by their nature, dichotomous, and can occur along a fairly broad continuum. In this model, however, disruptive events were defined at some level of occurrence that would enable logistic regression to correctly identify which variables best helped classify motor carriers that would be subject to the potential outcome. The impact of these events needed to be relatively uncommon and severe – not routine fluctuations in year-over-year results – and so sensitivity analyses were used to established a sufficiently substantial events for inclusion in the subsequent models.

It was assumed that the likelihood of these events – as severe as those that would be expected to be highly disruptive – would occur in less than 10% of motor carriers over the five-year span of the data; however, in order to be significant enough, it was similarly assumed that these events would happen in at least 1% of the instances measured. Sensitivity analyses run for each of the potentially negative outcomes revealed the following disruptive-event settings:

- Operating revenue – Year-over-year ***decreases*** of 20% occurred in 260 instances (3%)
- Operating ratio – Year-over-year ***increases*** of 5 points occurred in 572 instances (7%)
- Operating income – Year-over-year ***decreases*** of 100% occurred in 971 instances (11%)

Although the operating income event occurred slightly more often than the 10% maximum figure that was initially set, it was felt that to exceed 100% strained credibility (though clearly, given the frequency with which this event actually occurred, operating income was an extremely volatile measure in this industry, at least during this five-year timeframe). Given the five-year dataset and the previously described requirements for an exiting firm, 14 year-pair models resulted – four for each of the non-exit based models (3 models x each of 4 year-pairs) and two exit-based models (exiting in 2001 or 2002). These 14 disruption models were then subjected to logistic regression analysis.

4. Logistic Regression Analyses

Unlike most previous prediction studies which build models based on the results from one methodology, this schema uses logistic regression (or “logit”) to narrow the range of independent variables and ratios for further consideration. Although discriminant analysis and logistic regression analysis are frequently used compositional models and generally result in similar outcomes, Hair and associates (2006) suggested that logistic regression is preferable because it is more robust when assumptions of multivariate normality and equal variance-covariance matrices across groups cannot be made – which was believed to be the case for this model.

> Discriminant analysis relies on *strictly meeting* the assumptions of multivariate normality and equal variance-covariance matrices across groups – assumptions that are not met in many situations. Logistic regression does not face these strict assumptions and is much more robust when these assumptions are not met, making its application appropriate in many situations. (Hair et al, 2006, p. 355)

A matched set of motor carriers was constructed for each outcome model. The motor carriers were randomly drawn from the full dataset, except that for every carrier where the studied disruptive event occurred, another carrier was chosen in which the event did not occur; matching was *not* done in terms of any other characteristics, however. Applying forward stepwise logit analysis, the maximum probability for entry was set at 10%, thereby identifying which variables were most significant to the models' prediction capability.

Each model's classification accuracy was compared to chance which, given a matched set of motor carriers, was approximately 50:50. Following Hair and associates suggestion, "classification accuracy should be at least one-fourth greater than that achieved by chance … " (2006, p. 303), 62.5% or better prediction accuracy was required for both the analysis and the holdout sets. As shown in Table 3.2, of the 14 disruption-event models, only nine achieved classification accuracies of 62.5% or greater, and of those nine, four models' holdout sets failed to reach the minimum cutoff level for classification. Therefore, just five models were considered meaningful predictors at levels significantly better than mere chance,

and only the independent variables that were entered into the analysis from these models were set aside for further examination.

5. Model Attributes

Based on the results from logistic regression analysis in step 4, five models evidenced significant ability to accurately classify motor carriers impacted by disruptive events. Sixteen independent variables were culled from the list of 46, based on their presence in one of the five significant models. The 16 remaining variables were also classified into three tiers based on their combined frequency and order-of-entry scores; these tier designations would be further utilized in conducting the planned conjoint analysis. Three variables were considered High impact because they appeared as significant in more than one model; nine were Medium impact because, while they only appeared in one model, they were either the first or second variable entered (meaning they were the most significant); and four were Low impact because they appeared once at lower levels. (See Table 3.3 for a listing).

6a. Attribute Levels

Conjoint analysis requires that all independent variables be categorical; hence, each attribute was classified into categorical buckets, based on the number of levels required by the model.

Table 3.2. Logistic Regression Results

MODEL	EVENT	YEAR(S)	ANALYSIS	HOLDOUT	RETAINED
1	**Exit**	2000	69.6% (n = 224)	51.9% (n = 224)	NONE [1]
2		2001	57.5% (n = 204)	55.5% (n = 206)	NONE [2]
3	**Operating Revenue Decrease by 20%**	1999	60.4%) (n = 52)	58.1% (n = 52)	NONE [2]
4		2000	78.0% (n = 94)	64.0% (n = 94)	x17 x30 x33 x40 x42
5		2001	70.0% (n = 72)	62.5% (n = 70)	x09 x13 x19 x21
6		2002	80.0% (n = 44)	48.7% (n = 44)	NONE [1]
7	**Operating Ratio Increase by 5 Points**	1999	70.8% (n = 226)	60.2% (n = 224)	NONE [1]
8		2000	67.6% (n = 145)	58.1% (n = 144)	NONE [1]
9		2001	74.3% (n = 114)	64.8% (n = 114)	x03 x30 x37 x41
10		2002	79.5% (n = 88)	65.1% (n = 88)	x04 x07 x10 x20 x24 x27 x28 x33
11	**Operating Income Decrease by 100%**	1999	64.5% (n = 336)	51.0% (n = 336)	NONE [1]
12		2000	63.4% (n = 246)	53.4% (n = 246)	NONE [1]
13		2001	66.3% (n = 206)	63.2% (n = 208)	x21 x22 x30 x33 x35
14		2002	63.1% (n = 182)	58.1% (n = 182)	NONE [1]

NOTES:

[1] Analysis sample achieved minimum classification criterion of 62.5%, but Holdout sample did not.

[2] Neither Analysis nor Holdout sample achieved minimum classification criterion of 62.5%.

A key variant in conjoint analysis is the number of levels each attribute uses in establishing the various model “profiles.” There is substantial evidence that the number of levels presented directly affects the importance associated with the attribute (see for example Wittink et al, 1989), such that the more levels a factor had, the more important to the ultimate decision this attribute appeared to be. This assumes, however, that the profiles are subjectively ranked or scored by study participants who evaluated these choices, and hence that these preference decisions were impacted by reviewers’ perceptions of the attribute profiles.

This was not the case in this model’s use of conjoint analysis; the evaluations were determined by objectively ranking the performance of the carriers on objective scales (choice of which is described further below) and therefore it is not believed that the number of levels will directly affect attributes’ importance. Nevertheless, as part of this exploratory study, various numbers of levels will be used in order to determine the impact on the models’ “fit.” While not expected to alter the importance of an attribute, it is hypothesized that having more levels will lead to better model predictive ability.

The number of levels was established in two ways: (1) A fixed number of levels was set across all attributes included in the model, with the number of levels ranging from two to eight; and (2) A variable number of levels was set, related to the importance classification tiers discussed previously, with the highest number of levels assigned to the most impactful attribute (using the three-tier, High, Medium, and Low scale previously described). Thus, there were seven fixed-level models

Table 3.3. Logistic Regression Variables Retained for Inclusion in Conjoint Analysis

VAR	NAME	COUNT	ORDER	TIER
1 Financial Ratios				
x03	EBIT / Total Assets	1	1	MEDIUM
x04	Sales / Total Assets	1	1	MEDIUM
x07	Return on Sales	1	2	MEDIUM
x09	Net Current Assets / Total Assets	1	1	MEDIUM
x13	Total Fuel / Total Operating Property	1	2	MEDIUM
x20	Leverage (Total Debt / Total Equity)	1	4	LOW
x30	Wages et al / Total Operating Expenses	3	2.7	HIGH
x33	Interest / Total Op Expenses	3	5	HIGH
2 Operational Metrics				
x17	AGR	1	2	MEDIUM
x19	lnSize (Natural Log Revenue)	2	3.5	HIGH
x21	Market Share (% Revenue)	1	1	MEDIUM
x24	Service (Wages / Total Miles)	1	3	LOW
x41	Operating Income ($000)	1	4	LOW
3 Change Variables				
x22	Change in Operating Ratio	1	4	LOW
x40	Change in Operating Revenue *vs*. Change in TSI	1	1	MEDIUM
4 Control Variables				
x37	MCs in FMCSA Region by Year	1	2	MEDIUM

with 2, 3, 4, 5, 6, 7, or 8 levels for each attribute, and five variable-level models with 4/3/2, 5/4/3, 6/5/4, 7/6/4, and 8/7/6 attribute levels, for a total of 12 variants.

6b. Ranking Methods

SPSS Conjoint Analysis supports three methods of expressing preferences for a profile: Ranks, scores, and order. Although this model uses the most common form, ranks (the discussion as to why and the tradeoffs is considered beyond the scope of this study), the choice of what to rank was subject to analysis. The model examines the same three dependent variables that were considered in the logistic-analysis models (and whose impact was examined via sensitivity analyses – see section 3b, above) in terms of objective rankings: Operating revenue, operating ratio, and operating income. However, three separate bases for using these rankings were examined.

<u>Ranks</u> Ranked lists from best (1) to worst (n) were created for each of the three dependent variables for the specified target year.

<u>Changes</u> Ranked lists of the amount of change, year-over-year, from most positive (1) to most negative (n) was created for each of the three variables.

<u>Both</u> Combination of three ranked ranks and the three ranked changes.

7. Conjoint Analysis (Full Models)

In total, there were seven fixed and five variable attribute level models, each with three separate variants for the dependent. Based on these settings/selections (described in sections 6a and 6b, above), conjoint analysis was run using 36 distinct models. All 36 analyses ran successfully; there were no reversals for any of the models. (See Table 3.5 for a complete list of the conjoint analysis results.)

8a. Parsimonious Attributes

Prior to running conjoint, it was hypothesized that some attributes would contribute much more significantly to the models' results than would others. After running conjoint analysis with the full set of 16 attributes, and then examining the output, it was determined that not only were there factors that were more significant, but that these same attributes showed up repeatedly on the high-importance tables across numerous models.

Taking the results from the 12 Full models using the Both sets' rankings, six attributes were very important (Importance value greater than the average 5%) more than half of the time.

- **X19** ln Size (appeared 12 times; average importance: 10.61)
- **X41** Operating Income (appeared 11 times; average importance: 14.62)
- **X21** Market Share (appeared 9 times; average importance: 12.02)
- **X40** Change in Operating Revenue *vs*. Change in TSI (appeared 8 times; average importance: 13.90)
- **X07** Return on Sales (appeared 8 times; average importance: 9.94)
- **X17** Annual Growth Rate (appeared 8 times; average importance: 14.11)

Based on frequency of appearance, Size clearly matters most, followed closely (and not surprisingly) by operating income. If average importance value is considered most meaningful, instead of frequency of appearance, operating income is first, followed by annual growth rate, and change in operating revenue (and size is a fairly distant fifth place).

8b. Conjoint Analysis (Parsimonious Models)

Based on the Parsimonious (PARS) set of attributes, conjoint analysis was re-run using the same 36 distinct models with the same 12 attribute levels and three ranking methods. However, in this instance, only the six parsimonious-model attributes were considered; the non-parsimonious attributes were removed from the models. Again, all models ran successfully without reversals. (See Table 3.5 for a full set of descriptive statistics.)

9. Standardized Scores

As discussed at the outset, the intend of this research was to develop a standardized scoring model, similar in range to the well-known consumer-credit scoring model, anchored by 300 as the minimum score and 900 as the maximum possible. Raw utility scores from conjoint analysis were applied to the formula shown in Figure 6.

As a result of this standardization, there were 1,465 scores for each of the 72 models (since 227 carriers exited in 2001, they had no scores, accounting for all 1,692 motor carriers).

Table 3.4. Analysis Models

FULL MODELS			PARSIMONIOUS MODELS		
#	DV TYPE(S)	LEVELS	#	DV TYPE(S)	LEVELS
1	Both (Ranks & Changes)	2	37	Both (Ranks & Changes)	2
2	Both (Ranks & Changes)	3	38	Both (Ranks & Changes)	3
3	Both (Ranks & Changes)	4	39	Both (Ranks & Changes)	4
4	Both (Ranks & Changes)	5	40	Both (Ranks & Changes)	5
5	Both (Ranks & Changes)	6	41	Both (Ranks & Changes)	6
6	Both (Ranks & Changes)	7	42	Both (Ranks & Changes)	7
7	Both (Ranks & Changes)	8	43	Both (Ranks & Changes)	8
8	Ranks	2	44	Ranks	2
9	Ranks	3	45	Ranks	3
10	Ranks	4	46	Ranks	4
11	Ranks	5	47	Ranks	5
12	Ranks	6	48	Ranks	6
13	Ranks	7	49	Ranks	7
14	Ranks	8	50	Ranks	8
15	Changes	2	51	Changes	2
16	Changes	3	52	Changes	3
17	Changes	4	53	Changes	4
18	Changes	5	54	Changes	5
19	Changes	6	55	Changes	6
20	Changes	7	56	Changes	7
21	Changes	8	57	Changes	8
22	Both (Ranks & Changes)	4 / 3 / 2	58	Both (Ranks & Changes)	4 / 3 / 2
23	Both (Ranks & Changes)	5 / 4 / 3	59	Both (Ranks & Changes)	5 / 4 / 3
24	Both (Ranks & Changes)	6 / 5 / 4	60	Both (Ranks & Changes)	6 / 5 / 4
25	Both (Ranks & Changes)	7 / 6 / 5	61	Both (Ranks & Changes)	7 / 6 / 5
26	Both (Ranks & Changes)	8 / 7 / 6	62	Both (Ranks & Changes)	8 / 7 / 6
27	Ranks	4 / 3 / 2	63	Ranks	4 / 3 / 2
28	Ranks	5 / 4 / 3	64	Ranks	5 / 4 / 3
29	Ranks	6 / 5 / 4	65	Ranks	6 / 5 / 4
30	Ranks	7 / 6 / 5	66	Ranks	7 / 6 / 5
31	Ranks	8 / 7 / 6	67	Ranks	8 / 7 / 6
32	Changes	4 / 3 / 2	68	Changes	4 / 3 / 2
33	Changes	5 / 4 / 3	69	Changes	5 / 4 / 3
34	Changes	6 / 5 / 4	70	Changes	6 / 5 / 4
35	Changes	7 / 6 / 5	71	Changes	7 / 6 / 5
36	Changes	8 / 7 / 6	72	Changes	8 / 7 / 6

Table 3.5. Conjoint Analysis – Descriptive Statistics (Non-Standardized)

FULL MODELS

#	DV TYPE(S)	LVLS	MEAN	STD	MAX	MIN
1	Both (Ranks & Changes)	2	3.46	47.85	143.40	-116.55
2	Both (Ranks & Changes)	3	3.42	61.87	155.75	-145.17
3	Both (Ranks & Changes)	4	2.69	72.32	193.52	-169.83
4	Both (Ranks & Changes)	5	-10.54	67.31	188.05	-237.37
5	Both (Ranks & Changes)	6	307.83	3285.96	7434.80	-10138.60
6	Both (Ranks & Changes)	7	92.23	1359.58	3859.63	-3891.76
7	Both (Ranks & Changes)	8	-120.18	1144.39	2769.22	-2893.75
8	Ranks	2	4.16	91.73	215.03	-170.27
9	Ranks	3	5.29	111.84	238.24	-219.92
10	Ranks	4	-2.21	96.41	302.58	-269.11
11	Ranks	5	-7.27	115.96	275.71	-280.02
12	Ranks	6	426.52	3815.77	10967.62	-10701.80
13	Ranks	7	291.43	2037.31	7132.52	-4803.92
14	Ranks	8	-215.22	1472.09	4500.50	-3006.66
15	Changes	2	2.76	30.08	123.86	-106.36
16	Changes	3	1.55	37.55	107.27	-106.84
17	Changes	4	11.85	127.63	358.89	-363.04
18	Changes	5	-13.81	47.81	164.77	-224.99
19	Changes	6	247.79	4171.86	9633.94	-13619.48
20	Changes	7	-106.97	1312.78	3290.52	-3993.03
21	Changes	8	-49.80	1367.18	4140.66	-3944.19
22	Both (Ranks & Changes)	4 / 3 / 2	4.79	67.90	153.80	-219.27
23	Both (Ranks & Changes)	5 / 4 / 3	-15.06	69.15	178.79	-188.05
24	Both (Ranks & Changes)	6 / 5 / 4	39.11	2533.39	5250.10	-6647.65
25	Both (Ranks & Changes)	7 / 6 / 5	-6.74	70.38	211.65	-160.18
26	Both (Ranks & Changes)	8 / 7 / 6	1.86	75.39	225.29	-216.36
27	Ranks	4 / 3 / 2	6.93	122.92	251.35	-219.82
28	Ranks	5 / 4 / 3	-10.56	121.34	266.15	-272.28
29	Ranks	6 / 5 / 4	241.32	3237.82	6784.59	-8366.34
30	Ranks	7 / 6 / 5	-1.83	118.26	314.09	-274.93
31	Ranks	8 / 7 / 6	4.37	128.49	357.87	-294.76
32	Changes	4 / 3 / 2	2.65	39.45	108.35	-223.23
33	Changes	5 / 4 / 3	-19.56	46.20	202.83	-155.15
34	Changes	6 / 5 / 4	-163.10	3491.10	8889.20	-7599.83
35	Changes	7 / 6 / 5	-11.65	56.37	162.41	-222.06
36	Changes	8 / 7 / 6	-0.65	52.47	215.09	-220.40

Table 3.5. (continued)

PARSIMONIOUS MODELS

#	DV TYPE(S)	LVLS	MEAN	STD	MAX	MIN
37	Both (Ranks & Changes)	2	-0.047	1.55	2.54	-2.71
38	Both (Ranks & Changes)	3	-0.411	3.83	7.86	-12.93
39	Both (Ranks & Changes)	4	0.057	10.00	35.10	-26.22
40	Both (Ranks & Changes)	5	-0.582	18.94	47.76	-47.71
41	Both (Ranks & Changes)	6	2.464	261.64	454.76	-405.92
42	Both (Ranks & Changes)	7	3.441	225.19	575.36	-555.23
43	Both (Ranks & Changes)	8	-0.081	608.37	1452.43	-824.53
44	Ranks	2	0.037	2.95	4.07	-4.07
45	Ranks	3	0.146	8.89	18.77	-15.43
46	Ranks	4	0.597	20.90	43.30	-41.87
47	Ranks	5	0.141	34.46	72.04	-69.73
48	Ranks	6	3.482	321.92	492.30	-452.63
49	Ranks	7	4.268	273.39	690.76	-529.50
50	Ranks	8	3.497	542.73	1458.84	-711.90
51	Changes	2	-0.131	1.01	2.38	-4.21
52	Changes	3	-0.969	4.45	16.02	-22.89
53	Changes	4	-0.484	7.09	37.83	-22.26
54	Changes	5	-1.304	10.13	39.64	-51.41
55	Changes	6	1.446	283.26	630.39	-411.87
56	Changes	7	2.614	221.68	632.67	-635.22
57	Changes	8	-3.659	916.38	1681.17	-1672.95
58	Both (Ranks & Changes)	4 / 3 / 2	0.245	4.40	7.88	-8.25
59	Both (Ranks & Changes)	5 / 4 / 3	-0.020	9.29	22.36	-16.20
60	Both (Ranks & Changes)	6 / 5 / 4	-7.154	210.27	391.88	-425.40
61	Both (Ranks & Changes)	7 / 6 / 5	-1.351	33.05	87.68	-71.08
62	Both (Ranks & Changes)	8 / 7 / 6	-124.751	336.04	379.53	-819.67
63	Ranks	4 / 3 / 2	0.465	9.30	15.73	-15.57
64	Ranks	5 / 4 / 3	0.396	16.67	38.79	-29.25
65	Ranks	6 / 5 / 4	-4.863	286.34	665.23	-490.25
66	Ranks	7 / 6 / 5	0.483	60.36	129.56	-125.28
67	Ranks	8 / 7 / 6	-196.822	426.40	493.11	-997.98
68	Changes	4 / 3 / 2	0.026	3.76	11.17	-16.52
69	Changes	5 / 4 / 3	-0.432	6.95	19.19	-15.68
70	Changes	6 / 5 / 4	-9.445	254.34	498.76	-412.42
71	Changes	7 / 6 / 5	-3.184	19.35	65.70	-61.54
72	Changes	8 / 7 / 6	-52.680	319.74	464.23	-649.50

10. Analysis of Scores

Finally, detailed analysis was conducted to determine which of the scoring models produced the best – most reliable and useful – results. Full details of the analysis process and results are described in the following section.

$$\textbf{Raw MC Resilience Score}_{n} = \Sigma\ \textbf{Utility}_{1} + \textbf{Utility}_{2} + \textbf{Utility}_{3} + \ldots + \textbf{Utility}_{16\ (\text{Full})\ \underline{\textit{or}}\ 6\ (\text{PARS})}$$

$$\textbf{Standard MC Resilience Score}_{n} = 300 + \frac{(\textbf{MCR Score}_{n} - \textbf{MCR Score}_{\text{Raw Minimum}})}{(\textbf{MCR Score}_{\text{Raw Maximum}} - \textbf{MCR Score}_{\text{Raw Minimum}})} \times 600$$

Figure 6. Scoring Model. Standardized Scoring Model Calculation

Results

Despite using identical data, the 72 models that were created with this process produced a surprisingly wide range of results when applied to the 1,260 non-exiting motor carriers in this group. The question for this section of the study becomes, therefore, which model is best? Perhaps more importantly, given the exploratory nature of this research, how should the best model be determined? What are the most appropriate measures?

Nearly all of the extant literature in this general research field has focused on the model's prediction accuracy as the key success metric: How many of the firms that actually do fail (or file for bankruptcy) are predicted to do so by the model? Examining Type-I errors (i.e., not predicting companies that actually do fail, as such) is clearly an important benchmark of which model does the best job. Similarly, considering Type-II errors (incorrectly predicting companies to fail which *do not* fail) is equally problematic. Correctly classifying companies as failing or not, and minimizing the numbers of either type of errors, is the most desirable outcome; hence , minimizing both Type-I and -II errors is a critical measure of success.

In 2001, 227 motor carriers exited the industry, and another 205 carriers exited in 2002. As noted earlier, this study used Zingales (1998) definition of a motor carrier's exit as its disappearance from the American Trucking Associations database. Although carriers could cease reporting to U.S. Department of Transportation (whose data are cleaned and subsequently published by ATA) for several reasons, explained earlier, remaining in the dataset year over year is considered a reasonable surrogate for survival as a separate organization (Zingales 1998).

Given the resilience model that was developed, the expectation was that a high percentage of the 205 motor carriers that exited from the dataset in 2002 would attain low scores (i.e., below the mean value of 600) during 2001. Thus, the more motor carriers with scores that placed them in the lowest two quartiles (300 – 450 and 450 – 600) and actually did exit in the subsequent year, the higher the exit-capture rate. Model capture rates ranged from a high of more than 93% to a low of 0%: so depending on the model examined, from 0% to 93% of the following year's exits were correctly identified as having low or weak scores.

Model 50 which captured 93% of the exits with scores of less than 600, and therefore minimized Type-I errors, would generally be considered a contender for the best model title. (See Table 3.6 for a complete list of all 72 models' capture rates by quartile; Table 3.7 provides similar, cumulative capture rates.) But, careful examination of the underlying model scores suggests that these models produced very different score distributions, as well as scores themselves. Even a brief visual inspection of the histograms shows diverse results. (See Appendix B for Histograms of the scores' distributions for all 72 models). Distributions range from an evenly distributed dataset, with nearly equal numbers of motor carriers classified in each quartile, to highly skewed distributions, with large numbers of carriers classified at either end – or both ends – of the distribution. The model that produced a 93% capture rate was significantly skewed to the right – the reason that it captured such a high percentage of exits was that a very disproportionate number of carriers was classified as having low scores; more than 87% of the 1,465 motor carriers had scores of 600 or less. Stated differently, this model minimized the number of Type-I errors by not minimizing the number of Type-II errors.

Thus, an additional question emerged: What should the appropriate scores' distribution look like? With a binary-outcomes prediction model – exits versus non-exits – prediction accuracy would seem somewhat easily measured: Maximize the number of captured exits, thus minimizing Type-I errors, and simultaneously minimize Type-II errors. But this leaves a lot of territory unaccounted for, as only about 14% (205 of 1,465) of the motor carriers exited during the year being examined. Certainly, for example, there are weaker carriers that did not actually exit (their scores would be low, classifying them as Type-II errors – but their scores *should* be low). Similarly, there may be weak carriers, with scores just above the 600-point mean (and therefore *not* Type-I errors); only considering the exit-or-not conundrum ignores an important validity aspect of these scores.

Judging the Best Models

There are several different ways by which the models' scores could be classified as best; this section considers four such methods.

Capture Rates

A capture rate is determined by counting the number of exiting motor carriers that are captured by having scores of 300 to 600 (i.e., below the score-range mean). The higher the percentage of exits captured, the lower the Type-I errors and the better the model achieves its objectives; however, higher capture rates may also reflect significantly greater Type-II errors. (See Table 3.6 for a listing of capture rates by quartile; see Table 3.7 for cumulative captures by quartile.)

Table 3.6. Captures and Ranks by Quartile

FULL MODELS

#	DV TYPE(S)	LVLS	300-450 #	Rank	450-600 #	Rank	600-750 #	Rank	750-900 #	Rank
1	Both (Ranks & Changes)	2	50	29	90	26	58	31	7	63
2	Both (Ranks & Changes)	3	41	35	97	18	52	36	15	43
3	Both (Ranks & Changes)	4	50	29	91	24	57	33	7	63
4	Both (Ranks & Changes)	5	3	64	112	10	72	23	18	39
5	Both (Ranks & Changes)	6	33	40	41	60	101	12	30	17
6	Both (Ranks & Changes)	7	18	54	61	49	96	16	30	17
7	Both (Ranks & Changes)	8	20	50	112	10	50	37	23	28
8	Ranks	2	87	7	67	44	31	63	20	34
9	Ranks	3	70	16	77	36	37	56	21	31
10	Ranks	4	18	54	91	24	85	19	11	53
11	Ranks	5	49	32	89	29	47	41	20	34
12	Ranks	6	28	42	97	18	66	29	14	45
13	Ranks	7	27	43	***120***	***4***	48	38	10	54
14	Ranks	8	60	22	119	6	18	69	8	59
15	Changes	2	15	58	90	26	98	14	2	69
16	Changes	3	16	57	76	37	94	17	19	37
17	Changes	4	7	62	65	47	101	12	32	14
18	Changes	5	2	65	59	51	***131***	***4***	13	49
19	Changes	6	25	46	39	62	113	7	28	23
20	Changes	7	14	60	61	49	97	15	33	12
21	Changes	8	18	54	99	17	70	26	18	39
22	Both (Ranks & Changes)	4 / 3 / 2	2	65	100	16	76	21	27	25
23	Both (Ranks & Changes)	5 / 4 / 3	46	34	95	20	55	34	9	57
24	Both (Ranks & Changes)	6 / 5 / 4	40	36	69	42	68	28	28	23
25	Both (Ranks & Changes)	7 / 6 / 5	57	24	109	14	30	64	9	57
26	Both (Ranks & Changes)	8 / 7 / 6	19	51	116	9	58	31	12	50
27	Ranks	4 / 3 / 2	81	9	59	51	44	45	21	31
28	Ranks	5 / 4 / 3	68	17	73	38	48	38	16	42
29	Ranks	6 / 5 / 4	40	36	69	42	71	24	25	26
30	Ranks	7 / 6 / 5	57	24	95	20	38	52	15	43
31	Ranks	8 / 7 / 6	60	22	89	29	46	43	10	54
32	Changes	4 / 3 / 2	1	68	10	72	***131***	***4***	***63***	***5***
33	Changes	5 / 4 / 3	27	43	***141***	***1***	35	57	2	69
34	Changes	6 / 5 / 4	54	27	94	22	39	47	18	39
35	Changes	7 / 6 / 5	8	61	54	55	113	7	30	17
36	Changes	8 / 7 / 6	1	68	87	32	110	10	7	63

Table 3.6. (continued)

PARSIMONIOUS MODELS

#	DV TYPE(S)	LVLS	300-450 #	Rank	450-600 #	Rank	600-750 #	Rank	750-900 #	Rank
37	Both (Ranks & Changes)	2	***97***	***3***	30	66	38	52	40	9
38	Both (Ranks & Changes)	3	4	63	45	59	125	6	31	16
39	Both (Ranks & Changes)	4	49	32	***120***	***4***	33	61	3	68
40	Both (Ranks & Changes)	5	36	39	110	12	39	47	20	34
41	Both (Ranks & Changes)	6	***88***	***5***	66	45	2	71	49	8
42	Both (Ranks & Changes)	7	66	20	71	41	54	35	14	45
43	Both (Ranks & Changes)	8	***98***	***2***	57	54	38	52	12	50
44	Ranks	2	95	4	39	62	34	59	37	11
45	Ranks	3	73	13	86	33	25	66	21	31
46	Ranks	4	61	21	83	34	39	47	22	30
47	Ranks	5	77	11	66	45	39	47	23	28
48	Ranks	6	***88***	***5***	49	58	44	45	24	27
49	Ranks	7	50	29	117	8	24	67	14	45
50	Ranks	8	***119***	***1***	73	38	1	72	12	50
51	Changes	2	2	65	27	69	***146***	***1***	30	17
52	Changes	3	1	68	41	60	110	10	53	6
53	Changes	4	26	45	***130***	***2***	47	41	2	69
54	Changes	5	0	72	62	48	***135***	***3***	8	59
55	Changes	6	57	24	110	12	9	70	29	21
56	Changes	7	67	19	58	53	78	20	2	69
57	Changes	8	15	58	119	6	21	68	50	7
58	Both (Ranks & Changes)	4 / 3 / 2	72	14	53	56	48	38	32	14
59	Both (Ranks & Changes)	5 / 4 / 3	76	12	94	22	30	64	5	66
60	Both (Ranks & Changes)	6 / 5 / 4	33	40	21	70	113	7	38	10
61	Both (Ranks & Changes)	7 / 6 / 5	72	14	90	26	33	61	10	54
62	Both (Ranks & Changes)	8 / 7 / 6	19	51	15	71	70	26	***101***	***1***
63	Ranks	4 / 3 / 2	83	8	50	57	39	47	33	12
64	Ranks	5 / 4 / 3	78	10	78	35	35	57	14	45
65	Ranks	6 / 5 / 4	38	38	***125***	***3***	34	59	8	59
66	Ranks	7 / 6 / 5	68	17	73	38	45	44	19	37
67	Ranks	8 / 7 / 6	21	49	28	68	61	30	***95***	***2***
68	Changes	4 / 3 / 2	1	68	30	66	***145***	***2***	29	21
69	Changes	5 / 4 / 3	19	51	103	15	75	22	8	59
70	Changes	6 / 5 / 4	52	28	37	65	38	52	***78***	***3***
71	Changes	7 / 6 / 5	24	47	88	31	89	18	4	67
72	Changes	8 / 7 / 6	24	47	38	64	71	24	***72***	***4***

Bolded capture rates are among top five by quartile

Table 3.7. Cumulative Captures and Ranks

FULL MODELS

#	DV TYPE(S)	LVLS	300-450 #	300-450 Rank	300-600 #	300-600 Rank	300-750 #	300-750 Rank
1	Both (Ranks & Changes)	2	50	29	140	29	198	8
2	Both (Ranks & Changes)	3	41	35	138	31	190	29
3	Both (Ranks & Changes)	4	50	29	141	26	198	8
4	Both (Ranks & Changes)	5	3	64	115	46	187	32
5	Both (Ranks & Changes)	6	33	40	74	58	175	55
6	Both (Ranks & Changes)	7	18	54	79	56	175	53
7	Both (Ranks & Changes)	8	20	50	132	39	182	44
8	Ranks	2	87	7	154	15	185	37
9	Ranks	3	70	16	147	20	184	41
10	Ranks	4	18	54	109	48	194	20
11	Ranks	5	49	32	138	31	185	38
12	Ranks	6	28	42	125	41	191	26
13	Ranks	7	27	43	147	20	195	18
14	Ranks	8	60	22	***179***	***2***	197	14
15	Changes	2	15	58	105	51	***203***	***1***
16	Changes	3	16	57	92	53	186	35
17	Changes	4	7	62	72	59	173	58
18	Changes	5	2	65	61	64	192	24
19	Changes	6	25	46	64	60	177	49
20	Changes	7	14	60	75	57	172	61
21	Changes	8	18	54	117	45	187	33
22	Both (Ranks & Changes)	4 / 3 / 2	2	65	102	52	178	48
23	Both (Ranks & Changes)	5 / 4 / 3	46	34	141	25	196	15
24	Both (Ranks & Changes)	6 / 5 / 4	40	36	109	48	177	49
25	Both (Ranks & Changes)	7 / 6 / 5	57	24	166	8	196	15
26	Both (Ranks & Changes)	8 / 7 / 6	19	51	135	35	193	21
27	Ranks	4 / 3 / 2	81	9	140	29	184	41
28	Ranks	5 / 4 / 3	68	17	141	26	189	31
29	Ranks	6 / 5 / 4	40	36	109	48	180	47
30	Ranks	7 / 6 / 5	57	24	152	17	190	29
31	Ranks	8 / 7 / 6	60	22	149	18	195	18
32	Changes	4 / 3 / 2	1	68	11	72	142	68
33	Changes	5 / 4 / 3	27	43	***168***	***5***	***203***	***1***
34	Changes	6 / 5 / 4	54	27	148	19	187	33
35	Changes	7 / 6 / 5	8	61	62	61	175	53
36	Changes	8 / 7 / 6	1	68	88	55	198	8

Table 3.7. (continued)

PARSIMONIOUS MODELS

#	DV TYPE(S)	LVLS	300-450 #	300-450 Rank	300-600 #	300-600 Rank	300-750 #	300-750 Rank
37	Both (Ranks & Changes)	2	***97***	***3***	127	40	165	64
38	Both (Ranks & Changes)	3	4	63	49	66	174	57
39	Both (Ranks & Changes)	4	49	32	***169***	***4***	***202***	***5***
40	Both (Ranks & Changes)	5	36	39	146	22	185	38
41	Both (Ranks & Changes)	6	***88***	***5***	154	15	156	65
42	Both (Ranks & Changes)	7	66	20	137	33	191	26
43	Both (Ranks & Changes)	8	***98***	***2***	155	14	193	21
44	Ranks	2	***95***	***4***	134	36	168	62
45	Ranks	3	73	13	159	11	184	40
46	Ranks	4	61	21	144	23	183	43
47	Ranks	5	77	11	143	24	182	45
48	Ranks	6	88	5	137	33	181	46
49	Ranks	7	50	29	167	7	191	26
50	Ranks	8	***119***	***1***	***192***	***1***	193	21
51	Changes	2	2	65	29	71	175	55
52	Changes	3	1	68	42	68	152	67
53	Changes	4	26	45	156	12	***203***	***1***
54	Changes	5	0	72	62	61	197	12
55	Changes	6	57	24	167	6	176	51
56	Changes	7	67	19	125	41	***203***	***1***
57	Changes	8	15	58	134	37	155	66
58	Both (Ranks & Changes)	4 / 3 / 2	72	14	125	41	173	58
59	Both (Ranks & Changes)	5 / 4 / 3	76	12	***170***	***3***	200	7
60	Both (Ranks & Changes)	6 / 5 / 4	33	40	54	65	167	63
61	Both (Ranks & Changes)	7 / 6 / 5	72	14	162	10	195	17
62	Both (Ranks & Changes)	8 / 7 / 6	19	51	34	69	104	72
63	Ranks	4 / 3 / 2	83	8	133	38	172	60
64	Ranks	5 / 4 / 3	78	10	156	12	191	25
65	Ranks	6 / 5 / 4	38	38	163	9	197	11
66	Ranks	7 / 6 / 5	68	17	141	26	186	36
67	Ranks	8 / 7 / 6	21	49	49	66	110	71
68	Changes	4 / 3 / 2	1	68	31	70	176	52
69	Changes	5 / 4 / 3	19	51	122	44	197	12
70	Changes	6 / 5 / 4	52	28	89	54	127	70
71	Changes	7 / 6 / 5	24	47	112	47	201	6
72	Changes	8 / 7 / 6	24	47	62	61	133	69

Bolded capture rates are among top five by group

Table 3.8. Type I and Type II Errors

FULL MODELS

#	DV TYPE(S)	LVLS	Type I #	Type I Percent	Type II #	Type II Percent	Average Accur	Rank
1	Both (Ranks & Changes)	2	65	31.7%	673	53.4%	57.4%	29
2	Both (Ranks & Changes)	3	67	32.7%	650	51.6%	57.9%	23
3	Both (Ranks & Changes)	4	64	31.2%	683	54.2%	57.3%	32
4	Both (Ranks & Changes)	5	90	43.9%	545	43.3%	56.4%	36
5	Both (Ranks & Changes)	6	131	63.9%	256	20.3%	57.9%	22
6	Both (Ranks & Changes)	7	126	61.5%	579	46.0%	46.3%	63
7	Both (Ranks & Changes)	8	73	35.6%	688	54.6%	54.9%	40
8	Ranks	2	51	24.9%	717	56.9%	59.1%	9
9	Ranks	3	58	28.3%	670	53.2%	59.3%	7
10	Ranks	4	96	46.8%	738	58.6%	47.3%	56
11	Ranks	5	67	32.7%	650	51.6%	57.9%	23
12	Ranks	6	80	39.0%	581	46.1%	57.4%	30
13	Ranks	7	58	28.3%	916	72.7%	49.5%	48
14	Ranks	8	26	12.7%	965	76.6%	55.4%	39
15	Changes	2	100	48.8%	718	57.0%	47.1%	57
16	Changes	3	113	55.1%	595	47.2%	48.8%	52
17	Changes	4	133	64.9%	600	47.6%	43.8%	67
18	Changes	5	144	70.2%	460	36.5%	46.6%	59
19	Changes	6	141	68.8%	289	22.9%	54.1%	42
20	Changes	7	130	63.4%	549	43.6%	46.5%	61
21	Changes	8	88	42.9%	734	58.3%	49.4%	49
22	Both (Ranks & Changes)	4 / 3 / 2	103	50.2%	405	32.1%	58.8%	14
23	Both (Ranks & Changes)	5 / 4 / 3	64	31.2%	698	55.4%	56.7%	35
24	Both (Ranks & Changes)	6 / 5 / 4	96	46.8%	450	35.7%	58.7%	16
25	Both (Ranks & Changes)	7 / 6 / 5	39	19.0%	867	68.8%	56.1%	37
26	Both (Ranks & Changes)	8 / 7 / 6	70	34.1%	620	49.2%	58.3%	17
27	Ranks	4 / 3 / 2	65	31.7%	612	48.6%	***59.9%***	***3***
28	Ranks	5 / 4 / 3	64	31.2%	659	52.3%	58.2%	18
29	Ranks	6 / 5 / 4	96	46.8%	465	36.9%	58.1%	19
30	Ranks	7 / 6 / 5	53	25.9%	731	58.0%	58.1%	20
31	Ranks	8 / 7 / 6	56	27.3%	694	55.1%	58.8%	15
32	Changes	4 / 3 / 2	194	94.6%	85	6.7%	49.3%	50
33	Changes	5 / 4 / 3	37	18.0%	1052	83.5%	49.2%	51
34	Changes	6 / 5 / 4	57	27.8%	819	65.0%	53.6%	44
35	Changes	7 / 6 / 5	143	69.8%	468	37.1%	46.6%	60
36	Changes	8 / 7 / 6	117	57.1%	622	49.4%	46.8%	58

Table 3.8. (continued)

PARSIMONIOUS MODELS

#	DV TYPE(S)	LVLS	Type I #	Type I Percent	Type II #	Type II Percent	Average Accur	Rank
37	Both (Ranks & Changes)	2	78	38.0%	600	47.6%	57.2%	33
38	Both (Ranks & Changes)	3	156	76.1%	357	28.3%	47.8%	55
39	Both (Ranks & Changes)	4	36	17.6%	859	68.2%	57.1%	34
40	Both (Ranks & Changes)	5	59	28.8%	675	53.6%	58.8%	13
41	Both (Ranks & Changes)	6	51	24.9%	797	63.3%	55.9%	38
42	Both (Ranks & Changes)	7	68	33.2%	654	51.9%	57.5%	28
43	Both (Ranks & Changes)	8	50	24.4%	947	75.2%	50.2%	46
44	Ranks	2	71	34.6%	583	46.3%	59.5%	6
45	Ranks	3	46	22.4%	750	59.5%	59.0%	11
46	Ranks	4	61	29.8%	656	52.1%	59.1%	10
47	Ranks	5	62	30.2%	654	51.9%	58.9%	12
48	Ranks	6	68	33.2%	593	47.1%	***59.9%***	***2***
49	Ranks	7	38	18.5%	830	65.9%	57.8%	25
50	Ranks	8	13	6.3%	1089	86.4%	53.6%	43
51	Changes	2	176	85.9%	228	18.1%	48.0%	54
52	Changes	3	163	79.5%	488	38.7%	40.9%	71
53	Changes	4	49	23.9%	1124	89.2%	43.4%	68
54	Changes	5	143	69.8%	472	37.5%	46.4%	62
55	Changes	6	38	18.5%	909	72.1%	54.7%	41
56	Changes	7	80	39.0%	518	41.1%	***59.9%***	***1***
57	Changes	8	71	34.6%	810	64.3%	50.5%	45
58	Both (Ranks & Changes)	4 / 3 / 2	80	39.0%	579	46.0%	57.5%	27
59	Both (Ranks & Changes)	5 / 4 / 3	35	17.1%	861	68.3%	57.3%	31
60	Both (Ranks & Changes)	6 / 5 / 4	151	73.7%	433	34.4%	46.0%	64
61	Both (Ranks & Changes)	7 / 6 / 5	43	21.0%	764	60.6%	59.2%	8
62	Both (Ranks & Changes)	8 / 7 / 6	171	83.4%	389	30.9%	42.9%	69
63	Ranks	4 / 3 / 2	72	35.1%	574	45.6%	***59.7%***	***5***
64	Ranks	5 / 4 / 3	49	23.9%	758	60.2%	58.0%	21
65	Ranks	6 / 5 / 4	42	20.5%	808	64.1%	57.7%	26
66	Ranks	7 / 6 / 5	64	31.2%	620	49.2%	***59.8%***	***4***
67	Ranks	8 / 7 / 6	156	76.1%	493	39.1%	42.4%	70
68	Changes	4 / 3 / 2	174	84.9%	336	26.7%	44.2%	65
69	Changes	5 / 4 / 3	83	40.5%	753	59.8%	49.9%	47
70	Changes	6 / 5 / 4	116	56.6%	821	65.2%	39.1%	72
71	Changes	7 / 6 / 5	93	45.4%	721	57.2%	48.7%	53
72	Changes	8 / 7 / 6	143	69.8%	534	42.4%	43.9%	66

Bolded capture rates are among top five by group

As mentioned earlier, several models achieved high capture rates. The top five models all captured more than 80% of the exits (with scores below 600; in fact, most – though not all – of the eight models also captured more than 40% of exits with scores less than 450, placing these carriers in the lowest quartile of the distribution.

Type-I vs Type-II Errors

Comparing Type-I versus Type-II error rates provides a different insight on the scoring models' effectiveness. Viewing the models simply as above and below the mean score of 600, Type I errors are exiting motor carriers whose resilience scores are 600 and greater; Type II errors are non-exiting carriers with scores less than 600. Table 3.8 provides a list of Type I and II error rates as a percentage. Following Altman and Sabato (2007), column 8 is the complement of the average Type I and Type II error rates (note that percentage is used instead of ranking total errors, which would strongly favor fewer Type II errors because less than 15% of the carriers exit during the period, so the potential for many more Type II errors exists.)

Table 3.8 shows that the top five models, using this error rates' methodology, are 56, 48, 27, 66, and 63, in that order.

Odds Ratio

Calculating the odds ratio for exiting motor carriers for the lower quartiles of the model reflects the fewest Type-II errors, but may be at the expense of more Type-I errors. (See Table 3.9 for a complete listing of odds ratios and ranks for the lower two quartiles.) This table shows that the top five models, based on odds ratios for scores ranging from 300 to 600, are 5, 22, 24, 56, and 29, in that order.

Measures of Fit

While the goal of a failure-prediction model may be to maximize captures and minimize Type-I and -II errors, this is not necessarily the best case for a scoring model. Moreover, the literature is virtually silent with regard to what such a distribution should be expected to look like. For example, two possible distributions for consideration could include either an even distribution with a nearly equal number of scores in all four quartiles or a normal distribution of standardized scores around the forced mean of 600.

Three separate measures of fit and overall scores' distribution were calculated: (1) Kendall's Tau, calculated for both the estimation and holdout samples as part of conjoint analysis in SPSS; (2) Shapiro-Wilk's value, a measure of distribution normality, also available from SPSS; and (3) a distribution Alignment rating based on how evenly the models' scores were distributed across all four quartiles; and. These metrics, which are only available for the total distribution (and not by quarters) are provided in Table 3.10.

While there was little surprise that the Normality and Alignment scores results were almost opposites, it was somewhat startling that none of the three measures overlapped in any significant way, with just one exception – Model 63 has both a top-five Kendall's tau result, suggesting a good fit to the model, and a top-five alignment score, suggesting a fairly even distribution of scores across all four quartiles.

The top five based on Kendall's Tau were Models 37, 63, 45, 44, and 46; based on Shapiro-Wilk's were Models 35, 10, 17, 12, and 20; and using distribution Alignment score were Models 63, 58, 27, 72, and 70.

Table 3.9. Odds Ratios

FULL MODELS

#	DV TYPE(S)	LVLS	300-450 Ratio	300-450 Rank	450-600 Ratio	450-600 Rank	300-600 Ratio	300-600 Rank
1	Both (Ranks & Changes)	2	0.074	35	0.034	16	0.043	29
2	Both (Ranks & Changes)	3	0.101	26	0.035	14	0.045	22
3	Both (Ranks & Changes)	4	0.113	21	0.029	31	0.043	31
4	Both (Ranks & Changes)	5	0.020	54	0.046	7	0.045	27
5	Both (Ranks & Changes)	6	0.118	17	***0.066***	***3***	***0.084***	***1***
6	Both (Ranks & Changes)	7	0.038	45	0.016	66	0.019	59
7	Both (Ranks & Changes)	8	0.018	58	0.043	8	0.037	39
8	Ranks	2	0.066	37	0.031	20	0.046	19
9	Ranks	3	0.124	14	0.027	39	0.048	13
10	Ranks	4	0.019	57	0.022	51	0.022	53
11	Ranks	5	0.134	12	0.030	28	0.045	22
12	Ranks	6	0.180	7	0.035	12	0.046	18
13	Ranks	7	0.025	52	0.026	41	0.026	48
14	Ranks	8	0.027	48	0.039	9	0.034	41
15	Changes	2	0.055	40	0.019	59	0.021	54
16	Changes	3	0.027	49	0.023	48	0.024	52
17	Changes	4	0.006	67	0.016	64	0.014	66
18	Changes	5	0.020	54	0.017	62	0.018	60
19	Changes	6	0.121	15	0.032	18	0.049	11
20	Changes	7	0.031	47	0.017	63	0.019	58
21	Changes	8	0.046	44	0.023	49	0.025	50
22	Both (Ranks & Changes)	4 / 3 / 2	0.082	32	***0.063***	***4***	***0.063***	***2***
23	Both (Ranks & Changes)	5 / 4 / 3	0.149	10	0.027	38	0.041	33
24	Both (Ranks & Changes)	6 / 5 / 4	***0.221***	***5***	0.036	11	***0.059***	***3***
25	Both (Ranks & Changes)	7 / 6 / 5	0.059	39	0.030	30	0.037	40
26	Both (Ranks & Changes)	8 / 7 / 6	0.052	41	0.047	6	0.047	15
27	Ranks	4 / 3 / 2	0.077	34	0.034	17	0.052	9
28	Ranks	5 / 4 / 3	0.137	11	0.024	47	0.046	21
29	Ranks	6 / 5 / 4	***0.292***	***2***	0.031	21	***0.055***	***5***
30	Ranks	7 / 6 / 5	0.118	18	0.028	34	0.043	30
31	Ranks	8 / 7 / 6	0.112	22	0.030	27	0.046	20
32	Changes	4 / 3 / 2	0.111	23	0.015	67	0.017	63
33	Changes	5 / 4 / 3	0.016	61	0.028	33	0.026	49
34	Changes	6 / 5 / 4	0.114	20	0.020	55	0.033	43
35	Changes	7 / 6 / 5	0.102	25	0.015	68	0.018	61
36	Changes	8 / 7 / 6	0.001	71	0.022	52	0.020	55

Table 3.9. (continued)

PARSIMONIOUS MODELS

#	DV TYPE(S)	LVLS	300-450 Ratio	300-450 Rank	450-600 Ratio	450-600 Rank	300-600 Ratio	300-600 Rank
37	Both (Ranks & Changes)	2	0.061	38	0.021	53	0.045	26
38	Both (Ranks & Changes)	3	0.020	54	0.019	60	0.019	57
39	Both (Ranks & Changes)	4	0.119	16	0.028	35	0.039	37
40	Both (Ranks & Changes)	5	0.164	8	0.035	13	0.047	16
41	Both (Ranks & Changes)	6	0.048	42	0.028	36	0.037	38
42	Both (Ranks & Changes)	7	0.204	6	0.020	58	0.044	28
43	Both (Ranks & Changes)	8	0.022	53	0.038	10	0.027	46
44	Ranks	2	0.069	36	0.031	24	0.053	8
45	Ranks	3	0.078	33	0.031	22	0.045	25
46	Ranks	4	0.115	19	0.030	25	0.048	12
47	Ranks	5	0.163	9	0.020	56	0.048	14
48	Ranks	6	0.048	42	***0.066***	***2***	0.053	7
49	Ranks	7	0.085	31	0.032	19	0.040	35
50	Ranks	8	0.036	46	0.025	43	0.031	44
51	Changes	2	0.002	70	0.021	54	0.016	64
52	Changes	3	***1.000***	***1***	0.007	72	0.007	72
53	Changes	4	0.017	59	0.020	57	0.019	56
54	Changes	5	n/a	n/a	0.018	61	0.017	62
55	Changes	6	0.016	60	***0.057***	***5***	0.034	42
56	Changes	7	***0.239***	***4***	0.023	50	***0.058***	***4***
57	Changes	8	0.008	65	0.034	15	0.027	45
58	Both (Ranks & Changes)	4 / 3 / 2	0.085	30	0.025	42	0.047	17
59	Both (Ranks & Changes)	5 / 4 / 3	0.088	28	0.024	45	0.039	36
60	Both (Ranks & Changes)	6 / 5 / 4	0.011	64	0.030	26	0.016	65
61	Both (Ranks & Changes)	7 / 6 / 5	0.104	24	0.028	37	0.045	24
62	Both (Ranks & Changes)	8 / 7 / 6	0.007	66	0.009	70	0.008	71
63	Ranks	4 / 3 / 2	0.085	29	0.030	29	0.054	6
64	Ranks	5 / 4 / 3	0.092	27	0.024	44	0.042	32
65	Ranks	6 / 5 / 4	0.013	62	***0.070***	***1***	0.041	34
66	Ranks	7 / 6 / 5	0.131	13	0.029	32	0.052	10
67	Ranks	8 / 7 / 6	0.006	68	0.016	65	0.010	69
68	Changes	4 / 3 / 2	***0.250***	***3***	0.008	71	0.009	70
69	Changes	5 / 4 / 3	0.026	51	0.026	40	0.026	47
70	Changes	6 / 5 / 4	0.012	63	0.012	69	0.012	68
71	Changes	7 / 6 / 5	0.026	50	0.024	46	0.024	51
72	Changes	8 / 7 / 6	0.006	69	0.031	23	0.013	67

Bolded capture rates are among top five by group

Table 3.10. Measures of Fit and Ranks

FULL MODELS

#	DV TYPE(S)	LVLS	Kendall's Value	Kendall's Rank	Shapiro-Wilk's Value	Shapiro-Wilk's Rank	Alignment Value	Alignment Rank
1	Both (Ranks & Changes)	2	0.352	43	0.969	39	891	44
2	Both (Ranks & Changes)	3	0.377	41	0.983	25	715	30
3	Both (Ranks & Changes)	4	0.437	31	0.989	14	763	35
4	Both (Ranks & Changes)	5	0.438	30	0.985	23	1055	56
5	Both (Ranks & Changes)	6	0.217	57	0.939	55	1033	54
6	Both (Ranks & Changes)	7	0.054	69	0.995	10	927	45
7	Both (Ranks & Changes)	8	0.235	56	0.987	19	751	32
8	Ranks	2	0.527	19	0.929	57	361	6
9	Ranks	3	0.573	16	0.965	42	365	7
10	Ranks	4	0.632	12	***0.998***	***2***	1025	53
11	Ranks	5	0.628	13	0.977	30	645	23
12	Ranks	6	0.352	43	***0.997***	***4***	995	49
13	Ranks	7	0.161	61	0.982	26	999	50
14	Ranks	8	0.388	39	0.961	43	823	41
15	Changes	2	0.177	60	0.996	8	1275	68
16	Changes	3	0.211	58	0.996	7	965	47
17	Changes	4	0.252	54	***0.998***	***3***	989	48
18	Changes	5	0.257	52	0.996	9	1327	70
19	Changes	6	0.079	67	0.951	50	999	50
20	Changes	7	0.041	71	***0.997***	***5***	949	46
21	Changes	8	0.080	66	0.987	16	1065	58
22	Both (Ranks & Changes)	4 / 3 / 2	0.401	36	0.974	36	735	31
23	Both (Ranks & Changes)	5 / 4 / 3	0.426	33	0.986	21	875	43
24	Both (Ranks & Changes)	6 / 5 / 4	0.297	47	0.987	18	595	20
25	Both (Ranks & Changes)	7 / 6 / 5	0.462	25	0.977	31	753	33
26	Both (Ranks & Changes)	8 / 7 / 6	0.455	27	0.992	12	1053	55
27	Ranks	4 / 3 / 2	0.603	15	0.957	45	***169***	***3***
28	Ranks	5 / 4 / 3	0.613	14	0.979	28	493	17
29	Ranks	6 / 5 / 4	0.431	32	0.987	17	629	22
30	Ranks	7 / 6 / 5	0.642	11	0.972	37	665	24
31	Ranks	8 / 7 / 6	0.650	10	0.987	15	757	34
32	Changes	4 / 3 / 2	0.189	59	0.984	24	1273	67
33	Changes	5 / 4 / 3	0.240	55	0.994	11	1225	65
34	Changes	6 / 5 / 4	0.087	65	0.968	40	775	37
35	Changes	7 / 6 / 5	0.306	46	***0.999***	***1***	1163	63
36	Changes	8 / 7 / 6	0.275	50	0.996	6	1357	71

Table 3.10. (continued)

PARSIMONIOUS MODELS

#	DV TYPE(S)	LVLS	Kendall's Value	Kendall's Rank	Shapiro-Wilk's Value	Shapiro-Wilk's Rank	Alignment Value	Alignment Rank
37	Both (Ranks & Changes)	2	***0.897***	***2***	0.850	70	509	18
38	Both (Ranks & Changes)	3	0.560	17	0.986	20	671	25
39	Both (Ranks & Changes)	4	0.466	24	0.957	46	1057	57
40	Both (Ranks & Changes)	5	0.460	26	0.968	41	765	36
41	Both (Ranks & Changes)	6	0.278	49	0.903	64	677	26
42	Both (Ranks & Changes)	7	0.358	42	0.979	29	705	29
43	Both (Ranks & Changes)	8	0.019	72	0.790	71	775	37
44	Ranks	2	***0.908***	***1***	0.893	66	381	9
45	Ranks	3	***0.839***	***3***	0.936	56	417	14
46	Ranks	4	0.725	6	0.958	44	387	11
47	Ranks	5	0.692	8	0.972	38	365	7
48	Ranks	6	0.552	18	0.873	69	411	12
49	Ranks	7	0.514	20	0.916	62	819	40
50	Ranks	8	0.421	34	0.736	72	1097	62
51	Changes	2	***0.774***	***4***	0.926	59	1271	66
52	Changes	3	0.474	23	0.953	47	1191	64
53	Changes	4	0.343	45	0.974	35	1373	72
54	Changes	5	0.292	48	0.980	27	1323	69
55	Changes	6	0.113	63	0.874	68	687	28
56	Changes	7	0.135	62	0.941	53	1015	52
57	Changes	8	0.057	68	0.883	67	791	39
58	Both (Ranks & Changes)	4 / 3 / 2	0.499	21	0.952	48	***167***	***2***
59	Both (Ranks & Changes)	5 / 4 / 3	0.449	29	0.947	52	679	27
60	Both (Ranks & Changes)	6 / 5 / 4	0.052	70	0.894	65	861	42
61	Both (Ranks & Changes)	7 / 6 / 5	0.450	28	0.976	33	581	19
62	Both (Ranks & Changes)	8 / 7 / 6	0.411	35	0.915	63	619	21
63	Ranks	4 / 3 / 2	***0.771***	***5***	0.941	54	***153***	***1***
64	Ranks	5 / 4 / 3	0.714	7	0.949	51	427	15
65	Ranks	6 / 5 / 4	0.385	40	0.951	49	479	16
66	Ranks	7 / 6 / 5	0.672	9	0.976	34	413	13
67	Ranks	8 / 7 / 6	0.498	22	0.929	58	381	9
68	Changes	4 / 3 / 2	0.395	37	0.977	32	1077	60
69	Changes	5 / 4 / 3	0.393	38	0.992	13	1079	61
70	Changes	6 / 5 / 4	0.098	64	0.924	60	***355***	***5***
71	Changes	7 / 6 / 5	0.272	51	0.986	22	1069	59
72	Changes	8 / 7 / 6	0.256	53	0.916	61	***273***	***4***

Bolded capture rates are among top five by group

Combined Ranking

There is no clear "winner" among these models; depending on which metric is applied, a different set of top models emerges. For example, Table 3.11 summarizes the top five models for each of five separate metrics considered above; of this group, only three models appear on more than one top-five table, and none show up on more than two tables' lists.

Finally, Table 3.12 presents a combined ranking of models based on four potentially critical model metrics: (1) Type-I and -II errors; (2) Odds ratio; (3) Kendall's Tau (as a measure of model "fit"; and (4) Shapiro-Wilk's measure of distribution normality. Because the four raw scores cannot be combined in any meaningful way, the ranks are used (thereby standardizing the result) and then summed. When the ranks for these four criteria are summed and themselves ranked, five models emerge as "best" overall using the combined scoring metrics, including (in order) Models 66, 31, 29, 47, and 63. Among the key findings from the combined rankings for these models were that:

- Capture rates for the top five ranged from a low of 53.5% to a high of 72.7%.
- None of the five best models used Changes as the dependent variable; four of the five *only* used ranks.
- Four of five used a mixed number of factor levels.
- None of the models was the best in any ranked category; most models never cracked the top five for more than one criterion.

Table 3.11. Top Five Scoring Models by Ranking Method and Ranks

CAPTURES #	DV TYPE(S)	LEVELS	300-450 #	300-450 Rank	450-600 #	450-600 Rank	300-600 #	300-600 Rank
50	Ranks	8	119	1	73	38	192	1
14	Ranks	8	60	22	119	6	179	2
59	Both (Ranks & Changes)	5 / 4 / 3	76	12	94	22	170	3
39	Both (Ranks & Changes)	4	49	32	120	4	169	4
33	Changes	5 / 4 / 3	27	43	141	1	168	5

ERROR RATES #	DV TYPE(S)	LEVELS	Type I #	Type I Percent	Type II #	Type II Percent	Average Accur	Rank
56	Changes	7	80	39.0%	518	41.1%	*59.9%*	*1*
48	Ranks	6	68	33.2%	593	47.1%	*59.9%*	*2*
27	Ranks	4 / 3 / 2	65	31.7%	612	48.6%	*59.9%*	*3*
66	Ranks	7 / 6 / 5	64	31.2%	620	49.2%	*59.8%*	*4*
63	Ranks	4 / 3 / 2	72	35.1%	574	45.6%	*59.7%*	*5*

ODDS RATIO #	DV TYPE(S)	LEVELS	300-450 Ratio	300-450 Rank	450-600 Ratio	450-600 Rank	300-600 Ratio	300-600 Rank
5	Both (Ranks & Changes)	6	0.118	17	0.066	3	0.084	1
22	Both (Ranks & Changes)	4 / 3 / 2	0.082	32	0.063	4	0.063	2
24	Both (Ranks & Changes)	6 / 5 / 4	0.221	5	0.036	11	0.059	3
56	Changes	7	0.239	4	0.023	50	0.058	4
29	Ranks	6 / 5 / 4	0.292	2	0.031	21	0.055	5

Table 3.11. (continued)

KENDALL'S TAU #	DV TYPE(S)	LEVELS	ESTIMATION Score	Rank	HOLDOUT Score	Rank	AVERAGE Score	Rank
37	Both (Ranks & Changes)	2	0.897	2	0.674	3	0.786	1
63	Ranks	4 / 3 / 2	0.771	5	0.734	1	0.753	2
45	Ranks	3	0.839	3	0.633	5	0.736	3
44	Ranks	2	0.908	1	0.539	16	0.724	4
46	Ranks	4	0.725	6	0.691	2	0.708	5

NORMALITY #	DV TYPE(S)	LEVELS	SHAPIRO-WILK's Score	Rank
35	Changes	7 / 6 / 5	0.999	1
10	Ranks	4	0.998	2
17	Changes	4	0.998	3
12	Ranks	6	0.997	4
20	Changes	7	0.997	5

ALIGNMENT #	DV TYPE(S)	LEVELS	DISTRIBUTION Score	Rank
63	Ranks	4 / 3 / 2	153	1
58	Both (Ranks & Changes)	4 / 3 / 2	167	2
27	Ranks	4 / 3 / 2	169	3
72	Changes	8 / 7 / 6	273	4
70	Changes	6 / 5 / 4	355	5

Table 3.12. Combined Ranks – Errors, Odds Ratio, Kendall's, and Shapiro-Wilk's

FULL MODELS

#	DV TYPE(S)	LVLS	Avg Acc Rank	O.R. Rank	K Tau Rank	S-W Rank	Total	Rank
1	Both (Ranks & Changes)	2	29	29	37	39	134	32
2	Both (Ranks & Changes)	3	23	22	36	25	109	23
3	Both (Ranks & Changes)	4	32	31	32	14	108	22
4	Both (Ranks & Changes)	5	36	27	31	23	101	18
5	Both (Ranks & Changes)	6	22	1	54	55	124	28
6	Both (Ranks & Changes)	7	63	59	69	10	192	58
7	Both (Ranks & Changes)	8	40	39	50	19	174	47
8	Ranks	2	9	19	17	57	109	23
9	Ranks	3	7	13	16	42	78	9
10	Ranks	4	56	53	13	2	138	35
11	Ranks	5	23	22	12	30	86	13
12	Ranks	6	30	18	42	4	86	13
13	Ranks	7	48	48	61	26	198	60
14	Ranks	8	39	41	38	43	160	42
15	Changes	2	57	54	60	8	192	58
16	Changes	3	52	52	58	7	174	47
17	Changes	4	67	66	59	3	186	51
18	Changes	5	59	60	55	9	169	45
19	Changes	6	42	11	66	50	145	38
20	Changes	7	61	58	71	5	187	52
21	Changes	8	49	50	67	16	199	62
22	Both (Ranks & Changes)	4 / 3 / 2	14	2	34	36	81	12
23	Both (Ranks & Changes)	5 / 4 / 3	35	33	33	21	124	28
24	Both (Ranks & Changes)	6 / 5 / 4	16	3	43	18	70	6
25	Both (Ranks & Changes)	7 / 6 / 5	37	40	30	31	139	36
26	Both (Ranks & Changes)	8 / 7 / 6	17	15	27	12	79	10
27	Ranks	4 / 3 / 2	3	9	15	45	73	7
28	Ranks	5 / 4 / 3	18	21	14	28	80	11
29	***Ranks***	***6 / 5 / 4***	***19***	***5***	***25***	***17***	***61***	***3***
30	Ranks	7 / 6 / 5	20	30	11	37	105	21
31	***Ranks***	***8 / 7 / 6***	***15***	***20***	***10***	***15***	***60***	***2***
32	Changes	4 / 3 / 2	50	63	57	24	189	54
33	Changes	5 / 4 / 3	51	49	56	11	163	43
34	Changes	6 / 5 / 4	44	43	64	40	203	64
35	Changes	7 / 6 / 5	60	61	52	1	154	41
36	Changes	8 / 7 / 6	58	55	53	6	176	49

Table 3.12. (continued)

PARSIMONIOUS MODELS

#	DV TYPE(S)	LVLS	Avg Acc Rank	O.R. Rank	K Tau Rank	S-W Rank	Total	Rank
37	Both (Ranks & Changes)	2	33	26	1	70	130	30
38	Both (Ranks & Changes)	3	55	57	22	20	133	31
39	Both (Ranks & Changes)	4	34	37	23	46	134	32
40	Both (Ranks & Changes)	5	13	16	24	41	100	17
41	Both (Ranks & Changes)	6	38	38	46	64	190	56
42	Both (Ranks & Changes)	7	28	28	39	29	134	32
43	Both (Ranks & Changes)	8	46	46	72	71	247	71
44	Ranks	2	6	8	4	66	86	13
45	Ranks	3	11	25	3	56	101	18
46	Ranks	4	10	12	5	44	73	7
47	***Ranks***	***5***	***12***	***14***	***7***	***38***	***67***	***4***
48	Ranks	6	2	7	19	69	98	16
49	Ranks	7	25	35	18	62	149	39
50	Ranks	8	43	44	26	72	189	54
51	Changes	2	54	64	9	59	170	46
52	Changes	3	71	72	51	47	202	63
53	Changes	4	68	56	45	35	198	60
54	Changes	5	62	62	47	27	185	50
55	Changes	6	41	42	63	68	212	66
56	Changes	7	1	4	62	53	121	27
57	Changes	8	45	45	65	67	246	69
58	Both (Ranks & Changes)	4 / 3 / 2	27	17	21	48	101	18
59	Both (Ranks & Changes)	5 / 4 / 3	31	36	29	52	144	37
60	Both (Ranks & Changes)	6 / 5 / 4	64	65	70	65	246	69
61	Both (Ranks & Changes)	7 / 6 / 5	8	24	28	33	110	25
62	Both (Ranks & Changes)	8 / 7 / 6	69	71	34	63	221	67
63	***Ranks***	***4 / 3 / 2***	***5***	***6***	***2***	***54***	***69***	***5***
64	Ranks	5 / 4 / 3	21	32	6	51	117	26
65	Ranks	6 / 5 / 4	26	34	40	49	150	40
66	***Ranks***	***7 / 6 / 5***	***4***	***10***	***8***	***34***	***54***	***1***
67	Ranks	8 / 7 / 6	70	69	20	58	207	65
68	Changes	4 / 3 / 2	65	70	41	32	187	52
69	Changes	5 / 4 / 3	47	47	44	13	167	44
70	Changes	6 / 5 / 4	72	68	68	60	264	72
71	Changes	7 / 6 / 5	53	51	48	22	191	57
72	Changes	8 / 7 / 6	66	67	49	61	236	68

Bolded measures of fit are among top five by category

Based on this combined ranking methodology, Model 66 is deemed the best of the models created. It achieves top 10 ratings for fewest Type I and Type II errors, odds ratio, and Kendall's tau, though relatively weak with respect to the normality of its scores distribution. The next section considers how well Model 66 performs in terms of assessing motor carriers' resilience.

Using the model identified as the best from among the 72 versions created, several conclusions can be drawn. Table 3.13 shows that model scores were significantly different across the five years examined, with 2000 having (by far) the lowest mean value, well below the forced five-year midpoint of 600, with a mean score of just 565.0.

When viewed in total, it is noteworthy that years 1999 and 2000 had substantially more carriers in the lowest two quartiles (55% and 60%, respectively), suggesting that there were many more weak carriers in those years (see Table 3.14). (Note that this outcome is consistent with the low mean score for 2000.) However, as carriers that disappeared during those earlier years were excluded from the dataset, it is not clear just how these lower scores were resolved. A weak economy in 2000 likely led to a substantial reduction in demand, and thus fewer ton-miles produced, resulting in much lower motor carrier revenues.

Table 3.15 shows that the period from 2001 to 2002 appears to be the most volatile, with a low of just 40% of carriers remaining in the same quartile year over year. In fact, for that year-pair, 38% of the motor carriers in the sample experienced a decline (by at least one quartile) or exited altogether. Just as 2001 appeared to be rebounding from the lows of 2000, September 11 disrupted the fourth quarter, increasing costs for insurance

Table 3.13. Model 66 – Descriptive Statistics of Scores (1999 to 2003)

	1999	2000	2001	2002	2003
Number of Motor Carriers	1,692	1,692	1,465	1,260	1,260
Mean Resilience Score	596.5	565.0	596.1	603.2	602.8
Standard Deviation	165.4	148.8	142.1	149.4	149.4
Median	590.9	552.3	592.9	600.4	601.4

and drivers, while adding to delays for further inspections and at border crossings. The net result was an increase in expenses, a slowing of revenues, and overall weaker results. (See Chapter 2 for further discussion of the 9/11 outcomes.) Because operating margins in the motor carrier industry are slim even in the best of economic conditions, disruption of this sort crippled numerous providers and resulted in hundreds of exits.

There was, however, a modicum of silver lining for those carriers that remained. As noted earlier, these findings are based on what was determined to be the best fitting model of the 72 created: Model 66. The model is based on the parsimonious set of independent variables, which are largely revenue based. This suggests that those motor carriers with steady, dependable streams of revenue are more resilient when faced with a significant environmental disruption, such as September 11, 2001.

Hypotheses Testing

The resilience model's ability to accurately predict motor carriers' potential for exiting is shown in Table 3.16, below. When looking forward one year (i.e., using 2000 scores to predict 2001 exits), the model correctly captures 158 (69.8%) of the motor carriers that

Table 3.14. Model 66 – Distribution of Scores by Year and Quartile (1999 to 2003)

	1999	2000	2001	2002	2003
Quartile 1 (300 – 450)	377 22.3%	425 25.1%	256 15.1%	211 14.4%	217 17.2%
Quartile 2 (450 – 600)	557 32.9%	597 35.3%	505 29.8%	410 28.0%	403 32.0%
Quartile 3 (600 – 750)	381 22.5%	418 24.7%	434 25.7%	414 28.3%	417 33.1%
Quartile 4 (750 – 900)	377 22.3%	252 14.9%	270 16.0%	225 15.4%	223 17.7%
Exits	0 0%	0 0%	227 13.4%	205 14.0%	0 0%
Total Motor Carriers	1,692	1,692	1,692	1,692	1,692

do exit in 2001 as having low scores (i.e., below 600), and 141 (68.8%) of those that exit in 2002, by determining scores that reside in the two lowest quartiles. But, 603 carriers in 2000 and 480 in 2001 are also scored in the bottom quartiles, despite not exiting, and thus are considered Type-II errors.

Looking forward two years (i.e., using 1999 scores to predict 2001 exits), the model still does fairly well, correctly capturing 151 exits (66.5% for 2001), and 141 exits (68.8%) for 2002.

In fact, this model appears to do somewhat better when a two-year scoring window is applied. Instead of looking at just the scores from one or two years prior to the target year, both were considered; if scores for either of these years were in the lower two

Table 3.15. Model 66 – Summary of Quartile Changes

	1999 - 2000	2000 - 2001	2001 - 2002	2002 - 2003
No Change	1,028	842	580	754
	60.8%	49.8%	39.6%	59.8
Decrease (Lower Quartile)	441	208	351	314
	26.1%	12.3%	24.0%	24.9%
Increase (Higher Quartile)	223	415	329	192
	13.2%	24.5%	22.5%	15.2%
Exits	0	227	205	0
	0%	13.4%	14.0%	0%
Total Motor Carriers	1,692	1,692	1,692	1,692

quartiles, this was considered to indicate a likelihood of exiting. Using this alternate methodology, accurately capturing the 2001 exits rose to 75.3%, and for 2002 to 80.0%.

These results provide support for hypotheses $\mathbf{H_8}$ and $\mathbf{H_9}$, which predicted that the model could accurately identify potential motor-carrier exits one and two years before they actually occurred. Type I errors were relatively low for both years and for both one- and two-year predictions, each representing about 30% of the actual exits for the year examined. But Type II errors were high, generally exceeding 40%, and especially for the two-year prediction model.

These results also do not support $\mathbf{H_{10}}$, which hypothesized that the resilience model would do a better job at identifying exits than the grand average of the previous prediction models from the Aziz & Dar review study (2006), due to acquiring specialization (motor carrier industry) and using a new approach. It should be noted,

Table 3.16. Model 66 – Source Quartiles by Exit Years

ONE-YEAR PREDICTION			TWO-YEAR PREDICTION		
	-- EXITING IN --			-- EXITING IN --	
FROM	2001	2002	FROM	2001	2002
Quartile 1	84	68	Quartile 1	75	66
Quartile 2	74	73	Quartile 2	76	75
Quartile 3	48	45	Quartile 3	45	41
Quartile 4	21	19	Quartile 4	31	23
TOTAL	227	205	TOTAL	227	205
Type I Errors	69	64	Type I Errors	76	64
	30.4%	31.2%		33.5%	31.2%
Type II Errors	603	480	Type II Errors	871	620
	41.2%	38.1%		59.5%	49.2%

however, that unlike many of the predecessor models which used matched samples of 50-50 results (half of the sample was known to fail, and half was known NOT to fail), this study's sample was not matched in any way, and includes roughly 25% failures total, and less than 15% for each of the two years in which they occurred. Although it cannot be determined precisely, it may be that many of the models that Aziz and Dar (2006) considered contained favorable (to scores) biases.

Table 3.17. Study 2 – Research Hypotheses' Results

	STATEMENT OF HYPOTHESIS	SUPPORT?
H $_8$	Motor carriers with higher resilience scores (i.e., above the midpoint) are ***less likely to exit*** the industry in the following year; conversely, motor carriers with lower resilience scores (i.e., below the midpoint) ***are more likely to exit*** the industry in the following year.	Supported
H $_9$	Motor carriers with higher resilience scores (i.e., above the midpoint) are ***less likely to exit*** the industry in the second year following a high score; conversely, motor carriers with lower resilience scores (i.e., below the midpoint) ***are more likely to exit*** the industry in the second year following a low score.	Supported
H $_{10}$	The motor carriers' resilience scoring model accuracy will outperform the grand mean accuracy of previous, generic prediction models (i.e., better than 85% accuracy).	Not Supported

Additional Findings

Beyond identification of the "best" model – or a set of "bests" – based on various criteria, several other findings emerge from this exploratory analysis. (See Table 3.18 for details of a correlation analysis.)

- **Levels**

  Generally speaking, the number of levels did not affect the quality of the model in terms of captures or error rates. However, the number of levels in the model *was* positively correlated with Kendall's Tau and was highly significant (at the .01 level); thus, overall the more levels a model had, the better the fit. The use of multilevel models, with different numbers of levels depending on the presumed importance of the attribute, versus a single-level model, was not significant.

- **Full versus Parsimonious models**

  Parsimonious models did not correlate with improved capture rates or reduced error rates, but did have a positive and significant correlation with Kendall's Tau for the estimating sample. Parsimonious models also had negative and highly significant correlations with both the Shapiro-Wilk's measure of distribution normality and the alignment score. It therefore appears that use of a parsimonious models is related to less distribution normality and more evenness of scores across quartiles.

- **Choice of Dependent Variables**

  Using ranks as the dependent variable in the conjoint analyses models substantially outperformed the alternatives (i.e., changes or both). Four of the five "best" models highlighted in Table 3.11 used ranks as the DV, while change-based models never even appeared on the list. The choice of a dependent variable had a negative and significant correlation with capture rates and Kendall's Tau, such that changes were less favorable with respect to both of these measures. Ranks had a positive and highly significant correlation with capture rates, Kendall's Tau, and the alignment score, while changes had a negative and highly significant correlation with the same variables. Not especially surprising, the use of both DVs appeared to balance this out, but was insignificant.

Finally, it should also be particularly noted that the six independent variables in Model 66 passed through this three-stage process and remained very significant in predicting outcomes, regardless of which was determined to be the best model. These six variables were: (1) Market Share, (2) Return on Sales, (3) Annual Growth Rate (AGR), (4) Change in Operating Revenue vs. Change in DOT's Travel Services Index (TSI), (5) Size (revenue $, transformed to a natural log), and (6) Operating Income. Given that all six are directly related to the motor carriers' operating revenues, it would seem that revenue measures are particularly significant metrics in this industry – apparently more so than profitability, debt, and other generally used financial measures (including operating ratio, the benchmark used among motor carriers – and therefore worthy of additional, in-depth study to perhaps discern why. (See Table 3.19)

Table 3.18. Correlation Analysis (for Scores 300-600)

		Captures	Kendall's Tau	Shapiro Wilks	Align Score	# of Levels	PARS Model	Multi-level	DV Ranks	DV Changes	DV Both
Captures	Correlation										
	Sig. (2-tailed)										
Kendall's Tau Estimating	Correlation	**.239 ***									
	Sig. (2-tailed)	**.043**									
Shapiro Wilk's score	Correlation	-.206	-.051								
	Sig. (2-tailed)	.082	.670								
Alignment Score	Correlation	-.015	**-.364 ****	**.290 ***							
	Sig. (2-tailed)	.900	**.002**	**.014**							
# of Levels	Correlation	.089	**-.427 *****	-.121	.097						
	Sig. (2-tailed)	.456	**.000**	.309	.416						
Parsimonious Model	Correlation	.035	**.233 ***	**-.536 ****	**-.312 ****	.000					
	Sig. (2-tailed)	.772	**.049**	**.000**	**.008**	1.000					
Multilevel Model	Correlation	-.094	.054	.178	-.223	**.267 ***	.000				
	Sig. (2-tailed)	.433	.652	.134	.059	**.023**	1.000				
Dependent Var (Ranks)	Correlation	**.387 ****	**.583 *****	-.129	**-.346 ****	.000	.000	.000			
	Sig. (2-tailed)	**.001**	**.000**	.281	**.003**	1.000	1.000	1.000			
Dependent Var (Changes)	Correlation	**-.458 *****	**-.512 ****	.159	**.372 ****	.000	.000	.000	**-.500 *****		
	Sig. (2-tailed)	**.000**	**.000**	.181	**.001**	1.000	1.000	1.000	**.000**		
Dependent Var (Both)	Correlation	.071	-.072	-.031	-.025	.000	.000	.000	**-.500 *****	**-.500 *****	
	Sig. (2-tailed)	.553	.550	.798	.832	1.000	1.000	1.000	**.000**	**.000**	

*** Correlation is significant at the 0.001 level (2-tailed)

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

NOT significant

Table 3.19. Model 66 – Importance Values

FACTOR #	FACTOR NAME	AVERAGE IMPORTANCE
X21	Market_Share	23.84
X19	lnSize	19.07
X41	Op_Income	18.19
X40	Change_in_Op_Revenue_vs_Change_in_TSI	15.19
X17	AGR	13.62
X07	Return_on_Sales	10.09

Conclusions

Application of the final resilience score model – that is, Model 66, determined to be "best" – resulted in performance predictions that were considerably better than chance. While exiting carriers represented approximately 14 percent of the carriers in the dataset for each of the years studied, the resilience score accurately identified almost 70 percent of the weaker (i.e., less resilient) firms for both the one- and two-year prediction horizons. These results therefore support both $\mathbf{H}_8$ and $\mathbf{H}_9$ that carriers with lower resiliency scores are more likely to exit one and two years from when the scores were examined, respectively.

Support for $\mathbf{H}_{10}$ that the resilience score model would outperform previous prediction models, in light of its unique methodology and specific focus on the motor carrier industry, was not supported. As shown, the models resulted in just under 70 percent prediction accuracy, a far cry from the average of 85 percent attained by other models (Aziz & Dar, 2006).

However, in addition to finding support for two of the three hypotheses, this study also provided initial evidence that conjoint analysis can be used in a broader array of research studies. Although conjoint has a long history of extensive use in the develop of preference and decision making models, it has not been applied to models where the dependent variable is objectively (rather than subjectively) determined. As such, this study effectively opens the door for conjoint analysis to be considered in a wide range of future research types.

It should also be noted that this research also identified and posed several unanswered questions regarding how the results from scoring and prediction models should be evaluated. As noted in the Results section, there are numerous evaluative criteria, each seemingly resulting in different “best” models. Almost no research has been found regarding what the scores’ distribution should be, perhaps because most studies merely identified one final model, whereas this study identified 72 models then sought to determine which was best, but by what measure. This lack of research suggests that it is possible a significant opportunity exists to perform further studies examining these outcomes.

There is no known analysis in the literature about distribution of outcomes from prediction models, nor is there any certainty that the 1,465 motor carriers are a truly representative set (i.e., that there is no built-in bias such that this sample set is atypical). Furthermore, the timeframe chosen for this analysis – 2001 and 2002 – was picked specifically because of the discontinuous events that took place in 2001, and thus could affect the distribution of scores.

CHAPTER 4

CONCLUDING REMARKS

Although environmental changes can occur in a variety of ways, this research specifically examines how firms coped with an unexpected, disruptive change – in this case, September 11, 2001 – and its effects on the motor carrier industry.

Logically, there are two fundamental responses that can occur: (1) Strategic change, meaning that the motor carrier changes its marketing strategy in order to better align itself with the changed environment; or (2) Remain strategically unchanged, and attempt to adjust to the disruption through course correction and subtle modifications (but not a strategic change). The latter approach depends upon the carrier's ability to withstand the unanticipated environmental change, hence requiring at least a basic understanding of its resilience capacity.

Coincidentally, and unexpected at the outset of this research, the finding that strategic change was often not the appropriate response to an environmental surprise – thereby increasing the importance of a firm's resilience measure – links these two studies in a way that was not initially anticipated. Unlike several previous studies in this domain, this research concluded that strategic change was often not the best – or an even an appropriate – response to surprise.

Study 1

Several conclusions emerge from Study 1's exploratory research. First, the results of this study show that strategic change – as an end in and of itself – is not an appropriate response to strategic surprise for firms such as those in this sample group. LTL motor carriers that changed their strategies following 9/11 were generally worse off afterwards than those that did not change. To be successful, strategic change must place the organization in the right post-event generic strategic: *changing strategy along the right trajectory is key.* The generic strategy that these motor carriers pursued prior to 9/11, or changed to after the strategic surprise, had a significant impact on their operating-ratio performance.

Second, while several previous studies have shown significant evidence of various inertia-sustaining – or change-inhibiting – organizational characteristics (such as age, size, past performance, and focus), this study provided little evidence that such factors affected motor carriers' strategic changes. Only one dimension – age – was meaningful; among this sample group of carriers, being relatively younger resulted in significantly greater likelihood of strategic change following the event. Either there are other characteristics of LTL carriers that influence the likelihood of strategic change, or the nature of the event itself is impactful (i.e., a quicker, unanticipated event leads to different results).

Third, the research suggests that, following a surprise event, Porter's cost-leadership – or low-cost – strategy was most likely to perform well for these motor carriers. Examining the nine possible strategic-group trajectories (three initial strategies times three target strategies), all exhibited increases in their average operating ratios following

9/11; but the three trajectories where cost leadership was the target strategy showed an increase that was not statistically significant. Overall, the cost-leadership strategy was the most resilient under these circumstances, indicating that – at least for LTL motor carriers in this sample – this generic strategy works best when this type of disruptive event takes place in the external environment. Perhaps more interestingly, the results also suggest that carriers can actually flee to this strategy – regardless of their current approach – in the aftermath of a surprise, resulting in better strategic alignment and performance consequences.

One unexamined factor is that the nature of the event may matter more than simply whether or not it occurred. For example, Corsi et al (1991) found that, in the wake of a disruptive event such as deregulation, Porter's differentiation strategy worked best for LTL motor carriers, while a cost-focused strategy was unsuccessful. But deregulation significantly affected pricing and competition, resulting in less revenue and poorer operating ratios. Conversely, according to this study's results, 9/11 had greater impact on motor carriers' expenses – revenues were much less affected – so a greater focus on costs was key to superior post-9/11 performance.

It should also be noted that a single discontinuous event can have different effects on different industries. Even within the transportation segment, the impact of 9/11 depended on the industry being examined. For example, following this event, air carriers experienced a dramatic decline in passenger miles resulting in a huge drop in sales; for the airline industry profits were impacted by the decline in revenues while expenses were less affected. As noted above, however, the impact of 9/11 on motor carriers seems quite different. Within the sample group of LTL carriers, revenues actually increased following the event; but expenses grew far more quickly, overwhelming revenue growth, and negatively affecting operating ratios. So the nature of the event – *and its direct impact on the specific industry* – appears very important.

Finally, the choice of a metric to determine carriers' financial and operating performance was unexpectedly inconsistent. As noted, operating ratios increased across all strategic groups, although the increases for the cost-leadership cohort were not significant. But operating incomes, despite some enormous declines (e.g., more than 60% for stuck-in-the-middle firms), were not statistically significant for any strategic group. Throughout our research we saw that operating income was very volatile in this industry segment. For example, over the five-year history of the 270 firms studied, we counted more than 200 occasions of 50% increases in operating income; and in more than a third of the year-over-year comparisons, operating income declined by more than 50%. Thus, it appears that volatility in this measure is expected and may evidence less cause for alarm among motor carriers.

Study 2

As a result of the first study, Study 2's resilience score model appears to be even more important; the results of this second study provide several additional conclusions. First, the resilience model enables motor carriers to self-assess their ability to withstand a disruptive event in the marketing environment, such as 9/11. The model was able to correctly capture nearly 70% of carriers that ultimately exited from the industry with low scores (less than 600) on a scale from 300 to 900. Thus, motor carriers with weaker scores are more likely to exit – though clearly not guaranteed to do so. (Note also, the two-year window was almost equally effective.)

Second, the model itself provided evidence of where carriers should focus their attention in a post-surprise environment. After following multiple steps in the evaluation process, six factors came through as most significant to carriers' resilience as evidenced by the superiority of Model 66; in order they were: (1) Market share, (2) logged Size (operating revenues), (3) Operating income, (4) Change in operating revenue vs. change in TSI (Transportation Services Index), (5) AGR (average growth rate – revenues), and (6) return on sales. These should be the metrics to which disrupted carriers pay most attention following an environmental surprise. Notable here, is that debt and operating costs were not primary factors, and were only considered in the calculations of operating income and return on sales.

Third, whether directed at companies that depend upon the trucking industry, or at the motor carriers themselves, several elements of this study demonstrate substantial financial and operational volatility. While conducting sensitivity analyses, and again when examining the results from applying the best model to the underlying dataset, wide fluctuations were apparent. As a result, two considerations emerge. First, motor carriers should expect, and plan accordingly for, wide swings in operating revenue and (especially) operating income, with the latter experiencing changes of as much as 100% year over year. And second, supply chain members that rely on carriers should be prepared for such variance and not panic as a result. As also noted in Study 1, the motor carrier industry appears to be very turbulent with respect to performance measures.

One final note, in some respects the results from Study 1 and Study 2 appear to be at odds with one another. While Study 1 suggest that motor carriers that adopted a low-cost strategy and focused on reducing costs were more likely to perform better following a surprise in the marketing environment, Study 2 suggests that resilient carriers should attend to revenues and find ways to maintain and even grow this aspect of their business. How can these two, seemingly contradictory conclusions be reconciled?

Certainly, costs are a major consideration. In Study 1, those motor carriers that focused on containing/managing costs were more likely were more likely to do better – or, as the study showed, less worse – than carriers that did not pursue this direction. But firms cannot save their way to success; reducing costs can improve margins or operating ratios, but ultimately carriers must generate sufficient revenues to remain viable. The more operating revenue, and the steadier that revenue, the more resilient the carriers are under volatile conditions.

Motor carriers can control costs in the aftermath of an environmental disturbance. As often occurs following a disruptive event, revenues tend to remain flat, while costs spike.

In the post-9/11 environment, costs grew much faster than revenues, so those carriers that managed their costs more effectively performed better.

In addition, however, the two studies looked at different portions of the motor carrier industry, from separate perspectives. Study 1 focused on LTL (less-than-truckload) carriers, which have significant fixed costs related to managing facilities, retaining permanent employees, and serving scheduled routes. Study 2 looked at a much broader assemblage of motor carriers – including, but not limited to, LTL firms, as well as truckload and specialty carriers. With many carriers dealing with fewer fixed expenses, it is reasonable to assume that, in general, these carriers are less affected by costs and must focus more on revenues to remain in business and operational.

Research Limitations

While this research is believed to be generalizable, there are notable limitations. Although the research domain of motor carriers has been used several times before with meaningful outcomes, it does represent a particular segment of one industry, which may not be representative of all markets and industries, the entire transportation field, or even all motor carriers. Study 1 examines the less-than-truckload (LTL) sector, which may not be representative of the entire trucking industry. Study 2 only considers larger (Class I and II) carriers, which may not be completely representative, either.

Also, while evidence strongly suggests that September 11, 2001, had a significant impact on multiple industries, including motor carriers, there is no way to determine whether 9/11 typifies the effects of a strategic surprise, or if in some unknown way the event was atypical. It is also unlikely that all industries were affected equally (as noted much earlier, the airline industry appears to have been affected quite differently), so motor carriers may not be typical.

Some researchers have even suggested that 9/11 was not truly a strategic surprise – unexpected and unprecedented – because intelligence should have recognized the potential for such an event. While politically and militarily this may be the case, it is unlikely that any motor carrier (or any firm in any industry, for that matter) could have anticipated or planned for such an event. Therefore, this research assumes that the 'surprise value' of 9/11 remains regardless of what has been said about the event with respect to military and government intelligence.

In Study 2, the resilience scores produced did not achieve the level of accuracy that was hypothesized for unknown reasons. Although focused on a single, sizable industry, and using detailed data, these results fell below expectations. The research methodology, in addition to the study domain, was unique and has not been used in comparable studies, so it is possible that while conjoint analysis does produce favorable results, the outcomes are less satisfactory than methods like MDA and logistic regression. Only further use of conjoint analysis in these different research applications will determine whether this is a limitation of the methodology or of the study itself.

Future Research

Several possible additional research directions emerge from each of these exploratory studies.

First, as noted repeatedly throughout Study 2, it appears that the nature and impact of a discontinuous environmental change has a significant impact on both the results and the proper choice of action. Further study of responses to a variety of types of events may help clarify what strategic choices are best suited to the differing circumstances.

Second, given the unexpectedness and suddenness of a strategic surprise, is a *faste*r response necessary? Or, since such an event is by definition without precedent, and therefore firms have neither predetermined guidelines nor familiar patterns to follow, is a patient, reflective, wait-and-see reaction more appropriate? (Note, this impact though described in the background was not able to be tested with the data currently available.)

It should also be acknowledged that Study 2 offers numerous other research opportunities of its own. First, the methodology and use of conjoint analysis are unique to this study, so refining the approach and applying it to other industries is an obvious extension. While noting that this study was a first, other studies using different data from other domains is appropriate. Varying the conditions and assumptions used in conjoint analysis is worth exploring further. Finally, considering the different options available for determination of what a distribution of model scores should look like and what constitutes the best model is definitely worth pursuing further.

REFERENCES

Achrol, R. S., & Stern, L. W. (1988). Environmental Determinants of Decision-Making: Uncertainty in Marketing Channels. *Journal of Marketing Research (JMR)*, *25*(1), 36-50.

Aldrich, H. (1979). *Organizations and Environments*. Englewood Cliffs, NJ: Prentice-Hall.

Aldrich, H., & Auster, E. R. (1986). Even Dwarfs Started Small: Liabilities of Age and Size and Their Strategic Implications. *Research in Organizational Behavior*, *8*, 165-198.

Altman, E. I. (1971). Railroad Bankruptcy Potential. *Journal of Finance*, *26*(2), 333-345.

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*, *23*(4), 589-609.

Altman, E. I., & Sabato, G. (2007). Modeling Credit Risk for SMEs: Evidence from the U.S. Market. *ABACUS*, *43*(3), 332-357.

Altman, E. I., & Saunders, A. (1998). Credit Risk Measurement: Development Over the Last 20 Years. *Journal of Banking & Finance*, *21*(11/12), 1721-1742.

Amburgey, T. L., Kelly, D., & Barnett, W. P. (1993). Resetting the Clock: The Dynamics of Organizational Change and Failure. *Administrative Science Quarterly, 38*(1), 51-73.

Ansoff, H. I. (1980). Strategic Issue Management. *Strategic Management Journal, 1*(2), 131-148.

Ansoff, H. I. (1975). Managing Strategic Surprise by Response to Weak Signals. *California Management Review, 18*(2), 21-33.

Anderson, P., & Tushman, M. L. (2001). Organizational Environments and Industry Exit: The Effects of Uncertainty, Munificence and Complexity. *Industrial and Corporate Change, 10*(3), 675-711.

Argyris, C. & Schon, D. (1974). *Theory in Practice*, San Francisco, CA: Jossey Bass.

Audia, P. G., Locke, E. A., & Smith, K. G. (2000). The Paradox of Success: An archival and a Laboratory Study of Strategic Persistence Following Radical Environmental Change. *Academy of Management Journal, 43*(5), 837-853.

Aziz, M. A., & Dar, H. A. (2006). Predicting Corporate Bankruptcy: Where We Stand? *Corporate Governance*, *6*(1), 18-29.

Bacharach, S. B., Bamberger, P., & Sonnenstuhl, W. J. (1996). The Organizational Transformation Process: The Micropolitics of Dissonance Reduction and the Alignment of Logics of Action. *Administrative Science Quarterly*, *41*(3), 477-506.

Balcaen, S., & Ooghe, H. (2006). 35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and Their Related Problems. *The British Accounting Review*, *38*, 63-89.

Barr, P. S. (1998). Adapting to Unfamiliar Environment Events: A Look at the Evolution of Interpretation and Its Role in Strategic Change, *Organizational Science*, *9*(6), 644-669.

Baum, J. R., & Wally, S. (2003). "Strategic Decision Speed and Firm Performance," *Strategic Management Journal*, *24*(8), 1107–1129.

Beaver, W. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research, 1966 Supplement*, *4*(3), 71-111.

Blunk, S. S., Clark, D. E., & McGibany, J. M. (2006). Evaluating the Long-Run Impacts of the 9/11 Terrorist Attacks on Domestic Airline Travel. *Applied Economics, 38*(4), 363-370.

Boeker, W. (1991). Organizational Strategy: An Ecological Perspective. *Academy of Management Journal, 34*(3), 613-635.

Boeker, W. (1989). Strategic Change: The Effects of Founding and History. *Academy of Management Journal, 32*(3), 489-515.

Bourgeois III, L. J. (1985). Strategic Goals, Pereceived Uncertainty, and Economic Performance in Volatile Environments. *Academy of Management Journal, 28*(3), 548-573.

Bourgeois III, L. J. (1980). Strategy and Environment: A Conceptual Integration. *Academy of Management Review, 5*(1), 25-39.

Bourgeois III, L. J., & Eisenhardt, K. M. (1988). Strategic Decision Processes in High Velocity Environments: Four Cases in the Minicomputer Industry. *Management Science, 34*(7), 816-835.

Bowman, E. & Kunreuther, H. (1988). Post-Bhopal Behaviour at a Chemical Company. *Journal of Management Studies*, *25*(4), 387-402.

Boyer, K. D. (1993). Deregulation of the Trucking Sector: Specialization, Concentration, Entry, and Financial Distress. *Southern Economic Journal, 59*(3), 481-495.

Bracken, P., Bremmer, I., & Gordon, D. (Eds). (2008). *Managing Strategic Surprise*. Cambridge, UK: Cambridge University Press.

Byman, D. (2005). Strategic Surprise and the September 11 Attacks. *Annual Review of Political Science, 8*(1), 145-170.

Carroll, G. R. (1997). Long-term Evolutionary Change in Organizational Populations: Theory, Models and Empirical Findings in Industrial Demography. *Industrial & Corporate Change, 6*(1), 119-143.

Carroll, G. R. (1984). Organizational Ecology. *Annual Review of Sociology, 10*, 71-93.

Chakravarthy, B. (1997). A New Strategy Framework to Cope with Turbulence. *Sloan Management Review, 38*(2), 69-82.

Chandler, A. D., Jr. (1962). *Strategy and Structure: Chapters in the History of the American Industrial Enetrprise*. Cambridge, MA: The MIT Press.

Chattopadyay, P., Glick, W., & Huber, G. (2001). Organizational Actions in Response to Threats and Opportunities. *Academy of Management Journal, 44*(5), 937-955.

Cheng, L. & Grimm, C. (2006). The Application of Empirical Strategic Management Research to Supply Chain Management. *Journal of Business Logistics*. *27*(1), 1-17.

Child, J. (1997). Strategic Choice in the Analysis of Action, Structure, Organizations and Environment: Retrospect and Prospect. *Organization Studies*, *18*(1), 43-76.

Child, J. (1974). Managerial and Organizational Factors Associated with Company Performance – Part I. *The Journal of Management Studies*, *11*(3), 175-189.

Child, J. (1972). Organizational Structure, Environment and Performance: The Role of Strategic Choice. *Sociology, 6*(1), 1-22.

Cool, K. O., & Schendel, D. (1987). Strategic Group Formation and Performance: The Case of the U.S. Pharmaceutical Industry, 1963-1982. *Management Science*, *33*(9), 1102-1124.

Corsi, T. M., & Infanger, G. B. (2004). *Motor Carrier Industry Profile Study: Financial and Operating Performance Profiles by Industry Segment, 2001-2002*. Washington, D.C.: U.S. Dept. of Transportation, Federal Motor Carrier Safety Administration, Office of Information Management.

Corsi, T. M., Grimm, C. M., & Feitler, J. N. (1992). The Impact of Deregulation on LTL Motor Carriers: Size, Structure, and Organization. *Transportation Journal*, *32*(2), 24-31.

Corsi, T. M., Grimm, C. M., Smith, K. G., & Smith, R. D. (1991). Deregulation, Strategic Change, and Firm Performance Among LTL Motor Carriers. *Transportation Journal, 31*(1), 4-13.

Corsi, T. M., & Stowers, J. R. (1991). Effects of a deregulated environment on motor carriers: A systematic, multi-segment analysis. *Transportation Journal, 30*(3), 4-28.

Coutu, D. (2002). How Resilience Works. *Harvard Business Review*, *80*(5), 46-55.

Cunha, M. P., Clegg, S. R., & Kamoche, K. (2006). Surprises in Management and Organization: Concept, Sources and a Typology. *British Journal of Management*, *17*(4), 317-329.

Cybinski, P. (2001). Description, Explanation, Prediction - The evolution of Bankruptcy Studies? *Managerial Finance, 27*(4), 29-44.

D'Aunno, T., Succi, M., & Alexander, J. A. (2000). The Role of Institutional and Market Forces in Divergent Organizational Change. *Administrative Science Quarterly*, *45*(4), 679-703.

DeSarbo, W. S., Di Benedetto C. A., Song, M., & Sinha, I. (2006). Revisiting the Miles and Snow Strategic Framework: Uncovering Interrelationships Between Strategic Types, Capabilities, Environmental Uncertainty, and Firm Performance. *Strategic Management Journal, 26*(1), 47-74.

Dess, G. G., & Davis, P.S. (1984). Porter's Generic Strategies as Determinants of Strategic Group Membership and Organizational Performance. *Academy of Management Journal, 27*(3), 467-488.

Donath, M., Murray, D., & Short, J. (2005). Homeland Security and the Trucking Industry. *American Transportation Research Institute (ATRI)*, Alexandria, VA.

Duncan, R. B. (1972). Characteristics of Organizational Environments and Perceived Environmental Uncertainty. *Administrative Science Quarterly, 17*(3), 313-327.

DRI•WEFA, Inc. (2002). Truck Transportation: Industry Yearbook 2002.

Eisenhardt, K. M. (1990). Speed and Strategic Choice: How Managers Accelerate Decision Making. *California Management Review, 32*(3), 39-54.

Eisenhardt, K. M. (1989). Making Fast Strategic Decisions in High-Velocity Environments. *Academy of Management Journal, 32*(3), 543-576.

Emery, F. B., & Trist, E. L. (1965). The Causal Texture of Evolution of Organizational Environments. *Human Relations, 18*(1), 21-32.

Esterhuyse, W. P. (2003). The Challenge of Transformation: Breaking the Barriers. South African Journal of Business Management, *34*(3), 1-8.

Feitler, J. N., Corsi, T. M., & Grimm, C. M. (1998). Strategic and Performance Changes Among LTL Motor Carriers: 1976-1993. *Transportation Journal, 37*(4), 5-12.

Feitler, J. N., Corsi, T. M., & Grimm, C. M. (1997). Measuring Firm Strategic Change in the Regulated and Deregulated Motor Carrier Industry: An 18-Year Evaluation. *Transportation Research E (Logistics and Transportation Review)*, *33*(3), 159-169.

Freeman, J., & Boeker, W. (1984). The Ecological Analysis of Business Strategy. *California Management Review*, *26*(3), 73-86.

Freeman, J., Carroll, G. R., & Hannan, M. T. (1983). The Liability of Newness: Age Dependence in Organizational Death Rates. *American Sociological Review*, *48*(5), 692-710.

Forbes, D. (2005). Managerial Determinants of Decision Speed in New Ventures. *Strategic Management Journal, 26*(4), 355–366.

Forte, M., Hoffman, J. J., Lamont, B. T., & Brockmann, E. N. (2000). Organizational Form and Environment: An Analysis of Between-Form and Within-Form Responses to Environmental Change. *Strategic Management Journal, 21*(7), 753-773.

Galbraith, J. R. (1973). *Designing Complex Organizations*. Reading, MA: Addison-Wesley.

Ginn, G. O. (1990). Strategic Change in Hospitals: An Examination of the Response of the Acute Care Hospital to the Turbulent Environment. *Health Services Research, 25*(4), 565-591.

Ginsberg, A. (1988). Measuring and Modelling Changes in Strategy: Theoretical Foundations and Empirical Directions. *Strategic Management Journal, 9*(6), 559-575.

Ginsberg, A., & Bucholtz, A. (1990). Converting to For-Profit Status: Corporate Responsiveness to Radical Change. *Academy of Management Journal*, *33*(3), 445-477.

Glazer, R., & Weiss, A. M. (1993) Marketing in Turbulent Environments: Decision Processes and the Time-Sensitivity of Information. *Journal of Marketing Research*, *30*(4), 509-521.

Graham, K. R., & Richards, M. D. (1979). Relative Performance Deterioration: Management and Strategic Change in Rail-Based Holding Companies. *Academy of Management Proceedings*, 108-112.

Gray, C. S. (2005). Transformation and Strategic Surprise. Strategic Studies Institute, retrieved December 28, 2006, from *www.carlisle.army.mil/ssi*.

Green, P. E., Krieger, A. M., & Wind, Y. (2001). Thirty Years of Conjoint Analysis: Reflections and Prospects. Interfaces, *31*(3), S56-S73.

Green, P. E., & Srinivasan, V. (1978). Conjoint Analysis in Consumer Research. Journal of Consumer Research, *5*(3), 103-123.

Green, P. E., & Srinivasan, V. (1978). Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice, Journal of Marketing, *54*(4), 3-18.

Gresov, C., Haveman, H. A., & Oliva, T. A. (1993). Organizational Design, Inertia, and the Dynamics of Competitive Response. *Organizational Science, 4*(2), 181-208.

Grewal, R., & Tansuhaj, P. (2001). Building Organizational Capabilities for Managing Economic Crisis: The Role of Market Orientation and Strategic Flexibility. *Journal of Marketing*, *65*(2), 67-80.

Grimm, C. M., Corsi, T. M. & Smith, R. D. (1993). Determinants of Strategic Change in the LTL Motor Carrier Industry: A Discrete Choice Analysis. *Transportation Journal, 32*(4), 56-62.

Hamel, G., & Valikangas, L. (2003). The Quest for Resilience. *Harvard Business Review*, *81*(9), 52-63.

Hannan, M. T., & Freeman, J. (1984). Structural Inertia and Organizational Change. *American Sociological Review, 49*(2), 149-164.

Hannan, M. T., & Freeman, J. (1977). The Population Ecology of Organizations. *American Journal of Sociology, 82*(5), 929–984.

Harmatuck, D. J. (1992). Motor Carrier Cost Function Comparisons. *Transportation Journal*, *31*(4), 31-46.

Harmatuck, D. J. (1984). The Effects of Economic Conditions and Regulatory Changes upon Motor Carrier Tonnage and Revenues. *Transportation Journal, 24*(2), 31-39.

Haveman, H. A. (1993). Organizational size and change: diversification in the savings and loan industry after deregulation. *Administrative Science Quarterly, 38*(1), 20-50.

Haveman, H. A. (1992). Between a Rock and a Hard Place: Organizational Change and Performance under Conditions of Fundamental Environmental Transformation. *Administrative Science Quarterly, 37*(1), 48-75.

Henderson, A. D. (1999). Firm Strategy and Age Dependence: A Contingent View of the Liabilities of Newness, Adolescence, and Obsolescence, *Administrative Science Quarterly, 44*(2), 281-315.

Hrebiniak, L. G., & Joyce, W. F. (1985). Organizational Adaptation: Strategic Choice and Environmental Determinism. *Administrative Science Quarterly*, *30*(3), 336-349.

Jaeger, S. R., Hedderley, D., & MacFie, H. J. H. (2000). Methodological Issues in Conjoint Analysis: A Case Study. *European Journal of Marketing*, *35*(11/12), 1217-1237.

Jennings, D. F., & Seaman, S. L. (1994). High and Low Levels of Organizational Adaptation: An Empirical Analysis of Strategy, Structure, and Performance. *Strategic Management Journal*, *15*(6), 459-475.

Judge, W. Q., & Miller, A. (1991). Antecedents and Outcomes of Decision Speed in Different Environmental Contexts. *Academy of Management Journal*, *34*(2), 449-463.

Keats, B. W., & Hitt, M. A. (1988). A Causal Model of Linkages Among Environmental Dimensions, Macro Organizational Characteristics, and Performance. *Academy of Management Journal*, *31*(3), 570-598.

Kelly, D., & Amburgey, T. L. (1991). Organizational Inertia and Momentum: A Dynamic Model of Strategic Change. *Academy of Management Journal, 34*(3), 591-612.

Kim, E., & McIntosh, J. C. (1996). The Faster the Better: An Empirical Study of the Speed of Strategic Change. *Journal of Applied Business Research, 12*(2), 35-40.

Kim, E., & McIntosh, J. C. (1999). Strategic Organizational Responses to Environmental Chaos. *Journal of Managerial Issues*, *11*(3), 344-362.

Kling, R. W. (1990). Deregulation and Structural Change in the LTL Motor Freight Industry. *Transportation Journal, 29*(3), 47-53.

Kotha, S., & Nair, A. (1995). Strategy and Environment as Determinants of Preformance: Evidence from the Japanese Machine Tool Industry. *Strategic Management Journal, 16*(7), 497-518.

Kraatz, M. S., & Zajac, E. J. (2001). How Organizational Resources Affect Strategic Change and Performance in Turbulent Environments: Theory and Evidence. *Organizational Science, 12*(5), 632-657.

Lampel, J. & Shapira, Z. (2001). Judgmental Errors, Interactive Norms, and the Difficulty of Detecting Strategic Surprises. *Organizational Science, 12*(5), 599-611.

Lancioni, R., et al. (2005). Supply Chain Security Study. *Temple University & CLM Delaware Valley* (unpublished presentation).

Lant, T. K., Milliken, F. J., & Batra, B. (1992). The Role of Managerial Learning and Interpretation in Strategic Persistence and Reorientation: An Empirical Exploration. *Strategic Management Journal, 13*(8), 585-608.

Lengnick-Hall, C. A., & Beck, T. E. (2005). Adaptive Fit Versus Robust Transformation: How Organizations Respond to Environmental Change. *Journal of Management*, *31*(5), 738-757.

Lenz, R. T., & Engledow, J. L. (1986). Environmental Analysis: The Applicability of Current Theory. *Strategic Management Journal, 7*(4), 329-346.

Lohrke, F. T., Holloway, B. B., & Wooley, T. W. (2010). Conjoint Analysis in Entrepreneurship Research: A Review and Research Agenda. *Organizational Research Methods*, *13*(1), 16-30.

Lukas, B. A., Tan, J. T., & Hult, G. T. M. (2001). "Strategic Fit in Transitional Economies: The Case of China's Electronics Industry. *Journal of Management*, *27*(#), 409-429.

Lukas, B. A. (1999). Strategic Type, Market Orientation, and the Balance Between Adaptability and Adaptation. *Journal of Business Research*, *45*(2), 147-156.

Manuj, I., & Mentzer, J. T. (2008). Global Supply Chain Risk Management. *Journal of Business Logistics*, 29(1), 133-155.

Mavondo, F. T. (1999). Environment and Strategy as Antecedents for Marketing Effectiveness and Organizational Performance. *Journal of Strategic Marketing* 7(4), 237-250.

McCann, J., Sefsky, J., & Lee, J. (2009). *People & Strategy*. 32(3), 45-51.

Mellahi, K., & Wilkinson, A. (2004). Organizational failure: A Critique of Recent Research and a Proposed Integrative Framework. *International Journal of Management Reviews, 5/6(*1), 21–41.

Meyer, A. D. (1990). Environmental Jolts and Industry Revolutions: Organizational Responses to Discontinuous Change. *Strategic Management Journal, 11*(4), 93-110.

Meyer, A. D. (1982). Adapting to Environmental Jolts. *Administrative Science Quarterly, 27*(4), 515-537.

Meyer, C. (2001). The Second Generation of Speed. *Harvard Business Review, 79*(4), 24-25.

Michael, S. C., & Kim, S. M. (2005). The Organizational Ecology of Retailing: A Historical Perspective. *Journal of Retailing, 81*(2), 113-123.

Miles, R. E., & Snow, C. C. (1978). *Organizational Strategy, Structure and Process*. New York, NY: McGraw-Hill.

Miller, D. (1988). Relating Porter's Business Strategies to Environment and Structure: Analysis and Performance Implications. *Academy of Management Journal, 31*(2), 280-308.

Miller, D. (1987). The Structural and Environmental Correlates of Business Strategy. *Strategic Management Journal, 8*(1), 55-76.

Mintzberg, H. (1978). Patterns in Strategy Formation. *Management Science, 24*(9), 934-948.

Muller, G. H., Steyn-Bruwer, B. W., & Hamman, W. D. (2009). Predicting Financial Distress of Companies Listed on the JSE – A Comparison of Techniques. *South African Journal of Business Management*, *40*(1), 21-32.

Natarajarathinam, M., Capar, I., & Arunachalam, N. (2009). Managing Supply Chains in Times of Crisis: A Review of the Literature and Insights. International Journal of Physical Distribution & Logistics Management, *39*(7), 535-555.

Newman, K. L. (2000). Organizational Transformations During Institutional Upheaval. *Academy of Management Review*, *25*(3), 602-619.

Nickerson, J. A., & Silverman, B. S. (2003). Why Firms Want to Organize Efficiently and What Keeps Them from Doing So: Inappropriate Governance, Performance, and Adaptation in a Deregulated Industry. *Administrative Science Quarterly*, *48*(3), 433-465.

Olson, E. M., Slater, S. F., & Hult, G. T. M. (2005). The Performance Implications of Fit Among Business Strategy, Marketing Organization Structure, and Strategic Behavior. *Journal of Marketing*, *69*(3), 49-65.

Ooghe, H., & De Pricker, S. (2008). Failure Processes and Causes of Company Bankruptcy: A Typology. *Management Decision*, *46*(2), 223-242.

Oster, S. (1982). Intraindustry Structure and the Ease of Strategic Change. *The Review of Economics and Statistics, 64*(3), 376-383.

Ottesen, G. G., & Grønhaug, K. (2004). Exploring the Dynamics of Market Orientation in Turbulent Markets, *European Journal of Marketing, 38*(8), 956-973.

Parnell, J. A. (1998). Performance's Influence on Strategic Change: A Longitudinal Assessment. *Scandinavian Journal of Management, 14*(1/2), 19-36.

Pearson, C. M., & Clair, J. A. (1998). Reframing Crisis Management. *Academy of Management Review*, *23*(1), 59-76.

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring Supply Chain Resilience: Development of a Conceptual Framework. *Journal of Business Logistics*, *31*(1), 1-20.

Piesse, J., & Wood, D. (1992). Issues in Assessing MDA Models of Corporate Failure: A Research Note. *British Accounting Review*, *24*, 33-42.

Platt, H. D. & Platt, M.B. (2002). Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias. *Journal of Economics and Finance*, *26*(2), 184-199.

Platt, H. D. & Platt, M.B. (1990). Development of a Class of Stable Predictive Variables: The Case of Bankruptcy Prediction. *Journal of Business Finance & Accounting*, *17*(1), 31-51.

Platt, H. D., Platt, M.B., & Pedersen, J. G. (1994). Bankruptcy Discrimination with Real Variables. *Journal of Business Finance & Accounting*. *21*(4), 491-510.

Pollard, D., & Hotho, S. (2006). Crises, Scenarios and the Strategic Management Process, *Management Decision, 44*(6), 721-736.

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the Concept of Supply Chain Resilience. *The International Journal of Logistics Management*, *20*(1), 124-143.

Porter, M. E. (1985). *Competitive Advantage: Creating and Sustaining Superior Performance*. New York: The Free Press.

Porter, M. E. (1980). *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. New York: The Free Press.

Prescott, J. E. (1988). Environments as Moderators of the Relationship Between Strategy and Performance. *Academy of Management Journal, 29*(2), 329-346.

Rajagopalan, N., & Spreitzer, G. M. (1996). Toward a Theory of Strategic Change: A Multi-Lens Perspective and Integrative Framework. *Academy of Management Journal, 22*(1), 48-79.

Rakowski, J. P. (1988). Marketing Economies and the Results of Trucking Deregulation in the Less-Than-Truckload Sector. *Transportation Journal, 27*(3), 11-22.

Rakowski, J. P. (1977). Motor Carrier Size and Profitability. *Transportation Journal, 16*(4), 36-45.

Rao, S., & Goldsby, T. (2009). Supply Chain Risks: A Review and Typology. *The International Journal of Logistics Management*, *20*(1), 97-123.

Reidenbach, R. E., & Oliva, T. A. (1981). General Living Systems Theory and Marketing. *Journal of Marketing, 45*(4), 30-37.

Romanelli, E., & Tushman, M. L. (1994). Organization Transformation as Punctuated Equilibrium: An Empirical Test. *Academy of Management Journal, 37*(5), 1141-1166.

Schendel, D. E., & Patton, G. R. (1976). Corporate Turnaround Strategies: A Study of Profit Decline and Recovery. *Journal of General Management*, *3*(3), 3-11.

Sheffi, Y., & Rice, J. B., Jr. (2005). A Supply Chain View of the Resilient Enterprise. *MIT Sloan Management Review*, *47*(1), 41-48.

Silverman, B. S., Nickerson, J. A., & Freeman, J. (1997). Profitability, Transactional Alignment, and Organizational Mortality in the U.S. Trucking Industry. *Strategic Management Journal*, *18*(6), 31-52.

Singh, J. V., & Lumsden, C. J. (1990). Organizational Change and Organizational Mortality. *Annual Review of Sociology*, *16*, 161-195.

Singh, J. V., House, R. J., & Tucker, D. J. (1986). Organizational Change and Organizational Mortality. *Administrative Science Quarterly*, *31*(4), 587-611.

Slater, S. F., & Narver, J. C. (1994). Does Competitive Environment Moderate the Market Orientation-Performance Relationship? *Journal of Marketing, 58*(1), 46-55.

Smart, C., & Vertinsky, I. (1984). Strategy and the Environment: A Study of Corporate Responses to Crises. *Strategic Management Journal, 5*(3), 199-213.

Smith, K. G., & Grimm, C. M. (1987). Environmental Variation, Strategic Change, and Firm Performance: A Study of Railroad Deregulation. *Strategic Management Journal, 8*(Special Issue), 363-376.

Somers, S. (2009). Measuring Resilience Potential: An Adaptive Strategy for Organizing Crisis Planning. *Journal of Contingencies and Crisis Management*, *17*(1), 12-23.

Stoeberl, P. A., Parker, G. E., & Seong-Jong, J. (1998). Relationship between organizational change and failure in the wine industry: An event history analysis. *Journal of Management Studies*, *35*(4), 537-556.

Stonebraker, P. W., & Liao, J. (2004). Environmental Turbulence, Strategic Orientation: Modeling Supply Chain Integration. *International Journal of Operations & Production Management, 24*(10), 1037-1054.

Suarez, F. F., & Oliva, R. (2005). Environmental Change and Organization Transformation. *Industrial and Corporate Change*, *14*(6), 1017-1041.

Supply Chain Vulnerability: Executive Report (2002). Cranfield University School of Management.

Sutcliffe, K. M., & Zaheer, A. (1998). Uncertainty in the Transaction Environment: An Empirical Test. *Strategic Management Journal, 19*(1), 1-23.

Taffler. R. J. (1982). Forecasting Company Failure in the UK Using Discriminant Analysis and Financial Ratio Data. *Journal of Royal Statistical Society: Series A*, *145*(3), 342-358.

Timmermans, H. J. P., & Molin, E. J. E. (2009). Dealing with Increased Complexity in Conjoint Experiments: Background and Overview of Alternate Approaches. Transport Review, *29*(5), 557-567.

Tushman, M. L., Newman, W. H., & Romanelli, E. (1986). Convergence and Upheaval: Managing the Unsteady Pace of Organizational Evolution. *California Management Review, 29*(1), 29-44.

Venkatraman, N., & Prescott, J. E. (1990). Environment-Strategy Coalignment: An Empirical Test of its Performance Implications. *Strategic Management Journal, 11*(1), 1-23.

Vicente-Lorente, J. D., & Zúniga-Vicente, J. Á. (2006). Testing the time-variancy of explanatory factors of strategic change. *British Journal of Management, 17*(2), 93-114.

Wholey, D. R., & Brittain, J. W. (1989). Characterizing Environmental Variation. *Academy of Management Journal, 32*(4), 867-882.

Winter, S. G. (2004). Specialised Perception, Selection, and Strategic Surprise: Learning from the Moths and Bees. *Long Range Planning*, *37*(2), 163-169.

Wirtz, J. J. (2006). Responding to Surprise. *Annual Review of Political Science, 9*(1), 45-65.

Wischnevsky, J. D. (2004). Change as the Winds Change: The Impact of Organizational Transformation on Firm Survival in a Shifting Environment. *Organizational Analysis, 12*(4), 361-377.

Zajac, E. J., Kraatz, M. S. & Bresser, R. K. F. (2000). Modeling the Dynamics of Strategic Fit: A Normative Approach to Startegic Change. *Strategic Management Journal, 21*(4), 429-453.

Zajac, E. J., & Kraatz, M. S. (1993). A Diametric Forces Model of Strategic Change: Assessing the Antecedents and Consequences of Restructuring in the Higher Education Industry. *Strategic Management Journal, 14*(2), 83-102.

Zajac, E. J., & Shortell, S. M. (1989). Changing Generic Strategies: Likelihood, Direction, and Performance Implications. *Strategic Management Journal, 10*(4), 413-430.

Zazo, J. I. G., & Zúñiga-Vicente, J. A. (2005). Resources and Strategic Change in an UnsTABLE 1.Industry: The Case of Spanish Private Banking. *European Business Journal, 15*(2), 79-93.

Zingales, L. (1998). Survival of the Fittest or the Fattest? Exit and Financing in the Trucking Industry. *The Journal of Finance*, 53(2), 905-938.

Zúñiga-Vicente, J. Á., & Vicente-Lorente, J. D. (2006). Testing the Time-Variancy of Explanatory Factors of Strategic Change. *British Journal of Management, 17*(2), 93-114.

Zúñiga-Vicente, J. Á., de la Fuente-Sabaté, J. M., & Sua´rez-González, I. (2005). Facilitating and Inhibiting Factors Behind Strategic Change: Evidence in the Spanish Private Banking Industry, 1983–1997. *Scandinavian Journal of Management, 21*(3), 235–265.

APPENDIX A
STRATEGIC CHANGE EMPIRICAL RESEARCH (1982 THROUGH 2006)

	Author(s)	Year	Domain	Environmental Focus	Key Findings
1)	Ambergey et al.	1993	Newspapers	General environment	Organizational change increases hazard of subsequent failure and likelihood of further changes.
2)	Audia et al.	2000	Air carriers & Motor carriers	Deregulation	Better past performance, before radical change, leads to greater *strategic persistence* (i.e., less likelihood of change).
3)	Bacharach et al.	1996	Air carriers	Deregulation	Dramatic environmental changes lead to significant organizational transformation.
4)	Barr	1998	Pharmaceuticals	General environment	Interpretation of unfamiliar environmental changes occurs differently than interpretation of more familiar changes.
5)	Corsi et al.	1992	Motor carriers	Deregulation	Motor carrier management changes due to deregulation and characteristics of the new management team impact performance.
6)	Corsi et al.	1991	Motor carriers	Deregulation	Deregulation and poorer prior performance lead to greater likelihood of strategic change.

	Author(s)	Year	Domain	Environmental Focus	Key Findings
7)	D' Aunno et al	2000	Hospitals	General environment	Direction and likelihood of strategic change depends on market and institutional forces.
8)	Feitler et al.	1998	Motor carriers	Deregulation	Strategic change is positively linked to improved performance; poor prior performance, firm size and age lead to higher likelihood of strategic change.
9)	Feitler et al.	1997	Motor carriers	Deregulation	Strategic change is influenced by external and internal variables; external factors have negative impact, while industry turbulence, deregulation, firm age, and inertia have positive effects.
10)	Forte et al.	2000	Hospitals	Policy & regulation	Firms whose strategy is poorly aligned with a new environmental context transform themselves, but type and trajectory of change matters, and performance does not always improve.
11)	Ginn	1990	Hospitals	Policy & regulation	Strategic change occurs as turbulent environment changes; of several possible strategic factors, *only* prior strategy is predictor of strategic change.
12)	Ginsberg & Buchholtz	1990	HMOs	Policy & regulation	Several variables *jointly* affect likelihood of strategic change; support for contingent strategy model.

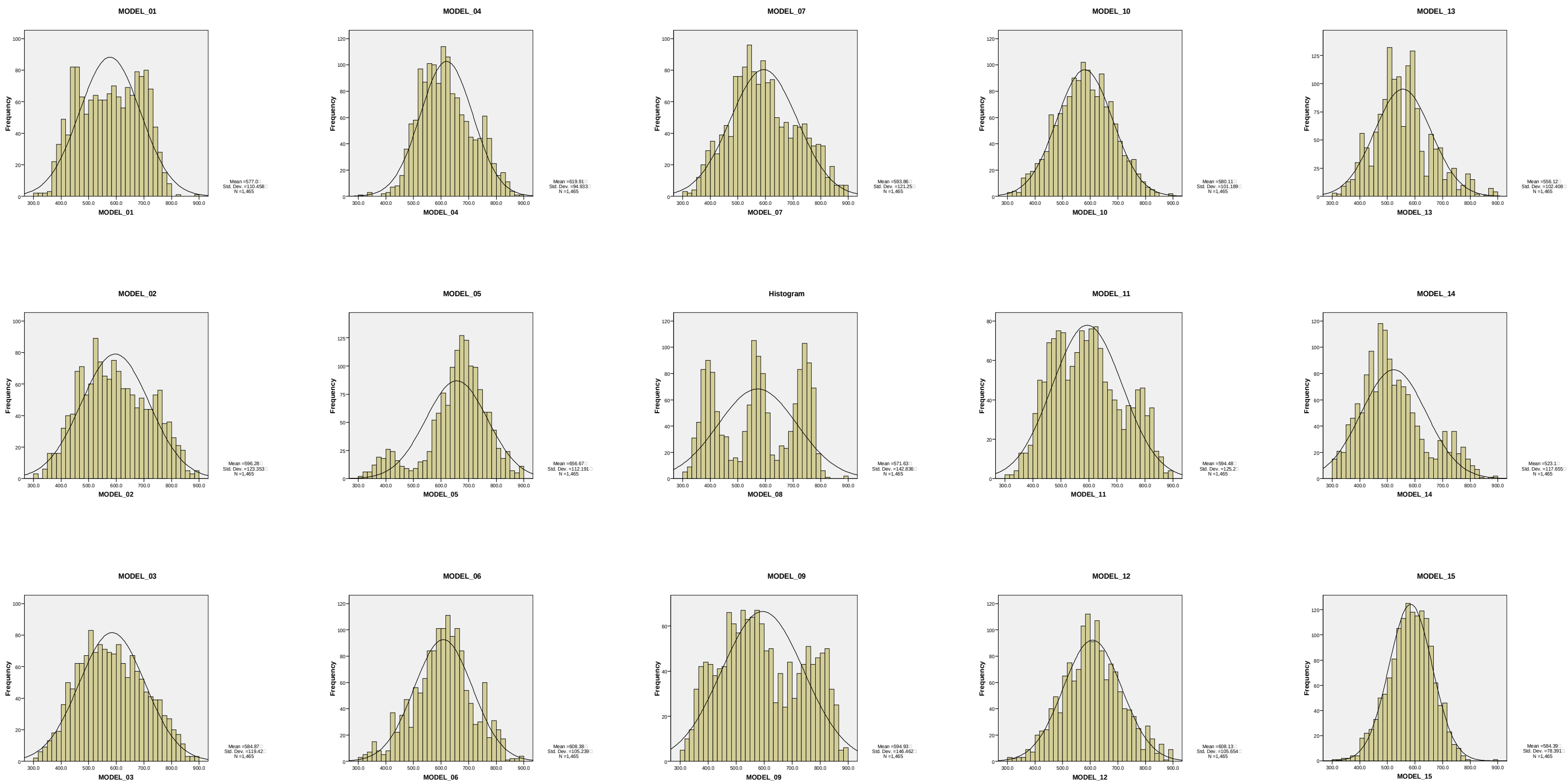
	Author(s)	Year	Domain	Environmental Focus	Key Findings
13)	Grimm et al.	1992	Motor carriers	Deregulation	Firm size and prior strategy affect firms' likelihood to change; prior financial performance, however, does not.
14)	Haveman	1993	Savings & loans	Policy & regulation	Strategic change survival in response to dramatic environmental change benefits both organization performance and likelihood of survival.
15)	Haveman	1992	Savings & loans	Policy & regulation	Support found for an inverted-U shaped relationship between size and change; larger firms are more likely to change than smaller, but this relationship reverses sign for very large firms.
16)	Kelly & Amburgey	1991	Air carriers	Deregulation	Discontinuous environmental change is not associated with increased probability of organizational change; change is unrelated to organization's chances of survival.
17)	Kim & McIntosh	1999	Motor carriers	Deregulation	In chaotic environments, there are different performance implications for different generic strategies.
18)	Kim & McIntosh	1996	Motor carriers	Deregulation	In highly uncertain environments, faster change does not necessarily improve firms' performance or survival.

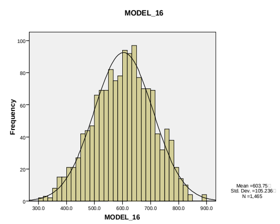
	Author(s)	Year	Domain	Environmental Focus	Key Findings
19)	Kraatz & Zajac	2001	Colleges / Higher education	General environment	Organizations possessing valuable, distinctive resources are less inclined to change strategies in response to environmental change; but this disinclination does not negatively affect organizational performance.
20)	Lant et al.	1992	Computer software & Furniture	General environment	Poor past performance (among other factors) increases the likelihood of strategic change, especially in more stable environments.
21)	Meyer	1982	Hospitals	Policy & regulation	A sudden, unprecedented environmental change (a "jolt") can be responded to adaptively.
22)	Nickerson & Silverman	2003	Motor carriers	Deregulation	Misaligned firms underperform relative to better-aligned rivals; but firms that adapt *too* quickly ultimately exit, versus those that change more deliberately and survive.
23)	Parnell	1998	Department stores	General environment	Poorer performing firms are more likely than top performers to change their strategies.
24)	Romanelli & Tushman	1984	Minicomputers	Economic turbulence	Support for "punctuated equilibrium" model of sudden strategic change.

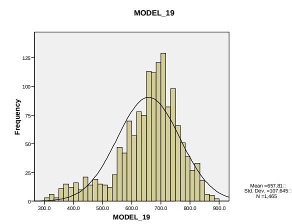
	Author(s)	Year	Domain	Environmental Focus	Key Findings
25)	Ruef	1997	Hospitals	General environment	Limited performance advantages gained from adaptation within volatile environments; adaptivity increases with size, but decreases with age and scope of organization's service portfolio.
26)	Silverman et al.	1997	Motor carriers	Deregulation	Several industry- and firm-level factors affect carriers' mortality in a deregulated environment, including density, size, profitability, and age.
27)	Smith & Grimm	1987	Railroads	Deregulation	Most firms change strategy in response to environmental change; those that change out-perform those that do not.
28)	Suarez & Oliva	2005	Latin America	Economic turbulence	Profound economic reforms – i.e., "avalanche changes" – result in abrupt internal transformations as means of adapting to changes.
29)	Wischnevsky	2004	Banking	Deregulation	Strategic transformation (change) does not negatively affect firm survival; firms that wait longer (due to inertia) are more likely to fail.
30)	Zajac & Kraatz	1993	Higher education	General environment	Strategic change is "predictable 1.and common, and performance-enhancing response" to environmental changes.

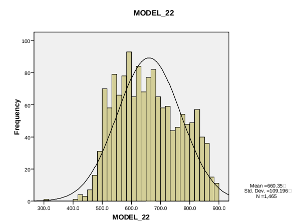
	Author(s)	Year	Domain	Environmental Focus	Key Findings
31)	Zajac & Shortell	1989	Hospitals	Policy & regulation	Changes in generic strategy are not uncommon; not all strategies are equally viable across time and in different environments.
32)	Zúniga-Vicente et al.	2004	Spanish banks	Economic turbulence	Banks change their competitive strategies in response to environmental changes, though changes can vary based on type of environment.
33)	Zúniga-Vicente & Vicente-Loronte	2006	Spanish banks	Economic crisis	Strategic change has a significant and positive impact on firms' survival odds.

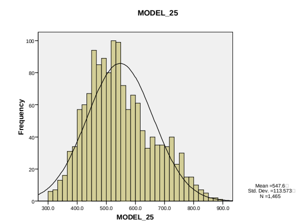
APPENDIX B
HISTOGRAMS OF RESILIENCE MODELS' SCORES

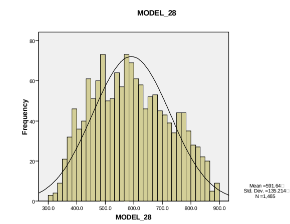


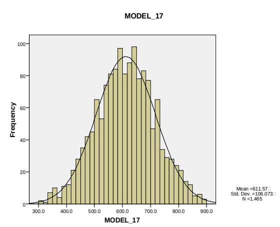

MODEL_16
Frequency
MODEL_16
Mean =603.75
Std. Dev. =105.236
N =1,465

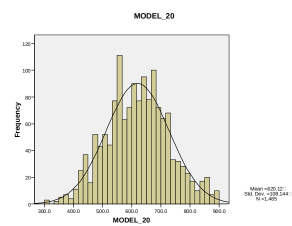

MODEL_19
Frequency
MODEL_19
Mean =657.81
Std. Dev. =107.645
N =1,465

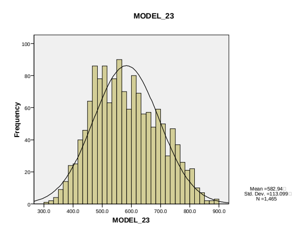

MODEL_22
Frequency
MODEL_22
Mean =660.35
Std. Dev. =109.196
N =1,465

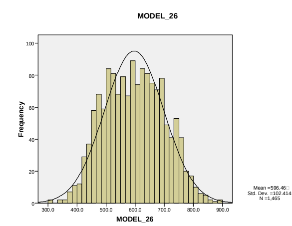

MODEL_25
Frequency
MODEL_25
Mean =547.6
Std. Dev. =113.573
N =1,465

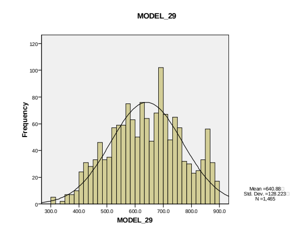

MODEL_28
Frequency
MODEL_28
Mean =591.64
Std. Dev. =135.214
N =1,465

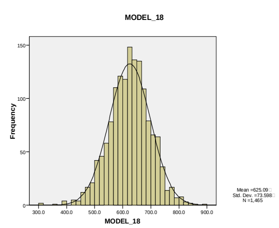

MODEL_17
Frequency
MODEL_17
Mean =611.57
Std. Dev. =106.073
N =1,465

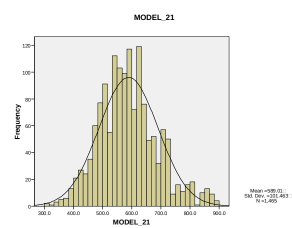

MODEL_20
Frequency
MODEL_20
Mean =620.12
Std. Dev. =108.144
N =1,465

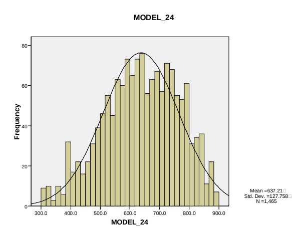

MODEL_23
Frequency
MODEL_23
Mean =582.94
Std. Dev. =113.099
N =1,465

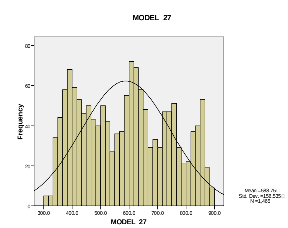

MODEL_26
Frequency
MODEL_26
Mean =596.46
Std. Dev. =102.414
N =1,465

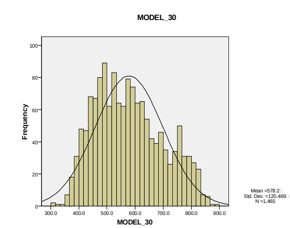

MODEL_29
Frequency
MODEL_29
Mean =640.88
Std. Dev. =128.223
N =1,465

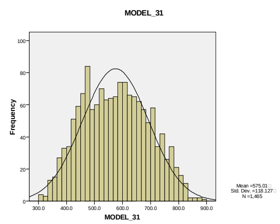

MODEL_18
Frequency
MODEL_18
Mean =625.09
Std. Dev. =73.598
N =1,465

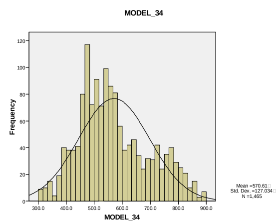

MODEL_21
Frequency
MODEL_21
Mean =589.01
Std. Dev. =101.463
N =1,465

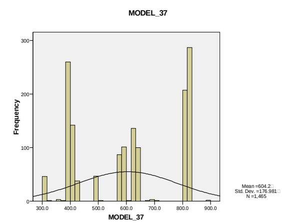

MODEL_24
Frequency
MODEL_24
Mean =637.21
Std. Dev. =127.758
N =1,465

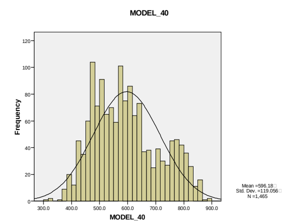

MODEL_27
Frequency
MODEL_27
Mean =588.75
Std. Dev. =156.535
N =1,465

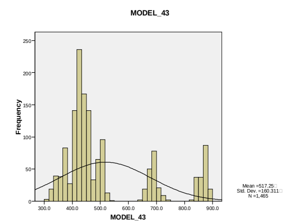

MODEL_30
Frequency
MODEL_30
Mean =578.2
Std. Dev. =120.469
N =1,465

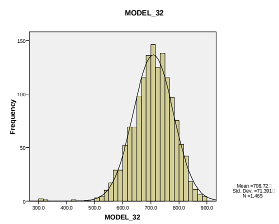

MODEL_31
Frequency
MODEL_31

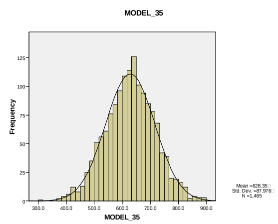

MODEL_34
Frequency
MODEL_34

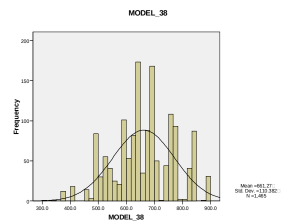

MODEL_37
Frequency
MODEL_37

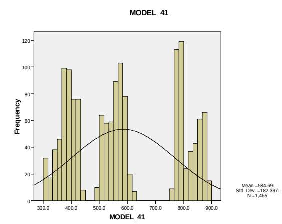

MODEL_40
Frequency
MODEL_40

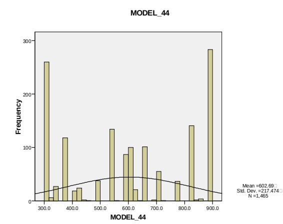

MODEL_43
Frequency
MODEL_43

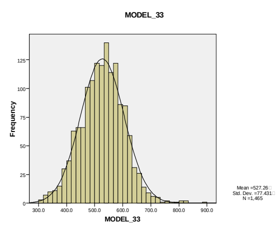

MODEL_32
Frequency
MODEL_32

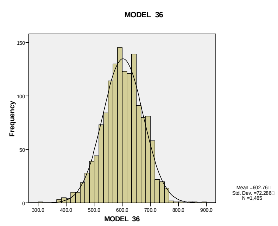

MODEL_35
Frequency
MODEL_35

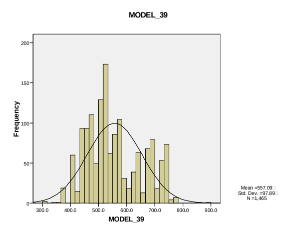

MODEL_38
Frequency
MODEL_38

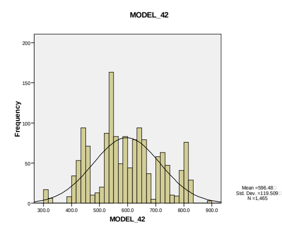

MODEL_41
Frequency
MODEL_41

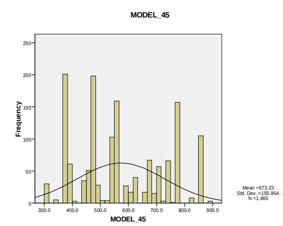

MODEL_44
Frequency
MODEL_44

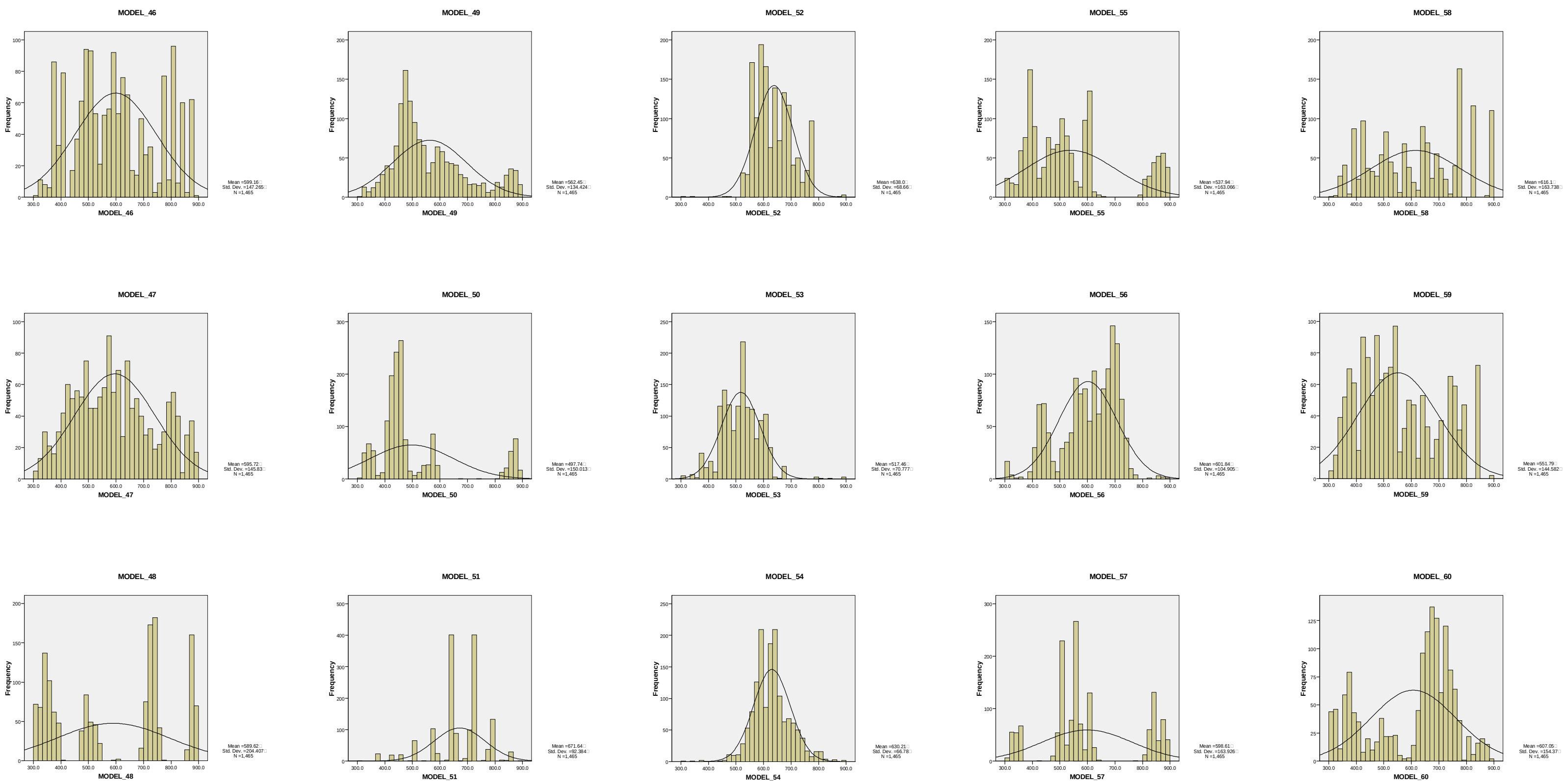

MODEL_33
Frequency
MODEL_33

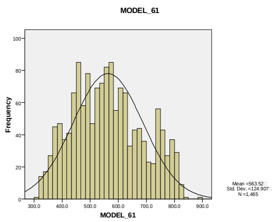

MODEL_36
Frequency
MODEL_36

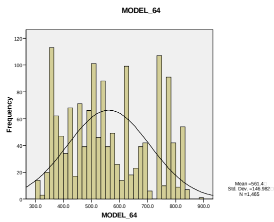

MODEL_39
Frequency
MODEL_39

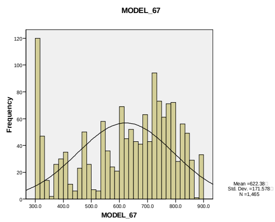

MODEL_42
Frequency
MODEL_42

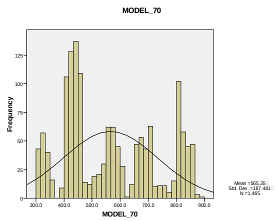

MODEL_45
Frequency
MODEL_45

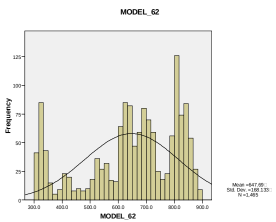

MODEL_46
MODEL_49
MODEL_52
MODEL_55
MODEL_58
MODEL_47
MODEL_50
MODEL_53
MODEL_56
MODEL_59
MODEL_48
MODEL_51
MODEL_54
MODEL_57
MODEL_60
Frequency

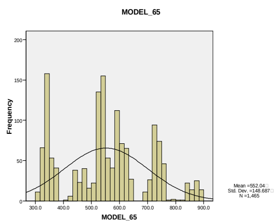

MODEL_61
Frequency
MODEL_61
Mean =563.52
Std. Dev. =124.907
N =1,465

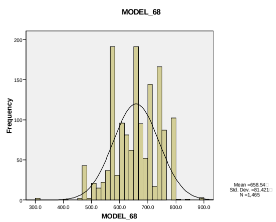

MODEL_64
Frequency
MODEL_64
Mean =561.4
Std. Dev. =146.982
N =1,465

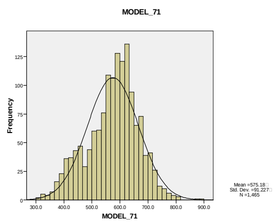

MODEL_67
Frequency
MODEL_67
Mean =622.38
Std. Dev. =171.578
N =1,465

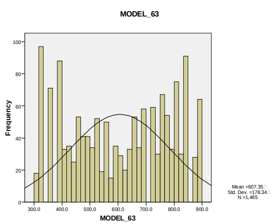

MODEL_70
Frequency
MODEL_70
Mean =565.35
Std. Dev. =167.481
N =1,465

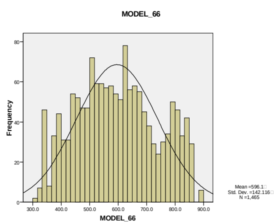

MODEL_62
Frequency
MODEL_62
Mean =647.69
Std. Dev. =168.133
N =1,465

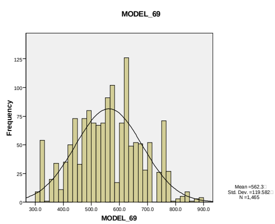

MODEL_65
Frequency
MODEL_65
Mean =552.04
Std. Dev. =148.687
N =1,465

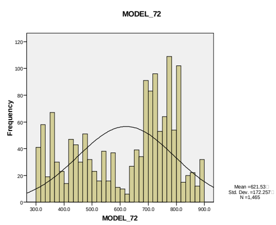

MODEL_68
Frequency
MODEL_68
Mean =658.54
Std. Dev. =81.421
N =1,465


MODEL_71
Frequency
MODEL_71
Mean =575.18
Std. Dev. =91.227
N =1,465


MODEL_63
Frequency
MODEL_63
Mean =607.35
Std. Dev. =178.34
N =1,465


MODEL_66
Frequency
MODEL_66
Mean =596.1
Std. Dev. =142.116
N =1,465


MODEL_69
Frequency
MODEL_69
Mean =562.3
Std. Dev. =119.582
N =1,465


MODEL_72
Frequency
MODEL_72
Mean =621.53
Std. Dev. =172.257
N =1,465